Board of Governors of the Federal Reserve System

Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit

Submitted to the Congress pursuant to section 215 of
the Fair and Accurate Credit Transactions Act of 2003

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EXECUTIVE SUMMARY

Credit scoring is a statistical technology that quantifies the credit risk posed by a prospective or current borrower. The technique is widely used to evaluate applications for credit, identify prospective borrowers, and manage existing credit accounts. The large savings in cost and time that have accompanied the use of credit scoring are generally believed to have increased access to credit, promoted competition, and improved market efficiency.

The expansion of the use of credit scoring, including by the adaptation of its methodology to insurance markets, has been accompanied by concerns that it may affect the availability and affordability of credit and insurance and that factors included in credit-scoring models may have adverse effects on certain populations, particularly minorities. Section 215 of the Fair and Accurate Credit Transactions Act of 2003 (Fact Act) directs the Federal Reserve Board and the Federal Trade Commission (FTC) to study how credit scoring has affected the availability and affordability of credit and insurance, to determine the relationship between credit scores and actual credit losses and insurance claims, and to determine how these relationships vary for the population groups protected under the Equal Credit Opportunity Act (ECOA).[1] In addition, section 215 directs the Board and the FTC to study the extent to which the consideration of certain factors included in credit-scoring and insurance-scoring models could have a negative or differential effect on populations protected under ECOA and the extent to which alternative factors could be used in credit scoring to achieve comparable results with less negative effect on protected populations

In preparing the study, the Federal Reserve took the lead in assessing the effects of credit scoring on credit markets, the subject of the present document; the FTC took the lead in the area of insurance and has issued a separate report on that topic.

In the broadest terms, the findings of the Federal Reserve study are as follows:

(1) The credit history scores evaluated here are predictive of credit risk for the population as a whole and for all major demographic groups. That is, over any credit-score range, the higher (better) the credit score, the lower the observed incidence of default. These conclusions are limited to credit history scores, that is, scores calculated exclusively on the basis of individuals' credit records as assembled by the three national credit-reporting agencies (Equifax, Experian, and TransUnion). Other kinds of credit scores were not studied here.

(2) Results obtained with the model estimated especially for this study suggest that the credit characteristics included in credit history scoring models do not serve as

[1] The Fact Act, Public Law 108-159, enacted December 4, 2003; section 215 is reproduced in appendix A of this report.

substitutes, or proxies, for race, ethnicity, or sex. The analysis does suggest, however, that certain credit characteristics serve, in part, as limited proxies for age. A result of this limited proxying is that the credit scores for older individuals are slightly lower, and those of younger individuals somewhat higher, than would be the case had these credit characteristics not partially proxied for age. Analysis shows that mitigating this effect by dropping these credit characteristics from the model would come at a cost, as these credit characteristics have strong predictive power over and above their role as age proxies.

Evidence also shows that recent immigrants have somewhat lower credit scores than would be implied by their performance. This finding appears to derive from the fact that the credit history profiles of recent immigrants resemble those of younger individuals, whose credit performance tends to be poor relative to the rest of the population. Expanding the information supplied to credit-reporting agencies to include rent, other recurring bill payments, nontraditional uses of credit, and the credit histories of the foreign-born in their countries of origin may provide a broader picture of the credit experiences of recent immigrants and other individuals.

(3) Different demographic groups have substantially different credit scores, on average. For example, on average, blacks and Hispanics have lower credit scores than non-Hispanic whites and Asians, and individuals younger than age 30 have lower credit scores than older individuals. Also, for given credit scores, credit outcomes—including measures of loan performance, availability, and affordability—differ for different demographic groups. Data limitations (for example, regarding individuals' wealth, employment, and education) prevented a complete assessment of these differences in score averages and outcomes among groups. The study found that many of these differences were reduced, at least in part, by accounting for the limited factors available for this study; however, differences—sometimes substantial—often remained.

(4) Evidence provided by commenters, previous research, and the present analysis supports the conclusion that credit has become more available over the past quarter-century. Credit scoring, as a cost- and time-saving technology that became a central element of credit underwriting during that period, likely has contributed to improved credit availability and affordability. However, in part precisely because the use of credit scoring became widespread decades ago, only limited direct information could be obtained on the contribution of credit scoring regarding availability and affordability. The increase in credit availability appears to hold for the population overall as well as for major demographic groups, including different races and ethnicities. There is no compelling evidence, however, that any particular demographic group has experienced markedly greater changes in credit availability or affordability than other groups due to credit scoring.

Data Used to Prepare the Report

Despite concerns about the potential effects of credit scoring on minorities or other groups, little research has been conducted on the issue, largely because of a lack of data linking credit scores to race, ethnicity, and other pertinent demographic information about individuals. With the exception of dates of birth, the credit records maintained by the credit-reporting agencies, which serve as the basis for most credit-scoring models, do not include any personal demographic information, and federal law generally prohibits the collection of such data on applications for nonmortgage credit. Even in the context of mortgage credit, for which some creditors are required to collect information on race, ethnicity, and sex, little information is publicly available.

This report was prepared using two types of information. The first type was gathered from public comments submitted for the report and from a review of previous research and surveys. The second type came from unique research conducted by the staff of the Federal Reserve Board specifically for this study. In that research, the Board's staff created a database that, for the first time, combines information on personal demographics collected by the Social Security Administration (SSA) with a large, nationally representative sample of the credit records of individuals. The sample comprised the full credit records of 301,536 anonymous individuals drawn in June 2003 and updated in December 2004 by TransUnion LLC (TransUnion), one of the three national credit-reporting agencies.[2]

Because the data set consisted of the credit records of the same individuals on two dates (June 30, 2003, and December 31, 2004), the Federal Reserve's staff was able to construct measures of loan performance, credit availability, and credit affordability and to create its own credit-scoring model (the FRB base model). Besides the FRB score created for this study, the data supplied by TransUnion for each individual in the database included two commercially generated credit scores—the TransRisk Account Management Score (from TransUnion) and the VantageScore (from VantageScore Solutions LLC).[3] The design of the FRB base model followed general industry practice to the extent possible. The three credit scores, together with the unique combination of credit and demographic information in the data set created for this purpose, allowed the Federal Reserve to address the questions posed by the Congress.

Access to Credit

The limited available evidence, including from public comments and previous research, suggests that credit scoring has increased the availability and affordability of credit. The

[2] Personal identifying information, such as names and Social Security numbers, was not made available to the Federal Reserve.

[3] TransRisk Account Management Score is a registered trademark of TransUnion LLC, and VantageScore is a service mark of VantageScore Solutions LLC. All other trademarks, service marks, and brands referred to in this report are likewise the property of their respective owners.

basic reason is that credit scoring allows creditors to quickly and inexpensively evaluate credit risk and to more readily solicit the business of their competitors' customers regardless of location.

Credit scoring likely increases the consistency and objectivity of credit evaluation and thus may help diminish the possibility that credit decisions will be influenced by personal characteristics or other factors prohibited by law, including race or ethnicity. Credit scoring also increases the efficiency of consumer credit markets by helping creditors establish prices that are more consistent with the risks and costs inherent in extending credit. By providing a low-cost, accurate, and standardized metric of credit risk for a pool of loans, credit scoring has both broadened creditors' access to capital markets and strengthened public and private scrutiny of lending activities.

Credit Scores and Loan Performance, Availability, and Affordability across Populations

The data assembled for this study are used to investigate the variation in credit scores across populations and the relationship between credit scores and loan performance, availability, and affordability across populations.

Credit scores differ among subpopulations: Blacks, Hispanics, single individuals, those younger than age 30, and individuals residing in low-income or predominantly minority census tracts have lower credit scores than other subpopulations defined by race or ethnicity, marital status, age, or location. Group differences in credit scores are narrowed, but not always eliminated, when differences in personal demographic characteristics, in residential location, or in a census-tract-based estimate of an individual's income are taken into account.

The analysis conducted for this study finds that credit scores consistently predict *relative* loan performance within all population groups; that is, for all populations, the percentage of individuals experiencing a serious delinquency on one or more of their credit accounts consistently declines as credit scores increase.

The analysis also finds that some groups perform worse (experience higher rates of serious delinquency) on their credit accounts, on average, than would be predicted by the performance of individuals in the broader population with similar credit scores. For example, on average, blacks perform worse than other racial and ethnic groups with similar credit scores. Similarly, single individuals and those residing in predominantly black or low-income census tracts perform worse on their loans than do their complementary demographic groups with similar credit scores. In contrast, the loan performance of Asians, married individuals, foreign-born individuals (particularly, recent immigrants), and those residing in higher-income census tracts was better than the performance predicted by their credit scores. The results hold after controlling for the other personal demographics of these individuals and for an estimate of the individuals' incomes and locations; other factors that could be important, such as differences in employment experience, were not available.

The study also finds that credit scores are consistently related to measures of loan pricing and loan denial rates inferred from credit inquires.[4] That is, for all populations, interest rates derived from the terms reported for closed-end loans and average inferred denial rates consistently decline as credit scores increase. As was the case for loan performance, some differences were observed across population groups after controlling for credit score: Most notably, younger individuals appear to experience somewhat higher inferred denial rates than older individuals; blacks appear to pay somewhat higher interest rates on auto and installment loans than do non-Hispanic whites; and Asians pay interest rates that, on average, are typically lower than, or about the same as, those paid by non-Hispanic whites across all loan categories for which rates could be estimated. Data limitations prevent a full assessment of the reasons for the remaining differences in credit outcomes.

Individual Credit Characteristics and Their Effects across Populations

This study reviewed the extent to which the consideration or lack of consideration of certain factors by credit-scoring systems could result in a negative or positive differential effect for different populations. By law and regulation, an individual's personal characteristics—such as race or ethnicity, national origin, sex, and, to a limited extent, age—must be excluded from credit-scoring models. A concern exists that, despite that prohibition, a credit characteristic may be included in a model not because it helps predict performance but because it is a substitute, or proxy, for a demographic characteristic that is correlated with performance.

The analysis of the data assembled for this report found that few credit characteristics, including those in the FRB base model, were correlated with personal demographics and that therefore they were unlikely to serve as proxies for demographic characteristics. Credit characteristics related to the age of an individual's credit record are the primary exception. The data show that some of these characteristics are often highly correlated with age. In addition, certain pertinent aspects of the credit files of recent immigrants tend to resemble those of younger individuals because they have not had sufficient time to build an extensive credit history in the United States.

To examine more closely whether the credit characteristics appearing in the FRB base model are serving, at least in part, as proxies for race or age, the model was reestimated in *race-neutral* and *age-neutral* environments. In each case, the FRB base

[4] Credit inquiries are requests by creditors for an individual's credit report. The lending industry uses the presence of credit inquiries without the issuance of new credit as an indication of loan denial. The data on credit inquiries are likewise used in this study to infer whether an individual likely experienced a credit denial.

model was reestimated with samples limited to a single race or age population respectively; in those reestimations, any credit characteristics serving solely as a proxy for race or age should have little weight in the reestimated model. Credit characteristics that have both an independent effect on performance and a correlation with race or age would be expected to have significantly different weights (either larger or smaller) in the reestimated models.

Reestimating the FRB base model in a race-neutral environment had little effect on credit scores. The result suggests that none of the credit characteristics included in the model serve, to any substantive degree, as proxies for race or ethnicity. However, when the FRB base model was reestimated in an age-neutral environment, credit scores did change: Scores for recent immigrants and younger individuals fell, and scores for older individuals rose.* These results were traced to the inclusion of a specific credit characteristic, namely, that which specifies the length of an individual's credit history. Further analysis showed that this credit characteristic served in part as a proxy for age. However, because the characteristic also had significant predictive power in an age-neutral environment, the effect could not be mitigated simply by excluding the credit characteristic from the FRB base model. An alternative means of mitigating the differential effect of this characteristic would be to use the weights derived from the age-neutral model. Use of the credit characteristic in this manner removes the differential effects relating to age with less loss of model predictiveness than would occur if this credit characteristic were excluded from the model entirely.

* Sentence as corrected August 23, 2007.

OVERVIEW OF THE REPORT

In recent decades, consumer credit markets in the United States have become increasingly national in scope as lenders have been better able to expand their geographic reach. These trends have been facilitated by the development of statistically derived credit-scoring models to mechanically evaluate credit risk, help establish loan prices, and manage consumer credit accounts. As a cost-saving technology, credit scoring has greatly affected consumer credit markets by allowing creditors to more inexpensively and readily gauge credit risk and expand their reach to consumers beyond the limits of their local offices.

The data maintained by credit-reporting agencies on the credit-related experiences of the majority of adults in the United States are at the heart of most credit-scoring models.[1] Although credit scoring has been a feature of consumer lending markets for some time, its role has expanded in recent years, in part because the data maintained by those agencies have become more comprehensive. Indeed, many credit-scoring models, particularly those used for screening users of unsecured revolving consumer credit, such as credit card customers, are now sometimes based entirely on information contained in the records of the credit-reporting agencies. The scores generated by those models, referred to here as *credit history scoring models,* have helped to substantially reduce the cost and time needed to make credit decisions and to identify prospects for new credit.[2]

The evaluation of creditworthiness, whether done judgmentally or on the basis of a credit score, is an inherently inexact science in that it attempts to predict the future: whether a loan will be repaid according to the agreed-upon terms. In building a credit-scoring model, the goal is to identify and use only those factors that have a proven relationship to borrower payment performance. By law and regulation, an individual's personal characteristics—such as race or ethnicity, national origin, sex, and, to a limited extent, age—must be excluded from credit-scoring models. In this way, credit scoring promotes consistency and objectivity in credit evaluation and may help diminish the possibility that such personal characteristics are considered in the lending process.

As the use of credit scoring has expanded, so have concerns about the extent to which it may affect access to credit and about whether scoring may have adverse effects on certain populations, particularly minorities or those that rely more heavily on nontraditional sources of credit. These concerns reflect, among other things, a belief that the effect of including certain credit-record items in the development of credit-scoring

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[1] Under the Fair Credit Reporting Act, these organizations are referred to as consumer-reporting agencies. Although these agencies are sometimes elsewhere referred to as credit bureaus, that term includes firms that do not collect information on credit accounts, and such firms are not considered in this report.

[2] Industry participants often refer to credit history scoring models as credit-bureau-based-scoring models.

models may have a differential effect on certain groups, particularly on racial and ethnic minority groups relative to non-Hispanic whites.

Little research has been conducted on the potential effects of credit scoring on minorities or other groups. Reliable data for conducting such research are not readily available. Creditors are generally prohibited from collecting race, ethnicity, and other personal demographic information on applications for credit, except in the case of mortgage credit. Even in the context of mortgage credit, only limited information is collected.[3] Consequently, with the exception of dates of birth, the credit records maintained by the credit-reporting agencies do not include any personal demographic information.

The Fair and Accurate Credit Transactions Act of 2003 (Fact Act) addressed the need for research in this area.[4] Section 215 of the Fact Act (reproduced in appendix A of the present report) directed the Federal Reserve Board and the Federal Trade Commission (FTC), in consultation with the Office of Fair Housing and Equal Opportunity of the Department of Housing and Urban Development (HUD), to study

1. the effects of the use of credit scoring on the availability and affordability of credit
2. the statistical relationship between credit scores and the quantifiable risks and actual losses experienced by businesses after accounting for personal demographics and other known risk factors
3. the extent to which the use of credit scores and credit-scoring models may affect the availability and affordability of credit to protected populations under the Equal Credit Opportunity Act (ECOA)
4. the extent to which the consideration or lack of consideration of certain factors by credit-scoring systems could result in negative or differential treatment of protected classes under ECOA
5. the extent to which alternative factors could be used in credit scoring to achieve comparable results with less negative effect on protected populations
6. the extent to which credit-scoring systems are used by businesses, the factors considered by such systems, and the effects of variables that are not considered by such systems

Section 215 also directed the study to include an analysis of these same questions for the use of credit scoring in insurance markets. In preparing the study, the Federal Reserve took the lead in assessing the effects of credit scoring on credit markets; the FTC

[3] Under the Home Mortgage Disclosure Act of 1975, as amended in 1989, covered lenders are required to collect and disclose information about the race or ethnicity and sex of individuals applying for mortgages covered by the law.

[4] The Fact Act, Public Law 108-159, was passed by the Congress on December 4, 2003.

took the lead in the area of insurance and is preparing a separate report on this subject. The present document focuses on credit scoring and credit markets.

Scope of the Analysis

Section 215 of the Fact Act essentially asks for four related analyses regarding the use of credit scoring in credit markets. The first is an analysis of the effect of credit scoring on the availability and affordability of financial products to consumers in general. The second is an analysis of the empirical relationship between credit scores and actual losses experienced by lenders. The third is an evaluation of the effect of scores on the availability and affordability of credit to specific population groups. The fourth is an evaluation of whether credit scoring in general, and the factors included in credit-scoring models in particular, may result in negative or differential effects on specific subpopulations and, if so, whether such effects could be mitigated by changes in the model development process.

Different approaches were taken to conduct each of these four analyses. The approach used to assess the general effect of credit scoring on the availability and affordability of credit was to rely on evidence from public comments, including those from government agencies, industry representatives, community organizations, and fair lending and fair housing organizations. The analysis also drew on evidence from previous studies on the topic and from indirect evidence obtained from an analysis of the Federal Reserve Board's Survey of Consumer Finances.

The approach taken to examine the empirical relationship between credit scores and actual losses experienced by lenders and to examine the effect of scores on the availability and affordability of credit to specific population groups relied on a nationally representative sample of individuals drawn from credit-reporting agency files at two points in time. Importantly, we were able to obtain information on race, ethnicity, sex, and other demographics from the Social Security Administration (SSA) that could be matched to the credit-record data. Such demographic data has not been available for previous research on credit scoring. The data set also included two commercially available generic credit history scores. In part because of the important role they play in credit markets and in part because of data issues, the analysis here focuses on generic credit history scores.

The data assembled here were also used to estimate a credit history scoring model emulating the process used by industry model developers. This model was used to investigate whether the factors included in credit-scoring models result in negative or differential effects on specific subpopulations and, if so, whether such effects could be mitigated by changes in the model development process.

Background

Before the introduction of credit scoring, the evaluation of creditworthiness was conducted manually and judgmentally by loan officers relying primarily on experience and subjective assessments of credit risk. Because loan officers differ in their experience and subjective assessments of different credit-risk factors, judgmental underwriting can be inconsistent and difficult to manage. Moreover, manual credit evaluation is time consuming and thus costly.

Both credit scoring and judgmental underwriting tend to be opaque processes. In the case of credit-scoring models, they are proprietary, and firms that develop them typically provide the public with only general information about how they were created and how well they perform. In the case of judgmental underwriting, methods are not likely consistent, even within a firm, because evaluators differ in their experience and judgment about credit risk and because it is difficult to establish clear guidelines that would address the numerous factual differences in the credit profiles of consumers.

After a period of rather slow acceptance, credit scoring had, by the 1970s, become widely used by most national lenders. Subsequently, the use of credit scoring expanded greatly with the development of generic credit history scores by Fair Isaac Corporation (FICO scores) and by Management Decisions Systems (the MDS Bankruptcy Score) in the 1980s. Some time after the introduction of these scores, the three national credit-reporting agencies (Equifax, Experian, and TransUnion) developed their own proprietary generic credit history scores, and recently the three agencies jointly developed a new generic credit history score named the VantageScore.[5] Credit scores derived from each of these models are marketed to lenders, and together they have become an important tool not only for credit evaluation but also for the prescreening and solicitation of new customers.

The Effects of Credit Scores on the Availability and Affordability of Financial Products

Although many of the broad effects of credit scoring are well understood, quantifying the effects of credit scoring on the availability and affordability of credit is difficult. The available evidence comes from three sources: comments received from the public on this study and previous research, original analysis of credit records obtained for this study, and an assessment of consumer survey data. Little specific evidence on these topics was provided in public comments or is available from earlier studies.

The available evidence indicates that the introduction of credit-scoring systems has increased the share of applications that are approved for credit, reduced the costs of underwriting and soliciting new credit, and increased the speed of decisionmaking. It has

[5] Trademarks, service marks, and brands referred to in this report are the property of their respective owners.

also made it possible for creditors to readily solicit the business of their competitors. Although credit-scoring systems can be expensive to develop, they can be operated at low marginal cost. To the extent that the lower costs and time savings are passed through to consumers, they will lead to lower interest rates and greater access to credit.

Credit scoring also increases the consistency and objectivity of credit evaluation and thus may diminish the possibility that credit decisions will be influenced by personal characteristics or other factors prohibited by law, including race or ethnicity. In addition, quicker decisionmaking also promotes increased competition because, by receiving information on a timelier basis, consumers can more easily shop for credit. Finally, credit scoring is accurate; that is, individuals with lower (worse) credit scores are more likely to default on their loans than individuals with higher (better) scores.

Credit scoring increases the efficiency of consumer credit markets by helping creditors establish prices that are more consistent with the risks and costs inherent in extending credit. Risk-based pricing reduces cross-subsidization among borrowers posing different credit risks and sends a more accurate price signal to each consumer. Reducing cross-subsidization can discourage excessive borrowing by risky customers while helping to ensure that less-risky customers are not discouraged from borrowing as much as their circumstances warrant. Finally, risk-based pricing expands access to credit for previously credit-constrained populations, as creditors are better able to evaluate credit risk and, by pricing it appropriately, offer credit to higher-risk individuals.

By providing a low-cost, accurate, and standardized metric of credit risk for a pool of loans, credit scoring has broadened creditors' access to capital markets, reduced funding costs, and strengthened public and private scrutiny of lending activities.

To better understand the potential effects of credit scoring on the availability and affordability of credit, data from the Survey of Consumer Finances were used to examine how the use of credit has changed from 1983 (the first year for which the survey results are comparable with those of later years) to 2004 (the most recent survey year). During this time, the first generic credit history models were introduced, so it is an appropriate period in which to assess at least some of the effects of credit scoring. However, such an analysis of credit *use* can provide only indirect evidence of the possible effects of credit scoring on *access* to credit. Moreover, other factors, including changes in the economic and demographic circumstances of households, technological innovations, and financial deregulation also have affected access to credit, making it difficult to distinguish the effects of credit scoring.

The survey data show that the share of families with any debt rose for nearly all populations; the steepest growth was in the ownership of bank-type or travel and entertainment cards. These trends are in broad alignment with the conjecture that credit scoring has helped increase the availability of credit since the early 1980s. It is difficult to draw a strong inference regarding changes in differences in credit use by race or ethnicity, age, and income. On the whole, the data do not provide clear and compelling evidence that the broader adoption of credit scoring disproportionately benefited populations that historically had lower rates of debt ownership; for the most part, differences in credit use across groups appear to have changed only slightly or even to have widened.

Assessment of Credit Scoring, Performance, Availability, and Affordability and Differential Effect

The remainder of the study focuses on the analysis of a data set assembled and analyzed by the Federal Reserve specifically for this study. The data, which do not have personally identifying information, are unique in that they combine information on credit accounts and credit scores with information on loan performance and a wide variety of demographic characteristics of a nationally representative sample of individuals. As noted above, legal restrictions have made it difficult to assemble a nationally representative database containing these three elements. The data are used to address several of the requirements of the section 215 study request.

The analysis and results are summarized as follows. Background information on the definition of differential effect and its specific use in this study is followed by a description of the data and the credit-scoring model developed for this study. The results are then presented in four parts: (1) a description of differences found in credit scores for different populations, (2) the relationship between credit scores and loan performance for different groups, (3) additional findings on the effect of credit scores on the availability and affordability of credit for different populations, and (4) findings on differential effect using a credit-scoring model developed by the Federal Reserve staff specifically for that purpose. The concluding section of this summary (and of the report) discusses limitations and qualifications of the research.

Discrimination and the Law

Under ECOA, it is unlawful for a lender to discriminate against a credit applicant on a prohibited basis in any aspect of a credit transaction.[6] Under both ECOA and the Fair Housing Act (FHA), it is unlawful for a lender to discriminate on a prohibited basis in a transaction related to residential real estate.[7] Despite the existence of federal anti-discrimination laws, longstanding concerns about discrimination in credit markets persist regarding essentially all aspects of the lending process—marketing, credit evaluation, establishment of loan terms, and loan servicing.

[6] Among the prohibited bases under ECOA are race, color, religion, sex, national origin, age, and marital status.

[7] Race, color, religion, sex, and national origin are prohibited bases under the FHA, as under ECOA. Additional prohibited bases under the FHA are handicap and family status but, unlike under ECOA, not age and marital status.

Analyses by the courts and federal regulators of credit discrimination often distinguish between discrimination that involves “disparate treatment” and “disparate impact.” Disparate treatment involves treating similarly situated applicants differently on the basis of one of the prohibited factors (for example, offering less-favorable terms to minority applicants).[8] Disparate impact refers to the outcome of a practice that the lender applies uniformly to all applicants but which has a discriminatory effect on a prohibited basis and does not have a sufficient business justification.

Some observers maintain that reliance on automated credit-evaluation systems such as credit scoring serves to reduce the potential for discrimination in lending because the automated nature of the process reduces the potential for bias to influence lending outcomes. Others contend that the credit-scoring process may have a disparate impact on protected populations because some of the factors used in credit-scoring models may disadvantage minorities or other segments of the population protected by fair lending laws.[9]

The Federal Reserve’s Regulation B, which implements ECOA, considers two broad types of credit evaluation: (1) traditional judgmental credit-evaluation systems, which may rely on the subjective evaluation of loan officers; and (2) credit-scoring systems that are empirically derived and demonstrably and statistically sound. Apart from the limited exception of age, which may be used as a predictive factor provided that those aged 62 or older are not assigned a negative factor or value, no prohibited factor may be used in a credit-scoring model.

Except, again, for age, credit-record data do not include personal or demographic characteristics, so such personal characteristics are unlikely to be an explicit part of a model.[10] Of course, disparate treatment could arise if lenders fail to apply credit scores evenhandedly, ignore them, or exercise “overrides” for some populations or in some circumstances.

Under court and regulatory agency interpretations, the test for disparate impact requires that a practice both have a disproportionate effect on a protected population and lack a sufficient business justification. An empirically derived, demonstrably and statistically sound credit-scoring model is likely to have a sufficient business rationale for the characteristics that constitute the model. Even a model that is empirically derived and demonstrably and statistically sound may, however, embody some avoidable disparate impact on a protected population in one or both of the following ways: (1) An alternative approach or specification might achieve the business goal with less discriminatory effect,

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[8] Some courts and agencies have referred to certain forms of particularly blatant discriminatory treatment on a prohibited basis as “overt discrimination.”

[9] Refer to Janet Sonntag (1995), “The Debate about Credit Scoring,” *Mortgage Banking* (November), pp. 46-52; Warren L. Dennis (1995), “Fair Lending and Credit Scoring,” *Mortgage Banking* (November), pp. 55-58.

[10] Some credit records include the date of birth or age.

and (2) the predictiveness of a variable in the model might stem primarily from the fact that it is serving as a proxy for a protected population.

Differential Effect Analyzed in this Study

In the previous section, the phrase *disparate impact* was used to refer to the possible differential adverse effects that credit-scoring models may have on various groups in a legal context. In this section, we define more precisely the meaning of the term *differential effect* as used in the statistical analysis of this study. Although related, the legal definition and the term "differential effect" used here are not the same. The concept of disparate impact embodies specific legal criteria and must be applied on a case-by-case basis after considering all relevant facts and circumstances, including any business justification. The concept of differential effect used here is a statistical concept and does not necessarily correspond to the legal concept.

In the present study, a credit-scoring model, or a credit characteristic used in the model, is said to have a statistical differential effect based on a demographic characteristic—say, age—if the model's predictiveness or the credit characteristic's contribution to the model's predictiveness stems, at least in part, from the fact that the score or the credit characteristic serves as a proxy for age. That is, if the model were estimated in an age-neutral environment, the resulting model would be less predictive of performance, or the credit characteristic's contribution to the model's predictiveness would decrease.

At a minimum, two conditions must hold for a demographic group to experience a differential effect from the presence of a credit characteristic in a credit-scoring model. First, the demographic characteristic must be correlated with performance; second, it must also be correlated with the credit characteristic used in the model. This relationship is a purely statistical one and does not imply causality in the relationship between the demographic characteristic and credit performance.

Defined this way, differential effect will generally be a zero-sum outcome. For example, if credit performance improves with age, then the *less* the credit characteristics in a credit-scoring model serve as a proxy for ("absorb") age, the higher the scores of *younger* individuals will be and the lower the scores of older individuals will be. Alternatively, the *more* a model absorbs the positive effect of age on performance, the higher the scores of *older* individuals will be. When younger individuals are the focus of attention, however, the use of a credit-scoring model that absorbs a substantial portion of the positive effect of age on performance is described here as having a "differential effect" on younger individuals as compared with a model in which less of the age effect is absorbed.

The congressional requirement for the present study focuses on the differential effects that the estimation and application of credit scores and credit-scoring models may have on individuals with different demographic characteristics, including, but not limited to, the demographic characteristics attributable to protected populations under ECOA. Some of those effects could raise questions about illegal discrimination under ECOA and the Fair Housing Act, but some clearly do not.

Data Used in the Study

Before the beginning of this study, the Federal Reserve had already obtained, for other purposes, a nationally representative sample of the credit records of 301,536 anonymous individuals as of June 30, 2003. The data were obtained from TransUnion LLC (TransUnion). This data set included two commercially available generic credit history scores for each individual in the sample—the TransRisk Account Management Score (TransRisk Score) and the VantageScore. The TransRisk Score was generated by TransUnion's proprietary model for assessing the credit risk of existing accounts. The VantageScore was developed by VantageScore Solutions LLC as a joint venture by Equifax, Experian, and TransUnion to create a measure of credit risk that scores individuals consistently across all three companies. The credit-record data include 312 credit characteristics that are representative of the credit characteristics used by the industry to develop generic credit history scoring models (appendix B lists the 312 credit characteristics).

The only personal demographic information included in an individual's credit record is the individual's date of birth (and many records do not even show that item). Thus, other demographic characteristics of the individuals in the credit records had to be obtained elsewhere. It was determined that the most accurate and comprehensive information on race or ethnicity, age, sex, and national origin could be obtained from records maintained by the SSA. Except for race and ethnicity, which are provided on a voluntary basis, all of that information must be provided by individuals who apply for Social Security cards. The SSA supplied this information for the individuals in the credit-record sample because the Federal Reserve Board is a federal agency and because conditions necessary to ensure the anonymity of the individuals were maintained.

Additional data were obtained for the individuals in the sample from a match between the census-block or census-tract place of residence derived from the credit records and Census 2000 data at the census-block and census-tract level of geography.[11] Finally, demographic information, most importantly marital status, was obtained from one of the leading demographic information companies for the individuals in the sample, again through a process that ensured individuals' anonymity.

To address the congressional directive, it was also necessary to construct measures of credit performance, availability, and affordability. A standard method used

[11] No specific addresses of individuals included in the sample of credit records were included in the data made available to the Federal Reserve.

by the industry to measure credit performance for model-building purposes is to draw credit records for individuals on two separate dates. The time between those dates is called the "performance period." Information from the credit records drawn for the later date shows which accounts became seriously delinquent or otherwise exhibited bad performance during the performance period. Information from the earlier date is used to predict subsequent loan performance.

This methodology was adopted in measuring performance for this study. The Federal Reserve's existing sample of credit records, drawn as of June 30, 2003, was updated as of December 31, 2004, to provide an 18-month performance period, a length of time within the range used by the industry in measuring performance.

This summary highlights two of the five performance measures used in the study: "any-account performance," which reflects whether any of an individual's new or existing accounts suffered some form of major shortfall in performance (major derogatory), such as becoming 90 days or more past due, over the performance period; and "modified new-account performance," which is limited to accounts opened sometime during the first six months of the performance period (that is, July through December 2003). Because the latter measure excludes loans in existence at the beginning of the performance period, it ensures that the borrower performance being evaluated is not already incorporated in the borrower's initial score.

Measures of the availability and affordability of credit were also developed by following typical industry practice. Information from the second draw of credit records was used to determine which individuals opened new credit accounts during the beginning of the performance period; for closed-end loans, information on loan terms was used to estimate the interest rate on these loans. Credit records do not include a direct measure of loan denials (a measure of credit availability); however, a proxy often used by the industry is to infer that individuals who have credit inquiries but who did not take out new credit during that period were denied. The presence of such inquiries during the beginning of the performance period was used to infer loan denials.

Thus assembled, the data set was still not sufficient to address the extent to which credit-scoring systems incorporate factors that result in differential effect for certain population groups. To address this aspect of the study, it was necessary to develop our own credit history scoring model, which we term the "FRB base model"; fortunately, the data that had been assembled were sufficient for us to undertake the development of the model. The FRB base model reflects closely the methodologies used by the credit-scoring industry in constructing generic credit history scoring models; however, it does not represent fully any particular model in use today. The estimated model was used to test for the potential for differential effects of credit scoring across groups in the context of model development.

Some information that may be relevant to understanding credit performance, availability, and affordability is not included in the data assembled for this study. Most notably, the data do not include the financial and nonfinancial circumstances of individuals, such as their wealth, income, employment experiences, or financial literacy.

Estimating the FRB Base Model

The FRB base model was developed using the large, nationally representative sample of the credit records of individuals described above. The data are of the same type used by the industry to build credit history scoring models.[12] To be as transparent as possible, the FRB base model departed somewhat from industry models in that the process of developing it was based entirely on rules. The rules selected, however, mimic general industry practice to the extent possible.

The model was developed with standard statistical techniques and was constructed using the 312 credit characteristics included in the data provided by TransUnion.[13] The model was designed to predict whether an individual would have at least one new or existing account that would become seriously delinquent during the 18-month performance period used in this study (the "any-account performance" measure). The credit-scoring industry typically segments the population into distinct subgroups and estimates separate credit-score models, or scorecards, for each group. In keeping with that industry practice, the FRB base model segments the population into three scorecards according to the number of credit accounts and past credit experience in each individual's record, or file: The "thin file" scorecard is for individuals with relatively few credit accounts; the "clean file" scorecard is, broadly speaking, for individuals whose credit records show no major derogatories; and the "major-derogatory file" scorecard is for individuals with at least one major derogatory account, collection account, or public record.[14] These three scorecards consist of the 19 credit characteristics (of the 312 available for this study) found to best predict loan performance.[15] The ability of the FRB base model to predict loan performance appears to be on a par with that of other generic credit-scoring models.

The Relationship of Credit Scores to Credit Performance, Availability, and Affordability for Different Populations

This section presents an assessment of the relationship of credit scores to credit performance and to credit availability and affordability for different populations. The

[12] The credit-record data excluded any personal identifying information.

[13] A "credit characteristic" is a summary measure of an aspect of an individual's credit record, such as the number of credit accounts or the months since the most recent delinquency.

[14] A major-derogatory account, as used in this study, is any account delinquent 90 days or more or that was involved in a repossession or charge-off.

[15] The 19 credit characteristics used in the FRB base model are listed in appendix C.

assessment focuses on (1) the distribution of credit scores across different populations; (2) the extent to which other demographic, credit, and economic characteristics explain differences in credit scores across populations; (3) the stability of the credit scores of individuals over time; (4) the relationship between credit scores and loan performance measured in a variety of ways; (5) the extent to which, given score, performance varies across populations; (6) the extent to which differences in credit availability and affordability across populations can be explained by credit score; and (7) whether differences in performance, credit availability, and pricing may be explained by factors not included in credit records.

Differences in Credit Scores

The data assembled provide information on the distribution of credit scores for different populations. Results are presented in this summary only for the TransRisk Score, though results for the VantageScore and the Federal Reserve's own estimated score (FRB base score) were also calculated and are virtually identical.

To compare the credit scores derived from different credit-scoring models, it was decided to normalize the scores to a rank-order scale ranging from 1 to 100. Each score was normalized so that each individual's score was defined by its rank order in the population; a score of 50 places that individual at the median of the distribution.

For the analysis here, nine different groupings of the sample population are considered: The nine population groups are determined by individuals' race or ethnicity (measured two ways); sex; marital status; national origin (foreign-born or not); age; and the relative income, degree of urbanization, and percent minority population of the census block or tract where the individual resides.[16]

Univariate differences in credit scores. Credit scores differ widely across populations, with blacks, Hispanics, individuals younger than age 30, unmarried individuals, and individuals residing in low-income or predominantly minority census tracts having lower credit scores than other subpopulations within their broader demographic group. Males and females have very similar credit-score distributions, and foreign-born individuals

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[16] Information on the race or ethnicity of individuals is generally not available in the data used to develop credit scores. However, if place of residence is known, the racial or ethnic composition of the census tract (or census block) can be used as an approximation of an individual's race or ethnicity. This approach has been used in previous studies that examine the relationship between credit scores and race or ethnicity.

For this report, in addition to the SSA classification of the individual's race or ethnicity, the adult racial or ethnic composition of the individual's census block (available for about 85 percent of the population) or census tract is used as an approximation of the individual's race or ethnicity. The proportion of the block belonging to each racial or ethnic group can be viewed as the probability that a random adult drawn from the block will have that race or ethnicity. The probability is used as a weight in forming the estimates presented in this study.

appear to have a score distribution that is virtually the same as that of the general population.

Differences in credit scores among racial or ethnic groups and age cohorts are particularly notable because they are larger than for other populations. For example, the mean normalized TransRisk Score for Asians is 54.8; for non-Hispanic whites, 54.0; for Hispanics, 38.2; and for blacks, 25.6 (figure O-1). Credit scores by age increase consistently from young to old: The mean TransRisk Score for individuals younger than age 30 was 34.3; for those aged 62 or older, it was 68.1.

Cumulative distributions show that the population differences suggested by the credit-score means generally hold for the entire score distribution for each population. For each level of credit score, the cumulative distribution indicates the proportion of a population with that score or lower. For example, the cumulative distributions of scores for blacks and Hispanics are consistently higher than those for non-Hispanic whites and Asians (figure O-2). Cumulative distributions by age are also consistently ordered, with younger individuals having a higher distribution than that of individuals aged 62 or older. Cumulative distributions for census-tract groupings by racial or ethnic population composition are also consistent with the patterns implied by the race or ethnicity of individuals.

Multivariate analysis of score differences. The univariate relationships described in the preceding section may in part reflect differences across demographic groups in other characteristics. To better understand the source of the differences in credit scores across different populations, a series of multivariate analyses were conducted to identify the independent effects of race or ethnicity, age, and sex on credit-score differences across populations. For race or ethnicity, a regression model was fit using only the non-Hispanic white individuals in the sample, controlling for their age, sex, marital status, and a census-tract-based estimate of individual income and other census-tract characteristics. Predicted values from this equation were then used to predict the scores for blacks, Hispanics, and Asians. Differences between individuals' actual credit scores and their predicted scores can be interpreted as "unexplained" racial or ethnic effects.[17] Results of this statistical analysis show that the gross difference in the TransRisk Score between non-Hispanic whites and blacks falls by more than one-half; the gross difference between non-Hispanic whites and Hispanics falls by about three-fourths. For age, regressions from a similar analysis suggest that only a minor portion of the relatively wide differences across age cohorts can be explained by the other factors available in the data.

[17] The term "unexplained" as used here is a statistical concept. The unexplained difference is defined as the difference in average scores in the scorable sample after other factors included in the multivariate regressions are accounted for. Thus, the size of the unexplained component depends on what other factors are included in the model. Adding factors to the model, or subtracting them, will affect the size of the unexplained differences.

Credit Scores and Loan Performance

Section 215 of the Fact Act requires an analysis of "the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the Equal Credit Opportunity Act and other known risk factors, between credit scores . . . and the quantifiable risks and actual losses experienced by businesses." Information on actual losses experienced by creditors was not available for the study, so the focus was on loans that became seriously delinquent or were in default as represented by the performance measures. Such loans nearly always result in some loss to the creditor.

In response to the congressional requirement, the analysis addresses the question of whether loan performance differs across population groups controlling for credit score. For the analysis here, individuals were grouped by their score as of June 30, 2003, and average performance on loans over the ensuing 18-month period was measured using the performance measures described above.

Univariate patterns of loan performance. Using each of the three credit scores available for this study and a number of different measures of loan performance, the analysis finds that, on average, credit scores are predictive of future loan performance for all groups and differentiate risk well within each population group (figure O-3).[18] The general shapes of the performance curves (curves that show the relationship between credit scores and loan performance) are similar across groups. Specifically, loan performance improves with credit score so that the curve declines as scores increase. Within a demographic population, the performance curves are not identical. Of particular interest for this study are performance curves for populations that are uniformly above or below those for others. A performance curve that is uniformly above (below) means that the group consistently underperforms (overperforms), that is, on average performs worse (better) on its loans than would be predicted by the performance of individuals in the overall population with similar credit scores.

Blacks, single individuals, and individuals residing in lower-income or predominantly minority census tracts show higher incidences of bad performance than would be predicted by their credit scores. Similarly, Asians, married individuals, the foreign-born (particularly, recent immigrants), and those residing in higher-income census tracts perform better than predicted. Results for age were mixed: Younger individuals exhibited a higher incidence of bad performance than would be predicted for two of the three credit scores used in this study; for the third credit score, performance on some measures was better than predicted.

[18] The figures in this overview present results only for the TransRisk Score. Figure O-3 is further restricted to the modified new-account performance measure [this footnote as corrected August 23, 2007].

Multivariate analysis of differences in loan performance. In interpreting the patterns of differential effect discussed above, it is important to recognize that the assessments of overperformance and underperformance are based on univariate statistics. It is possible that the performance assessments for one population at least partly reflect effects coming from other factors. To address this possibility, multivariate analyses were conducted. First, an analysis was conducted in a manner similar to that performed for score levels that sought to determine whether performance differences across groups were related to other personal demographics and census-tract-related characteristics. Results show that controlling for other personal demographic and census-tract characteristics has only a modest effect on the assessment of overperformance or underperformance for populations.

Another possible explanation for performance differences may be that different populations take out different types of credit, borrow from different types of lenders, and receive different loan terms even when they have similar credit scores. Consequently a second analysis was conducted that added to the multivariate performance regressions information on loan terms (including amounts borrowed and derived interest rates), date of the loan, type of lender, and type of loan. The analysis was restricted to performance on modified new accounts.

Results show that there are some differences in the types of loans taken out by different groups. Nevertheless, differences in loan terms and interest rates explain virtually none of the differences in overperformance and underperformance by race, sex, or age. This is true when loan terms and interest rates are considered without other controls or along with other demographic and location factors. Thus, despite differences in the kinds of loans used by different populations, this factor does not appear to be the source of differences in performance once credit score is taken into account.

Credit Scores and the Availability and Affordability of Credit across Populations

The study asks for an assessment of the extent to which, if any, the use of credit-scoring models and credit scores affect the availability and affordability of credit by geography, income, race, color, national origin, age, sex, or marital status. The credit-record data assembled for this study are used to provide evidence on the effects of credit scores on the availability and affordability of credit across populations. The analysis here considers several indicators of credit availability by credit score across populations, including differences in credit use patterns, in “inferred” denial rates for credit, and in estimated interest rates.

Credit-record data can provide only limited insights into the effects of credit scores on credit availability and affordability, particularly as it has changed over time. A limitation of the credit-record data is that, although they contain loans extended before June 2003, the data do not contain the credit scores used to underwrite those loans.

However, the credit scores as of June 2003 arguably are likely representative of the scores used to underwrite new loans acquired at the beginning of the performance period used for this study (July–December 2003). Thus, the analysis presented here focuses on the extent to which population differences in the incidence of new credit, inferred denial rates, and the interest rates derived from terms reported for closed-end credit (installment, auto, and mortgage), as described earlier, can be explained by the June 2003 credit score. Of course, the incidence and pricing of new credit, as well as the decision to accept or deny a loan, are affected by many factors beyond credit score, including both demand and supply elements such as wealth, employment experience, the presence of collateral for the loan, and the loan-to-value ratio for mortgages or other loans.

Results indicate that individuals with credit scores in the lowest credit-score quintile are substantially less likely to have taken out a new loan over the first six months of the performance period than individuals with higher credit scores. The strong relationship between credit scores and the incidence of new credit holds across all populations.

Individuals with lower credit scores experience higher inferred denial rates. This relationship is found across all population groups; after controlling for credit score, however, blacks and Hispanics, younger individuals, and individuals that live in low-income areas show somewhat higher inferred denial rates than other groups (figure O-4). Credit scores and interest rates are inversely related, a relationship that holds for all populations. However, black borrowers experienced higher interest rates than non-Hispanic whites in each loan category for which interest rates can be determined (figures O-5 and O-6 show the rates on new mortgages and auto loans). Interest rates paid by Asians are, on average, typically lower than, or about the same as, those paid by non-Hispanic whites across all credit-score quintiles and each product category for which rates could be estimated.

Multivariate analyses were also conducted for inferred denials and estimated interest rates. Controlling for credit score, loan type, lender and amount borrowed, and location factors reduces differences in interest rates by race and ethnicity, although not completely. The multivariate analysis had less effect in accounting for differences in inferred denial rates.

Accounting for Economic and Financial Factors Not Available for this Study

The multivariate analyses in the previous sections were, perforce, restricted to information contained in the credit records, the SSA file match, and factors based upon an individual's location. Thus, the data assembled for this study can provide only limited insights into the relationship of credit scores to credit performance, availability, and affordability (and essentially no insight into whether the relationship is one of cause and effect). The data do not contain key variables that would need to be taken into account.

Missing data include other underwriting factors, such as loan-to-value ratios in the case of mortgages, and the weight given to credit scores relative to these other factors. Missing data also include underlying differences in socioeconomic factors such as wealth and employment experience; only a rough estimate of individual income is available. Moreover, the credit-record data used here are for a brief period in time and therefore cannot reflect changes over time in the relationship between credit scores and the availability or affordability of credit.

The multivariate analysis found unexplained differences in performance residuals among racial and ethnic groups and among age groups. Unexplained differences in accessibility and affordability in the multivariate regressions were also found among racial and ethnic groups. In this section, we use information from the Federal Reserve Board's 2004 Survey of Consumer Finances (SCF) to explore the possibility that differences in, for example, wealth, employment history, and financial experience might explain some, or perhaps all, of the remaining differences in performance, availability, and affordability across groups. Inferences from this analysis are only suggestive because the information cannot be linked either to the individuals in the study sample or to their credit-related performance or loan terms.

Assessment of the SCF data shows that younger families differ substantially from older families over a wide variety of financial dimensions. Variations across age groups in income, wealth, and their components and in debt-payment burdens and savings largely reflect the life-cycle pattern of income; that is, income rises as workers progress through their careers and falls sharply upon retirement. Also, younger individuals are more likely to experience recent bouts of unemployment. None of these factors were explicitly accounted for in the multivariate performance analysis conducted with the credit-record data.

The SCF data show that income, wealth, and holdings of financial assets are substantially lower for black and Hispanic families than for non-Hispanic white families. Debt-payment burdens and propensities for unemployment are also higher for blacks and Hispanics. These racial patterns generally hold even after accounting for age, income, and family type.

Differences in educational attainment and credit-market experience may relate to financial literacy. For example, high-school and college graduation rates among Hispanics are below those for blacks, which, in turn, are lower than those for non-Hispanic whites. Each of these factors, none of which were included in the credit-record analysis, may at least partially explain differences in performance across racial or ethnic groups.

The Relationship between Individual Credit Characteristics, Credit Scores, and Differential Effect across Populations

Another provision of section 215 of the Fact Act requires an assessment of "the extent to which the consideration or lack of consideration of certain factors by credit-scoring systems could result in negative or differential treatment of protected classes under the Equal Credit Opportunity Act." This study uses a variety of approaches to address concerns about whether credit-scoring models, or the individual characteristics that constitute the models, embody differential effect.

The Fact Act requires an analysis of the potential for differential effects arising from the use of individual credit characteristics in a credit-scoring model. As noted earlier, it was determined that the best way to address this issue was to develop our own credit-scoring model, mimicking the process used by the credit-scoring industry. Only in this way would we be able to identify the specific credit characteristics included in a model that may have a differential effect by evaluating the consequences on different groups of adding, removing, or otherwise altering the way the characteristics are used. As discussed above, these steps are necessary to address the differential effect of a specific credit characteristic.

The estimated model is used to provide information of three types. The first type of information involves successively dropping each credit characteristic contained in the estimated model and evaluating the change in normalized credit scores for different populations and the overall model predictiveness when these changes are made. If large changes in credit scores for a population occur when a credit characteristic is dropped, there is an inference that the characteristic embodies differential effect. The second complementary type is to successively add credit characteristics that were not included in the estimated model and then evaluate how such additions would affect scores. Again, significant score changes would suggest differential effect.

These two types of information provide only inferential indicators about differential effect. As noted earlier, to fully assess differential effect, it is necessary to compare credit scores and weights assigned to credit characteristics derived from the FRB base model with those obtained from models estimated in demographically neutral environments. Thus, additional credit-scoring models were estimated in race- and age-neutral environments using several different methods to define *neutrality*. The third type of information focuses on the comparison of scores and weights from these models with those from the FRB base model and forms the basis of the assessment of differential effect.

The Effects of Dropping and Adding Characteristics

One way of drawing an inference about differential effect for a credit characteristic included in a model is to examine the effect on the credit scores of each demographic group of dropping the credit characteristic. This analysis, which was conducted separately for each scorecard of the FRB base model, proceeded by dropping each individual credit characteristic from the FRB base model, reestimating the model, renormalizing the scores, and comparing the scores with those produced by the FRB base model.

Results of this analysis indicate that for most populations dropping any single credit characteristic (even those found to be highly predictive of loan performance) has a very minimal effect on mean credit scores, typically 1 point or less. Thus, such changes have virtually no impact on mean score differences between population groups. The small change in mean scores when a single credit characteristic is dropped reflects the high degree of correlation among the credit characteristics in the scoring model.

The one exception to this pattern is the credit characteristic "average age of accounts on credit report" on the clean-file scorecard.[19] Dropping this credit characteristic from the clean-file scorecard increases mean credit scores for individuals younger than age 30 (5.4 points) and recent immigrants (6.7 points). The net effect is to reduce the mean score differences on the clean-file scorecard between individuals younger than age 30 and those aged 62 or older by about one-fourth. The lower mean scores for the young and recent-immigrant populations when this credit characteristic is included on the clean-file scorecard suggest that including this credit characteristic in a model may have a differential effect on these two populations.

Dropping credit characteristics does not provide any information about credit characteristics not included in the model. An inference about differential effects from excluded credit characteristics can be derived by examining the effect on the credit scores of each demographic group of adding individual excluded credit characteristics. This analysis, which was conducted separately for each scorecard of the FRB base model, proceeded by adding an additional credit characteristic to the FRB base model, reestimating the model, renormalizing the scores, and comparing the new scores with those produced by the FRB base model.

Across population groups, credit scores change very little after the addition of a new credit characteristic. Changes in mean scores for all population groups are approximately 1 point or less regardless of the credit characteristic added. Among the credit characteristics examined were those related to finance company accounts. These characteristics deserve particular note because concerns have been raised about their inclusion in credit-scoring models. However, when added to the FRB base model, credit characteristics related to finance company accounts had essentially no effect on the mean credit scores of any racial, ethnic, or other demographic group. (Note that dropping the

[19] Calculated as the average age of all credit accounts in an individual's credit record.

one credit characteristic related to finance company accounts included in the FRB base model had little effect on mean score differences across populations.)

Race- and Age-Neutral Models

The analysis above points to only two broad demographic categories, race and age, that are potentially proxied for by credit characteristics in our model and, thus, may have the potential for a differential effect. (Tests were also run for sex, with no differential effects observed.) Consequently, we focus on these two population taxonomies in estimating a model in a "group neutral" environment. Two methods are used to define *neutrality* for each population taxonomy. The first method is to restrict the sample used in model estimation to a single race (the "white only" model that uses only non-Hispanic whites for estimation) or to an age range (the "older-age" model that uses only individuals aged 40 or older for model estimation).[20] The second method uses the entire sample in estimation but includes racial-intercept or age-intercept shifts (referred to, respectively, as the "racial-indicator variable" and "age-indicator variable" models). We test for differential effect by freezing the credit characteristics and attributes of the FRB base model and reestimating the attribute weights in the four demographically neutral environments described above.

Reestimating the attribute weights in demographically neutral environments is not a complete test of the potential for differential effect. It is possible that the presence of a large differential effect could mute the importance of a credit characteristic, and consequently that credit characteristic might not be included in a model estimated in a demographically neutral environment. To test for this possibility, each of the credit characteristics not included in the FRB base model was added one at a time to the race- and age-neutral versions of the model, and their effects on scores for different populations were evaluated.

Race-neutral models. A comparison of the white-only and the racial-indicator-variable models with the FRB base model shows little difference in fit regardless of how model predictiveness is defined. There are also virtually no differences between the group mean and median credit scores for different populations. The overall assessment of differential effect can also be looked at by examining changes in the underperformance or overperformance (conditioned on credit score) for different population groups. For all

[20] The choice of the population group (in this case, non-Hispanic whites) was driven by considerations of sample size alone. In principle, any group could serve as the base population for estimating a model. The non-Hispanic white population was the only population in the sample of sufficient size to provide a basis for model estimation. In general, the selection of the base group may affect conclusions reached regarding differential effect of various credit characteristics.

performance measures, the underperformance or overperformance for different demographic groups is virtually unchanged for the two racially neutral models.

The only evidence of differential effect for any racial or ethnic group is a slight negative differential effect for recent immigrants. That is, the credit scores of recent immigrants are somewhat lower for the FRB base model than would have been the case had the model been estimated in a racially neutral environment. However, the overall foreign-born population showed no evidence of such an effect. Further, as described below, recent immigrants show a differential effect going in the opposite direction when evaluated in an age-neutral environment.

Tests of adding credit characteristics to the white-only and the racial-indicator-variable models showed no evidence of important excluded credit characteristics. Results were similar to those described above regarding the addition of characteristics to the FRB base model.

Age-neutral models. As with estimations in a race-neutral environment, shifting from the FRB base model to an age-neutral model appears to lead to little decline in predictive power. However, unlike estimations in the racially neutral environment, mean credit scores and mean performance residuals change for certain age groups in the older-age model and the age-indicator-variable model. Overall, for individuals younger than age 30, the credit scores derived from these two models are somewhat lower than the scores derived from the FRB base model. Recent immigrants show a similar pattern. However, scores for individuals aged 62 and older are higher when estimated in an age-neutral environment. Changes in underperformance and overperformance are consistent with these score changes. Results from adding credit characteristics showed no evidence that important credit characteristics were left out of the FRB base model.

Overall, these results suggest that the FRB base model embeds a modest negative differential effect for individuals aged 62 and older and an even more modest (and opposite) differential effect for individuals younger than age 30 and recent immigrants. These effects derive primarily from the weights assigned to credit characteristics related to the length of an individual’s credit history. These characteristics have somewhat more muted effects in the FRB base model than would be the case had the model been estimated in an age-neutral environment.

Recent immigrants appear to have somewhat lower scores in the FRB base model than would be appropriate given their performance. However, this overperformance is not due to a negative differential effect (indeed, as just stated, recent immigrants experience a positive differential effect). Rather, it is attributable to the tendency of recent immigrants to have credit profiles similar to those of young people in terms of the lengths of their credit histories, as reflected in their U.S. credit records.

The scores of recent immigrants might be made more consistent with performance by changes in the credit-reporting process. For example, it might be possible to gather information on the credit histories of recent immigrants from their home countries to supplement the credit records maintained by the three national credit-reporting agencies in the United States. More generally, ongoing industry efforts to incorporate into credit records items traditionally not collected (such as utility and rental payments) and experiences with nontraditional sources of financing (such as payday lenders and pawn shops) would broaden the information included in credit records and might serve to lengthen the period over which individuals would be recorded as having a credit record.

Limitations of the Analysis

Section 215 of the Fact Act asks for four related analyses regarding the use of credit scoring in credit markets. The first is an analysis of the effect of credit scoring on the availability and affordability of financial products to consumers in general. The second is an analysis of the empirical relationship between credit scores and actual losses experienced by lenders. The third is an evaluation of the effect of scores on the availability and affordability of credit to specific population groups. The fourth is an evaluation of whether credit scoring in general, and the factors included in credit-scoring models in particular, may result in negative or differential effects on specific subpopulations and, if so, whether such effects could be mitigated by changes in the model development process.

Different approaches were taken to conduct each of these four analyses. The approach used to assess the general effect of credit scoring on the availability and affordability of credit was to rely on evidence from public comments and previous studies on the topic and to obtain indirect evidence from the Survey of Consumer Finances. The ideal way of addressing this question would have been to conduct a "before and after" study of the effects of the introduction of credit scoring on the availability and affordability of credit. Such an endeavor was not possible because credit scoring has been in use for many years, and the distinction between the effects of scoring and those of economic and other changes that took place over the same period is difficult to discern. Also, the available public research is quite limited, perhaps because most analytical studies were proprietary and are not part of the public record. The approach taken here cannot conclusively address these concerns. Thus, our conclusions in this area can only be suggestive.

The approach taken to examine the empirical relationship between credit scores and actual losses experienced by lenders and to examine the effect of scores on the availability and affordability of credit to specific population groups relied on a nationally representative sample of individuals drawn from credit-reporting agency files. There are several limitations to this approach. First, the analysis was limited to credit history scores. Second, the data included only two commercially available credit scores. Third, the definition of performance was dictated by the time periods for which the samples were drawn. The resulting 18-month performance period is on the short end of the time frames considered by many in the industry. Further, the time period used to evaluate performance represented a relatively favorable period of macroeconomic performance. Consequently, the absolute levels of performance observed here may overstate the performance one would expect in a less favorable economic climate.

The issues of loan performance and the availability and affordability of credit to different populations were addressed using multivariate analyses, which were restricted to information contained in the credit records supplemented by demographic information from the SSA and data based on location. However, population groups differ widely along many financial and nonfinancial dimensions not reflected in credit records that may affect credit performance and the conclusions one might draw about differences across populations. So, for example, the overperformance or underperformance of a demographic group may be attributable to financial or nonfinancial characteristics (such as employment experience or wealth) that bear on performance and that are correlated with the demographic characteristic but that are not included in the credit records.

Another issue in this section of the analysis is the fact that performance and loan terms could be ascertained only for individuals receiving credit. It is reasonable to expect that individuals denied credit would have experienced both worse performance and higher interest rates; however, these outcomes are not included in the data. To the extent that individuals experiencing denials disproportionately have low credit scores, inclusion of these outcomes would likely have made the performance or interest rate curves steeper.

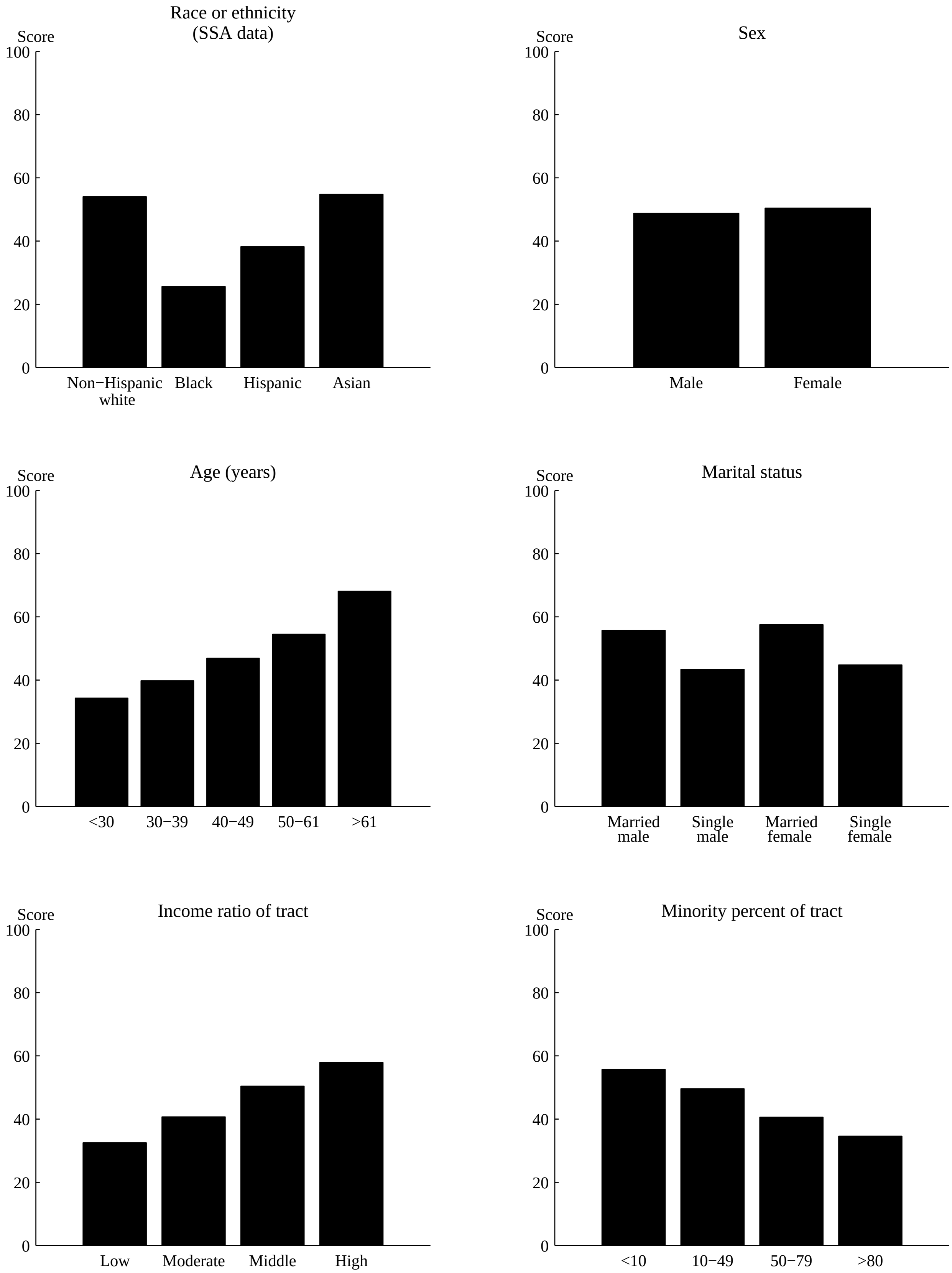
The assessment of denial rates using the inquiry proxy is subject to the same limitation. Individuals who know that they have a low credit score, or believe that they do, may act under the assumption that they will be denied credit if they apply for it. If so, they are being "discouraged" from applying for credit, and the observed relationship between credit score and denial rate would then be less steep than it would be if everyone wanting credit applied for it. A final issue in this section is the fact that information on demographic characteristics had to be imputed for a portion of the sample. Tests suggest that the results here are generally robust. However, for some population segments, such as marital status, concerns may still remain.

The fourth analysis was conducted using a credit history scoring model developed by Federal Reserve staff. We attempted to emulate the process used by the credit industry's model developers in estimating credit-scoring models. However, the industry adheres to no single methodology, so our approach was inevitably approximate. For example, data restrictions forced a number of limitations to our approach. Moreover, the fact that industry modelers may have made different decisions or relied upon different samples clearly limits the generalizations that can be made from our results. These limitations would arise under any circumstances involving the construction of a new model.

Additional concerns are raised about our model development because of the relatively small sample used for estimation. The small sample size prevented evaluation of the FRB base model on an out-of-sample basis (that is, on a sample of individuals different from that used to develop it). Also because of the small sample, the FRB base model was developed with fewer scorecards than are typically used in the industry's credit history scoring models; consequently, the model has fewer credit characteristics than is typical in the industry. Having relatively few scorecards makes it difficult to identify credit characteristics that might have a differential effect on populations that could constitute other possible scorecards.

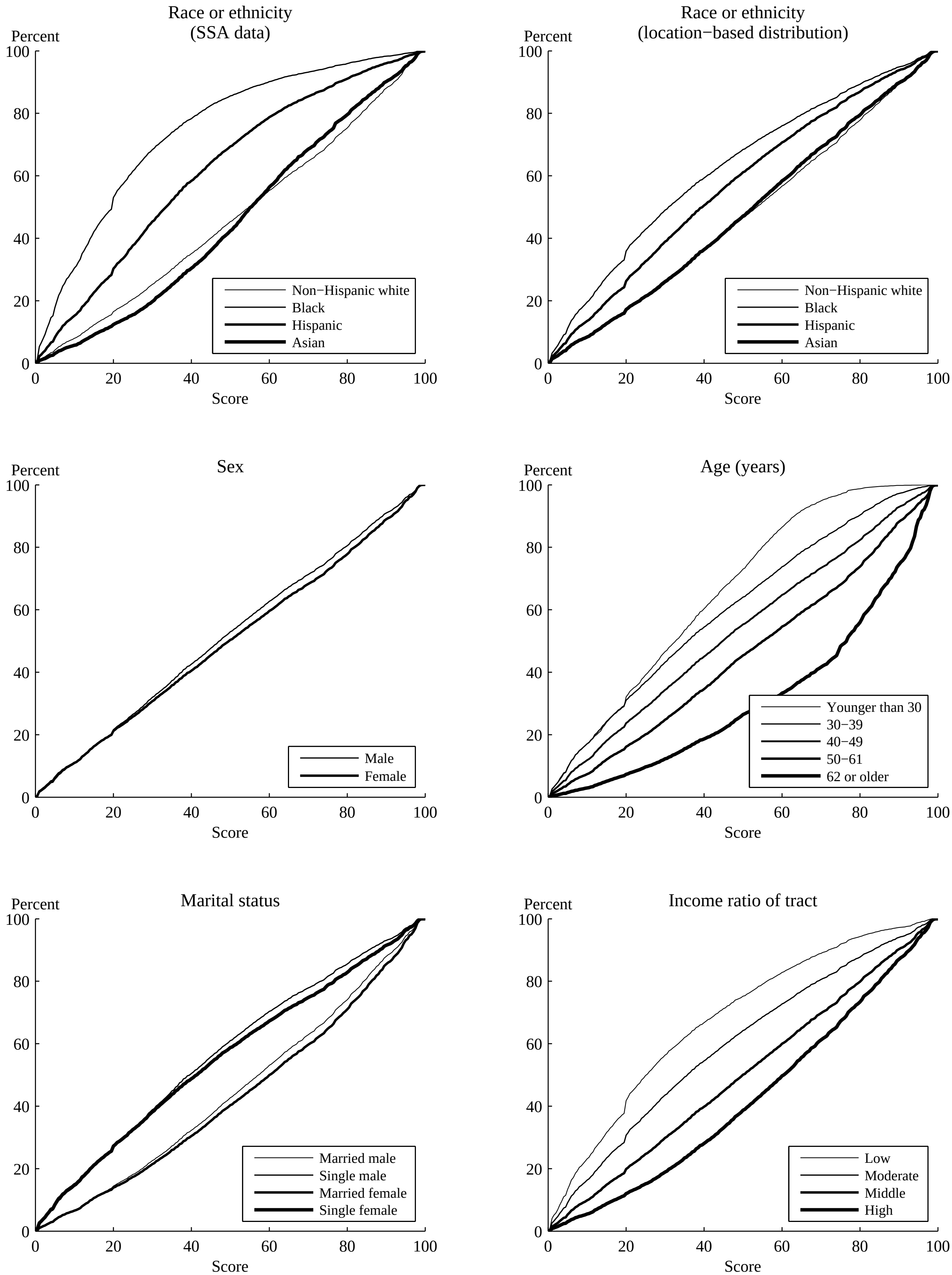
A limitation that runs through all four of the analyses is the decision to focus on credit history scoring models, as opposed to the broader class of scoring models. Much of the underwriting and pricing of credit relies upon credit-scoring models that incorporate factors not included in the records of credit-reporting agencies. Further, the underwriting process may use other information that is judgmentally combined with credit scores in making final decisions on underwriting and pricing. The role of some of these other factors could mitigate or alter some of the conclusions reached in this study.

Figure O−1. Mean TransRisk Score, by Demographic Group



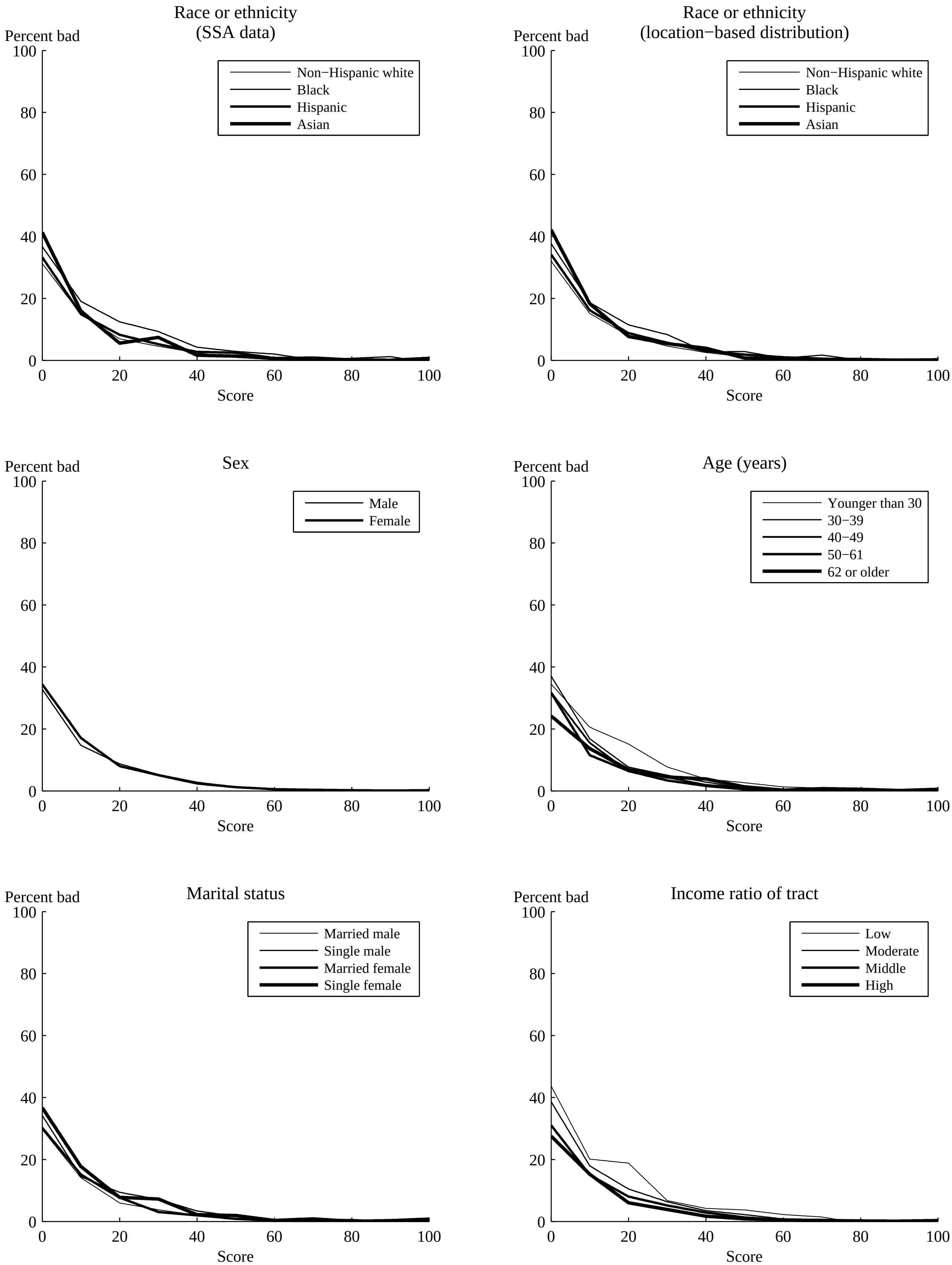
Note. For definition of characteristics, refer to notes to table 9.

Figure O−2. TransRisk Score: Cumulative Percentage, by Demographic Group



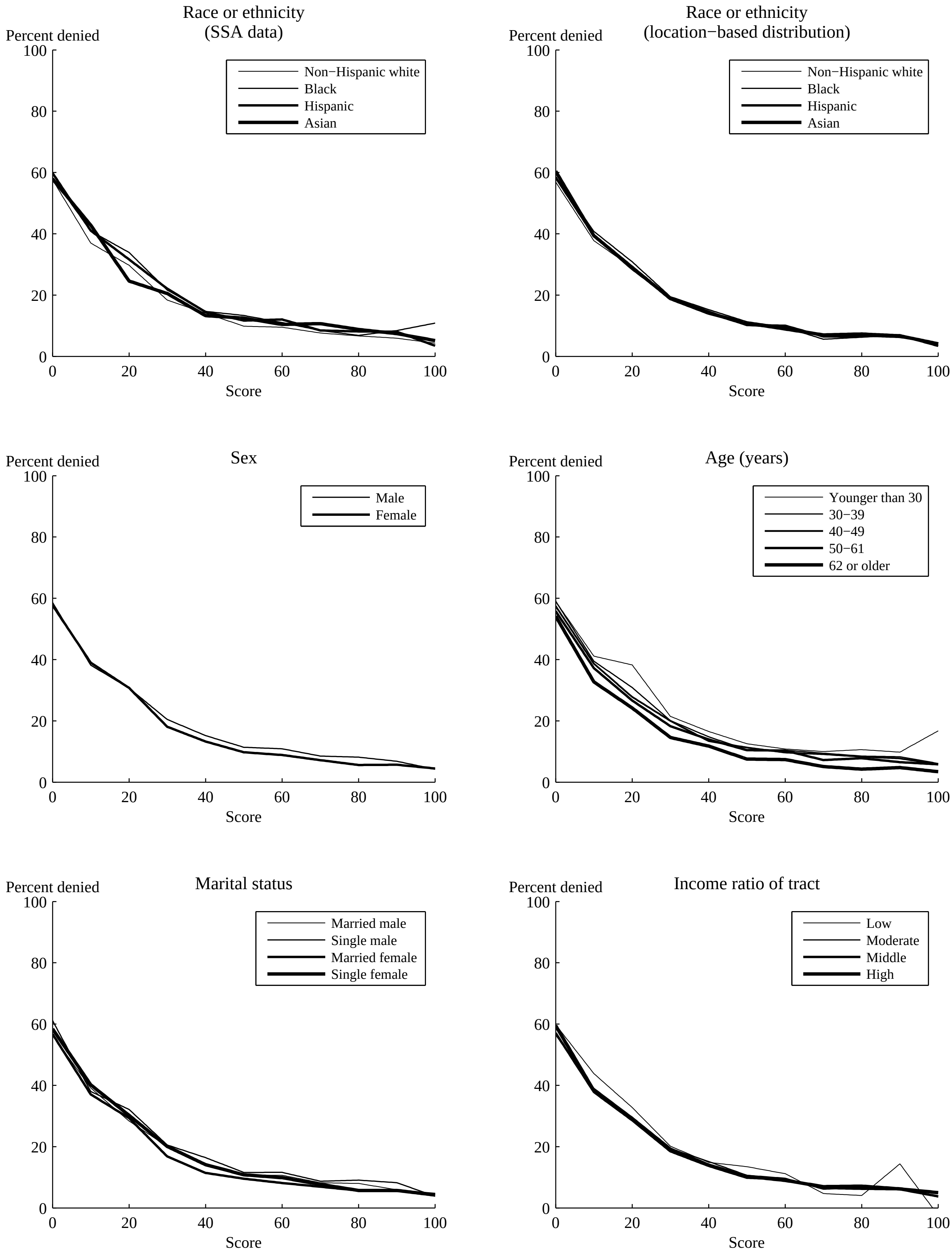
Note. For definition of characteristics, refer to notes to table 9.

Figure O−3. TransRisk Score: Modified New−Account Performance (Percent Bad), by Demographic Group



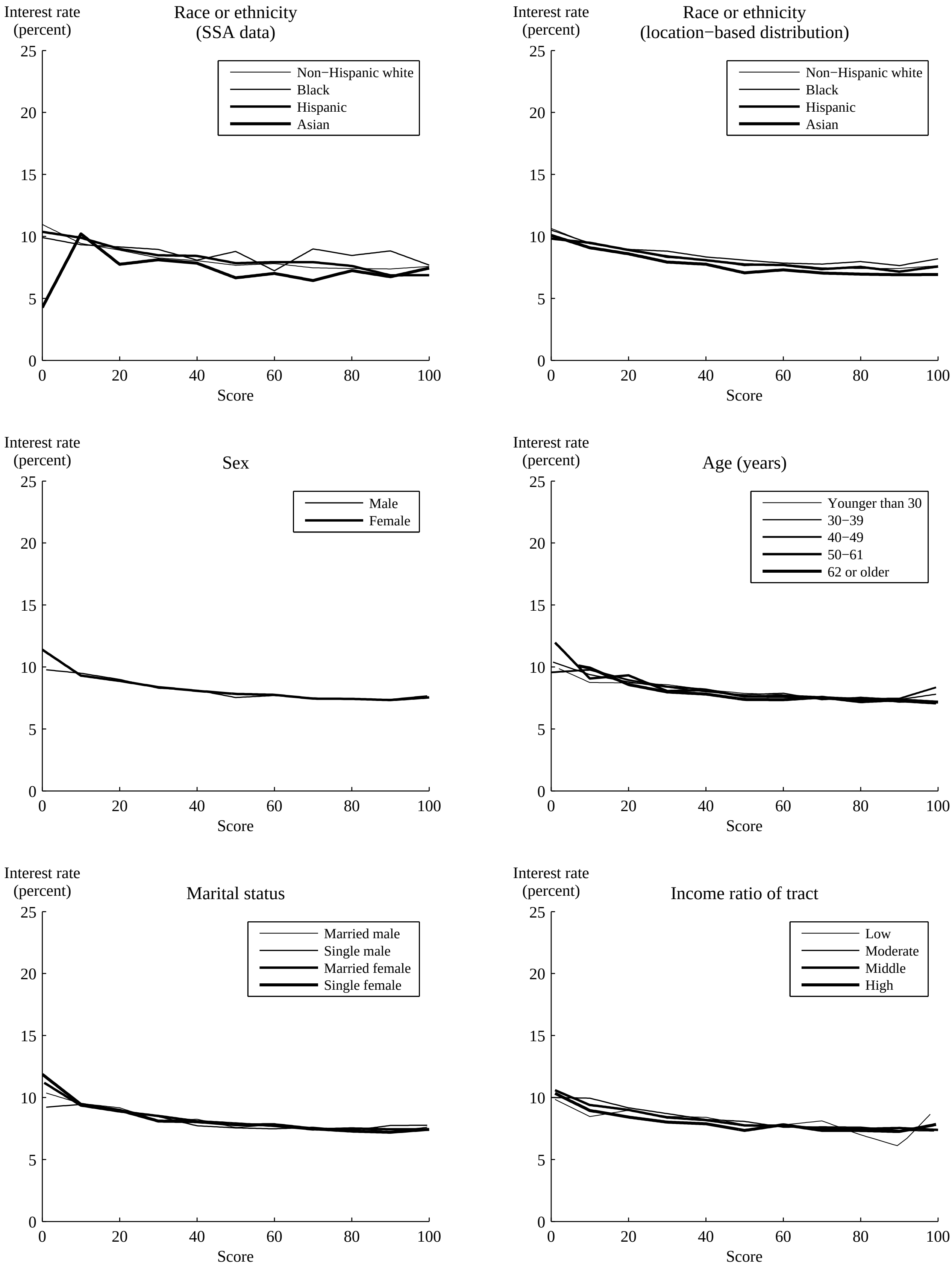
Note. For definition of characteristics, refer to notes to table 9.

Figure O−4. TransRisk Score: Inquiry−Based Proxy for Denials, by Demographic Group



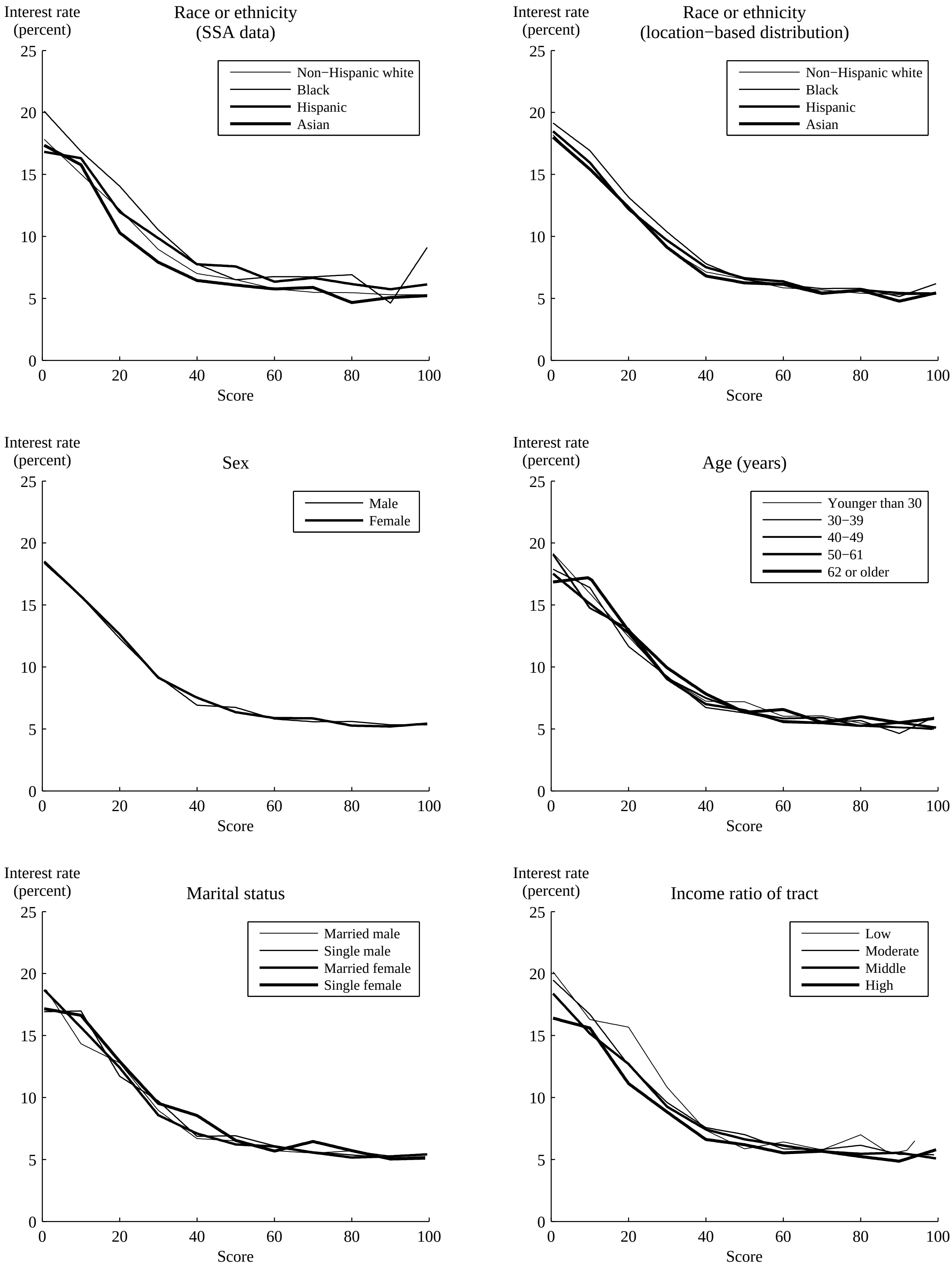
Note. For definition of characteristics, refer to notes to table 9.

Figure O−5. TransRisk Score: Mortgage Interest Rate, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

Figure O−6. TransRisk Score: Auto Loan Interest Rate, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

REPORT TO THE CONGRESS ON CREDIT SCORING AND ITS EFFECTS ON THE AVAILABILITY AND AFFORDABILITY OF CREDIT

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INTRODUCTION

All aspects of the consumer lending process—including the identification of prospective customers, loan underwriting and pricing, and account management—changed dramatically in the last third of the twentieth century. Advances in information technology have lowered the costs of credit, opened new markets to lenders, and increased the speed of lenders' decisionmaking. Borrowers have seen a proliferation of products and services offered at prices more closely tied to the anticipated risks and costs of lending. The new methods have also generated concerns about the loss of individualized treatment of credit applicants and about the possibility of hidden biases in the technologies being used.

One of the keys to these changes in credit markets has been the automation of the lending decision through credit scoring. Credit scoring is any automated, statistically based system (or "model") that quantifies the credit risks posed by a prospective or current borrower relative to other borrowers and calculates a summary numerical "credit score" for each individual. Credit-scoring technologies may be used to support judgmental decisionmaking (that is, the judgment of the loan underwriter) or may serve as the sole basis for credit decisions.

Before the advent of credit scoring, individual credit analysts, or underwriters, manually reviewed applications and evaluated them on the basis of their own experience, sometimes in conjunction with specific rules or other non-empirically derived credit guides established by the creditor. However, such judgmental decisionmaking is time consuming, costly, and subject to inconsistency because different underwriters may weigh individual factors differently. In contrast, it is maintained that underwriting based on credit scoring is quick, inexpensive, and consistent. Moreover, credit scoring can potentially improve the accuracy of credit decisions and may reduce the potential for prohibited forms of discrimination to the extent it removes subjectivity from credit decisions.

Credit scoring was initially focused on the decision to accept or reject an application for credit. Over time, its use expanded into other aspects of the lending process, including loan pricing, various aspects of account maintenance, and the solicitation of new credit accounts. Credit-scoring technologies are now routinely used by lenders to help identify prospective customers and to make "firm offers" of credit to them. The increasing use of unsolicited offers of credit as a primary channel for consumer lending has likely promoted competition among lenders by allowing them to inexpensively reach beyond the traditional geographic markets served by their branch offices.

A number of concerns have been raised about the efficacy of credit-scoring technologies and how they are used in the marketplace. First, some have questioned whether risk estimation based on credit scoring affects population segments differently based on factors other than risk. Second, concerns have been raised about whether some of the specific factors used to estimate credit scores may have an adverse effect on individuals grouped by their race, ethnicity, sex, or other personal or demographic characteristics.

Third, some observers believe that automated technologies disadvantage individuals with nontraditional credit experiences because creditors offering such products may be less likely to furnish information to credit-reporting agencies (credit-reporting agencies are firms that gather and make available through credit reports and other techniques information on the credit-related behavior of consumers). These observers often maintain that individuals with nontraditional credit histories are better served by judgmental credit evaluations, which can consider information not included in credit reports and thus may provide a more accurate profile of credit risk. For example, sometimes lenders give weight to explanations provided by consumers regarding extenuating circumstances associated with credit problems they have encountered.

Fourth, it has been suggested that judgmental evaluations may be better able than credit-scoring technologies to detect errors or other inaccuracies in the information used to evaluate creditworthiness. And fifth, some observers argue that discrimination in lending markets has caused disadvantaged individuals to pay more for credit than is warranted or caused them to use less desirable sources of credit. Either outcome could lead to a greater possibility of loan payment problems and consequently tarnished credit histories, outcomes that would be reflected in poorer credit scores.[1]

To assess these concerns about credit scoring, the Congress mandated, in section 215 of the Fair and Accurate Credit Transactions Act of 2003 (Fact Act), a study of the effects of credit scoring on the availability and affordability of credit.[2] The study is to include an analysis of the statistical relationship that controls for demographic characteristics between credit scores and the quantifiable risks and actual losses experienced by businesses. In addition, the study is to address "the extent to which, if any, the use of credit-scoring models, credit scores, and…impact on the availability and affordability of credit to the extent information is currently available or is available through proxies, by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, and creed, including the extent to which the consideration or lack

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[1] A discussion of different patterns of borrowing across racial groups and their consequences is in Sheila D. Ards and Samuel L. Myers (2001), "The Color of Money: Bad Credit, Wealth and Race," *American Behavioral Science*, vol. 45 (October), pp. 223-39.

[2] Section 215 directs the Board of Governors of the Federal Reserve System and the Federal Trade Commission, in consultation with the Office of Fair Housing and Equal Opportunity of the Department of Housing and Urban Development, to conduct the study. Section 215 also directed that similar issues be examined for the use of credit scoring in insurance markets. In preparing the report, the Federal Reserve Board focused on the relationship between credit scoring and credit and the Federal Trade Commission addressed the use of credit scoring in insurance markets.

of consideration of certain factors by credit-scoring systems could result in negative or differential treatment of the protected classes, under the Equal Credit Opportunity Act (ECOA), and the extent to which, if any, the use of underwriting systems relying on these models could achieve comparable results through the use of factors with less negative impact."[3]

Scope of the Report

This report provides the results of the assessment of the effects of credit scoring on credit and was prepared by the Federal Reserve Board. The report draws on secondary sources of information, such as public comments and previous studies or analyses as well as on an analysis of a credit-scoring model constructed specifically for this report.

Public Comment on the Study

The Federal Reserve Board and the Federal Trade Commission sought comments and suggestions from government agencies, members of the public, industry groups, and other interested parties, including community organizations and fair lending and fair housing organizations. Comments and suggestions came largely in three ways: First, in response to two *Federal Register* notices seeking answers to a wide range of specific questions about the use of credit scoring in credit and insurance and about ways to conduct the study; second, in meetings with interested parties to gain further insight on how to conduct the study, to learn about available data and analytic approaches, and to hear concerns regarding the agencies' plans for the study; and third, through detailed discussions with leading builders of credit-scoring models to learn about the techniques for building such models.[4]

Approaches Considered in Conducting the Study

Section 215 of the Fact Act essentially asks for a review of three related concerns regarding credit scoring. The first is the effect of credit scoring on the availability and affordability of financial products to consumers in general. The second is whether the relationship between credit scores, on the one hand, and credit performance, availability, and affordability, on the other, vary across demographic groups. The third is whether

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[3] The full text of section 215 is in appendix A of this report.

[4] Federal Trade Commission (2004), "Public Comment on Methodology and Research Design for Conducting a Study of the Effects of Credit Scores and Credit-Based Insurance Scores on the Availability and Affordability of Financial Products," notice and request for public comment (RIN 3084-AA94), *Federal Register,* vol. 69 (June 18), pp. 34167-68 (comments received are available at www.ftc.gov/os/comments/creditscoresstudy/index.shtm; and Federal Trade Commission (200f), "Public Comment on Data, Studies, or Other Evidence Related to the Effects of Credit Scores and Credit-Based Insurance Scores on the Availability and Affordability of Financial Products," notice and request for public comment (RIN 3084-AA94), *Federal Register,* vol. 70 (February 28), pp. 9652-55 (comments received are available at www.ftc.gov/os/comments/FACTA-implementscorestudy/index.htm).

credit scores in general, and the particular factors included in credit-scoring models, may result in negative or differential treatment of specific subpopulations and, if so, whether that treatment could be mitigated by changes in the model development process.

Regarding the first concern—the effect on the availability and affordability of credit—commenters provided only limited information. Some described in general terms how credit scoring has affected credit availability and affordability but gave little specific information or direct evidence. The relative paucity of specific evidence provided by commenters is not surprising, as much of the data, particularly regarding the effectiveness of risk evaluations based on judgment versus credit scoring, is proprietary and often based on evaluations conducted many years ago. Nonetheless, the present study reviews the information provided by commenters, and by other reports in the public domain, regarding the effects of credit scoring on credit availability and affordability. The study also analyzes data gathered over the years by the Federal Reserve Board in its Survey of Consumer Finances. These data provide indirect evidence of the effects of credit scoring on credit availability and affordability over time.

Commenters suggested ways in which the study could address the second and third issues in the section 215 requirement: whether the relationship between credit scores and credit performance, availability, and affordability varies across populations and whether credit scoring, in general, as well as particular factors included in credit-scoring models may disadvantage specific subpopulations and whether any improvements could be found in changes to the models. The suggestions fell into two broad types of inquiry. The first type was a series of "disparate impact audits" of existing major credit-scoring models. The audits would focus on the appropriateness of the factors used in model development and of the weights attached to those factors and on the relationships between credit scores and loan performance. The second type—the "model building" option—would address the potential for creating disparate impact in the process of developing a credit-scoring model. This approach would evaluate the creation and use of a generic credit-scoring model rather than of any model that already exists. The information collected to develop this model could also be used to empirically evaluate the relationship between credit scores and credit performance, availability, and affordability.

The audit approach would either be restricted to an evaluation of analyses conducted by the model builders themselves or would require the auditing entity to have access to the actual samples used to estimate each model and all of the model weights and components. In contrast, the model-building approach requires original work to create a credit-scoring model that corresponds to the process followed by the industry and to collect data against which to test and evaluate it; it therefore offers the potential for a much wider scope of analysis and can address issues and methods not considered in the self-assessments of the industry's model builders. However, the second approach—

model building—is limited in that it cannot offer a definitive conclusion about any particular model; rather, its results are only suggestive of the issues that arise in the process of model development. The issue of representativeness is important to both approaches. The audit approach requires that the models reviewed be representative of those used by the industry.[5] The model-building option requires that the process of creating and estimating the model be representative of industry practice.

There was little choice in deciding which of the two approaches to use. A strict audit approach was not feasible because necessary data on the personal demographic characteristics of credit applicants and borrowers generally is not available, except for data identifying the sex, race, and ethnicity of home mortgage applicants. Although a few suggestive studies have been conducted by relying on the racial composition of neighborhoods to represent the race or ethnicity of individuals, they do not satisfy the requirements of section 215.

A modified audit approach was considered. It would entail gathering information on the racial, ethnic, and other personal characteristics required and appending them to the actual samples of data on individuals used by model developers for a representative sample of industry credit-scoring models. This would allow each model to be evaluated for the issues identified in section 215. However, even the modified approach was not feasible. Model developers generally use estimation samples stripped of personal identifying information such as name and Social Security number. Obtaining this information would have required going back to the original data sources and attempting to gather this information with appropriate legal safeguards. The logistics of such an undertaking were sufficiently complex and daunting that this approach could have been at best used for one or two models. Narrowing the scope strips the audit approach of one of its principal strengths, namely, coverage of a large number of models in use today. Moreover, unless this approach relied on the original sample of observations used for the actual model development, it could no longer be represented as an audit of the actual credit-scoring model being evaluated.

These limitations led the Board to adopt the second approach for conducting this study—creating a model from scratch and assembling a data set with which to evaluate

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[5] The audit approach would have to be quite broad in its reach to fully represent the credit-scoring models used by the industry. Some models are designed only to evaluate applicants for new accounts, others to predict performance on existing credit accounts; and still others to address both purposes. Also, credit-scoring models use different models or "scorecards" for different segments of the population. For example, a credit-scoring model may have separate scorecards for individuals with "thin" credit files (individuals with few if any records of credit accounts), with "clean" track records (individuals with no record of a serious delinquency), and with track records with a "major derogatory" (individuals with a record of one or more serious delinquencies), to name a few. Each scorecard can be based on different credit-related factors. Finally, credit-scoring models are routinely re-estimated and changed to reflect new technologies and the availability of updated information on the credit experiences of consumers. Thus, the credit-scoring systems and factors that constitute the models are ever changing.

issues related to the relationship between credit scores and credit performance, availability, and affordability. Having made a choice of approach, other issues needed to be addressed, the most important of which was to choose the types of credit-scoring models to assess.

Types of Credit-Scoring Models

Credit-scoring models differ from each other along three distinct dimensions: (1) the factors used to form the prediction, (2) the type of borrower performance the model is designed to predict, and (3) the population used to estimate the model (that is, the population used to empirically derive the model's predictions).

The narrowest set of factors used to form predictions is drawn from information included in the credit records maintained by credit-reporting agencies. Models that limit the factors to that set are the most widely used and are commonly referred to as *credit history scoring models*.[6] Other credit-scoring models derive their predictions from a broader or different set of data, such as the information recorded on applications for credit (much of which does not appear in records of the credit-reporting agencies) or a creditor's own data on experiences with their customers.

Among other things, the models seek to predict borrower performance for a specific credit product, such as home mortgages, automobile loans, and credit cards or performance for *any* type of credit account. (A later section of this study provides a more extensive discussion of what credit-scoring models seek to predict and how they are used.)

When the populations used for estimation include a creditor's current or prospective customers, the model is typically referred to as a *custom* credit-scoring model. When the population is based on a representative sample of all individuals in credit-reporting agency records, the resulting model is typically referred to as a *generic* credit-scoring model. A generic credit-scoring model in which the predictive factors are limited to the information contained in credit records is generally referred to as a *generic credit history scoring model*. For reasons described below, the model developed specifically for this study and those used to evaluate the relationship between credit scores and credit performance, availability, and affordability are generic credit history scoring models.

Reasons for Focusing on Generic Credit History Scoring Models

Thousands of custom credit-scoring models are in use today by lenders to support their underwriting, account management, and marketing, whereas generic credit history

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[6] Credit history scoring models are often referred to as credit-bureau based scoring models by industry participants.

scoring models are relatively few in number and made available by only a small number of firms.[7] However, although they are few in number, generic credit history scoring models are central to the operations of the credit industry.

As a summary of the credit histories of individuals, generic credit history scores are widely used by lenders to supplement and support various aspects of the lending process. For example, (1) lenders use them even when they also draw on a broader range of information such as data from applications for credit, (2) a generic credit history score alone often provides the credit history component of lending evaluations that are conducted manually, (3) lenders that have developed their own (that is, custom) credit history scoring models often use generic scores to facilitate loan sales and to enhance portfolio management, and (4) lenders commonly use generic credit history scores as a criterion, often the sole criterion, in deciding who should receive so-called "prescreened" solicitations for new accounts. It is this central role played by generic credit history scoring models that placed them, rather than some custom model or a model looking at factors other than credit history, at the center of this study.

The choice to focus on generic credit history scoring models has limitations. Decisions about loan pricing and assessments of credit risk are likely to be based on credit-scoring models that include a broader set of information than those used to estimate credit history scoring models. Thus, empirical assessments of the relationship between generic credit history scores and credit performance, availability, and affordability may not be fully reflective of the relationships that would be observed between the credit scores actually used to underwrite credit and subsequent credit outcomes.

Further, because the factors evaluated in this study are restricted to items included in credit-reporting agency files, the results related to assessments of possible differential effect will not be applicable to other types of information considered in credit underwriting or other uses. And even for the credit-record items reviewed here, the assessment of differential effect may not necessarily be consistent with an analysis that would simultaneously consider other types of information often included in credit evaluations. Despite these limitations, the approach taken here is likely to be suggestive of results for other existing models, whether they are generic history scores or are based on other types of information.

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[7] Elizabeth Mays (2004), *Credit Scoring for Risk Managers*: *The Handbook for Lenders* (Mason, Ohio: South-Western), p. 17. As noted above, a generic credit history score is generated by a model (1) that draws on a representative sample of all individuals in credit-reporting agency records (a feature that makes the model *generic*) and (2) in which the predictive factors are limited to information contained in credit-reporting agency records (which focuses the model on credit *history*).

General Background

This section provides background information in areas that were central to the preparation of this report: (1) credit-risk evaluation systems, (2) the emergence of credit scoring, (3) the credit-reporting agencies, (4) the content of credit records, (5) the development and estimation of credit-scoring models, (6) generic credit history scores, and (7) the current uses of credit scores.

Credit-Risk Evaluation Systems

The ability to quantify credit risk—the risk that a borrower will not pay back a loan as agreed—is central to the core aspects of lending: soliciting accounts, extending credit, pricing (that is, setting the interest rate or fees or other terms), and managing existing credit accounts. As noted earlier, systems in which the credit decision is made manually by a loan officer or other person are referred to here as *judgmental* systems; those in which the credit decision is made mechanically on the basis of a statistical model are commonly termed *credit-scoring* systems. Although these systems differ in how the credit decision is made, they can rely on similar information in reaching the decision. For example, both judgmental and credit-scoring systems ordinarily consider individuals' past experiences with credit as reflected in the credit records maintained by credit-reporting agencies. Moreover, a factor considered in many judgmental systems is a statistically derived credit score.[8]

Both judgmental systems and credit-scoring systems assume that past experience can be used to predict future performance, but not with certainty: Even the best-rated loans might suffer default, and even the worst-rated loans might be repaid as agreed. Rather, the basic goal of any credit-risk evaluation system is simply to differentiate loans that are more likely to be repaid from those that are less likely to be repaid.

Assessments of credit risk have been conducted as long as credit has been offered: Lenders collect information that they believe is relevant to the question of whether a loan will be repaid, and the summary of that information determines whether to make the loan. Whereas judgmental assessments generally rely on less standardized information that may be subjectively evaluated, statistically based procedures draw on types of information that will be similar for all borrowers and evaluate the data through a mathematical process that yields a numerical score.

[8] Although most credit-scoring systems are based on statistically derived models, they need not be. For instance a creditor may use a rigidly implemented system of rule-based decisions in which the rules have not been statistically derived. More background information is in Robert A. Eisenbeis (1980), "Selection and Disclosure of Reasons for Adverse Action in Credit-Granting Systems," *Federal Reserve Bulletin*, vol. 66 (September), pp. 727-35.

Judgmental systems continue to be the only practical approach for the few large loans (in relation to the large number of smaller consumer loans) a lender will make to larger businesses. In such multimillion-dollar agreements, the specific attributes of the loans and the circumstances of the borrowers tend to be unique and often highly complex and thus unsuitable for a standardized system. However, judgmental systems—which entail detailed attention to each case—are expensive for lenders to apply to the vast size of their consumer lending portfolio, particularly different types of revolving credit and personal installment loans.

If applied to the same loan application, the judgmental and statistical methods of credit-risk assessment will not always produce the same predictions of repayment likelihood or result in the same decision of whether to lend. Part of the reason is that in judgmental systems, evaluation criteria are often set up as distinct "hurdles" such as a maximum debt-to-income ratio or minimum loan size; as soon as an application is confronted by a hurdle it cannot surmount, it may be rejected without ever being tested against other hurdles. In contrast, in credit-scoring systems, shortfalls or weaknesses in one area may be offset by strength in one or more other areas.

The potentially inconsistent treatment of information is another reason that a judgmental system may reach an outcome that differs from a statistically based decision. Judgmental systems rely on the experiences of individual loan officers to discern the factors that will be good predictors of loan repayment and to identify the tradeoffs among those factors. Differences in loan officers' experiences may lead them to consider different factors and make different tradeoffs among factors.

In evaluating information, statistical systems rely on automated statistical procedures, not on the experience and judgment of loan officers. The statistical procedures consider many credit-related factors simultaneously, statistically identify the relative ability of these factors to measure risk, and assign corresponding weights to each factor. Unlike judgmental systems, credit-scoring systems are consistent in their treatment of information; different outcomes arise entirely from differences in the underlying information and not from the inconsistent treatment of information from case to case.

Credit-scoring systems generally involve significant fixed costs to develop, but their "operating" cost is extremely low—that is, it costs a lender little more to apply the system to a few million cases than it does to a few hundred. This low "marginal" cost—or the highly "scalable" nature—of the credit-scoring system greatly enhances the lending process by allowing lenders to compete for a wider range of customers and by making their management of existing account relationships more efficient.

Emergence of Credit Scoring

Credit scoring first emerged in the late 1950s to support lending decisions by the credit departments of large retail stores and finance companies.[9] By the end of the 1970s, most of the nation's largest commercial banks, finance companies, and credit card issuers used credit-scoring systems. Over these two decades, the primary use of credit scoring was in evaluating new applications for credit, and creditors used their own experience and data, sometimes with the aid of consultants, to develop the models. Although often available at the time from local credit bureaus (today more commonly referred to as credit-reporting agencies), credit history records were limited in scope and relatively expensive to access. Thus, lenders essentially had no practical way of obtaining the complete credit histories of noncustomers and so could not effectively target them for solicitations on the basis of credit history.

By the late 1980s much had changed. Creditors were no longer restricted to the credit histories of their own customers and credit applicants. Rather, lenders could purchase the generic credit history scores of individuals who were not their account holders and, with that data, market consumer credit products tailored to various credit scores to appropriate potential borrowers.

The use of credit scoring then spread to additional loan products including home mortgage and small-business lending. Scoring technologies also were applied in new ways, such as in assessments by institutions of whether to purchase individual loans or pools of loans backing securities.[10] Finally, credit-scoring technologies were developed to focus on outcomes beyond credit-risk assessment to include, for example, account profitability and various aspects of account management.

Changing Patterns of Credit Use

As the use of credit scoring was growing, so was the demand for consumer credit and the number of credit instruments offered to finance such activities. Since the early 1900s, merchants have been offering installment credit to allow customers to stretch out their payments for the purchase of furniture, major appliances, and other large durable goods. Charge cards, such as those offered by oil companies and large retailers, first emerged in the 1950s, but in most instances full payment were expected within the billing cycle. In

[9] "The first commercial [credit-scoring] systems were developed by Bill Fair and Earl Isaac in 1958 for American Investment, a finance company based in St. Louis; refer to Hollis Fishelson-Holstine (2004), "The Role of Credit Scoring in Increasing Homeownership for Underserved Populations," prepared for "Building Assets, Building Credit: A Symposium on Improving Financial Services in Low-Income Communities"; Working Paper Series BABC 04-12 (Cambridge, Mass.: Joint Center for Housing Studies, February).

[10] For example, in 1994, Fannie Mae and Freddie Mac began to use the scores in their automated underwriting systems; refer to John W. Straka (2000), "A Shift in the Mortgage Landscape: The 1990s Move to Automated Credit Evaluations," *Journal of Housing Research*, vol. 11 (no. 2), pp. 207-32.

the 1960s, retailers began converting their charge cards into credit cards, a credit instrument that allowed the consumer to extend payments over a long period.

Generic revolving credit, that is, a re-usable credit account not tied to a specific retailer, dates to the 1950s with the emergence of the first bankcards, but it begin to flourish with the introduction of credit cards carrying the Visa and MasterCard logos; its usage more than doubled over the 1970s, with much of that growth taking the place of small installment loans.[11] The substitution accelerated in the 1980s and 1990s as credit cards—some tied to home equity lines of credit—became widely accepted for the purchase of larger durable goods and as a ready source of funds through cash advance features.

The development of statistical methods to evaluate credit risk was necessary for the emergence of large-scale open-ended consumer lending, that is, the extension of very large numbers of relatively small loans, each of which has only a small expected return to the lender. In all likelihood, making such loans at the rates they are offered today would not have been possible had it not been for the advances in credit scoring, which have dramatically reduced the cost of offering such credit. Likewise, in the home mortgage market, the application of credit-scoring technologies in the 1990s lowered the costs of both underwriting and funding and promoted greater competition as lenders extended their reach far beyond their traditional branch office locations.

Credit-Reporting Agencies

Borrowers with poor payment histories have incentives both to seek out new sources of credit and to withhold information about their credit histories. In the latter part of the nineteenth century, private-sector firms arose to share credit information among lenders and others who were allowed to subscribe to their service. These firms, known today as credit-reporting agencies, do not make credit decisions; rather, they collect, standardize, and disseminate to their subscribers information on a wide range of consumer activity by individuals over time. The activity covers loans, leases, non-credit-related bills, and money-related public records such as court-ordered collections and bankruptcy.[12] The agencies also record, and report, the requests for such information that have come from

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[11] In 1958, Bank of America, based in San Francisco, issued BankAmericard, the first "revolving credit" card with widespread acceptance by merchants of all types. The revolving-credit feature allowed cardholders the option of paying their account balance in installments, with a monthly finance charge applied to the remaining balance. In 1966, Bank of America, through a subsidiary, began licensing banks outside of California to issue the cards to their customers.

[12] Some of the items reported to the credit-reporting agencies are not comprehensive. For example, some reporters provide information only on delinquent accounts. Some items such as lawsuits are often not reported or collected from public entities. Consequently, some of the data include in the credit-reporting agency data are not fully representative of all credit-related activity or public records. For more information see, Robert B. Avery, Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner (2003), "An Overview of Consumer Data and Credit Reporting," *Federal Reserve Bulletin*, vol. 89 (February), pp. 47-73.

their subscribers, which include not only lenders but employers and others with a legally sanctioned interest in the information.

Credit-reporting agencies, historically referred to as "credit bureaus," were initially established by localized retail establishments and personal finance companies to share information on their customers.[13] In 1906, the bureaus established a trade association, the Associated Credit Bureaus, Inc. (ACB), to facilitate the sharing of credit-related information across the country. The membership of the ACB grew substantially, as did the number of individuals covered. However, as late as the 1960s, technological limitations restricted the coverage of even the largest credit bureaus to only a few cities.

As retail establishments sought to serve customers beyond the reach of their local outlets and as consumers became more mobile, the demand intensified for the credit bureaus to efficiently obtain comprehensive information on consumers in many different markets. At the same time, commercial banks, particularly those involved in regional or national credit card lending, had a growing need to gather information about prospective customers in geographically dispersed markets. Technological advances ultimately enabled the bureaus and banks to meet their needs. Those advances also encouraged consolidation among credit bureaus as the smaller entities found the costs of adopting the new technologies prohibitive.

As improved technology reduced costs and increased capabilities over the late 1970s and 1980s, the current national system of gathering and reporting credit-related information emerged. Today the credit-reporting industry is dominated by three national credit-reporting agencies, although the industry still includes a number of smaller firms with only local or regional scope.

The three national credit-reporting agencies—Equifax, Experian, and TransUnion LLC (TransUnion)—seek to collect comprehensive information on all lending to individuals in the United States; as a consequence, the information maintained by each agency is vast.[14] Each of these national credit-reporting agencies has records on perhaps as many as 1.5 billion credit accounts held by approximately 225 million individuals. Together, the three national agencies generate more than 1 billion credit reports each year. The vast majority of these reports are provided to creditors, employers, and insurers and individuals have also long been able to purchase a copy of their own report. To improve consumer awareness and understanding of the information included in credit records and to help individuals identify potential errors in their reports, a 2003 amendment to the 1970 Fair Credit Reporting Act (FCRA) provides that individuals may

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[13] Robert M. Hunt (2005), "A Century of Consumer Credit Reporting in America," Working Paper 05-13 (Philadelphia: Federal Reserve Bank of Philadelphia, June).

[14] Information on each agency is available at www.equifax.com, www.experian.com, and www.transunion.com.

obtain a copy of their credit report free of charge from each of the credit-reporting agencies once a year.[15]

The Content of Credit Records Maintained by Credit-Reporting Agencies

Credit records a wealth of information about the credit-related experiences of individuals (indeed, all the information needed to construct a comprehensive credit history score; however, they include limited information about individuals apart from name, date of birth, Social Security number, and current and previous home addresses. In particular, credit records do not identify the race, ethnicity, sex, national origin, marital status, or religion. Credit scores are not maintained as part of credit records but rather calculated upon request using the information in the credit records. (A credit score may also be based on additional information not maintained in credit records.) There is a time dimension to a credit record. The credit-reporting agencies can produce a report that shows what an individual's credit record included at any point in time.

Credit records contain information from four broad sources: (1) creditors and some other entities such as utility companies and medical facilities, who report detailed information on the status of current and past loans, leases, and non-credit-related bills such as utility and medical bills (each such loan, lease, and bill is referred to here as a credit account); (2) monetary-related legal records of bankruptcy, foreclosure, tax liens (local, state, or federal), garnishments, and other civil judgments (these records are referred to here as public records); (3) collection agencies, who report on actions associated with delinquent credit accounts and unpaid non-credit-related bills (the credit accounts and bills being handled by collection agencies are referred to here as collection agency accounts); and (4) the credit-reporting agencies' record of inquiries about an individual's credit record made by creditors and others legally entitled to the information.[16]

Credit accounts constitute the bulk of the information in the typical individual's credit record, and thus the information on credit accounts represents most of the information maintained by the agencies. Credit-account records include the following details about each account: the date it was established, closed (if applicable), last reported on by the creditor, and last used; type of account, such as revolving, installment, or home mortgage; current balance owed; highest balance owed; credit limits (if applicable); and payment performance, such as the extent to which payments are, or have been, in arrears.

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[15] Free credit reports may be requested at www.annualcreditreport.com. State laws in Colorado, Georgia, Maine, Maryland, Massachusetts, New Jersey, and Vermont also require that their residents be allowed to obtain a copy of their credit report free of charge.

[16] A detailed assessment of the contents of credit records is provided by Robert B. Avery, Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner (2003), "An Overview of Consumer Data and Credit Reporting," *Federal Reserve Bulletin*, vol. 89 (February), pp. 47-73.

The information available on public records, collection agency accounts, and creditor inquiries is significantly less detailed than the data covering credit accounts. In the public records and collection accounts, only the amount of money involved, the type of creditor, and the date last reported are generally available. Entries for inquiries show only the type of inquirer and the date of the inquiry. Inquiry information is retained for up to 24 months; information from public records is retained longer, generally seven or ten years depending on the type of information. Information on credit accounts has no legally mandated time limits except for those that relate to adverse information such as records of delinquency or default.

Information Providers and the Rules Governing Reporting

Credit-reporting agencies collect information from more than 30,000 sources, primarily creditors, governmental entities (mostly courts at the state and local level), collection agencies, and third-party intermediaries. Generally the agencies collect data from each source every month, and they typically update their records within one to seven days of receiving new information. According to the Consumer Data Industry Association (CDIA), credit-reporting agencies receive more than 4.5 billion items of information each month.[17]

No law requires creditors or others to report data to the agencies. However, although participation in the credit-reporting process is voluntary, entities that do report to the agencies, and the agencies themselves, are subject to rules and regulations governing credit reporting. Access to credit-related information held by a credit-reporting agency and maintenance of each credit report held by the agencies is governed by conditions spelled out in the FCRA.[18]

The information provided to the credit-reporting agencies has expanded and become much more comprehensive over time.[19] However, not all creditors report to the agencies, and not all always report or provide updates on all requested items.[20] For these

[17] The CDIA (www.cdiaonline.org), the successor to the Associated Credit Bureaus, is the trade association for the credit-reporting industry.

[18] A discussion of how the FCRA governs and encourages accurate credit reporting is in Michael E. Staten and Fred H. Cate (2004), “Does the Fair Credit Reporting Act Promote Accurate Credit Reporting?” prepared for “Building Assets, Building Credit: A Symposium on Improving Financial Services in Low-Income Communities”; Working Paper Series BABC 04-14 (Cambridge, Mass.: Joint Center for Housing Studies, February).

[19] For example, the average number of accounts per credit record in general, and the number of mortgage accounts in particular, has increased substantially in the past decade or so. Also, in the past, each of the three national credit-reporting agencies tended to collect much of their information from a different specific region of the country. Regional differences have largely disappeared, as each of the companies now receives comprehensive information nationwide (Fishelson-Holstine, “The Role of Credit Scoring in Increasing Homeownership for Underserved Populations”).

[20] Entities besides creditors, including public utilities and telecommunication firms, sometimes provide bill-payment information to the credit-reporting agencies, but most do not. Information on such bills tends to appear in credit records via reports from collection agencies on unpaid bills.

reasons the information on an individual is not always complete. Moreover, reporters do not always report to each of the national credit-reporting agencies, and if they do, they may not report the same information or at the same time to each agency. As a consequence, the information on an individual may differ across the agencies.

The information on an individual may also differ across agencies because each applies its own rules in determining how to assign reported information to a given individual. Such rules are necessary because reporters are not always able to provide a Social Security number when furnishing information or the reported number may be wrong. Also, individuals may have accounts under different names (because of marriage or variations in the use of a middle name or initial) or different addresses (because of changes in residence).[21]

The Accuracy of Credit Records

Fundamental to any underwriting process (that is, the process of evaluating the credit risk of a prospective borrower) is the accuracy and completeness of the information considered. Numerous studies have reviewed the degree to which credit report information is accurate and complete and the implications of data limitations for credit availability and pricing. These studies have reached quite different conclusions.[22]

Inaccurate data may cause some consumers to pay more, or less, for credit than is warranted by their true circumstances. For the full benefits of the credit-reporting system to be realized, credit records must be reasonably complete and accurate. Yet, under the country's voluntary system of credit reporting, complete information is not always reported to the credit-reporting system. Moreover, data accuracy is an issue under any credit-reporting system. The accuracy of the data affects both credit scoring and judgmental evaluations because both techniques rely on the quality of the information included in credit reports. Judgmental underwriting, which requires a loan officer's individual attention to an application, provides an opportunity to identify inaccuracies that credit scoring does not.

Despite the importance of accurate and complete credit reports, the subject is beyond the scope of this study. However, section 319 of the Fact Act directs the FTC to conduct ongoing studies of the quality of the data in credit reports and report its findings to the Congress.

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[21] Address changes are very common; according to the 2000 census, about 15 percent of the U.S. population moves each year (http://factfinder.census.gov).

[22] A discussion of these issues and references to the research are in Robert B. Avery, Paul S. Calem, and Glenn B. Canner (2004), "Credit Report Accuracy and Access to Credit," *Federal Reserve Bulletin*, vol. 90 (Summer), pp. 297-322.

Developing and Estimating Credit-Scoring Models

Developing an effective credit-scoring model is complex, time consuming, and costly. By contemporary standards, early credit-scoring models were built on less robust databases and often focused on information derived from applications, but advances in computing power, access to more-comprehensive credit history information, and improved empirical methods have made credit-scoring models more sophisticated and effective. This section provides a general description of the development of credit-scoring models. A detailed description of the specific, generic credit history scoring model developed for this study is presented in a later section.

The Data Used in Developing a Model

Development of a credit-scoring model begins with the collection of data on a sample of individuals and accounts that is broadly representative of the accounts whose performance is to be predicted. Typically, the sample of credit records drawn for estimation is a stratified random sample that includes a larger representation of credit accounts with specific characteristics, such as elevated delinquencies rates, to ensure the model predicts well for each segment of the population. The data must include the outcome of interest—typically, whether the borrower defaulted on a loan—as well as information that may be used to predict the outcome of interest, such as data contained in credit records or data collected as part of the loan application process. The predictive information typically includes the data contained in loan applications and thus antedates the outcomes. When complete, the model can be applied to the data in a new application for credit to generate a quantitative score—the credit score; in most systems the highest possible number represents the greatest certainty that the account holder will pay as agreed.

For the predictive information (termed the "explanatory variables") in a loan-default model to be useful in determining whether a borrower will repay as agreed, the data must include a fairly large number of each type of outcome (termed the "dependent variable")—both defaults and proper repayments. Most accounts are in good standing (such an account is commonly referred to as a "good"); thus, the challenge most often is to acquire a data set that has a substantial number of defaults ("bads"). A traditional rule of thumb for loan-default models is that the sample must include at least 1,500 bads although some use fewer.[23]

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[23]Edward M. Lewis (1992), *An Introduction to Credit Scoring* (San Rafael, Calif.: Athena Press). Some other researchers recommend a minimum of 300 or 500 "bads" (refer to Gary Chandler, 1985, "Credit Scoring: A Feasibility Study," *Credit Union Exec,* vol. 25, pp. 8-12 or Elizabeth Mays (2004), *Credit Scoring for Risk Managers*: *The Handbook for Lenders* (Mason, Ohio: South-Western). Typically, many accounts cannot be straightforwardly identified as either "bad" or "good"; they are labeled "indeterminate" and eliminated from the estimation sample. For example, an account that is 30 days or 60 days in arrears may be treated as indeterminate while accounts that are 90 days or more in arrears may be

Creating Characteristics and Estimating a Model

After assembling the sample of data (for example, credit records), the model builder creates explanatory or predictive variables from the data, often referred to as *characteristics*. Characteristics then are the key inputs of the model used to generate credit scores. Although credit records can be used to create hundreds of characteristics, only those proven statistically to be the best predictors of future credit performance are included in the final model.

The specific characteristics and the weights assigned to each can vary according to the purpose of the model. For example, to support the evaluation of specific loan products, such as home mortgages or automobile loans, a model will typically include characteristics (for example, loan-to-value and debt-to-income ratios) derived from loan applications, as well as information drawn from records of the credit-reporting agencies.

More generally, characteristics representing two types of data are typically used to develop credit-scoring models: continuous data and data that can take only a limited set of values. For characteristics that represent continuous data, such as outstanding balances or the degree of credit utilization (outstanding balance divided by the maximum amount the individual is authorized to borrow), the model builder generally simplifies the data by defining ranges that differentiate meaningfully among different levels of risk. For example, credit utilization might be represented by ranges such as above 90 percent, between 50 percent and 90 percent, and below 50 percent.[24] The options are by definition more limited for characteristics that can take only a limited number of values, such as "yes" or "no" (for example, for the characteristic that represents whether or not an individual has an entry for a public records).

Finally, each value of each characteristic—including each range for a continuous characteristic—is assigned a specific point count, and the credit score for any given individual is equal to the sum of these point counts over all characteristics considered in the model. The point counts and selection of the specific characteristics used in the model are derived from a statistical analysis of the relationship between characteristics at an initial point in time and credit performance over a subsequent period. The statistical model typically used in predicting loan performance takes the form of a so-called logistic regression, in which the dependent variable is the logarithm of the odds ("log-odds") of the probability of default versus nondefault. Specifically, the log-odds is the logarithm of

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considered bad. The rule of thumb of 1,500 "bads" may still be relevant for custom credit-scoring systems developed for small portfolios, but the most widely used consumer credit scores are estimated from samples with hundreds of thousands or even many millions of accounts and thus with numbers of "bads" far exceeding recommended minimums.

[24] In David J. Hand and Niall M. Adams (2000), "Defining Attributes for Scorecard Construction in Credit Scoring," *Journal of Applied Statistics,* vol. 27 (no. 5), pp. 527-40, is a discussion of empirical methods for determining the number of ranges and their appropriate end points.

the ratio of the number of “good” accounts to the number of “bad” accounts in the estimating sample.

The model estimation undertaken to identify and assign weight to each characteristic to reflect their relative importance in determining borrower performance is generally done using multivariate techniques. Because the characteristics that bear on credit risk are likely to be correlated with each other, the weights assigned in a multivariate analysis are likely to differ from the weights that would be assigned if each characteristic was used to predict performance in isolation. It also may be the case that characteristics which are highly predictive when considered in isolation may contribute little in a multivariate framework. The converse can also be true. A characteristic can have a significant role in a multivariate model even when it does not exhibit strong predictive power in a univariate setting. A tendency for a high degree of correlation among credit risk characteristics is one reason that scoring models ordinarily include only a relatively small number of distinct characteristics. According to industry sources, a typical credit-scoring model will include eight to fifteen characteristics.

Validating Model Effectiveness and Establishing a Credit Score

An important stage of model development involves validation of its predictive accuracy through a series of statistical tests. One common validation method is to establish a “hold-out” sample (a portion of the original sample not used to estimate the model) to test how well the estimated model predicts the outcome of interest. Two of the most widely used statistical measures of accuracy are the *Kolmogorov-Smirnov (KS) test statistic* and the *divergence statistic* (refer to box “The Kolmogorov-Smirnov and Divergence Statistics”).

These sorts of statistical measures are used not only to determine the overall effectiveness of a model but also to help determine the number of characteristics to include in the model. Typically, the final choice involves a tradeoff between the additional effect of a characteristic on the model’s predictive accuracy and a desire to keep the complexity of the model manageable. The hold-out sample is useful in deciding the issue. Testing the model against the hold-out sample reveals whether each characteristic included in the model is predictive using data not used to construct the model. Characteristics that do not prove predictive for the hold-out sample would likely be dropped from the final model.

The final stage of model development typically involves translating, or “normalizing,” the raw statistical output, which is typically a log-odds prediction, into an easily understood score. Such normalizations must preserve the relative order among individuals.

The Kolmogorov-Smirnov and Divergence Statistics

The Kolmogorov-Smirnov (KS) test statistic is the maximum, across all credit-score values, of the difference in the cumulative proportions (in percentage points) of goods and bads. A zero value for the KS statistic means that the two credit-score distributions are the same and indicates that the credit score fails to differentiate between defaulters and nondefaulters; a value equal to 100 indicates that the credit score perfectly differentiates defaulters from nondefaulters. The KS statistic for a given credit-scoring system is the maximum vertical distance between the two curves for that system.

Whereas the KS statistic describes the ability of a credit-scoring model to differentiate goods from bads at a single point, the divergence statistic compares how the entire distributions of defaulters and nondefaulters differ. The divergence statistic is calculated as the square of the difference of the mean of the goods and the mean of the bads, divided by the average variance of the score distributions. When the model performs poorly, so that the average credit score of bads is not much different from the average score of goods, the divergence statistic will be close to zero. As the model's performance improves, increasing the difference between the mean scores of bads and goods, the divergence statistic increases. The larger the divergence statistic, the greater the predictive power of the model.

Information Not Considered in Developing Credit Scores

Under the Federal Reserve's Regulation B (Equal Credit Opportunity), a credit-scoring system that considers age must be empirically based, must be demonstrably and statistically sound, and cannot use "prohibited" information, which is information about an individual the use of which by creditors is prohibited by the Equal Credit Opportunity Act.[25] Prohibited information includes of race, ethnicity, national origin, religion, sex, and marital status. Certain information, such as age, receipt of child-support, and receipt of income from public assistance can be used, but only in restricted ways.

Creditors also exclude from their credit-scoring systems still other information available to them. Such information consists mostly of certain inquiries made to the credit-reporting agencies to check on the status of an individual's credit record. These inquiries consist of those made by consumers to check on their own credit reports; by employers or insurance companies; and by lenders either considering extending an unsolicited credit offer or checking for changes in the credit circumstances of their

[25] Federal Reserve, Regulation B, Equal Credit Opportunity, 12 CFR 202. The regulation implements title VII (Equal Credit Opportunity Act) of the Consumer Credit Protection Act. State and federal regulators (depending on jurisdiction) responsible for the safety and soundness of banking institutions specifically examine them to ensure that they are adhering to consumer protection laws, and the examinations include a review of credit-scoring systems. Nonbanking financial institutions, such as finance and mortgage companies, are subject to oversight variously by HUD, the FTC, the Department of Justice, and in many cases state regulators.

existing customers. However, inquiries made by creditors evaluating credit applications from the individual may be included in credit-scoring systems because they are consistently found to be predictive of future performance.

A concern has been raised in recent years about the possible adverse effect on credit scores of multiple inquiries stemming from credit shopping. From a credit-risk perspective, multiple inquiries arising from shopping for a specific loan for a specific purpose are not as significant as those arising from simply trying to obtain as much credit as possible. In an attempt to implement this distinction, generic credit history scoring models now customarily attempt to consolidate into one inquiry those that are similar (typically, from the same type of lender or for the same type of loan) and made over, say, a rolling two-week period.[26]

Generic Credit History Scores

A new type of credit score emerged at the end of the 1980s—one based entirely on the information included in the credit records maintained by credit-reporting agencies: a *generic credit history score*. Previously, most credit-scoring models were custom models developed with information specific to an individual lender and product. The demand for credit scores that could be used to acquire new customers for a variety of loan products stimulated the development of generic credit history scores. Developing the models for such a score became affordable only when computer technology and the structure of the credit-reporting agency industry had sufficiently evolved.

FICO and Other Generic Credit History Scores

Over time the lending industry and firms that support their activities have developed a great many versions of a generic credit history score. The first two widely available scores were the MDS Bankruptcy Score introduced in 1987 and produced by Management Decision Systems, Inc., and the FICO Prescore, developed by Fair Isaac Corporation (Fair Isaac).[27] The FICO Prescore scores were used in underwriting new credit card accounts. TransUnion was the first credit-reporting agency to offer a credit history based score with an online, real-time credit report in 1987.

The use of generic credit history scores expanded over time to a wider array of loan products and uses. In the mid-1990s, Fannie Mae and Freddie Mac recommended the use of both FICO scores and the MDS Bankruptcy Score for the underwriting of the home mortgage loans they purchased. According to Fair Isaac, FICO scores are involved each year in more than 10 billion credit decisions of all types. Fair Isaac also estimates

[26] More information is available at www.myfico.com/CreditEducation/CreditInquiries.aspx.

[27] Fair Isaac Corporation was founded in 1956; its credit-scoring systems were first used in 1958 and were based on custom models (www.fairisaac.com).

that FICO scores are involved in more than 75 percent of all mortgage originations (refer to box "FICO Scores").[28]

The FICO score, like most other generic credit scores, ranks consumers by the likelihood that they will become seriously delinquent on any of their credit accounts in

FICO Scores

Fair Isaac has developed generic credit history scoring models that focus on different populations. Versions of the models are used for varying purposes, such as for underwriting automobile credit and credit cards. Two of these versions (which Fair Isaac calls the Classic FICO score and the NextGen FICO score) generate ratings on the basis of data drawn from the general public. A third model, designed for use with individuals who have little or no credit history in the files of the three national credit-reporting agencies, generates a rating called the Expansion score.

Each of those three credit-scoring models is calibrated separately for several subpopulations; each group has one or more distinguishing characteristics in common (a technique discussed in more detail later in the main text). The model for the Classic FICO score has ten variations (called "scorecards" by Fair Isaac); the NextGen model has eighteen scorecards. The selection of scorecards is analytically driven to more effectively predict risks in certain key subpopulations, such as those that have severe derogatory information in their records. Compared with the Classic FICO score, the NextGen model seeks to better distinguish individuals who are likely to perform well (or worse) on multiple credit obligations. The NextGen model also focuses on individuals with credit records that evidence little use of credit or that contain only limited information (individuals for whom the conventional FICO model often cannot generate a score at all). Fair Isaac estimates that the NextGen model increases the proportion of such individuals who are scorable, principally those with little credit experience, by about 2 percent. The firm also reports that, in tests, the NextGen scores substantially outperform the Classic scores.*

Each of the credit-reporting agencies offers Fair Isaac credit scores to lending institutions and the broader public under a unique name, in part to reflect the fact that the model created to generate the score was calibrated from the agency's own particular data. The Classic FICO score, for example, is called the Beacon score at Equifax; the Experian/Fair Isaac Risk Model score at Experian; and the FICO Risk score, Classic (formerly the Empirica score) at TransUnion. The NextGen FICO score is known as Pinnacle at Equifax; the Experian/Fair Isaac Advanced Risk Score at Experian; and FICO Risk Score, NextGen, at TransUnion.

* Matthew Hubbard and Steve Gregg (2001), "NextGen FICO Scores: More Predictive Power in Account Management," a Fair Isaac Paper (September), www.fairisaac.com.

[28] Trademarks, service marks, and brands referred to in this report are the property of their respective owners.

the near future (typically over the next 18 to 24 months). The most commonly used FICO score ranges in value from 300 to 850 (the higher the number, the lower the credit risk). Each of the three national credit-reporting agencies calculates a FICO score, to the extent possible, for each individual in its records. In doing so, each agency uses models developed by Fair Isaac specifically for that agency and with that agency's data. Upon request by a creditor or others, the agencies calculate an individual's FICO score using the most up-to-date information in each individual's credit record.

Because each national credit-reporting agency uses a Fair Isaac model developed specifically for that agency and its data, the models differ to a certain degree. In addition, information on an individual may differ across the three agencies. Hence, an individual credit score may differ across the three agencies.

Besides the FICO score, each of the three national credit-reporting agencies makes available a generic credit history score derived from its own models. Recently, a new generic credit history score named the VantageScore became available to the marketplace. The VantageScore was developed by VantageScore Solutions LLC, a joint venture by Equifax, Experian, and TransUnion to create a measure of credit risk that scores individuals consistently across all three companies.[29] The VantageScore applies a single credit-scoring model to the data at each of the national credit-reporting agencies to ensure that the only reason that the credit score for an individual might vary across the three agencies would be differences in the data maintained by these firms.[30] The VantageScore ranges in value from 501 to 990, with lower scores representing greater credit risk. As with the FICO models, the algorithm used to generate the VantageScore involves multiple scorecards.

Proprietary models can be developed and used by individual lenders instead of, or in addition to, the generic scoring systems described above. Little information is publicly available about proprietary credit-scoring models; however, they may supplement credit history information with information beyond that included in credit records. Although the various credit history scoring models differ in their scoring ranges, in their estimation samples, and in their methods of measuring performance, they all rely exclusively on credit-record data from the national credit-reporting agencies.

Characteristics Used in the Development of Generic Credit History Scoring Models

The characteristics created for a generic credit history scoring model tend to be similar across such models. These characteristics are generally of five broad types: (1) payment

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[29] Refer to www.vantagescore.com.

[30] An important aspect of the VantageScore is its "leveling" of the characteristics used in the model. Characteristic leveling ensures that the model interprets information from each of the credit-reporting agencies in the same manner.

history, (2) indebtedness, (3) length of credit history, (4) types of credit used, and (5) acquisition of new credit.[31] These five types are not of equal importance in determining credit scores. For example, for the general population, Fair Isaac reports that payment history characteristics are the most important type, accounting for about 35 percent of the FICO score's predictive accuracy; consumer indebtedness accounts for about 30 percent; length of credit history, 15 percent; and types of credit used and acquisition of new credit, each about 10 percent. These proportions may vary for particular subgroups of individuals, such as those with only a short history of credit use.

Payment history. In general, the most important characteristics considered in credit-risk evaluation are those that relate to an individual's history of repaying credit and any evidence of money-related public actions or non-credit-related collections. The essential issue captured by payment history is timely repayment. Specific measures include the frequency of delinquencies, the severity of delinquencies, their age and dollar amount, and how recently they occurred. Repayment performance is evaluated on the full range of accounts that an individual holds, distinguishing among accounts by type (revolving, installment, mortgage, and others) and source (banking institution, finance company, retailers, and others). In general, an individual whose credit record includes a major-derogatory account, collection account, or public record will find qualifying for new credit difficult, may face higher interest rates for the credit received, or may be limited in further borrowing on existing revolving accounts.[32]

Indebtedness. When evaluating credit history, creditors also consider the type and amount of debt an individual has and the proportion of available credit in use (credit utilization). For revolving accounts, credit utilization is measured as the outstanding balance divided by the credit limit, which is the maximum amount the individual is authorized to borrow on the account. For mortgage and installment accounts, credit utilization is generally measured as the unpaid proportion of the original loan amount. High rates of credit utilization may reflect a financial setback, such as a loss of income or an inability to manage debt, and thus are generally viewed as an additional risk in credit evaluations.

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[31] A more detailed discussion of factors considered in credit evaluation, including the relative weights assigned to different factors, is available at www.myfico.com. Refer also to Robert B. Avery, Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner (1986), "Credit Risk, Credit Scoring, and the Performance of Home Mortgages," *Federal Reserve Bulletin*, vol. 82 (July), pp. 621-48.

[32] A major-derogatory account, as used in this study, is any account that is delinquent 90 days or more or that is involved in a repossession or charge-off; a collection account involves a failure to pay a loan or non-credit-related bill; and a public record is a monetary-related public action such as bankruptcy.

Length of credit history. The age of credit accounts is relevant to an evaluation of credit quality because it provides information on the extent of experience an individual has had with credit. New accounts may convey little information other than that the consumer had a very recent need for additional credit and was approved for credit.

Types of credit used. The use of many or all of the several types of credit accounts (revolving, retail, automobile, and mortgage) by an individual, together with how recently they have been used, has been found to have a bearing on credit risk.

Acquisition of new credit. Searching for new credit, as well as obtaining it, provides information about credit risk. A relatively large number of new accounts or efforts to obtain loans as indicated by recent inquiries from creditors tend to indicate elevated risk.[33] For example, the recent opening of a relatively large number of accounts may signal that an individual is becoming overextended.

Estimation of Generic Credit History Scoring Models

Like characteristics, the estimation process used in the development of generic credit history scoring models is similar across such models. The goal of the estimation process is to choose the characteristics that best predict borrower performance and assign weights to them to reflect their relative importance.

Typically, the estimation process uses a representative sample of individuals available at two points in time separated by 18 to 24 months. Performance of the borrower is measured by delinquencies or defaults that take place in that period. The predictive characteristics are calculated entirely from the initial sample.

Although a generic credit history score can be estimated over the entire sample, experience has shown that the predictive accuracy of the model may be improved by first segmenting the sample of individuals into distinct subpopulations (scorecards) for purposes of estimation. A separate model is then estimated for each scorecard. The predictive characteristics and their weights will generally differ across scorecards given the differences in the information in the credit records for each subpopulation. The final choice of characteristics for each scorecard is guided by, among other things, the marginal predictiveness of each characteristic and whether the implied statistical relationship between the values of the characteristic and performance is reasonable.[34]

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[33] Refer to www.myfico.com/CreditEducation/CreditInquiries.aspx.

[34] Reasonableness often takes the form of imposing constraints on the relationship between characteristics and performance. One such constraint is "monotonicity," which requires that increasing values of a characteristic have either a consistently positive or negative relationship to the predicted outcome. Additional information on model estimation is in Lyn C. Thomas (2000), "A Survey of Credit and Behavioral Scoring: Forecasting Financial Risk of Lending to Consumers," *International Journal of Forecasting,* vol. 16 (no. 2), pp. 149-72; Fractal Analytics (2003), *Comparative Analysis of Classification*

Generic credit history score models, like other types of credit-scoring systems, need to be periodically re-estimated to reflect changing conditions in credit markets, although the models have been found to be robust over differing economic conditions. There is no formal timetable for re-estimation, but typically it is undertaken every couple of years. Periods that have witnessed substantial volatility or notable changes in the credit environment warrant more frequent re-estimation than other periods. The FICO score models developed using data from each of the credit-reporting agencies are not re-estimated at the same time.

The final credit score for an individual normalizes the results from each scorecard to a common scale representing a prediction of future performance. When models are updated through re-estimation, typically the credit scores are normalized in a way that aligns with a risk-to-score relationship observed at a given point in time.

In most credit-scoring systems, a higher credit score represents a lower degree of estimated credit risk.[35] Each lender determines, on the basis of its own business strategy, which credit scores represent an acceptable degree of credit risk or at which points in the continuum of scores it will establish different interest rates.

National Distribution of Credit Scores, Rank Ordering of Risk, and Associated Interest Rates

As noted, FICO scores are the most widely used generic credit history score. According to Fair Isaac, nearly 60 percent of individuals with credit records that are scorable have FICO scores of 700 or more; about 15 percent of individuals have FICO scores below 600 (table 1). The median FICO score for the population of scorable individuals is about 720.

Fair Isaac's analysis of the relationship between payment performance on loans and FICO credit scores finds that individuals with low credit scores are much more likely to experience a serious delinquency or default than individuals with higher scores (table 2). For example, for new accounts extended to individuals with FICO scores below 520, about 40 percent subsequently experienced a "bad" (a delinquency of at least ninety days or other serious derogatory such as bankruptcy), compared with a "bad" rate of less than 1 percent for accounts extended to individuals with FICO scores of 760 or more.

Techniques: A Fractal Non-Hispanic Whitepaper (Jersey City, N.J.: Fractal); Nick Ryman-Tubb (2003), "An Overview of Credit Scoring Techniques," *Credit Control,* vol. 21 (no. 1/2), pp. 39-45; David J. Hand and William E. Henley (1997), "Statistical Classification Methods in Consumer Credit Scoring: A Review," *Journal of the Royal Statistical Society, Series A (Statistics in Society),* vol. 160 (no. 3), pp. 523-41; Rosenberg and Gleit, "Quantitative Methods in Credit Management: A Survey"; David J. Hand (1994), "Deconstructing Statistical Questions," *Journal of the Royal Statistical Society, Series A (Statistics in Society),* vol. 157 (no. 3), pp. 317-56; and Hand and Adams, "Defining Attributes for Scorecard Construction in Credit Scoring."

[35] For example, the NextGen FICO score ranges in value from 150 to 950, the Classic FICO score from 300 to 850, and the VantageScore from 501 to 990.

Moreover, according to Fair Isaac, default rates on new credit decrease consistently with increasing credit scores.

Not surprisingly, then, many lenders underwrite and set the price (interest rate or fees) on their loans according to risk as estimated by credit score. Both previous research and fair lending reviews conducted by banking institution supervisory agencies indicate that, all else being equal, individuals with lower credit scores or weaker credit histories are more likely to have their applications for credit denied.[36]

The connection between loan price and credit score is not rigid or uniform. For most lending, the credit history score is only one of several factors used to assess credit risk, and creditors differ in their willingness to bear risk. Consequently, no universally established credit-score threshold exists to define acceptable risk, and no universally established correspondence exists to link a specific score to a specific loan price. Nevertheless, information on the relationship between credit scores and interest rates made available by Fair Isaac shows that better credit scores are associated with lower interest rates on credit (table 3). This relationship is routinely observed in the "rate sheets" used by loan officers when establishing the interest rate on new credit.[37]

Alternative Generic Credit History Scores

Industry estimates suggest that between 35 million and 50 million individuals either do not have a credit record at a national credit-reporting agency (so-called no-file individuals) or have a record with too little credit experience to reliably calculate a traditional generic credit history score (so-called thin-file individuals).[38] Individuals lacking robust credit records disproportionately include young adults and students; recent immigrants; recently divorced or widowed individuals; and those who do not use much credit or rely primarily on non-mainstream sources of financing, such as pawn shops or payday lenders.[39]

The inability to calculate credit scores for some individuals may limit their access to credit. For example, they may not be included in solicitations for credit that rely only on credit-reporting agency records. And because creditors may not be able to reliably gauge the credit risk posed by individuals lacking a credit score or because they do not wish to spend the time or money required to gather additional information, such individuals may find it more difficult obtain credit or receive it on the best terms available. Creditors are, however, more likely to expend extra time or money to gather

[36] Refer, for example, to Alicia H. Munnell, Geoffrey M.B. Tootell, Lynn E. Browne, and James McEneaney (1996), "Mortgage Lending in Boston: Interpreting HMDA Data," *American Economic Review*, vol. 86 (March), pp. 25-53.

[37] Rate sheets provide information to loan officers on the relationship, for a given day, between underwriting factors (such as a credit score and loan-to-value ratio) and interest rates for a particular lender.

[38] Steve Bergsman (2007), "The Thin-File Problem," *Mortgage Banking*, vol. 67 (March), pp. 32-41.

[39] Bergsman, "The Thin-File Problem," p. 34.

information about the credit-related experiences of individuals applying without a credit score for larger loans, such as home mortgages or automobiles.

Given the tens of millions of individuals without a credit score, the credit industry has an incentive to develop cost-effective techniques and sources of information to determine which individuals present a profitable lending opportunity.[40] In response, alternatives to the traditional credit history score have emerged recently.[41] These alternative credit scores are based on information gathered to supplement the data in traditional credit-reporting agency records, including information related to deposit account records, payday loans, purchase payment plans (rent-to-own transactions), rent and utility payments, and regular child-care payments.[42] These expanded data are used to develop a more informative credit record for individuals that may be used to generate *nontraditional* credit scores. These alternative scores may be used by creditors to underwrite and establish the terms of loans and for marketing purposes. By expanding the information available to judge credit risk, alternative credit-scoring systems and the expanded data upon which they are built allow creditors to better assess credit risk and offer credit to more consumers and on terms more consistent with the risks they pose.

The Current Uses of Credit Scores

Creditors vary greatly in their use of credit scores for credit evaluation and pricing. Even for a given creditor, the use of credit scoring may differ markedly across loan products: The weight accorded the score in judging creditworthiness may vary, and for some products a specific score may be established to define unacceptable risk.

Perhaps more common for loan underwriting, however, is to associate particular score ranges with particular interest rates. Creditors often distribute rate sheets to underwriters to specify the interest rates corresponding to various credit-score levels. The rate sheets are sometimes rendered as a grid, with each cell representing a combination of a credit-score level and the level of another key underwriting factor, such as the loan-to-value ratio. In this type of underwriting structure, the creditor is defining the tradeoffs between changes in credit-score level and offsetting changes in the other

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[40] Refer, for example, to Information Policy Institute (2005), *Giving Underserved Consumers Better Access to the Credit System: The Promise of Non-Traditional Data,* Political and Economic Research Council (New York: IPI); Michael A. Turner, Alyssa Stewart Lee, Ann Schnare, Robin Varghese, and Patrick D. Walker (2006), *Give Credit Where Credit Is Due: Increasing Access to Affordable Mainstream Credit Using Alternative Data* (Washington, D.C., and New York: Brookings Institution Urban Markets Initiative and Political and Economic Research Council); and Katy Jacob and Rachel Schneider (2006), *Market Interest in Alternative Data Sources and Credit Scoring*, Center for Financial Services Innovation, an Affiliate of ShoreBank Corporation (Chicago: CFSI).

[41] For example, Fair Isaac offers the FICO Expansion Score, First American offers the Anthem Score (www.credco.com/anthem), and LexisNexis offers RiskView (www.lexisnexis.com/riskview).

[42] For example, the firm Pay Rent, Build Credit, Inc. (www.prbc.com), is a credit-reporting agency that specializes in gathering information on payments for recurring expenses such as rent and utilities and on payments to payday lenders to establish an alternative database to support credit decisions.

factor that will maintain an essentially unchanged credit risk and, consequently, unchanged pricing.

Over time, however, credit scores have increasingly been applied to other aspects of the lending process, including prescreening and account marketing, loan pricing, account management and loan servicing, fraud detection, estimating loss in the event of default, and estimating account profitability.

- *Prescreening and account marketing.* Credit scoring is widely used to determine whether or not a lender should extend to an individual a "firm offer" of credit.[43] Response rates on unsolicited credit offers tend to be very low (for example, on the order of ½ percent for credit cards), so lenders can reduce their marketing expenses considerably by predicting the probability that recipients will respond to their offers and then marketing only to those most likely to accept a loan.[44] Experience in credit card marketing indicates that the consumers most likely to respond to an unsolicited credit offer are generally those least likely to repay, so prescreening also seeks to rank-order likely respondents by repayment probability. Prescreening thus serves both marketing and risk-evaluation functions.

- *Loan pricing.* Lenders set interest rates for each loan according to its estimated risk. Scoring allows the establishment of prices that can be tied empirically to gradations of credit risk.[45]

- *Account management and loan servicing.* Lenders use credit scores to aid in account management. So-called behavioral-scoring methods—that is, those that consider information about a borrower's use of credit—are used to modify credit

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[43] Section 604(c) of the Fair Credit Reporting Act regulates how creditors and insurers may use credit report information to send unsolicited firm offers of credit or insurance. The law allows a credit-reporting agency to give lenders information only if all of the following three conditions are met: (1) "the transaction consists of a firm offer of credit or insurance," (2) prescreening is used solely to offer credit or insurance, and (3) the consumer has not elected to "opt out" of such solicitations. A more expansive discussion of marketing and solicitation practices and the legal framework governing such practices is provided in Board of Governors of the Federal Reserve System (2004), *Report to the Congress on Further Restrictions on Unsolicited Written Offers of Credit and Insurance* (Washington: Board of Governors).

[44] Refer to Board of Governors of the Federal Reserve System (2006), *The Profitability of Credit Card Operations of Depository Institutions*, annual report submitted pursuant to section 8 of the Fair Credit and Charge Card Act of 1988 (Washington: Board of Governors, June), www.federalreserve.gov/pubs/reports_other.htm.

[45] Phillip Booth and Duncan Walsh (2001), "Cash Flow Models for Pricing Mortgages," *IMA Journal of Management Mathematics,* vol. 12 (no. 2), pp. 157-172, discuss the development of risk-based pricing models in the context of mortgages. Also refer to Wendy Edelberg (2003), "Risk-Based Pricing of Interest Rates in Household Loan Markets," Finance and Economics Discussion Series 2003-62 (Washington: Board of Governors of the Federal Reserve System, December); and Alan M. White (2004), "Risk-Based Mortgage Pricing: Present and Future Research," *Housing Policy Debate,* vol. 15 (no. 3), pp. 503-531.

limits or other loan terms (including the interest rate), either at the lender's initiative or in response to the borrower's request.[46]

Another aspect of account management is the servicing of delinquent loans. Borrowers tend to react differently to the various options used by lenders to recover delinquent loan payments. For example, a reminder that a payment due date was missed will be appreciated by some account holders but will antagonize others. The costs of the various recovery options—ranging from letters and telephone calls to legal action—also vary greatly. Credit and behavioral scoring are used to predict the actions that are likely to have the highest return net of expenses.[47] Perhaps most important, lenders and loan servicers have found that credit scoring can be used to target delinquent borrowers for early intervention to help avoid default and minimize losses.[48] Credit scores are also used for monitoring and auditing purposes in the context of account management.

- *Fraud detection*. Lenders use credit scoring and information about the pattern of use of a credit card or other open-ended loan to determine whether a given transaction should be interrupted and whether a loan is being used fraudulently.[49]

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[46]See, for example, Margaret S. Trench, Shane P. Pederson, Edward T. Lau, Lizhi Ma, Hui Wang, and Suresh K. Nair, "Managing Credit Lines and Prices for Bank One Credit Cards," *Interfaces* 33 (5), 2003, pp. 4-21.

[47]Lyn C. Thomas, J. Ho, and William T. Scherer, "Time Will Tell: Behavioural Scoring and the Dynamics of Consumer Credit Assessment," *IMA Journal of Management Mathematics* 12 (1), 2001, pp. 89-103; cite Mary A. Hopper and Edward M. Lewis, "Behaviour Scoring and Adaptive Control Systems," In *Credit Scoring and Credit Control*, eds. Lyn C. Thomas, Jonathan N. Crook and David B. Edelman, Oxford: Oxford University Press, 1992, pp. 257-276; and Helen McNab and Anthea Wynn, *Principles and Practice of Consumer Credit Risk Management*, Canterbury, England: Financial World Publishing, 2000 on how "behavioral scoring can be used for deciding how to deal with those in arrears. They advocate experimentation using a champion challenger approach. In this, one splits the customers randomly and applies different collection policies to each to find out which works best on which band of behavioral scores. One uses the existing policy (the champion) for the majority of the customers and tries the new policy (the challenger) on a much smaller subset until it is clear which is the more successful."

[48]Refer especially to Amy C. Cutts and Richard K. Green (2005), "Innovative Servicing Technology: Smart Enough to Keep People in Their Houses?" in Nicholas P. Retsinas and Eric S. Belsky, eds., *Building Assets, Building Credit: Creating Wealth in Low-Income Communities* (Washington: JCHS/Brookings Press), who note that "automated credit scoring based servicing tools . . . emerged in wide use in the late 1990s. These tools risk-rank delinquent accounts to identify loans that are likely to benefit from early interventions to avoid foreclosure. The tools also are used to underwrite loan workouts, helping borrowers keep their homes." Cutts and Green, using data from delinquent loans scored with Freddie Mac's Early Indicator scoring system for mitigating losses, find empirical evidence that "the total population of delinquent borrowers, and among them low-to-moderate income borrowers and borrowers in underserved areas, are less likely to lose their home if they are in a repayment plan or other workout."

[49] Among many recent discussions of the application of particular credit-scoring methods to fraud detection are Richard J. Bolton and David J. Hand (2002), "Statistical Fraud Detection: A Review," *Statistical Science,* vol. 17 (no. 3), pp. 235-55; José R. Dorronsoro, Francisco Ginel, Carmen Sánchez, and Carlos Santa Cruz (1997), "Neural Fraud Detection in Credit Card Operations," *IEEE Transactions on Neural Networks,* vol. 8 (no. 4), pp. 827-34; Richard Wheeler and Stuart Aitken (2000), "Multiple Algorithms for Fraud Detection," *Knowledge-Based Systems,* vol. 13 (nos. 2-3), pp. 93-99; and Phillip A.

- *Estimating loss in the event of default.* The credit score was developed to predict a borrower's likelihood of default. But borrowers vary widely in terms of the likely losses they will impose on the creditor if they default—for example, some borrowers will stop using their credit cards when they encounter difficulty making payments, while many others will use their credit cards most intensively just before default. Lenders have a strong incentive to estimate *expected loss* since it directly affects profitability and the market perceptions of an institution's financial stability. Credit scores are used to help estimate expected losses.

- *Estimating account profitability.* Lenders recognize that each loan's profitability is a function not just of price (interest rate) and expected loss but also of how the loan is used and any fees (for example, late fees and over-the-limit penalties) collected. Profitability scoring is the use of credit-scoring methods to predict all of these behaviors and therefore the profitability of each individual loan. Credit scoring also enhances creditors' opportunities to build highly diversified loan portfolios that serve to substantially mitigate credit risk. Not only can creditors estimate the likelihood of default for an individual borrower and type of consumer loan, but they can also use credit scoring to help build a book of business that includes borrowers that tend to experience credit problems at different times (their covariance of default is low), thereby reducing the expected losses for the entire portfolio.[50]

A credit-scoring model developed for one purpose (for example, to answer the question, What is the likelihood of default?) may be ineffective when used to answer a different question. Moreover, a credit-scoring system generally applies only to borrowers who are similar to the group of borrowers used in developing the scoring system. Thus, to use scoring methods to answer a different question or to ask the same question but for a different group of borrowers generally requires gathering new data and developing an entirely new scoring model.

THE EFFECTS OF CREDIT SCORING ON THE AVAILABILITY AND AFFORDABILITY OF CREDIT

Assessing the effects of credit scoring on the availability and affordability of credit is difficult. As noted, the *Federal Register* notice seeking public comment on this topic and

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Chan, Wei Fan, Andreas L. Prodromidis, and Salvatore J. Stolfo (1999), "Distributed Data Mining in Credit Card Fraud Detection," *IEEE Intelligent Systems,* vol. 14 (no. 6), pp. 67-74.

[50] David K. Musto and Nicholas S. Souleles (2005), "A Portfolio View of Consumer Credit," paper presented at the Carnegie-Rochester Conference on Public Policy, Columbia University, September, pp. 1-43.

the various meetings jointly sponsored by the FTC and the Federal Reserve revealed relatively little specific evidence. Such a response was not surprising. Creditors long ago incorporated credit scoring into their systems for underwriting, account maintenance, and marketing. So the question of the effects of scoring, to a large extent, involves gathering information about experiences that may have been decades in the past, a task all the more difficult because credit scores were often implemented in conjunction with the use of automated credit-underwriting systems. Adding to the complexity are changes in the availability and affordability of credit that were contemporaneous with the advent of credit scoring but unrelated to it. Three of the most prominent of these broader changes were technological advances, interest rate deregulation, and a relaxation of rules limiting the geographic reach of banking institutions.

First, the second half of the twentieth century was marked by tremendous technological advances that sharply reduced the costs of data processing and telecommunications and provided opportunities for creditors to expand access to credit and to reduce prices. These advances affected all aspects of the lending business and, even in the absence of credit scoring, likely would have increased the availability of credit.

Second, financial deregulation has also affected credit availability.[51] For example, until the late 1970s, state usury laws established limits on the interest rates credit card issuers could charge on outstanding balances, which limited issuers' ability to price for credit risk. Beginning in the late 1970s, court decisions and legislation by some states relaxed restrictions on credit card rates, which in turn allowed national banks to charge market-determined rates throughout the country. The ability to more accurately price for credit risk encouraged lenders to offer credit to higher-risk individuals, who previously went without credit or obtained it from sources outside of the mainstream financial markets. In competitive markets, the ability to price customers according to the risks they pose also works to reduce cross-subsidization; that is, risk pricing reduces the need to charge lower-risk customers higher rates than necessary to help pay for losses to higher-risk customers who weren't paying an appropriate price. Reducing prices for the lowest-risk borrowers may encourage further use of credit.

Third, the easing of certain federal restrictions on the geographic scope of banking institutions, primarily during the 1980s, encouraged competition in credit markets and thus likely further broadened access to credit. Relaxation of limits on the ability of banks to purchase other institutions and to establish branch offices both within and across state boundaries may have further promoted competition.

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[51] Refer to Robert B. Avery, Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner (1997), "Changes in the Distribution of Banking Offices," *Federal Reserve Bulletin*, vol. 83 (September), pp. 707-26.

Concurrent with these changes in the lending environment were changes in the structure of the credit-reporting industry. In the 1970s and earlier, a creditor wanting to assemble an electronic file of the credit histories of a nationally representative sample of individuals, to use either in model development or for marketing purposes, would have had to obtain credit records from many local credit-reporting agencies and integrate the information from each to obtain a relatively comprehensive credit history on these individuals. If a creditor wanted to develop a credit history scoring model, it would have had to assemble an initial set of data on the credit histories of a group of individuals and then repeat the process later to gather information on how these individuals had performed on their accounts.

By the late 1980s, such tasks were both much simpler and much less expensive. A creditor could approach any one of the national credit-reporting agencies to gather the needed information, including historical files that eliminated the need for data requests at two distinct points in time. If a creditor was willing to rely on a generic credit history score, it simply purchased such a score from the credit-reporting agencies. The availability of inexpensive generic credit history scores for most individuals encouraged competition by allowing creditors to solicit the business of individuals for whom they had no previous lending experience.

The confluence of technological advances and the easing of regulatory restrictions obscure the effects of credit scoring on the availability and affordability of consumer credit in general as well as on specific credit products. The past three or four decades have seen substantial changes in how consumers use credit, including an expansion in the practice of substituting one form of credit for another. For example, revolving credit, particularly credit card debt, has substituted for small installment loans because of its ease of use and availability. Similarly, home mortgage debt has substituted for all types of consumer credit through equity extraction done most often through cash-out refinancings or home equity loans.[52] These substitutions are attributable to relative price changes among credit instruments, appreciation in home values (allowing more equity extraction), and economies in offering different credit services. Credit scoring likely has contributed to changing uses among credit instruments, but differentiating its effects is likely impossible.

The three sections that follow provide more discussion of the ways in which credit scoring has affected the availability and affordability of credit. The first section is a theoretical discussion of how credit scoring as a technological advance would be expected to affect access to credit. The second is a review of previous research or other evidence on the actual effects of credit scoring on access to credit. The third is an

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[52] A description of the uses of funds raised during cash-out refinancing and other forms of home equity borrowing is in Glenn Canner, Karen Dynan, and Wayne Passmore (2002), "Mortgage Refinancing in 2001 and Early 2002," *Federal Reserve Bulletin*, vol. 88 (December), pp. 469-81.

analysis of data from surveys of consumer use of credit that provides indirect evidence on the question of how credit scoring may have affected access to credit.

Expected Effects of Credit Scoring

In considering how credit scoring may have affected access to credit, it is useful to view credit scoring as a technological innovation in credit underwriting and ask, What effect would one expect such a technological innovation to have had on access to credit?

Effects of Credit Scoring as a Technological Innovation

Viewed as a technological innovation, credit scoring raises the efficiency of the credit underwriting system. The efficiency can be expressed in two dimensions—cost and accuracy; that is, greater efficiency can lower the cost of underwriting, or increase its accuracy, or to some extent both, depending on the way lenders respond to the gain in efficiency. If lenders use all the efficiency gain to reduce costs, then the underwriting system may not be more accurate and could be less so. If lenders use all the efficiency gain to improve accuracy, then the costs of the underwriting system may not go down and could even rise.

Changes in costs or accuracy have distinct effects on consumer access to credit, and these effects can be opposite in direction. Regarding a change in cost, the effects on access to credit will almost always be in a predictable direction. Regardless of competitive conditions, if costs are reduced, one would expect that at least some of the reduction in costs would be passed through to consumers in lower rates or fees. Lower interest rates and fees would be expected to increase access to credit, both by attracting more borrowers and by encouraging borrowers to use more credit. If costs rise (perhaps as lenders go beyond the efficiency gain to improve accuracy even more), then credit becomes more expensive, and the effect on access would be negative.

In contrast, regarding a change in accuracy, the effects on access to credit are ambiguous—knowing the direction of change in accuracy is not sufficient to determine whether access to credit will expand or contract. For example, given an increase in accuracy, access will increase (or decrease) if the number of borrowers who previously would have been denied credit but now qualify is larger (or smaller) than the number who previously would have been granted credit but now do not qualify. A similar logic applies given a decrease in accuracy (such a decrease could arise if lenders go beyond the efficiency gain to reduce costs to the point at which accuracy declines).

Effects of Facilitating Product or Service Acquisition and Credit Shopping

An advantage of credit scoring is that it allows a quicker decision than manual, or judgmental, underwriting. Increased speed benefits consumers. First, faster credit decisions allow consumers to purchase, and thus benefit from, products or services more quickly. Second, faster decisions more quickly give consumers the feedback they need for credit shopping. Receiving such feedback informs consumers about their circumstances; the more quickly they get it, the more efficient will be their credit shopping and decisionmaking. Increasing the efficiency of credit shopping may increase the competitiveness of loan markets.

Another way that credit scoring may increase the efficiency of credit shopping is by reducing lenders' costs of prescreening potential borrowers (through targeted solicitations). The lower costs encourage creditors to conduct more prescreening, which benefits consumers by giving them more information about alternatives.

Promoting Consistency and Discouraging Discrimination

One feature of credit scoring generally not shared by judgmental underwriting is its objectivity and consistency; judgmental systems are by their nature subjective and may not produce consistent decisions between applicants with substantially similar credit histories. Credit scoring applies an algorithm to standardized credit information, so a *given* set of such information produces a given credit score no matter when it is prepared or for which borrower it is prepared. In judgmental underwriting, on the other hand, multiple analysts evaluate credit history in different ways, often emphasizing different factors; thus, the same inputs do not always lead to the same interpretation. For a given level of accuracy, improved consistency can lower costs by reducing costly management oversight that is necessary to ensure that different loan underwriters are applying a firm's lending rules in a manner consistent with company policy and applicable legal requirements. In competitive markets, such cost savings would be expected to be passed on to consumers in the form of reduced loan interest rates or fees.

Some observers argue that consistency is not always unambiguously beneficial because it may involve inaccuracy. Credit scoring relies on a database of historical performance to predict future performance. Statistical models will tend to predict well when evaluating individuals whose financial profiles are similar to those included in the historical files used to develop the models. However, statistical models may not work as well in predicting performance for individuals whose profiles are substantially different from those in the estimating database. Judgmental credit evaluation may work better for these individuals. This issue is less likely to be present in credit-scoring models estimated over large populations with diverse experiences with credit that can be used to separately model (for example, by using different scorecards) the behavior of relatively small subpopulations.

Adoption of a mechanical, consistent system for credit evaluation reduces the opportunities for engaging in illegal discriminatory behavior. In contrast, judgmental, subjective decisionmaking offers opportunities for discriminatory behavior, whether such behavior is intentional or not. For example, in a judgmental system, a credit rater may assign different credit ratings to two borrowers who pose identical credit risks if one is, say, a friend or member of the rater's social club, or a credit rater may assign different evaluations to prospective borrowers with identical credit histories on the basis of impermissible extraneous data such as the borrower's ethnicity, religion, national origin, or sex. Such actions are illegal, but in a judgmental underwriting system they are easier to disguise if deliberate, and they slip through more easily if unconscious.[53]

A rule-based system, if applied consistently, works to deter discrimination unless the rules themselves are discriminatory. Credit-scoring systems explicitly avoid making use of impermissible data, a fact that can be readily verified. Moreover, as noted previously, the records maintained by credit-reporting agencies on the credit experiences of individuals do not include information on personal characteristics such as race, ethnicity, sex, and marital status. However, other factors included in a credit-scoring model may raise discrimination concerns if they are correlated with impermissible data and are assigned an inappropriate weight (a topic addressed in a later section of the report).

Effect of Increased Transparency

Credit scoring can enhance the transparency of lending activities and the credit risks they involve, particularly if the score is estimated independently of the lender and intended for general use. Loans that carry a standardized and accurate metric of risk, such as a credit score, are more "transparent"—that is, because of that score, the risk posed by the loans can be more readily seen by all who would make decisions on the basis of the risk. Such decisionmakers include prospective purchasers of individual loans or loan portfolios, regulators, and credit-rating agencies evaluating the credit risks of a pool of loans or the financial condition of a creditor.

By reducing uncertainty about the credit risks inherent in a portfolio of loans, increased transparency can lower the costs of funding, either by reducing the amount of capital a firm must maintain or by facilitating funding through loan securitization. In a competitive market, cost savings are likely both to broaden opportunities for creditors and to lower prices for consumers.

Credit Scoring with Closed-End and Open-End Credit

As a technological innovation, credit scoring improves the efficiency of underwriting for credit applications (whether for closed-end loans such as home mortgages or automobile

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[53]For example, one study notes that "the subjectivity of the approval and feedback process under manual underwriting makes [consumer] lending more vulnerable to fair lending violations, intended or otherwise [than under automated systems]" (Susan W. Gates, Vanessa G. Perry, and Peter M. Zorn, 2002, "Automated Underwriting in Mortgage Lending: Good News for the Underserved?" *Housing Policy Debate,* vol. 13, no. 2, p. 373).

loans or for open-end credit such as revolving credit card accounts) and for the ongoing monitoring of existing borrowers using open-end credit.

As noted in the preceding section, the improved efficiency can increase accuracy, or reduce costs, or both. If lenders choose to reduce costs, then borrowers are likely to benefit from the cost savings to the extent they are passed along. If lenders choose to increase accuracy, then credit scoring will have made the system fairer—that is, fewer creditworthy applicants will be rejected, and fewer noncreditworthy applicants will be accepted.

Moreover, the greater accuracy offered by credit scoring can help ameliorate the problem of "adverse selection" that arises when lenders offer a single interest rate to potential borrowers with varying credit risks.[54] It can also ameliorate the problem of cross-subsidization of borrowers that arises when lenders use an inaccurate risk-based pricing system. If credit scoring permits the introduction of a more accurate risk-based pricing system, so more borrowers will be charged prices that more closely reflect the credit risks they pose, the result is a system that is more fair and efficient.

The introduction of credit scoring in the ongoing management of open-end accounts could result in benefits far greater than those realized at the underwriting stage. In the absence of the transparency offered by the credit-scoring system, the performance of current borrowers is information that only the lender, and not any of the lender's competitors, is likely to know. With such "asymmetric" information about current borrowers, a competitor may be reluctant to solicit the customers of another lender for fear of what is often termed the "winner's curse": The lender will compete to keep its lower-risk customers and let the soliciting institution—the "winner"—take on the bad risks. If customers are not solicited, the resulting lack of competition would allow

[54] When the interest rate charged by a lender is appropriate for the average credit risk of a pool of prospective borrowers but is either too low or too high for some of the individual borrowers, the pool can suffer adverse selection, that is, a rise in the relative number of high-risk borrowers. High-risk borrowers—those for whom the correct *individual* interest rate would be higher than the *average* interest rate—will perceive the single-rate offer as a good deal and accept the terms, perhaps borrowing more than they would if charged a rate more consistent with their risk profile. In contrast, lower-risk borrowers—those for whom the correct interest rate would be lower than the average interest rate—may be able to find credit on better terms from another lender and decline the terms offered. If credit at lower interest rates is not available to these lower-risk individuals, they may choose not to borrow or to borrow less than they would otherwise.

Credit rationing—not extending loans to individuals judged to pose higher credit risk—is a response to the result of adverse selection, which is an actual pool of loans with an average credit risk higher than appropriate for the interest rate charged. An alternative to credit rationing—raising the interest rate to reflect the average risk of the actual borrowers—is unlikely to help; indeed, it may worsen adverse selection, thereby further increasing the average level of risk of the remaining borrowers. A discussion of adverse selection and credit rationing is in Joseph E. Stiglitz and Andrew Weiss (1981), "Credit Rationing in Markets with Imperfect Information," *American Economic Review*, vol. 71 (June), pp. 393-410; Marco Pagano and Tullio Jappelli (1993), "Information Sharing in Credit Markets," *Journal of Finance*, vol. 48 (December), pp. 1693-718; and Dwight M. Jaffee and Thomas Russell (1976), "Imperfect Information, Uncertainty, and Credit Rationing," Symposium: The Economics of Information, *Quarterly Journal of Economics*, vol. 90 (November), pp. 651-66.

lenders to charge higher rates to their current customers than would be appropriate given the risks they pose.

To the extent credit scoring allows creditors to accurately and inexpensively assess the creditworthiness of all open-end credit customers, it can increase competition and produce customer pricing that is better aligned with credit risk. The result is access to credit at a more appropriate price and a fairer and more efficient credit system.

Evidence on the Effects of Credit Scoring

The previous section described the potential ways that credit scoring could have affected access to credit as it became fully integrated into the credit system. Some of the expectations drawn from theory are clear-cut, and others are ambiguous. For example, theory suggests that credit scoring should cause creditors to reduce costs for a given level of accuracy or improve accuracy for a given level of costs. However, theory does not tell us at what point creditors will strike a balance between these two approaches. For example, with new technology a lender could take all of the gains in cost savings and tolerate a decrease in accuracy. Theory is also ambiguous on whether credit scoring would increase or decrease the number or size of loans. On all of these points, the actual outcomes could differ from product to product and lender to lender.

Theory tells us what the potential benefit would be if the ability to use credit scoring enables risk-based pricing. However, theory does not tell us if all the conditions necessary to adopt risk-based pricing will be met. The ability to accurately rank-order credit risk may be only one component of a lender's decision to offer loans with prices that are tied to risk. Thus, the answer to the question of what the adoption of credit-scoring has done to the availability of credit, and to the more basic question of the degree to which credit scoring is more accurate or less costly than judgmental underwriting, remains largely empirical. However, firms that have analyzed these questions have generally considered their results proprietary; thus, the public domain contains relatively little specific evidence to help answer the questions, perhaps because academics and others interested in the topic may not have been able to gain access to needed data. Nevertheless, some limited evidence was provided in the public comments received for this study, and other evidence is available in the literature.

The Accuracy of Credit Scoring

A number of academic studies have compared the accuracy of credit scoring to that of judgmental credit-evaluation systems. These studies consistently find that credit-scoring systems outperform judgmental systems in predicting loan performance. Chandler and Coffman (1979), for example, review evidence indicating that "empirical models are able to outperform their judgmental counterparts *on the average*" (emphasis in original). Rosenberg and Gleit (1994) review several studies comparing credit scoring with judgmental credit evaluation and report that "a good scoring system outperforms human experts." Thomas (2000) reports on studies finding that credit scoring in the credit card arena reduced default rates 50 percent relative to the rates under judgmental underwriting. Hand and Henley (1997) find that credit-scoring methods "produce more-accurate classifications than subjective *judgmental* assessments by human experts" (emphasis in original).[55] In a comment submitted for this study, Chandler reported on the experience of a large credit card issuer that performed a controlled experiment designed to compare the effectiveness of judgmental and credit-scoring methods. Relative to judgmental methods, the credit-scoring system approved 15 percent more applicants using the established creditworthiness cutoff used by the card issuer, and, after a two-year performance period, the lender experienced an 11 percent lower default rate.[56]

Additional evidence on the effectiveness of credit scoring comes from Fair Isaac, which reports that in its experience in working with lenders, a change from judgmental credit evaluations to credit scoring substantially improves decisionmaking. Fair Isaac cites findings from a case study in the credit card arena: By switching from judgmental evaluations to credit scoring, "the issuer would have been able to either double its approval rate without increasing its credit risk, or reduce its credit risk by half without decreasing its approval rate."[57] More generally, Fair Isaac estimates that "when a creditor switches from judgmental decisions to credit scoring, it is common to see a 20 percent to 30 percent reduction in credit losses, or a 20 percent to 30 percent increase in the number of applicants accepted with no increase in the loss rate."[58]

In the home mortgage lending arena, Straka (2000) reports that an internal analysis by Freddie Mac found that credit-scoring evaluation outperformed judgmental evaluations on a pool of loans purchased by Freddie Mac under their Affordable Gold Loan program.[59] Straka also reports that an analysis conducted by Freddie Mac found

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[55] Gary G. Chandler and John Y. Coffman (1979), "A Comparative Analysis of Empirical vs. Judgmental Credit Evaluation," *Journal of Retail Banking Services,* vol. 1 (2), pp.15-26; Eric Rosenberg and Alan Gleit (1994), "Quantitative Methods in Credit Management: A Survey," *Operations Research*, vol. 42 (July-August), pp. 589-613; Lyn C. Thomas (2000), "A Survey of Credit and Behavioural Scoring: Forecasting Financial Risk of Lending to Consumers," *International Journal of Forecasting,* vol. 16 (April-June), pp. 149-72; and D.J. Hand and W.E. Henley (1997), "Statistical Classification Methods in Consumer Credit Scoring: A Review," *Journal of the Royal Statistical Society, Series A: Statistics in Society,* vol. 160 (3), pp. 523-41.

[56] Public comment submitted in response to the February 28, 2005, *Federal Register* notice requesting comment on the present study; received December 4, 2006.

[57] Public comment submitted by Fair Isaac Corporation on April 25, 2005, in response to the February 28, 2005, *Federal Register* notice requesting public comment on the present study, p. 5.

[58] Hollis Fishelson-Holstine (2004), "The Role of Credit Scoring in Increasing Homeownership for Underserved Populations," Working Paper Series, Joint Center for Housing Studies, Harvard University, BABA 04-12, February; and Javier Martell, Paul Panichelli, Rich Strauch, and Sally Taylor-Shoff (1999), "The Effectiveness of Scoring on Low-to-Moderate-Income and High-Minority Area Populations" (San Rafael, Calif.: Fair Isaac).

[59] John W. Straka (2000), "A Shift in the Mortgage Landscape: The 1990s Move to Automated Credit Evaluations," *Journal of Housing Research*, vol. 11 (no. 2), pp. 207-32.

that generic credit history scores "worked as a statistically significant and strong predictor in a home mortgage default equation."[60]

The studies cited in this section generally compare the performance of a "pure" judgmental credit-evaluation system with a "pure" credit-scoring system in controlled tests involving actual extensions of credit. They do not address how a system combining both judgmental assessment and credit scoring might perform. Nor do they quantify the results of credit scoring in actual operation rather than in controlled tests.

Cost and Time Savings

The public realm provides relatively little quantitative information on the savings in time and cost that accrue because of credit scoring. The available evidence for home mortgage lending indicates that credit scoring has helped reduce the time needed to make credit decisions from several weeks to a matter of a few minutes.[61] Regarding cost savings, lenders that integrated automated underwriting systems into their home mortgage loan origination process are estimated to have reduced origination costs by as much as 50 percent, or roughly $1,500.[62] Other research found that underwriting expenses fell 27 percent and "back office" costs dropped 15 percent when larger proportions of loans in pools of home mortgages were evaluated with credit-scoring processes.[63] Regarding credit card activities, it is estimated that most credit card issuers can make a decision on a credit card application in less than sixty seconds when a real-time credit-scoring system is used, compared with five minutes in the quickest manual underwriting systems.[64] To the extent that the savings in cost and time resulting from credit-scoring systems are passed through to consumers, the savings twill lead to lower interest rates and greater access to credit.

Access to Credit

As noted earlier, relatively few studies have directly examined the effects of credit scoring on access to credit. Using evidence from U.S. banks, Jeong (2003), for example,

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[60]Straka, "A Shift in the Mortgage Landscape," p. 210. Refer also to Thomas M. Holloway, Gregor D. MacDonald, and John W. Straka (1993), "Credit Scores, Early-Payment Mortgage Defaults, and Mortgage Loan Performance," paper presented at the American Real Estate and Urban Economics Association Mid-Year Meeting, June 2, Washington, D.C.

[61] A comment letter submitted for the present study cites statistics indicating that upwards of 75 percent of mortgage evaluations are made within two or three minutes with automated underwriting systems (comment letter submitted by Experian Information Solutions on the FACT Act scoring study matter P044804, August 20, 2004, p. 6). Refer also to Straka, "A Shift in the Mortgage Landscape," p. 216.

[62] Comment letter submitted by Experian Information Solutions, August 20, 2004, p. 7.

[63] Straka, "A Shift in the Mortgage Landscape," p. 216.

[64] Refer to public comment submitted for this study by the American Financial Services Association, dated April 25, 2005, pp. 7 and 8.

finds that more-accurate credit screening leads to increased lending.[65] In home mortgage lending, Gates, Perry, and Zorn (2002) report that home mortgage approval rates were higher when applications were evaluated with Freddie Mac's automated underwriting system than when the same loans were evaluated by manual underwriting techniques.[66] Some of the studies bearing principally on accuracy also found a higher number of approved applicants.[67]

Information on the volume of credit solicitations also suggests that credit scoring has affected access to credit. The number of solicitations for credit cards has increased substantially over the past fifteen years, a period in which generic credit scores became available, and both the proportion of consumers with credit cards and the average number of cards per person have increased. For example, the number of mailed credit card solicitations increased from 1.1 billion in 1990 to 5.2 billion in 2004. Because credit scoring is the primary technology used for prescreened solicitations, these figures provide indirect evidence that credit scoring has expanded access to credit.[68]

Evidence from the Survey of Consumer Finances on the Effects of Credit Scoring on Access to Credit and on the Use of Credit

The availability of credit scores and their use in lending have grown over the past twenty-five years. Increased use of credit scoring could affect the availability of credit in at least three ways. First, credit scoring provides lenders with information on the creditworthiness of a large number of individuals whose credit risk was previously unknown or was difficult or costly to ascertain because the borrower and prospective lender had no previous credit relationship. As a result, credit scores could allow lenders to identify borrowers who are reasonable credit risks but who were previously underserved, thereby expanding credit access for these borrowers. Second, a shift from lender-specific evaluations of existing customers to those based on a credit score may affect which applicants are approved by offering a different—potentially more accurate—assessment of individuals' relative creditworthiness. If so, credit availability may increase for some borrowers while declining for others. Finally, to the extent credit scoring reduces the cost of lending or facilitates more effective risk-based pricing of

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[65] Hyung-Kwon Jeong (2003), "Screening Technology and Loan Portfolio Choice," Working Paper, Institute for Monetary and Economic Research, Bank of Korea.

[66] Gates, Perry, and Zorn, "Automated Underwriting in Mortgage Lending," p. 369.

[67] Public comment submitted in response to the February 28, 2005, *Federal Register* notice requesting comment on the present study, received December, 4, 2006.

[68] Refer to Board of Governors of the Federal Reserve System (2006), *Report to the Congress on Practices of the Consumer Credit Industry in Soliciting and Extending Credit and their Effects on Consumer Debt and Insolvency*, submitted pursuant to section 1229 of the Bankruptcy Abuse and Consumer Protection Act of 2005 (Washington: Board of Governors, June), www.federalreserve.gov/pubs/reports_other.htm.

loans, increased use of credit scoring may expand the range of applicants to whom lenders are able to make loans profitably.

It is commonly believed that widespread adoption of credit scoring has, on the whole, contributed to an increase in the availability of credit. Nevertheless, access to credit may not have improved uniformly for all populations. For example, racial or ethnic differences in credit access could narrow if non-Hispanic whites historically have experienced greater access to credit than blacks or Hispanics and if adoption of credit scoring increased access to credit for all individuals but disproportionately benefited minorities. Conversely, if the adoption of credit scoring increased access to credit for all individuals but disproportionately benefited non-Hispanic whites, gaps in credit access could widen. Hence, the consequences of increased use of credit scores for differences in the availability of credit across demographic groups are ambiguous.

Data from the Survey of Consumer Finances (SCF) can be used to assess how differences in credit use across demographic groups have changed over time. The SCF provides the most comprehensive information available on the net worth, assets, and liabilities of U.S. families, including detail on the types and amounts of debt held by families.[69] However, like any data with information on only outstanding loans, the SCF data do not directly measure credit availability, that is, the supply of credit; instead, the data on credit use reflect the confluence of both supply and demand factors. Differences in credit use across subpopulations over time measure the effect of credit scoring on differences in access to credit only if the effect of other factors that influence the availability of credit as well as shifts in the demand for credit were comparable across groups. Though this strong assumption almost surely does not hold perfectly, we nonetheless interpret changes in the differences between groups' use of credit as indirect, suggestive evidence regarding the potential effects of credit scoring on differences in access to credit.

The SCF has been conducted every three years since 1983, and the most recent data available are from the 2004 survey.[70] Thus, a time-series of families' credit use between 1983 and 2004 can be constructed to contrast trends in credit use by race or ethnicity, income, and age.[71] We also examine whether growth in credit scoring

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[69] Brian K. Bucks, Arthur B. Kennickell, and Kevin B Moore (2006), "Recent Changes in U.S. Family Finances: Evidence from the 2001 and 2004 Survey of Consumer Finances, *Federal Reserve Bulletin*, vol. 92 (March 22), pp. A1-A38, www.federalreserve.gov/pubs/bulletin/2006/06index.htm.

[70] The number of families surveyed in each year of the SCF ranges from 3,143 to 4,519. The 1986 survey was a limited telephone-only re-interview of a subset of households that had participated in the 1983 survey and is not used in the analysis. Bucks, Kennickell, and Moore, "Recent Changes in U.S. Family Finances," offer additional detail on the design of the SCF as well as an overview of results from the 2004 survey.

[71] In contrast to the credit-score data used elsewhere in this report, most data in the Survey of Consumer Finances are collected at the family level. Families are classified in the tables on the basis of the characteristics of the head of the family. An exception is for race and ethnicity, which is reported by the survey respondent, who may not be the head of the family as defined by the SCF.

increased the use of some types of credit more than others by comparing trends in families' ownership of several types of debt. The analysis compares the prevalence of credit card debt relative to mortgages and other closed-end installment loans, since credit scoring may have had different effects on the use of collateralized and unsecured credit. A further differentiation is made between credit cards that can be used only at a specific retailer ("store or gas cards") and those—such as MasterCard or Visa cards—that may be used more broadly ("bank-type and travel or entertainment cards").

Changes in Credit Use across Populations

Taken as a whole, the estimates from the Survey of Consumer Finances are generally consistent with the conjecture that adoption of generic credit scores contributed to an expansion in credit availability and, in particular, to greater ownership of bank-type or travel and entertainment cards (tables 4–6). The largest change in credit usage over this period was the increase in the prevalence of bank-type or travel and entertainment cards, which rose 25 percentage points or more for each of the racial or ethnic groups. In turn, the fraction of families with credit cards that had only store or gas cards declined, though not as steeply. The prevalence of installment debt also declined for all groups.

Trends in unadjusted differences in credit usage for blacks, Hispanics, and other families relative to non-Hispanic white families differ across types of debt and do not suggest a clear effect of expansions in credit scoring on differences in access to credit for these minority groups (table 4). On the one hand, with the exception of non-education installment debt, the estimates imply that the differences between blacks and non-Hispanic whites for each type of debt narrowed, on net, between 1983 and 2004. On the other hand, the trends in the gap between Hispanic and non-Hispanic whites are mixed: Differences tended to increase for mortgages, installment loans, and bank-type or travel and entertainment card ownership and declined for other measures. Further, the implied changes in the gaps are often modest relative to the fluctuations across surveys and the magnitude of the gaps.

Moreover, interpretation of the unadjusted differences is not straightforward since they potentially reflect not only racial or ethnic differences in debt ownership rates for otherwise similar families but also differences in the distribution of economic and demographic characteristics across the subgroups. The distributions, for instance, of age and income—which are correlated with debt ownership—differ by race or ethnicity and thus contribute to observed differences in credit use. Similarly, trends in the unadjusted differences may be driven in part by differential rates of change in other demographic characteristics. For example, credit use generally rises with income, so faster income growth over time for blacks than for non-Hispanic whites would narrow differences in debt ownership even if the racial difference in ownership rates for families with similar incomes was unchanged.

Accounting for Changing Demographics

To account for differences in the levels and trends in demographic characteristics across racial or ethnic groups, adjusted differences were estimated using multivariate regressions. The first group of regression-adjusted differences provides estimates of the differences in credit use within each year that remain after accounting for differences in other family characteristics. The adjustments are based on logit regressions that model debt ownership as a function of age, income, and marital status and that are estimated over non-Hispanic white families.[72] The fitted model is used to estimate counterfactual shares of families with debt that would be observed if the relationship between demographic characteristics and credit use for non-Hispanic whites held for all racial and ethnic groups. The adjusted gap for credit cards for blacks and non-Hispanic whites, for instance, is the average difference between the actual share of black families with cards and the counterfactual percentage predicted from the model estimated over non-Hispanic white families.

Accounting for differences in demographic characteristics typically reduces the estimated level of the gaps between blacks and non-Hispanic whites in each year, with the exception of ownership of only store or gas cards.[73] The adjusted differences in the shares with mortgage debt, any credit card, and bank-type or travel and entertainment cards between Hispanics and non-Hispanic whites tend to be smaller than the unadjusted differences, but other gaps widen on average. This pattern of changes likely reflects the fact that blacks are particularly concentrated in the lower portion of the income distribution, whereas Hispanics are especially overrepresented among younger families.[74] Because debt ownership tends to rise with income, counterfactual ownership rates for blacks are lower than the overall share of non-Hispanic white families with debt, so adjusted gaps are smaller than the unadjusted differences. Similarly, the adjusted Hispanic-white differences are larger for those types of debt, such as non-education installment loans, that are more common among younger borrowers. In most cases, the trends for both blacks and Hispanics point to slight increases in differences in credit

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[72] Specifically, we model ownership of each type of debt separately by cells defined by year and several age ranges. The regressions control for family income, age, and whether the head is single or is married or living with a partner. For cells with fewer than fifty families and cells for which all or no families have a given type of debt, the predicted value is equal to the average percent within the cell. The within-cell average ownership rate is also used to estimate the counterfactual rate of owning only store or gas cards, which is difficult to model in a regression framework, in part because it is a rare outcome, particularly in later years.

[73] The insensitivity, to this and the subsequent adjustment, of the estimated probabilities of owning only store or gas cards is likely due in large measure to the comparatively simple model used.

[74] Pooling years of the SCF, 44 percent of black families have income in the bottom quartile, compared with 37 percent of Hispanics and 20 percent of non-Hispanic whites. Thirty-seven percent of Hispanic family heads are younger than 35, compared with 28 percent of black and 23 percent white, non-Hispanic family heads.

usage relative to non-Hispanic whites. The disparity in ownership of only store or gas cards reversed as the share of minorities with a credit or charge card that owned only a store or gas card became greater than that of non-Hispanic whites, though the proportions are low in recent years for all groups.

The first set of adjusted differences focused on how the typical difference in credit usage attributable to race or ethnicity alone has changed over time as a result of changes in credit markets as well as shifts in the economic and demographic characteristics of families in each racial and ethnic group. An alternative technique controls for demographic shifts by holding the age, income, and marital status of families constant at their 2004 levels. Here, logit models, like those described above, are estimated for each racial or ethnic group and used to predict two counterfactual debt ownership probabilities. To calculate, say, the adjusted difference in mortgage ownership rate for Hispanics in 1983, we contrast the rates predicted by applying the fitted Hispanic and white models in 1983 to Hispanic families in 2004. As with the other adjustment technique, racial or ethnic gaps implied by varying only the relationship between debt ownership and demographic and economic factors are evaluated. In this instance, however, the counterfactuals are estimated using the characteristics of 2004 Hispanic families rather than those of Hispanic families in 1983. By using the 2004 characteristics to predict counterfactual rates in each year, we attempt to control for differences in demographic shifts across groups when examining the evolution of racial and ethnic gaps in credit usage over time.

The estimated rate of increase in the gaps in debt ownership between blacks and non-Hispanic whites is generally slightly higher after holding the distributions of other characteristics fixed, suggesting that differential rates of demographic changes for blacks and non-Hispanic whites over the period served, on net, to narrow such differences in debt ownership. The trends in the counterfactual gaps between Hispanics and non-Hispanic whites tend to be smaller after fixing age, income, and marital status at their 2004 values. The differences both between blacks and non-Hispanic whites and between Hispanics and non-Hispanic whites increased for ownership of non-education installment debt and bank-type or travel and entertainment cards. The predicted fraction of Hispanic families with a credit card rose faster than the share of non-Hispanic whites, decreasing the disparity in this measure. Other changes in the gaps between Hispanics and non-Hispanic whites were smaller or more sensitive to the model used to predict counterfactual ownership rates.

The next portion of the analysis considers how debt ownership rates changed across income groups in the 1983 through 2004 SCF surveys (table 5). The table compares the credit use of families in the top and bottom thirds of the income distribution with the proportion of middle-income families with each type of debt.[75] Credit use rises with income, except in the case of the proportion of families that own only store or gas cards. The unadjusted gaps between high- and middle-income families declined for all types of debt but especially the shares with bank-type or travel and entertainment cards and outstanding credit card balances. The differences in credit usage between lower- and middle-income borrowers declined for overall debt, credit card balance, and credit card ownership. The fraction of middle-income families with a mortgage rose notably in 2004, a shift that contributed substantially to a decline in the gap relative to higher-income families and a widening in the gap relative to lower-income families.

As expected, the adjusted differences across income groups narrow after accounting for differences in other demographic characteristics in each survey year.[76] The shifts in the levels were roughly comparable across years so that in most cases conclusions regarding trends in gaps are largely unchanged. The counterfactual gaps and trends in credit use for both sets of adjustments shown are also similar to one another. Use of most types of credit rose more steeply among middle-income families than for other families, on average, over the period. As a result, differences between lower- and middle-income families grew, whereas those between middle- and higher-income families narrowed for many measures. An exception to this pattern are the differences in the shares of families with credit cards and credit card balances, which narrowed across income groups. The relatively large increases in prevalence of revolving credit among lower-income borrowers did not carry over to bank-type or travel and entertainment cards, however, for which credit scoring might be expected to have had the largest effect on credit availability.

The final portion of the analysis considers changes in debt ownership rates across age groups (table 6). Trends in credit use within each of the four age ranges mirror those discussed above, with the exception of the increase in installment borrowing among families with a head aged 62 or older. As illustrated by the first columns, the oldest families are the least likely to have debt. Rather than taking one age group as the basis for comparison, the counterfactual estimates are the predicted level of debt ownership for a family with a 48-year-old head but otherwise identical demographic and economic characteristics.[77] The adjusted differences, presented in the second and third columns,

[75] The percentile cutoffs that determine the income categories are calculated within years.

[76] The regressions underlying the adjustments are estimated separately within income groups by year and category of debt. The models control for age, age squared, indicators for whether the family head was married/living with a partner, and indicators for whether the head was either black or Hispanic. Regressions for ownership of only store- or gas-type cards control only for age.

[77] The counterfactuals are predicted based on separate regressions for each year for blacks and Hispanics on the one hand, and for non-Hispanic whites, Asians, and other racial categories on the other. The regressions control for income, age, whether the head is single or married/living with a partner, and whether the head had any college education (including a college degree). For ownership of only store or gas cards, the regressions control for age.

indicate that, in most cases, credit use rose more quickly for the oldest group than would have been predicted based on a similar 48-year-old, while increases for other age groups were more similar. As shown in the leftmost columns, the percentage of families with a head younger than age 35 that carried a credit card balance increased at least as steeply as the shares for the next two age groups. Accounting for differences in other characteristics, however, the fraction with a balance did not rise as quickly as would have been predicted for a similar 48-year-old. In contrast, the fractions of both the youngest and oldest families that owned a bank-type or travel and entertainment card rose comparatively quickly. Looking across types of debt, gains for the oldest set of families were generally at least as large as those for the youngest group. To the extent that lower rates of debt among retirement-age families reflect comparatively low demand for credit, the narrowing of differences in credit usage among older families suggests that shifts in demand play an important role in the observed trends over time.

Taken together, the foregoing analyses of differences in credit use by race or ethnicity, income, and age suggest only tentative conclusions. Importantly, the data provide very little evidence that the expansion in credit scoring disproportionately benefited population subgroups that historically had low rates of debt ownership. Instead, trends in gaps relative to other groups with greater credit use appear in many instances to have changed only slightly or to have widened, particularly after attempting to adjust for differences in the level and trends in key demographic variables across groups. Year-to-year fluctuations in estimates and variation across groups likewise prevent conclusive inference.

Limitations of the data and the approach also suggest that the results should be interpreted with caution for several reasons. First, though the SCF data provide a lengthy time series on U.S. families' use of a variety of types of debt, as noted earlier, the data measure credit use rather than access to credit. Many other factors that changed over the 1983–2004 period could have influenced the use of credit by various demographic groups. Differing trends in families' demand for credit, for example, could also have resulted in changes over time in the observed gaps in credit use across groups. Second, since the use of credit scoring began to grow in the late 1970s, the earliest effects of credit scoring precede the 1983 SCF, the first with data on debt use comparable with that gathered in later surveys. Third, regression adjustments like those in this analysis are commonly used to examine differences in outcomes across groups, but other work has often found that estimates of counterfactual gaps may be sensitive to the regression specification, including the set of demographic characteristics incorporated in the model. The need to estimate regressions over each subgroup and the available sample size limits the complexity of the models that can be estimated. The results of this analysis are generally robust to small changes in the model, but estimates based on other reasonable specifications may differ more substantively. Finally, the choice of base and comparison groups can affect the magnitude of estimated counterfactual gaps.

CREDIT SCORING AND DEMOGRAPHIC GROUPS: DEFINING DIFFERENTIAL EFFECT

Section 215 of the Fact Act asks for several empirical analyses regarding the relationships between credit scores and other factors for different demographic populations. These include an analysis of the empirical relationship between credit scores and actual losses experienced by lenders; an evaluation of the effect of scores on the availability and affordability of credit; and an evaluation of whether credit scoring in general, and the factors included in credit-scoring models in particular, may result in negative or differential effects on specific subpopulations and, if so, whether such effects could be mitigated by changes in the model development process.

As noted earlier, there has been little research previously on these topics because reliable data for conducting such research is not readily available. Creditors generally are prohibited from collecting race, ethnicity, and other personal demographic information on applications for credit, except in the case of mortgage credit. Even in the context of mortgage credit, only limited information can be collected.[78] Likewise, with the exception of dates of birth, the credit records maintained by the credit-reporting agencies do not include any personal demographic information. The empirical analysis advanced in this section uses data from the Social Security Administration (SSA) to supplement credit-record data to make this research possible.

The analysis presented here to address the empirical issues raised in the Fact Act is conducted using a large, nationally representative sample of individual credit records drawn from the credit records maintained by TransUnion. The credit-record data are supplemented with information on personal demographic and economic characteristics obtained from records maintained for other purposes by the SSA and other sources. In addition, two commercially available credit scores for each individual were provided by TransUnion. Both the credit scores and the credit-record data were obtained for individuals as of two dates separated by 18 months. For that period, the information was sufficient to assess loan performance, to identify which individuals were able to obtain new credit, and to determine the pricing on a portion of those new loans.

The assembled data set was used to address questions related to the relationship between credit scores and actual losses experienced by lenders (proxied by loan performance) and the effect of scores on the availability and affordability of credit.

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[78] Under the Home Mortgage Disclosure Act of 1975, as amended in 1989, covered lenders are required to collect and disclose information about the race or ethnicity and sex of individuals applying for mortgages covered by the law.

Addressing the question of possible differential effects on different populations was more complicated. As noted earlier, it was determined that this issue could be best addressed by the development of an original credit-scoring model. The information in the assembled data set was sufficient to estimate a generic credit history scoring model using a method that emulated standard industry definitions and procedures. The analysis of possible differential effect across populations relies on the estimated model with the estimation procedures varied in several ways designed to investigate various aspects of this issue.

This section presents background information on discrimination and lending and discusses the concept of differential effect as used in the present study. The three subsequent sections describe the data set and the process used to develop the credit-scoring model used in this study; present results related to the relationship between credit scores on the one hand and loan performance and credit availability and affordability on the other; and present the results related to an assessment of differential effect.

Discrimination and Lending Markets

Under the Equal Credit Opportunity Act (ECOA), it is unlawful for a lender to discriminate against a credit applicant on a prohibited basis in any aspect of a credit transaction. The prohibited bases under ECOA include race, color, religion, sex, national origin, age, and marital status. Under both ECOA and the Fair Housing Act (FHA), it is unlawful for a lender to discriminate on a prohibited basis in a transaction related to residential real estate, although the prohibited bases under the FHA differ somewhat from the prohibited bases under ECOA.[79]

Unlawful discrimination on a prohibited basis can take a variety of forms, such as

- failing to provide information or services or providing different information or services in connection with any aspect of the lending process
- discouraging potential applicants from applying or selectively encouraging applicants to apply for credit
- refusing to extend credit or using different standards in determining whether to extend credit
- varying the terms of credit offered, including the amount, interest rate, duration, or type of loan
- using different standards to evaluate collateral
- treating a borrower differently in servicing a loan or invoking default remedies
- using different standards for pooling or packaging a loan in the secondary market

[79] Race, color, religion, sex, and national origin are prohibited bases under the FHA, as under ECOA. Additional prohibited bases under the FHA are handicap and family status, but, unlike under ECOA, not age and marital status.

A creditor may not express, orally or in writing, a preference for applicants on a prohibited basis or indicate that it will treat applicants differently on a prohibited basis. A creditor may not discriminate on a prohibited basis because of the personal characteristics of a person associated with a credit applicant (for example, a co-applicant, spouse, business partner, or live-in aide) or the present or prospective occupants of the area where property to be financed is located. Finally, the FHA requires lenders to make reasonable accommodations for a person with disabilities when such accommodations are necessary to afford the person an equal opportunity to apply for credit.

Despite the existence of federal (and state) antidiscrimination laws, longstanding concerns about discrimination in credit markets persist regarding all aspects of the lending process, including marketing, credit evaluation, the establishment of loan terms, and loan servicing.

Discrimination and Credit Scoring

From a legal standpoint, discrimination in lending generally involves the concepts of "disparate treatment" and "disparate impact." Disparate treatment is deemed to have occurred when a lender treats similarly situated applicants differently based on one of the prohibited factors (for example, offering less favorable terms to minority applicants).[80] Disparate impact occurs when a practice that the lender applies uniformly to all applicants has a discriminatory effect on a prohibited basis and does not have a sufficient business justification.

Discriminatory treatment is considered intentional if the lender takes into account the protected characteristic of the individual subject to the discriminatory treatment. Allegations of disparate impact do not presume intentional behavior but rather simply assert the existence of a disproportionate adverse effect on a protected group.

Some observers maintain that increased reliance on automated credit-evaluation systems, including credit scoring, serves to reduce the potential for discrimination in lending because the automated nature of the process reduces the opportunities for bias, whether overt or inadvertent, to influence lending outcomes. Others have expressed the view that the credit-scoring process itself and some of the factors within credit-scoring models may disadvantage minorities or other segments of the population protected by fair lending laws.[81]

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[80] Courts and agencies have sometimes referred to certain forms of particularly blatant discriminatory treatment on a prohibited basis as "overt discrimination."

[81] Refer, for example, to Janet Sonntag (1995), "The Debate About Credit Scoring," *Mortgage Banking* (November), pp. 46-52; and Warren L. Dennis (1995), "Fair Lending and Credit Scoring," *Mortgage Banking* (November), pp. 55-58.

Regulatory Criteria for a Credit-Scoring System

The Federal Reserve's Regulation B, which implements ECOA, notes that there are two broad types of credit evaluation: (1) traditional judgmental credit-evaluation systems, which may rely on the subjective evaluation of loan officers, and (2) credit-scoring systems that are empirically derived and demonstrably and statistically sound.[82] A judgmental system may rely on a traditional, subjective evaluation by loan officers.

A "credit-scoring system" is a system that evaluates an applicant's creditworthiness mechanically, based on key attributes of the applicant and aspects of the transaction, and that determines, alone or in conjunction with an evaluation of additional information about the applicant, whether the applicant is deemed creditworthy. Section 202.2(p) of Regulation B sets forth several criteria that a credit-scoring system must satisfy to be considered an empirically derived, demonstrably and statistically sound credit-scoring system. First, the system must be based on data that are derived from an empirical comparison of sample groups or the population of creditworthy and noncreditworthy applicants who applied for credit within a reasonable preceding period of time. Second, the system must be developed for the purpose of evaluating the creditworthiness of individuals with respect to the legitimate business interests of the creditor utilizing the system. Third, the system must be developed and validated using accepted statistical principles and methodology. Fourth, the system must be periodically revalidated by the use of appropriate statistical principles and methodology and adjusted as necessary to maintain predictive ability.

The data from which to develop such a system may be obtained from either a single credit grantor or multiple credit grantors. A creditor is responsible for ensuring its system is validated and revalidated based on the creditor's own data.

An empirically derived, demonstrably and statistically sound credit-scoring system may include age as a predictive factor (provided that those aged 62 or older are not assigned a negative factor or value). Besides age, no other prohibited basis may be used as a factor in a credit-scoring model.

Disparate Impact and Credit-Scoring Models

Developers of credit-scoring models may not legally consider race, ethnicity, or other prohibited bases in model development. Thus, so long as the models do not include these characteristics, it is very unlikely that the use of credit scoring would result in discriminatory treatment. Of course, discrimination could arise if lenders fail to apply credit scores evenhandedly, ignore the scores, or exercise overrides for some populations or in some circumstances. These scenarios, however, are beyond the scope of this study.

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[82] Regulation B, 12 CFR 202.2(p) and (t).

Under the law, the test for disparate impact requires that a practice have a disproportionate impact on a protected population without a sufficient business justification for that impact. In a well-designed, empirically derived, demonstrably and statistically sound credit-scoring system, the attributes in the model must have a clear predictive value and a sufficient business rationale. The issue of disparate impact may arise, however, if an alternative approach or specification can achieve the business objective with less discriminatory effect or if the predictiveness of the variable stems primarily from the fact that it is a proxy for a protected population.

A banking bulletin issued by the Office of the Comptroller of the Currency (OCC) regarding credit scoring discusses in some detail the circumstances that can lead to disparate impact in the use of credit scoring.[83] According to the OCC,

> "Disparate impact may occur in a credit scoring system when:
> - A variable used in the credit scoring system is facially neutral; that is, it does not discriminate on any prohibited basis overtly.
> - That variable is applied evenly, without regard to any prohibited basis.
> - That variable disproportionately adversely affects a segment of the population that shares a common characteristic that may not be considered legally.
> - That variable cannot be justified by business necessity, or the business necessity can be achieved by substituting a comparably predictive variable that will allow the credit-scoring system to continue to be validated, but also operate with a less discriminatory result."

Each of those circumstances must be present to violate fair lending laws under "disparate impact."

Previous Research on Discrimination and Credit Scoring

Relatively little research has been undertaken to assess the potential disparate impact of credit scoring.[84] Fair Isaac conducted such an analysis assessing the potential disparate impact of credit scoring using a nationally representative sample of roughly 800,000

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[83] More information is available at www.ffiec.gov/ffiecinfobase/resources/retail/occ-bl-97-24_credit_scor_models.pdf.

[84] Refer to Gregory E. Elliehausen and Thomas A. Durkin (1989), "Theory and Evidence of the Impact of Equal Credit Opportunity: An Agnostic Review of the Literature," *Journal of Financial Services Research,* vol. 2 (no. 2), pp. 89-114; Straka, "A Shift in the Mortgage Landscape"; Elaine Fortowsky and Michael LaCour-Little (2001), "Credit Scoring and Disparate Impact," Working Paper, Wells Fargo Home Mortgage; and M. Cary Collins, Keith D. Harvey, and Peter J. Nigro (2002), "The Influence of Bureau Scores, Customized Scores and Judgmental Review on the Bank Underwriting Decision Making Process," *Journal of Real Estate Research,* vol. 24 (no. 2), pp. 129-52.

credit records of individuals obtained from TransUnion.[85] Because the personal characteristics of the individuals were not known to Fair Isaac (or TransUnion) the Zip code for the individual's place of residence was matched to 1990 census data to determine the proportion of minority population (black or Hispanic) where the individual lived. In the study, areas with relatively large minority populations (70 percent or more) were termed "high-minority areas."

One area of concern addressed in the study is that certain population segments may be underrepresented in the credit-record files maintained by the national credit-reporting agencies and that, as a consequence, credit-scoring models developed from these data may not provide an accurate indication of the credit use, and therefore credit risks, posed by these underrepresented populations. The Fair Isaac analysis found that there was a reasonably close correspondence between the share of minority population residing in areas with a high concentration of minorities and the overall share of credit records from individuals in such areas. This was taken as an indication that generic credit-scoring model development is based on credit records that reflect a wide range of racial and ethnic groups.

The analysis also revealed that the share of individuals from high-minority areas with relatively low credit scores was about twice as large as the share of individuals from other areas. The research further found that for the high-minority areas and other populations, credit scores performed well in rank ordering future loan performance. Finally, the analysis built separate scorecards for individuals residing in high-minority areas and for the sample as a whole and found that there were no factors that were predictive in one scorecard that were not predictive in the other and that the predictive factors aligned quite well in descending order of importance in both scorecards. The analysis concluded that Fair Isaac credit scores are both effective and "fair" in assessing risk for both populations.

Defining Differential Effect for this Study

In the previous section, the phrase *disparate impact* was used to refer to the possible differential adverse effects that credit-scoring models may have on various groups in a legal context. In this section, we define more precisely the meaning of the term *differential effect* as used in the statistical analysis of the present study. Although related, the legal term "disparate impact" and the term "differential effect" used here are not the same. The concept of disparate impact embodies specific legal criteria, must be applied on a case-by-case basis, and must consider all relevant facts and circumstances, including any business justification. The concept of differential effect used here is a statistical concept and does not necessarily correspond to the legal concept.

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[85] Martell, Panichelli, Strauch, and Taylor-Shoff, "The Effectiveness of Scoring on Low-to-Moderate-Income and High-Minority Area Populations."

The congressional directive does not distinguish between legal or illegal disparate impact (refer to appendix A). Rather, it focuses on the potentially adverse effect that credit scores may have on classes of individuals grouped by personal demographic, economic, and locational characteristics; some of those effects may potentially be illegal, and some may not.

The first step in defining the phrase “differential effect” is to define “effect.” In developing a statistical credit-scoring model to predict credit performance, “effect” represents an association between the demographic characteristic (for example, age) and credit performance, controlling for the predictive factors in the model that are related to credit performance in a demographically neutral environment. Thus, “effect” cannot exist unless the demographic characteristic itself (for example, age) is related to (or correlated with) credit performance. An implication of this is that individuals of different ages would not be expected to have the same average performance after controlling for the predictive factors in the model that are related to credit performance in an age-neutral environment.

This definition is a purely statistical one and does not imply causality in the relation between the demographic characteristic and credit performance; for example, it may reflect variables that are not included in the model. Thus, the concept of effect is model specific and, indeed, will depend on the specific sample and methodology used to measure performance as well as on the set of predictive factors included in the model.

If the demographic characteristic, such as age, is not used explicitly in developing a credit-scoring model, one of three outcomes is possible. First, a set of predictive factors in the model may be highly correlated with age and effectively serve as a proxy for age in predicting performance. These factors will be assigned weights that will reflect their direct effect on predicted performance (in an age-neutral environment) as well as their role as proxies for age. If these predictive factors are perfect proxies, they will absorb the entire effects of age on performance. If so, there will be no difference in the expected performance of individuals with the same credit scores and different ages.

The second possibility is that none of the predictive factors in the model are correlated with age. If so, the weights assigned these factors will reflect purely their direct effects on predicted performance, and the scoring model itself will not reflect any of the correlation between age and performance. Factor weights in the model would be the same as those estimated in the age-neutral environment. In this case, individuals with the same score but different ages would not be expected to perform the same. For individuals of different ages, the expected difference between their actual performance and their performance predicted on the basis of the model would represent the “age effect” on performance.

The third possibility is a hybrid of the first two. That is, the predictive factors are imperfect proxies for age. If so, factor model weights will reflect some, but not all, of the effects of age on performance. Here, as in the second case, one would not expect individuals of different ages but with the same scores to perform equivalently; however, the expected differences in performance will be smaller than in the second case, in which the predictive factors absorb none of the age effects.

In the cases just described, the issue is the extent to which the predictive factors in the model represent, or "absorb," the effects of age. For the most part, the extent will depend upon the correlations between age and the predictive factors in the model. If the correlations are high, one would expect the model to absorb much of the effects of age; if the correlations are low, one would expect the model to absorb little of those effects.

The above discussion defines "effect" as used in the term "differential effect." The "differential" portion of the term is a relative concept used for subgroups of a population, not a population as a whole. It focuses on the portion of the effect of a characteristic that is absorbed by other characteristics. Specifically, use of model A can be defined to have differential effect for a specific subgroup, such as younger individuals, relative to model B as follows: The absorbed component of the age effect in model A is larger than the absorbed component of the age effect in model B, and, as a consequence, younger individuals have lower credit scores (that is, higher risk assessments) with model A, controlling for credit performance, than when model B is used.

Defined this way, differential effect will generally be a zero-sum outcome. For example, if good credit performance is positively related to age, then the *less* a credit-scoring model absorbs age effects, the higher the scores of *younger* individuals will be. Alternatively, the *more* a model absorbs the age effects, the higher the scores of *older* individuals will be. If younger individuals were the focus of attention, then use of a credit-scoring model that absorbs a substantial portion of the age effect would be described as having a differential effect for that group as compared with a model in which less of the age effect is absorbed.

In general, the subgroups that, all else being equal, perform worse will be those most likely to show negative differential effect when a group characteristic is used. However, patterns can be complex. Totally different groups may be affected when a credit-scoring model absorbs the effects of a population characteristic if they happen to have credit profiles similar to those of the portion of the population group with poor performance. For example, if older recent immigrants have short credit histories (as do younger individuals), and length of credit history earns a place in a credit-scoring model only because it absorbs the impact of age, then older recent immigrants may also experience a differential effect from the use of this credit characteristic. In this case, the adversely affected subgroup need not show poor performance.

The concept of differential effect used here applies only to the group as a whole; the outcomes for specific individuals will vary when different models are employed. It is only on average that younger individuals will be more adversely affected (receive lower scores) the more a model absorbs age. Depending upon their specific financial experiences, some younger individuals may have higher scores the more age is absorbed into the model.

THE DATA AND MODEL

This section describes the data set and the process used to develop the credit-scoring model employed in this study.

Data Used for this Study

Here are the types of data used for this study and the sources from which they were drawn:

1. the complete credit records of a nationally representative sample of individuals (from TransUnion, one of the three national credit-reporting agencies)
2. two commercially available generic credit history scores (supplied by TransUnion for each individual in the sample of credit records)
3. the race, ethnicity, sex, place and date of birth, and date of first application for a Social Security card for each individual in the sample of credit records (from the Social Security Administration)
4. the race, ethnicity, date of birth, sex, marital status, language preference, country of origin, and religion of each individual in the sample of credit records (from a leading national demographic information company)
5. demographic and economic characteristics of the block groups or census tracts of the place of residence of each individual in the credit-record sample (from the Census Bureau data on the 2000 decennial census)
6. a file of mean credit scores by census tract for individuals both with and without a mortgage (from TransUnion).

The Sample of Credit Records

The Federal Reserve obtained from TransUnion the full credit records (excluding any identifying personal or creditor information) of a nationally representative random sample of 301,536 individuals as of June 30, 2003.[86] The Federal Reserve subsequently received updated information on the credit records of these individuals as of December 31, 2004. Some individuals (15,743) in the initial 2003 sample no longer had active

[86] Agency files include personal identifying information that allows the credit-reporting agencies to distinguish among individuals and construct a full record of each individual's credit-related activities. Files include the individual's name, current and previous addresses, and Social Security number. Other demographic characteristics sometimes found in credit files include date of birth, telephone numbers, name of spouse, number of dependents, income, and employment information. Except for date of birth, such information was removed from the sample for this study.

credit records as of December 31, 2004, in some instances because the individual had died. However, other factors may also have limited the ability to update records. A total of 285,793 individuals still had active credit files as of December 31, 2004.[87]

Characteristics of the sample of credit records. In the aggregate, the sample of credit records used for this study contained information on about 3.7 million credit accounts (also referred to as “tradelines”), more than 318,000 collection-related actions, and roughly 65,000 monetary-related public actions. Not every individual has information of each type. In the sample, approximately 260,000, or 86 percent, of the individuals had records of credit accounts as of the date the sample was drawn (table 7).[88] Although a large portion of individuals had items indicating public-record actions, collection agency accounts, or credit inquiries, well less than 1 percent of the individuals with credit records had only public-record items or only records of a creditor inquiry. However, for about 12 percent of the individuals in the sample, the only items in their credit records pertained to collection agency accounts.

Credit characteristics. TransUnion included a file of 312 precalculated summary variables (“credit characteristics”) in the data provided to the Federal Reserve (appendix B provides a list of the 312 credit characteristics). These credit characteristics are summary measures of the individual items that constitute a credit record. These characteristics (such as one representing the age of an individual’s oldest account) were created by TransUnion for model development according to its own needs and those of its customers. The credit characteristics provided to the Federal Reserve are those commonly offered to model builders by TransUnion.[89] The characteristics reflect only credit-related factors, not personal or demographic information, as such information is not included in the credit records maintained by credit-reporting agencies.

Computing performance measures from the credit records. Credit records can be used to estimate various measures of payment performance for each individual or account. Credit records contain information on the payment performance of most accounts for the 48 months preceding the date the record was drawn. For these accounts, the information is sufficient to assess performance over any performance period within the 48 months.

[87] An additional sample of 15,743 individuals with credit records established after June 30, 2003, was obtained by the Federal Reserve to achieve a representative sample of individuals with credit records as of December 31, 2004. The data on these individuals were used only in the robustness analysis.

[88] The credit-account information was provided by 92,000 reporters, 23,000 of which were reporting at the time the sample was drawn.

[89] The credit characteristics were those created by TransUnion as of June 2003. Since that time, they may have expanded the number of characteristics available to model builders. Model builders may also create their own characteristics from the raw credit records.

Similarly, filing dates for collection and public records determine the precise date when such events occurred. However, month-by-month payment records are not available for all accounts, particularly those that are seriously delinquent. For those accounts, the only information available is the date of last delinquency; it is not possible to determine if the accounts were also delinquent in the months preceding that point. For this reason, in model development, performance is typically measured over a specific period of time, usually 18–24 months, and the end point of that period is the date on which the credit record was drawn.

Typically, for the reasons cited above, performance is determined by whether any of the individual's accounts suffered any of a specific group of problems during the performance period, rather than, for example, by how often a problem occurred during the period. As described later in this study, we measure performance over an 18-month backward-looking period as constructed from credit records drawn on December 31, 2004.

Credit Scores of Individuals in the Sample

TransUnion provided two different generic credit history scores for each individual in the sample—the TransRisk Account Management Score (TransRisk Score) and the VantageScore. The two scores used here are as of the date the sample was drawn. The TransRisk Score was generated by TransUnion's proprietary model for assessing the credit risk of existing accounts. In particular, the TransRisk Score was constructed with a selected group of factors drawn from the credit records of individuals to predict the likelihood that at least one existing credit account would become seriously delinquent over an ensuing performance period.

As with other commonly used consumer credit history scores, larger values for the TransRisk Score indicate a lower risk of default. About 20 percent of individuals in the sample received neither the VantageScore nor the TransRisk Score, primarily because they had too few active credit accounts. Most individuals who had a credit account but no credit score were those who could use the account but were not legally responsible for any debt they owed. About 7 percent of the sample had a TransRisk Score but not a VantageScore, as the latter had more-restrictive rules for determining which credit records could be scored.

As noted earlier, the VantageScore was developed jointly by Equifax, Experian, and TransUnion to create a measure of credit risk that scores individuals consistently across all three companies.[90] The model was developed from a national sample of approximately 15 million anonymous credit files of individuals drawn from each of the agencies' credit files. The data extracted for model development were taken from the

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[90] More information about the model is available at www.vantagescore.com/pressreleases.html.

same points in time by all three agencies.[91] The initial point was June 2003 (the same as in the sample used for the present study). Credit records from that time provided the characteristics used in model development; account performance was measured as of June 2005 (a 24-month performance period in contrast to the 18-month performance period used in this study). The VantageScore predicts the likelihood that a random credit account of an individual will become seriously delinquent over the performance period. Again, higher values of the score are associated with a lower risk of default.

TransUnion supplied a file of its TransRisk Score by census tract for individuals both with and without a mortgage. As with all other data used for this report, the file contained no personal identifying information. The data were based on a nationally representative sample of about 27 million individuals drawn from all credit records maintained by TransUnion as of December 31, 2004. The database was used to determine the mean score for individuals in the census tract as a weighted average of the scores of those with mortgages and those without.

Demographic and Locational Characteristics of Individuals in the Federal Reserve Sample of Credit Records

The only personal *demographic* information included in an individual's credit record is the individual's date of birth (date of birth is not present in about one-third of the credit records). However, the credit records contain additional types of information—name, Social Security number, and current and previous addresses—which can be used to obtain further demographic information on the individual from other data sources. For purposes of this study, TransUnion, at the request of the Federal Reserve, provided information to other data repositories—the U.S. Social Security Administration (SSA) and a demographic information company—to obtain demographic data on the individuals in the credit sample. These matches involved a double-blind process between TransUnion and the other data sources so that the integrity and privacy of each party's records were maintained.

TransUnion supplied locational information (but not exact residential addresses) on the individuals in the sample to the Federal Reserve when it provided the credit-record information.

[91] The specific information in the credit records of an individual in the sample used to develop VantageScore may differ across the three agencies, primarily because the agencies do not always receive the same data from reporters, they receive data at different times, and reporters do not all furnish information to all three agencies.

Social Security Administration data. The SSA gathers demographic information on the form used by individuals to apply for a Social Security card.[92] Information from the SSA records was made available to the Federal Reserve solely for purposes of preparing this report to the Congress. The procedures followed for this study ensured that the SSA received no information included in the credit records of the individuals other than the personally identifying information needed to match the administrative records maintained by the SSA. The Federal Reserve received from the SSA a data file that included the demographic characteristics of the individuals in the sample but no personally identifying information. TransUnion did not receive any information from the SSA or the Federal Reserve on the demographic characteristics of the individuals in the sample. The SSA data are the same items that are made available to other researchers and government agencies conducting studies that require personal demographic information.

With the names and Social Security numbers provided by TransUnion, the SSA extracted and provided to the Federal Reserve the following information for each matched individual to the extent available: citizenship, the date the individual filed for a Social Security card, place of birth, state or country of birth, race or ethnic description, sex, and date of birth. All of the above information except the race or ethnicity of the applicant is required on the application form for a Social Security card; race or ethnicity is requested on the form, but the applicant is not required to supply it.

Two aspects of the SSA administrative records bear importantly on the analysis in this study. First, some individuals failed to provide some demographic characteristics when completing their applications. Also, some applied more than once for a Social Security card (SSA card) and so had more than one opportunity to report their demographic characteristics; the SSA provided the Federal Reserve the information reported by these individuals on each of their applications, and in some cases the information was inconsistent.[93] For example, some individuals reported different dates of birth, sex, or country of origin on their various applications.

Second, the SSA in 1981 changed the options offered to individuals for reporting their racial or ethnic status. For the years preceding 1981, individuals had three choices, from which they were asked to select one—“White,” “Black,” or “Other.” Beginning in 1981, individuals have had five options, from which they choose only one—(1) “Asian, Asian American, or Pacific Islander”; (2) “Hispanic”; (3) “Black (Not Hispanic)”; (4) “North American Indian or Alaskan Native”; and (5) “White (Not Hispanic).”

[92] The application form for a Social Security card is form SS-5 (05-2006), www.ssa.gov/online/ss-5.html.

[93] Individuals may have applied multiple times for a Social Security card for several reasons, including loss of the original card or a change in legal name. Individuals are allowed to obtain up to three cards in a year and up to ten over a lifetime except for applications in response to a change in legal name, which are unlimited. Individuals always receive the same Social Security number when they make additional applications.

Data from a national demographic information company. To obtain yet more, or further corroborating, information on the demographic and economic characteristics of the individuals in the sample, the Federal Reserve obtained data from one of the nation's leading demographic information companies. The data received by the Federal Reserve is the same as the information made available to creditors or other entities that use the data for marketing and solicitation activities.

The demographic information company develops information in two ways. It infers language preference, country of origin, ethnicity, and religion by analyzing first and last names in combination with geographic location; consequently, these items were available for all individuals in the company's records. The company gathers other demographic and economic information from thousands of public and private sources nationwide, so not all of these are available for all individuals in its records. The national demographic information company validates the accuracy of its data in various ways, including personal interviews with people from all ethnic and religious groups, immigration records, biographical sources, and other primary databases.

For each individual whose information existed in the records of both TransUnion and the national demographic information company, the Federal Reserve received the following information to the extent available: race, education, sex, marital status, language preference, religion, occupation, income range, and date of birth.

Locational information from Census 2000 data. At the request of the Federal Reserve, TransUnion "geocoded" the current address of each individual in the sample to help identify the year 2000 census-block group of the person's residence.[94] The census-block location of about 15 percent of the sample could not be identified, and for an additional very small number of individuals in the sample (544), not even the census tract could be identified. This geographic information was matched to Census 2000 files at the U.S. Bureau of the Census; those data include the racial or ethnic makeup and income of each census-block group and census tract as of April 2000.

Resolving Inconsistencies in Demographic Characteristics

Collectively, the sources described above provide information on age, marital status, sex, race, ethnicity, religion, language preference, country of origin, income, and geographic location. Problems of inconsistency and missing data had to be resolved, however, before the information could be used for the present analysis. First, some demographic

[94] A census-block group is a cluster of census blocks (up to nine) within the same census tract. Census blocks vary in size, often relatively small in urbanized areas but much larger in rural areas. Census-block groups, which generally contain between 600 and 3,000 individuals, have an optimum size of about 1,500. Census tracts typically include about 4,000 individuals (www.census.gov). No specific addresses of individuals in the sample of credit records used for this study were provided to the Federal Reserve.

characteristics for a given individual were provided by multiple sources, and in some of those cases the information was inconsistent. Inconsistency extended even to the SSA records for some individuals because, as noted above, some individuals provided different information for the same item when completing applications for replacement Social Security cards. Second, the information on some demographic characteristics was simply missing.

To resolve inconsistencies across different data sources for race, ethnicity, sex, and age, we chose to rely on the data provided in the records maintained by the SSA unless we had strong reason to believe that this information was incorrect, in which case we deemed it "missing." The SSA data were preferred because applicants are required to provide all information, with the exception of race or ethnicity, to receive a Social Security card and because the data were collected and maintained in a consistent way. Alternative assignments of certain characteristics—race, ethnicity, sex, and age from the national demographic information company; date of birth from TransUnion; and characteristics not available in the SSA data including religion and language preference were used only to impute SSA data when it was not available. The only information obtained form the national demographic company that was used in the primary analysis was marital status.[95]

Details about the availability of specific demographic items from each source of data are provided in table 8. Overall, almost 80 percent of the 301,536 individuals in the sample could be matched to SSA records. An even larger proportion, 90 percent of those with a credit score as of June 30, 2003—the sample most relevant for this analysis—could be matched to SSA records.

Age and sex were available for virtually all of the individuals matched to the SSA records. Although information on race or ethnicity was available for almost 97 percent of the individuals matched to the SSA records, data on about 40 percent of the individuals was collected before the SSA changed the race and ethnicity categories it tracks, an aspect of the data discussed below.

In general, demographic information on an individual from multiple data sources was largely consistent across the sources. For example, sex was consistently reported across the sources 96 percent of the time. Reported age, within three years, was consistent 96 percent of the time between the demographic information company and the SSA, and 98 percent of the time between TransUnion and the SSA.

For demographic items not included in the SSA data, the incidence of missing or unreported data varied widely. For example, country of origin was provided for only 10

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[95] It was determined that information on religion, national origin and ethnicity, and language preference was derived mainly from the individual's name and not from a primary source. Consequently, these demographic categories were not used except to help impute race or ethnicity for the SSA data as described below.

percent of the 301,536 individuals in the sample. In contrast, religion was available for 86 percent of the individuals, and marital status was provided for 71 percent of the individuals. Census tract of residence was available for virtually everyone in the sample, and a census-block group was identified for 86 percent of the sample.

Inconsistency within the SSA data. Several issues had to be addressed before the SSA data could be used. First, about 51 percent of the sample individuals had more than one SSA filing, and the data in some of those cases were inconsistent. Second, the age information supplied by the SSA was sometimes implausible because it implied that the individual was extremely old or young or because it was inconsistent with the age of the individual's oldest account in their credit record.[96] Third, the question on race and ethnicity on the application form for a Social Security card changed in 1981. These issues were dealt with as follows.

In general, when individuals filed more than one application for a Social Security card, we used information from the most recent filing. The only exception to this rule involved age and sex; when such information from the most recent filing was implausible or was inconsistent with information provided by the demographic information company or TransUnion's credit records, we used the information from an earlier filing if it was consistent with information from these other sources.

Various rules were used to identify and address implausible values for age in the SSA data. The basic rule was that if the date of birth in the SSA records indicated that the individual was younger than 15 or greater than 100 years of age at the time the credit records were drawn, then the reported age was deemed to be implausible. In addition, regardless of the age reported in the SSA data, if the age of the oldest credit record in the individual's credit files implied that the person took out credit when the person was younger than 15, then the SSA age data were again deemed implausible. An implausible age suggested that the SSA record and the credit records had potentially been mismatched, and in such cases *all* SSA data for demographic items—age, race, ethnicity, and sex—were treated as "missing." In total, only about 2 percent of the sample had ages deemed to be implausible.

Only 0.5 percent of individuals in the sample gave inconsistent responses on sex when they completed more than one application for an SSA card. If information on sex from the demographic information company was available, it was used to resolve the SSA inconsistency. Otherwise, sex was determined by the individual's most recent application for an SSA card.

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[96] To be included in the study sample, an individual must have had a credit record as of June 30, 2003. Individuals who were, for example, younger than 15 years of age are highly unlikely to have had credit records. Consequently, such an age for individuals with credit records likely represents a mismatch between the credit-reporting agency records and the SSA records.

The most difficult inconsistency in the SSA data came from the change in the options provided to individuals for identifying their race or ethnicity when applying for SSA cards.

Change in categories of race and ethnicity in the SSA data. As noted, before 1981, individuals were asked to choose one of only three options—white, black, or other. Beginning in 1981, individuals were asked to choose one of five options—(1) Asian, Asian American, or Pacific Islander; (2) Hispanic; (3) black (not Hispanic); (4) North American Indian or Alaskan Native; and (5) white (not Hispanic).

To employ a single set of categories for race and ethnicity and retain the greater detail available after 1980, we chose to use the five post-1980 categories. The problem then focused on "pre-1981" individuals, those whose only application for a Social Security card was before 1981; their set of three responses would have to be distributed across the set of five responses available after 1980. We chose to "predict" whether a pre-1981 individual who chose white or black would have instead selected one of the three options unavailable before 1981 if they had had the opportunity to do so: Asian, Asian American, or Pacific Islander (hereafter, Asian); Hispanic; or North American Indian or Alaskan Native (hereafter, Native American). For those answering "other," the question is which of the five options, including white or black, they would have chosen since the option other would no longer have been available.

The "prediction" is the probability that an individual would select one of the missing options; the probability is calculated from a multinomial logistic model estimated with data from individuals applying for Social Security cards in the 1981-85 period. Those individuals were chosen for the estimation sample because it was believed that they would be most similar in age and other characteristics to the pre-1981 sample. The independent variables used in the predictive model were age, sex, and country of origin (from SSA records); ethnicity and race (Hispanic, Asian, black, and Native American), language preference, religion, and marital status (from the demographic information company); and percent of the population according to the Census 2000 data that was Asian, Hispanic, black, or Native American in the census-block group of the individual's residence (or in the census tract, if census-block group was not available) The model was validated against the responses of individuals who filed applications for Social Security cards before 1981 and then filed again in 1981 or later.[97]

[97] An alternative would have been to use the validation sample—those who filed in both time periods—for the model estimation. An advantage to this approach would have been the ability to estimate a separate model for each available response (white, black, and other) for those who applied in both periods. Ultimately this approach was rejected because the number of observations available for estimation was too small, for example, only 4,187 individuals classified themselves as "other" before 1981 and subsequently refiled in the later period. An additional concern was that those pre-1981 individuals who subsequently refiled might not be representative of the broader pre-1981 population.

Pre-1981 individuals classifying themselves as white were assigned a zero probability of being black; the model coefficients were used to assign one of the other four choices for the individual. A similar rule was applied for pre-1981 individuals classifying themselves as black—that is, they were assigned a zero probability of being white—and in addition they were assigned a zero probability of being Native American. No restrictions were imposed for pre-1981 individuals classifying themselves as "other."

This procedure does *not* result in imputation of race for all pre-1981 sample individuals. With the exception of one small group, whose race was imputed to be black or white by the model, all of the pre-1981 individuals treated as black or non-Hispanic white in the disparate-impact analysis would have reported their race in corresponding terms to the SSA if they had applied for a Social Security card after 1980. The exception was a small number of pre-1981 individuals who classified themselves as "other" and were not assigned high probabilities of being Hispanic, Native American, or Asian. The major impact of the procedure is on the Asian, Hispanic, and Native American groups, whose entire pre-1981 portion of the sample had to be "carved out" from the pre-1981 white, black, and "other" groups.

Basic Sample Statistics

In total, there are 301,536 individuals in the study sample. These individuals are separated into three groups for most of the analysis. The primary group is the 232,467 individuals with both a TransRisk Score and a VantageScore (table 9). This is the base sample used to evaluate credit-score and performance differences across populations. A subset of this sample is the 200,437 individuals used to estimate the FRB base model described in the next section. The third group is the 69,069 remaining individuals lacking at least one score that were not used for most of the analysis.[98]

Nine different demographic groupings are used to describe the population for much of the analysis: Two measures of race or ethnicity (SSA data and the location of

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Specifically, the prediction process was conducted as follows. The estimation sample was divided into cells by age (two groups: one older than 30 and the other 30 or younger), marital status, and sex. A set of dichotomous indicator variables were generated on the basis of an individual's reported SSA race or ethnicity selection. White was the excluded category for the estimation. Each nonwhite SSA race choice was then regressed using a logistic model form on a combination of variables relevant to the race in question. These variables included ethnic background, foreign-born status, language preference, religion, a measure of racial and ethnic composition in the individual's census block or census tract, and this measure of composition interacted with the individual's ethnicity and language preference. The variables involving racial and ethnic concentration were capped at 0.001 and 0.999 and then log-odds transformed. In cells for which logistic regression was impossible, a linear probability model was used. These models were used to predict the racial or ethnic choice that would have been made by individuals whose only SSA application was earlier than 1981. After all five probabilities were generated, they were normalized to sum to 1.

[98] Nineteen individuals in the sample were missing the TransRisk Score but were assigned a VantageScore; 17,533 were missing the VantageScore but had a TransRisk Score; 51,517 were missing both credit scores.

residence);[99] sex; marital status; national origin (foreign-born or not); age; and characteristics of the census block or tract where they reside. The characteristics of the census block or tract are relative income, percentage of the population that is of a racial or ethnic minority, and whether it is urban or rural.[100] For most of these categories, there is an "unknown" group where the characteristic could not be determined.

For each demographic group, summary statistics are presented that show the contents of credit-record files for the three sample definitions and nine demographic groupings. Not surprisingly, individuals in the full sample of credit records provided by TransUnion differ some from the records of scorable individuals or those used to estimate the FRB base model. The principal difference is in the mean number of credit accounts for individuals, which is much lower for the full sample than for either the scorable sample population or the estimation sample. The mean number of trade accounts for the same population group differs little between the scorable sample population and the estimation sample.

Because credit scores reflect the content of credit records, a review of the differences in content across demographic groups provides useful context for the analysis that follows. The patterns found hold both for the scorable population and the somewhat smaller population used to estimate the FRB base model.

The content of credit records differs greatly across populations. For example, blacks are less likely than other racial or ethnic groups to have a revolving or mortgage account and much more likely to have either a public record or a reported medical or other collection item. Also, compared with other populations, blacks and Hispanics evidence elevated rates of at least one account 90 days or more past due. Married individuals, whether male or female, are more likely to have either revolving, installment, or mortgage credit than single individuals, are less likely to have a public record or

[99] Racial and ethnic identity is not available (except for mortgage) in the data used to develop credit scores. Consequently, the locational approach has been used in previous studies that examine the relationship between credit scores and race or ethnicity. In the locational approach, the adult racial or ethnic composition of the individual's census block (available for about 85 percent of the individuals) or census tract is used as an approximation of the individual's race or ethnicity. The proportion of the block belonging to each racial or ethnic group can be viewed as the probability that a random adult drawn from the block will have that race or ethnicity. The probability is used as a weight in forming the tables presented in this section and for analytic work presented later.

[100] Census tracts were placed into four income groups—low, moderate, middle, and high—according to the median family income in the tract relative to the median in the metropolitan statistical area (MSA) or nonmetropolitan portion of the state in which the tract is located: In a low-income tract, the median family income is less than 50 percent of the median in the wider area; in a moderate-income tract it is 50-79 percent; middle income is 80-119 percent; and high income is 120 percent or more.

The census tracts were also placed into four groups according to the proportion of their population that was minority, that is, nonwhite or Hispanic: less than 10 percent, 10-49 percent, 50-79 percent, and 80 percent or more.

Urban census tracts are those within MSAs as of June 2003; the remainder are rural census tracts.

collection account, and are less likely to have one or more accounts 90 days or more delinquent.

Differences by age are also found. Individuals younger than age 30 are less likely to have a revolving or mortgage account but more likely to have an installment account than older individuals. Younger individuals have a lower incidence of a public record item, but a higher incidence of a nonmedical-related collection account, than older individuals. Also, the incidence of at least one account reported as delinquent 90 days or more declines with age after age 40.

Representativeness of the sample. The sample of credit records of individuals obtained for this study is nationally representative of the individuals included in the credit records of the national credit-reporting agencies.[101] Further comparisons were made to evaluate how closely the sample mirrors the population of U.S. adults (those aged 18 or more). The distribution of individuals in the sample population arrayed by their state of residence is quite similar to the distribution of all adults (individuals 18 or more) in the United States as of June 2003 as estimated by the Bureau of the Census (table 10). Also, the racial or ethnic characteristics of the sample population as assigned here closely mirror the distribution of race and ethnicity for all adults in the United States as reflected in the census, although the proportion of Hispanics in the sample population is somewhat lower than in the population overall (table 11). Also, males are slightly overrepresented in the credit-record sample and younger individuals are underrepresented. The data further show that the distribution by race and age of scorable individuals differs from the distribution of individuals for whom scores were not available. Blacks, younger individuals and individuals residing in lower-income census tracts and census tracts with larger shares of minority population were less likely to have been scored.

Developing the Credit-Scoring Model Used in this Study

The desire to maximize the transparency of the credit-scoring model building process used in this study led us to rely entirely on a set of rules (algorithms) to create and select credit characteristics and attributes to be included in the model. This approach differs from industry practice in the construction of such models, which often relies on the experience of the model developer to supplement the automated rules they use. The rules we selected for the development of the present model are intended to mimic general industry practice to the greatest extent possible.

To recall, although the approach used for this study is informative and allows an assessment of the potential for differential effect across groups of individuals, it will not necessarily reflect what the results of a differential effect analysis would be if applied to

[101] The sample was drawn as a systemic sample where individuals were ordered by location. The sampling rate was about 1 out of 657.

any specific credit-scoring model currently used by the credit industry. Also, the results here, covering credit-related experiences over the 2003-04 period, may not match results for a different period because credit use and economic conditions change over time.

The development of any model requires decisions about several broad issues, including type of model, sample, and time period. Regarding type of model, the model could be designed to predict performance for new accounts, existing accounts, or a combination of the two. Further, it could predict that at least one account will go bad; that a specific account will go bad; or that a specific category of accounts, such as credit cards, will go bad. Also to be chosen would be the size of the estimating sample and the "performance period," that is, the period over which performance would be tracked. Finally, decisions also have to be made about which credit characteristics would be used as predictive factors in a model.

Choosing the Type of Model

Two types of generic credit history models are widely used in the credit industry: one to generate a *new account acquisition* score and one to generate an *account maintenance* score. New account acquisition models are designed to predict delinquency or default over a performance period on accounts that are opened during the beginning of that period. New account models are used in soliciting accounts and to help underwrite responses to solicitations as well as for the review of other applications for credit. Account maintenance models are designed to predict delinquency or default on accounts that were in active use and not delinquent at the beginning of the performance period. Account maintenance models are used to help adjust credit limits, interest rates, and other features on existing accounts.

In addition, the industry often uses "hybrid" models that are combinations of the above two types. Hybrid models predict performance for any account—new or existing—during the performance period. Largely because of sample-size considerations, the model developed for this study is a hybrid type. Including data on both new and existing accounts makes better use of the available sample.

An additional decision in developing the model was whether to make the model "account based" or "person based." Account-based models assess the probability that a specific account will become delinquent or default, whereas person-based models assess the likelihood that any of an individual's accounts will become delinquent or default over the performance period. Given that both types could be estimated equally well and that the person-based type is the more commonly used in the industry for estimating generic credit history models such as the one here, we chose to estimate a person-based model.

Finally, many credit scores are designed to predict performance for a specific type of product, such as credit cards or automobile loans. Others are generic, designed to predict performance for any loan. As noted above, the model estimated here is generic and thus considers performance on all types of accounts.

In sum, the model we developed is

- a hybrid type—covering both new and existing accounts
- person based—predicting the likelihood that any of an individual's accounts will become delinquent or default over the performance period
- generic—covering performance on all types of accounts

Sample Size and the Performance Period

Before this study began, the Federal Reserve had obtained, for other purposes, the nationally representative sample of the credit records of approximately 300,000 individuals as of June 30, 2003, that was described earlier in this section.[102] This sample size was deemed sufficient to estimate either an account-maintenance model or a hybrid type; a new account acquisition model would likely have required a larger sample. For reasons discussed above, we chose to use the sample to estimate a hybrid model.

All model development uses credit records for individuals drawn at two different points in time. The length of time between these two dates dictates the performance period used in model development. At the time this study was initiated, the decision on the timing of the updated sample had not been made. Industry practice is to use a performance period ranging from 18 months to 24 months; 24 months is likely the most common for the development of a generic credit history score. The 24-month time frame is desirable because it tends to reduce the effect of seasonality in the use of credit. The time frame established for this study by the Congress led us to select December 31, 2004 for the updated sample of credit records. This implies an 18-month performance period. Although it is on the short-end of industry practice, this performance period is long enough to provide a sufficient number of defaults and delinquencies to build a viable credit-scoring model.

Measuring Performance in Model Estimation

The choice of model dictates, for the most part, the performance measure. Our choice of a hybrid, person-based model meant that the appropriate performance measure should cover all new and existing accounts for a given individual. Implementing this measure required additional decisions.

First, "new" and "existing" accounts must be defined. Industry practice varies. We defined a new account as one reported as having been opened during the first six

[102] Robert B. Avery, Paul S. Calem, and Glenn B. Canner (2004), "Credit Report Accuracy and Access to Credit," *Federal Reserve Bulletin*, vol. 90 (Summer), pp. 297-322.

months of the performance period (July 2003–December 2003).[103] Existing accounts were those opened before the performance period and not closed before the beginning of the period. ("Closed" means that either the account has been paid off or has been "frozen," generally due to poor performance.)

Generally, accounts are closed when they become seriously delinquent. Thus, the requirement that existing accounts not be closed before the beginning of the performance period implies that accounts that were seriously delinquent before the beginning of the performance period would generally be excluded from the calculation of the performance measure (see below). Because minor delinquencies generally do not result in the closing of an account, accounts with such delinquencies were most likely not excluded from the calculation of the performance measure.

The second decision involved how to assess payment performance on an account and payment performance by a person. Payment performance on an account has many dimensions. One could count, for example, the number of times an account has been delinquent; the severity of the delinquency; or the dollar amount past due on the account. The industry uses each of these measures. A common way of measuring performance, and the one used here, is to classify accounts as "good," "bad," or "indeterminate" on the basis of the most severe level of delinquency during the performance period. A credit account that was delinquent for 90 days or more or was involved in bankruptcy, repossession, charge-off, or collection was defined as "bad." An account that exhibited no delinquency whatsoever, showed no other "bad" indicators, and showed satisfactory performance was classified as "good." All other accounts—for example, those 30 days or 60 days delinquent—were classified as "indeterminate."

Payment performance by a person is based on the good, bad, and indeterminate performance (as defined above, with one small adjustment) of all the person's accounts. An individual's payment performance was classified as "bad" if any of that person's accounts was bad. Further, as stated earlier, performance was determined for the 18-month period from June 30, 2003, to December 31, 2004. By law, accounts with major-derogatory information of the sort we use to define "bad" generally must be removed from the credit record after a period of seven to ten years, depending on the type of derogatory. Accounts without such serious delinquency can remain in the credit record forever. Hence, with one exception, all accounts that were active at any point during the performance period should have performance information present in the December 2004 database. The exception is seriously delinquent accounts transferred to a collection agency; the credit-reporting agency would delete from those accounts the information reported by the original lender. To account for this possibility, if the individual shows evidence of new collections as reported by a collection agency or new public records

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[103] Accounts that met this requirement but that also showed evidence of activity before July 2003 were excluded from the performance measure.

during the performance period, the individual is categorized as bad.[104] This treatment of collections and public records is a common industry practice.

An individual's payment performance was classified as "good" if all of that person's accounts were good and they had no new public records or record of collection agency accounts. The payment performance of all other individuals was classified as "indeterminate." The small adjustment involved individuals whose payment performance was good with the exception of one account that had a delinquency of, at most, 30 days—the payment performance of such individuals was treated as good.

Determining Predicative Variables Eligible for the Model

Since the full credit records of each individual were available for this study, it would have been possible to have created any credit characteristic that could have conceivably been used in model development. However, in the spirit of the rule-based process of model development used here, the decision was made to restrict the variables eligible for inclusion in the model to the 312 credit characteristics included in the data provided for this study. These characteristics are quite comprehensive and are typical of those used in the industry.

Determining Which Individuals Should Be in the Estimation Sample

An additional restriction for the estimation sample is that each individual's credit record had to be "scorable" as of June 30, 2003. Credit records with limited credit history information or lacking relatively recent credit activity typically do not contain sufficient information to predict performance and are typically excluded from model development. Industry practice differs in terms of what information is necessary for an individual credit record to be scorable. For the model developed here, the credit records of individuals that had been assigned a TransRisk Score and a VantageScore as of June 30, 2003, were treated as scorable. A review of the credit records of individuals not assigned a credit score indicates that most of them had no credit accounts, and those that did typically had only inactive or extremely new accounts.

The resulting estimation sample consisted of 200,437 individuals who were scorable and also had either good or bad performance for the any-account performance measure used in model estimation. (See table 9 for sample statistics for the estimation sample.).

[104] Following industry practice, collections, tradelines, and public records involving alimony or child support and collection agency accounts for amounts of less than $100 were not included in the measure of performance.

Estimating the Model

After the sample of credit records had been drawn and the dependent variable defined and constructed, the sample was segmented, attributes were created, and characteristics were selected. The model was then empirically estimated. Each of these steps is described below.

Segmentation

On the basis of their credit records, individuals were segmented into three groups (following industry practice, these segments are termed "scorecards"): those with two or fewer accounts ("thin-file scorecard"), and two groups of those with three or more accounts—those with a major-derogatory account, collection account, or public record ("major-derogatory scorecard") and those without the credit-record blemishes that define the major-derogatory scorecard ("clean-file scorecard").[105] Typically, industry credit history models are based on a multiple scorecard segmentation scheme. Greater predictive power is achieved by segmenting the population and building specific scorecards for subpopulations with distinct credit-risk patterns. However, these models are usually estimated with at least 1 million individuals and often many more. Because the sample size for the present model is only one-fourth the size of the typical industry sample, the number of scorecards had to be limited. The three scorecards chosen here are those generally viewed as the most important by industry model developers. Attribute creation and model estimation were performed separately for each of the three groups.

Attribute Creation

A series of attributes was created from each of the 312 credit characteristics included by TransUnion in the data provided to the Federal Reserve.[106] An attribute is a dichotomous indicator variable (that is, a variable that can only take on values of zero or 1) constructed from a credit characteristic and reflects a specific range of values of the characteristic. An attribute is assigned a value of 1 when the value of the characteristic falls within the range specified for the attribute, and zero otherwise. Many attributes can be created for each characteristic, and together they cover all possible values of the characteristic. The number of attributes used to cover the range of all possible values is determined by the model builder. For example, the characteristic "total number of months since the oldest account was opened" might be assigned three attributes: one attribute for individuals whose oldest account is one or two years old, a second for individuals whose oldest

[105] For the definitions of major-derogatory account, collection account, and public record, refer to note 32.

[106] The credit characteristics were those created by TransUnion as of June 2003. Since that time, they may have expanded the number of characteristics available to model builders.

account is three to seven years old, and the third for individuals whose oldest account is eight or more years old; however, it could be assigned just two attributes or many more.

Given the myriad ways of subdividing characteristics into attributes, rules and procedures have been developed by the industry to simplify this task. To create the attributes for the present model, we employed a statistically based procedure that roughly approximates the approach used by industry model developers. For each individual, an initial process was applied to each characteristic for each scorecard, as follows.

First, an attribute was created for each characteristic with a missing value. Second, the process evaluated all possible divisions of the characteristic's range of nonmissing values into two attributes, each attribute covering a compact set of sequential values. The division selected was the one that best predicted performance for that scorecard. The prediction was formed by assigning a performance probability equal to the average performance of the individuals assigned to each of the two implied attributes.[107] An additional constraint for the division was that the difference in the mean performance for individuals in the two implied attributes had to be statistically significant. This rule implied that, for some characteristics, no subdivisions could be created; these characteristics are unrelated to performance.

Once each characteristic was subdivided into two attributes for nonmissing values, further subdivisions of each attribute were evaluated. For each attribute, every possible subdivision into two was evaluated. The same rules and evaluation procedures were employed as in the initial process. Again, only statistically significant subdivisions were allowed. For example, for the characteristic "total number of months since the oldest account was opened," suppose the initial process created the attributes "three years or less" and "four years or more" (for age counted only in whole years). The next step would involve looking at all possible subdivisions of each of those two attributes. For example, subdivision of the "three years or less" attribute would look at two possible further subdivisions, (1) "one year or less" and "two or three years" and (2) "two years or less" and "three years." If neither of these further subdivisions had a statistically significant relationship to performance, then the attribute "three years or less" would not be subdivided. Otherwise, the subdivision that was most predictive of performance would be selected, and the attribute would be split into two attributes.

The process of subdivision continued until there were no remaining attributes with statistically significant splits. At each step, only subdivisions of existing attributes were considered. Thus, for example, if "total number of months since the oldest account was opened" was subdivided into "three years or less" and "four years or more," no subdivisions that would cut across this initial division (for example, an intermediate

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[107] The definition of best prediction is the minimum sum of squared residuals, in which the residual for a given individual is the difference between the individual's performance (bad or good) and the mean performance of all individuals on that scorecard with the same attribute.

range of "three years and four years") would be considered. Because this analysis was done separately for each scorecard, the attributes selected for a characteristic do not have to be the same across the three scorecards; in fact, they do differ, as shown below.

Although the creation of attributes was governed by the mechanical application of the procedure outlined above, the process was somewhat more complicated than implied by the preceding discussion. In particular, the process also required that successive attributes imply that the characteristic as a whole be consistently positively or negatively related to performance (referred to here as "monotonicity"). Again using "total number of months since the oldest account was opened" as an example, assume that the attribute "four years or more" had an average performance of 0.5 and that a split of the other attribute, "three years or less," was being considered that would create the subdivisions "one year or less" and "two or three years." An average performance of less than 0.5 for the "one year or less" subdivision and of greater than 0.5 for the "two or three years" subdivision would result in a non-monotonic relationship between the value of the characteristic and performance and would not be considered for that reason.

Selection of Characteristics

Once attributes were created, each characteristic was evaluated for potential inclusion in the model through a process of "forward stepwise regression" applied separately to each scorecard. That technique sequentially chooses from among the 312 available characteristics according to whether inclusion improves the predictive power of the model. When evaluating a characteristic for potential inclusion in the model, all attributes of that characteristic were considered. In some cases, however, some individual attributes were combined to ensure monotonicity in the weights assigned to each attribute.[108]

As noted earlier, industry practice limits the number of characteristics that are included in a functioning model. The process of determining that number varies across model developers and applications. For the model developed here, the number of characteristics in each scorecard was limited by requiring that the last characteristic added to the model contribute to the predictive power by more than a threshold amount. The threshold was selected somewhat arbitrarily and was defined as a 0.75 percent increase in the "divergence statistic" that results from the inclusion of an additional characteristic.[109] For each scorecard, characteristics that were not included in the final model would not have materially improved the predictiveness of the model.[110]

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[108] Attributes were also combined to avoid perfect collinearity, which could arise if two attributes of two different characteristics had the same values for each individual.

[109] Different thresholds were evaluated; the 0.75 percent level was selected because it resulted in scorecards with numbers of credit characteristics consistent with industry practice.

[110] The "divergence statistic" measures how well a scorecard separates good and bad distributions of outcomes, such as performance on loans. The distribution of bads and goods in loan performance can be

To carry out the forward stepwise regression, the single characteristic among the full set of 312 whose attributes best predicted performance for individuals on that scorecard was identified. With that characteristic now included in the model, the remaining 311 characteristics were evaluated, and the one among those 311 that most improved the predictiveness of the model was added as the second characteristic. This process was used to select all subsequent characteristics that improved predictiveness by more than the threshold amount.

Once the stopping point has been reached, a second phase commences in which all of the characteristics in the model are tested to determine their individual, marginal contribution to the divergence statistic. That is, for each characteristic that has been included, the divergence statistic for the model is calculated without that characteristic and then with that characteristic. If the divergence statistic does not rise more than 0.75 percent when the characteristic is restored to the model, then that characteristic is dropped. Each time a characteristic is removed, the abridged model is re-estimated to ensure that the contribution of each of the remaining characteristics to the divergence statistic is above the threshold; if it is, then new characteristics are considered for inclusion in the model. New characteristics are added if the percentage improvement to the divergence statistic exceeds 0.75 percent. New characteristics are added until there is no additional characteristic that produces an improvement in the divergence statistic that is above the 0.75 percent threshold, and each included characteristic's contribution to the divergence statistic is above this threshold. As with the rest of the model development process, the characteristic selection process is conducted separately for each scorecard.

The FRB Base Model

The credit-scoring model developed for this study, the "FRB base model," consists of three scorecards that incorporate 19 of the 312 credit characteristics available in the data provided by TransUnion (the 19 characteristics are listed in appendix C). Some credit characteristics appear on more than one scorecard, and the number of attributes associated with them varies (tables 12.A–C). The thin-file scorecard has 8 credit characteristics and includes 9.9 percent of the individuals in the estimation sample. The clean-file scorecard has 8 credit characteristics and covers 58.9 percent of the estimation sample. The major-derogatory scorecard has 10 credit characteristics and includes 31.2 percent of the sample.

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measured by the percentage of loans that either pay on time or are seriously delinquent or default at different credit-score ranges. Ideally, a credit-scoring model will assign worse scores to loans that eventually go bad and better scores to loans that perform well. The further apart the distributions of good and bad loans, the better the credit-scoring model is doing in predicting outcomes. The divergence statistic is calculated as the square of the difference of the mean of the goods and the mean of the bads, divided by the average variance of the score distributions.

Each characteristic and its associated attributes are assigned a certain number of credit points; the points represent the weight assigned to each characteristic in calculating an individual's credit score. On the thin-file scorecard, for example, the characteristic with the widest range of possible credit points is "total number of public records and derogatory accounts with an amount owed greater than $100." This characteristic has five attributes. The attribute associated with the largest number of possible credit points is "five or more" (that is, five or more public record and derogatory accounts); that attribute accounts for negative 425 points. About 8 percent of the individuals on the thin-file scorecard are associated with this specific attribute. To derive an individual's credit score, one would sum the number of credit points across the various characteristics on the scorecard applicable to that individual.

Because performance is not inherently scaled, a normalization was necessary to estimate the model. In estimating the model here, the dependent variable was defined as a dichotomous variable that took a value of 1000 to represent good performance and zero to represent bad performance and that was estimated using ordinary least squares. Thus, the predicted value from the regression is 1000 times the probability that an individual would have good performance. Scores (or individual predictions from the model) of 1000 represent an estimated probability of 1 that an individual's performance will be "good"; scores of zero represent a probability of 1 that an individual's performance will be "bad." A score of 500 represents an estimated probability that an individual's credit performance has an equal chance of being either good or bad. For the empirical analysis presented in the forthcoming sections of this study, all the credit scores are further normalized to a rank-order scale of zero to 100 (described below). Converting the FRB base score to this normalized score requires a nonlinear transformation (table 13).

The three scorecards differ greatly from each other in terms of the percentage of individuals who experience bad performance over the 18-month performance period (using the measure of bad performance used to estimate the model). The proportion of individuals on the clean-file scorecard who experienced bad performance was 7.4 percent; on the thin-file scorecard, 34.8 percent; and on the major-derogatory-file scorecard, 64.7 percent (shown earlier in tables 12.A–C). Overall, 28.0 percent of the individuals in the sample experienced bad performance over the 18-month performance period (data not shown in table).

Predictiveness of the FRB Base Model

As noted earlier, the industry uses a variety of metrics to assess the ability of a credit-scoring model to position individuals on an ordinal scale (that is, "rank order" them) according to the credit risk they pose. The KS statistic is the primary metric used in this study. The higher the KS score, the better the model separates goods from bads. Overall, the KS statistic for the FRB base model is 73.0 percent, which, according to industry representatives, is in line with other generic credit-scoring models that use the same measure of performance for estimation. The ability of the FRB base model to separate goods from bads is illustrated in figure 1, panel A, where the cumulative distribution of scores for individuals exhibiting good performance over the 18-month performance period is consistently and substantially below the distribution of individuals with bad performance. The figure shows that the cumulative distributions of goods and bads in the FRB base model (panel A) are comparable to those of the TransRisk Score (panel B) and the VantageScore (panel C) as measured over the same population and performance measure.

The ability of the FRB base model to predict loan performance appears to be on a par with other generic credit-scoring models. The ability of the three scorecards to distinguish between the goods and the bads differs significantly: The scorable sample KS statistic for the thin-file scorecard is 72.3 percent; for the clean-file scorecard, 53.4 percent; and for the major-derogatory scorecard, 61.7 percent. Industry experience indicates that this variation in KS statistic is to be expected. The KS statistic for individual scorecards typically varies depending upon, among other things, the specific sample of credit records used to estimate the scorecard, the time period evaluated, and the measure of performance that is used in estimation.

Limitations of the Model

The credit-scoring model developed here is an approximation of the generic credit-scoring models used by the lending industry. As explained earlier, for purposes of the study, this approximation has many virtues. However, it is only an approximation and, for a number of reasons, does not fully reflect industry models.

First, the model developed here divides the sample of credit records into only three scorecards because of the relatively small size of the credit-record sample. To better classify individuals according to credit risk, the industry commonly uses larger samples and more scorecards.[111] Second, whereas the performance period used here is 18 months, industry models more commonly use 24 months. Compared with use of the longer period, the use of 18 months produces fewer observations of loans becoming delinquent and reduces somewhat the precision of the model specification. Third, the definition of a "bad" outcome used here is likely quite similar to, but may differ in nuance from, the definition used commonly in the industry because the definition of a "bad" is typically proprietary. Fourth, the determination of the stopping point for adding characteristics to the three scorecards used here was an arbitrary threshold based on the

[111] Some industry models are developed with a rolling sample, that is, a sample of individuals drawn over a period rather than at one point in time. For example, rather than selecting the entire sample of credit records on a given date, a rolling sample would consist of subsamples drawn successively a few months apart. This approach is intended to minimize any seasonality in the use of credit that could distort estimation.

divergence statistic. Industry model developers may use other techniques or select different thresholds to determine a stopping point. Fifth, the 312 characteristics in the credit-record database used here were those provided by the TransUnion; model developers may create and use their own characteristics. Sixth, model developers typically assume a logistic relationship between the predictive characteristics and model performance. For model estimation here, a linear probability model was assumed and estimated with least squares because of data processing costs.[112] Finally, model developers have long experience in developing scorecards, and through that experience may have learned to create more effective attributes; as a consequence, the specific attributes of characteristics in the model here may differ from those used in some industry models.

FINDINGS ON LOAN PERFORMANCE AND CREDIT AVAILABILITY AND AFFORDABILITY

This section presents an assessment of the relationship of credit scores to loan performance and to the availability and affordability of credit for different populations. The assessment begins with a discussion of the three credit scores considered in the study that serve as the basis for the analysis. The assessment then focuses on (1) the distribution of credit scores across different populations; (2) the extent to which other demographic, credit, and economic characteristics explain differences in credit scores across populations; (3) the stability of the credit scores of individuals over time; (4) the relationship between credit scores and loan performance measured in a variety of ways; (5) the extent to which, given score, performance varies across populations; (6) the extent to which differences in credit availability and affordability across populations can be explained by credit score; and (7) whether differences in performance, credit availability, and pricing may be explained by factors not considered in our analysis.

The Three Credit Scores Used in the Study

The distribution of credit scores for the whole population of scorable individuals is publicly available, but much less is known about the distribution of credit scores for subpopulations.[113] The analysis that follows does address subpopulations. It reports the

[112] Although not used throughout the process, the FRB base model was reestimated with a logistic model form as a robustness check. The correlation between the scores constructed using the two methods is greater than 0.99. Differences were almost entirely in the extremes of the distributions, that is, individuals in the top and bottom deciles of the score distribution. The two different scores tended to rank order individuals within these two deciles somewhat differently. Between these two extremes, rank orders were virtually identical.

[113] The national distribution of scores generated by the FICO model is at www.myfico.com/CreditEducation/CreditScores.aspx. The distributions of scores generated by other credit-scoring models may differ from the distribution of FICO scores.

distribution of the three credit scores used in this study—the TransRisk Score, the VantageScore, and the Federal Reserve's estimated base score (FRB base score)—across individuals grouped by their race or ethnicity; national origin, sex and marital status, and age; and by the relative income, degree of urbanization, and racial composition of the census tracts in which they reside. The report of the distribution for each subpopulation consists of summary statistics, cumulative distributions, and a decomposition of the demographic characteristics of the individuals at different credit-score ranges.

Comparing credit scores derived from different credit-scoring models requires "normalizing" the scores to a common scale. However, no natural, universal normalization formula exists. Because the particular normalizations used for the TransRisk Score and VantageScore are unknown, it was decided to renormalize each of the scores used in this study, including the FRB base score, to a common rank-order scale. The normalization was based on the 232,467 individuals in our sample for whom all three credit scores were available as of June 2003. Individuals were ranked by the raw values of each of the three credit scores, with a higher rank representing better performance. Individuals at the 5 percent cumulative distribution level for each credit score were assigned a score of 5; those at the 10 percent level were assigned a score of 10; and so on, up to 100 percent. Linear interpolations were used to assign credit scores within each 5 point interval to ensure the functional form was smooth.

Under this method of normalizing, each individual's rank in the population is defined by his or her credit score: For example, a score of 50 places that individual at the median of the distribution, and a positive change of 5 points in an individual's credit score means that individual moves up 5 percentage points in the distribution of credit scores. Because each score is normalized in exactly the same way, comparisons of the overall distributions across the three scores are not meaningful. However, the normalization facilitates comparisons across different populations for each of the three scores.

The Distribution of Credit Scores

Mean score, median score, standard deviation of score, and the proportion of individuals in the lowest score deciles vary widely across subpopulations and across the three credit scores (tables 14.A–C and figures 2.A–C). Differences in credit scores among racial or ethnic groups and age cohorts are particularly large. For example, according to self-reported (SSA) data on race or ethnicity, the mean TransRisk Score for Asians is 54.8; for non-Hispanic whites, 54.0; for Hispanics, 38.2; and for blacks, 25.6. The proportions of the subpopulations in the lowest two score deciles also differ greatly: The proportions of the subpopulations in the lowest two score deciles is, for Asians, 12.3 percent; non-Hispanic whites, 16.3 percent; Hispanics, 30.1 percent; and blacks, 52.6 percent.

Foreign-born individuals appear to have a score distribution similar to the general population, with a smaller representation at the extremes of the distribution.[114]

When the racial composition of the census block is used as a proxy for the race or ethnicity of the individual, the differences in scores across groups, although still substantial, are smaller than when the individual's race or ethnicity derived from SSA data are used. For example, when the census-block proxy for race is used, the mean difference in the TransRisk Score between blacks and non-Hispanic whites falls from 28.4 points to 15.1 points.

The distribution of credit scores for unmarried and married individuals also differs. For all three score measures, the mean score for married individuals is about 12 points higher than for a single individual of the same sex. Scores vary little by sex.

Credit scores differ substantially by age and increase monotonically from young to old. The mean TransRisk Score for individuals younger than age 30 was 34.3; for those aged 62 and older, it was 68.1. The range is wider for the VantageScore; the mean VantageScore for individuals younger than age 30 was 31.1 and for those aged 62 and older, 67.7.[115] The proportion of individuals younger than age 30 in the lowest two TransRisk Score deciles was 31.7 percent; the proportion for those 62 and older was 7.2 percent.

Mean credit scores for individuals grouped by the income or minority proportions of their census tract also differ notably. Individuals in high-income census tracts have a mean TransRisk Score of 57.9; in low-income census tracts, the mean is 32.5. The mean TransRisk Score for residents of census tracts with less than 10 percent minority population was 55.7; for individuals in census tracts with 80 percent or more minority population, it was 34.6. Individuals living in urban and rural areas have very similar credit-score distributions.

Cumulative Distributions

The summary statistics described above do not fully convey the credit-score differences across populations. A fuller picture is obtained with cumulative distributions (figures 3.A–C). Here, a cumulative distribution aggregates the number of individuals at each score point, starting with the lowest score; by the time the highest score point—100—is reached, 100 percent of the individuals have been counted. If, for example, 50 percent of a group has been counted up through a score of 20, then 50 percent of that

[114] These credit-score patterns by race or ethnicity are consistent with those presented in an analysis of consumer perceptions of creditworthiness. Refer to Marsha Courchane, Adam Gailey, and Peter Zorn (2007), "Consumer Credit Literacy: What Price Perception," paper presented at Federal Reserve System Conference, Financing Community Development: Learning from the Past, Looking to the Future, Washington, March 29-30.

[115] The wider range of scores for the VantageScore likely stems from the choice of performance measure used to estimate the model rather than from any particular treatment of age-related characteristics.

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group has a score of 20 or less. More generally, if a group's cumulative distribution of scores is uniformly above another, then at *each* credit-score level, the population with the higher distribution has a larger percentage of its individuals with credit scores *below* that level than does the other population.

Cumulative distributions show that the credit-score patterns suggested by the means and medians hold for the various subpopulations. For example, across all three credit-score measures, the cumulative distributions of scores for blacks and Hispanics are consistently higher than those for non-Hispanic whites and Asians. Cumulative distributions by age are also consistently ordered, with the cumulative distribution of younger individuals higher than that of individuals aged 62 or older. Cumulative distributions for census-tract groupings by racial or ethnic composition or relative income are also consistent with the patterns implied by the summary statistics for these groups.

Demographic Composition of Score Deciles

Another way of describing differences in credit-score distributions across groups is to look at the demographic composition of the populations in each credit-score decile (figures 4.A–C). With the exception of sex, the composition of the population varies greatly across deciles. Taking the TransRisk Score as an example, 27.2 percent of the individuals in the lowest decile are black, whereas in the highest decile, 3.0 percent are black. Similarly, 23.7 percent of those in the lowest decile are younger than 30 years of age versus 0.3 percent of those in the highest decile.

Notable differences in the composition of the population are also evident when individuals are sorted by the relative income. For example, 7.9 percent of the individuals in the lowest TransRisk Score decile reside in low-income areas, compared with 1.5 percent in the highest score decile.

Multivariate Analysis of Differences in Credit Scores

Demographic factors may be correlated. For example, some of the differences in credit scores by race or ethnicity could arise from differences in the distribution by age or marital status of the different racial or ethnic groups. This section presents the results of a multivariate analysis conducted to isolate the effects of each demographic or census-tract characteristic by controlling for the other characteristics.

The first step in identifying the independent effect of race or ethnicity on credit-score differences across populations was to fit a regression model to predict credit scores of non-Hispanic whites according to their age (using linear splines for each of the five age cohorts), sex, and marital status. The age splines were fully interacted with sex and marital status (that is, for each sex and marital status, a separate linear spline was created). Predicted values from this equation were then used to predict the scores for blacks, Hispanics, and Asians. Differences between a group's actual credit scores and its predicted scores can be interpreted as unexplained racial or ethnic effects.[116]

Credit records generally do not include information about individuals' economic or financial circumstances, such as their income, wealth, and work-related experience, nor do the other databases against which the credit-score sample was matched. Thus, this information is not available for this study. As discussed in a later section, populations differ widely along many economic and financial dimensions, and variations in credit scores may reflect such differences. Ideally, one would like to account for the effects of these other circumstances in explaining differences in credit scores across populations. The credit-record data do, however, include information on the location of residence. This information was used to construct a number of additional control variables, and the multivariate analysis was broadened to include these additional measures.

A proxy measure of income was developed from census information. The 2000 decennial census provides the distribution of income for each racial or ethnic group segmented in seven age categories for each census tract. These distributions allow a calculation of an estimated average income for each racial or ethnic group by age within each census tract. This variable was used as an estimate of the income for each individual in the sample. (Individuals missing race or ethnicity were assigned the mean for their age group in their census tract of residence.)

The empirical estimation was expanded to include the following location-based controls: the estimated income variable, the relative income of the census tract of residence, and the mean TransRisk Score of the individual's census tract of residence.[117] Because the TransRisk Score was used as the dependent variable in the regression and to derive the mean score for each census tract, the equation using the mean census-tract credit score can be interpreted as a "fixed effects" model, that is, a model structured to fully account for all types of socioeconomic differences among census tracts.

The sample used for the multivariate estimation was reduced 11 percent by excluding individuals with unknown age or census tract. As shown in table 15, panel A, the gross difference between non-Hispanic whites and blacks for the TransRisk Score in the multivariate estimation sample was 28.3 credit-score points (54.0 minus 25.6 with rounding). The difference between non-Hispanic whites and blacks declines to 22.8 points when marital status and age are accounted for; the difference falls to 18.7 points when census-tract income and the estimated income of the individual are taken into

[116] The term "unexplained" as used here is a statistical concept. The unexplained difference is defined as the difference in average scores in the scorable sample after other factors included in the multivariate regressions are accounted for. Thus, the size of the unexplained component depends on what other factors are included in the model. Adding or subtracting factors to the model will affect the size of the unexplained differences.

[117] The mean TransRisk Scores by census tract were normalized in the same manner as the TransRisk Score for the sample individuals.

account. Accounting for the mean census-tract credit score causes the difference to fall further, to 13.4 points. The gross difference in mean TransRisk Scores between Hispanics and non-Hispanic whites (15.7 points, again with rounding) falls relatively more than for blacks and non-Hispanic whites; after accounting for all factors, only a 3.9 point differential remains unexplained.

When the census-block proxy is used to identify the race or ethnicity of individuals, a similar reduction is observed in the differences across racial or ethnic groups once other factors are taken into account (table 15, panel B). These results differ from those using individual race or ethnicity; however, differences in that gross score and the differences that remain after all available factors are taken into account are smaller. For example, the analysis using the census-block proxy for race or ethnicity finds an unexplained difference of 2.5 points between non-Hispanic whites and blacks. In contrast, an unexplained difference of 13.4 points remains between these two groups when the individual's race or ethnicity is used in the analysis.

Identifying the independent effects of sex on credit scores involved an analysis similar to that conducted for race or ethnicity. A regression model was fit to predict the credit scores of males by age, race or ethnicity, and marital status. Additional models were estimated adding the same demographic or location characteristics used in the race or ethnicity analysis. Controlling for these additional factors does little to explain the gross difference of 1.6 points in the mean TransRisk Score between females and males (table 15, panel C).

The analysis to account for differences by age was conducted in a somewhat different manner from that for race or ethnicity because there was no natural comparison or base group. Using the same approach for estimating an age-neutral model, to be described in a later section, age was included as a regressor in the estimation to estimate coefficients for the other variables in as age-neutral a way as possible. Scores for each group were then predicted under the assumption that the age of each individual was the average age for the population. Residuals for each age group were expressed as differences from the mean residuals of those aged 62 or older.

The regressions suggest that only a minor portion of the differences across age cohorts can be explained by the other factors (table 15, panel D). For example, the gross difference of 33.9 points in the mean TransRisk Score between those younger than age 30 and those aged at least 62 is reduced only to 29.4 points when these factors are taken into account.

The Stability of Credit-Score Differences over Time

The data obtained for this study provide an opportunity to assess changes in credit scores over time for each population group. The data contain credit scores at the beginning of the performance period (June 2003) and at the end, 18 months later (December 2004); the scores for both periods are normalized in the same way using the rank-order distribution of the June 2003 population.

A population group disproportionately subject to adverse economic shocks (such as a job loss) or other so-called trigger events (such as illness or divorce) are expected to exhibit greater reductions in credit scores than other groups.[118] Moreover, if the reductions in scores are caused primarily by temporary trigger events, then scores of individuals in the lower credit-score ranges would tend to rise over time. That increase in scores would, however, be only gradual, as adverse information is removed from credit records only after a number of years.

Changes in the TransRisk Score for individuals in each population group are shown in table 16. The mean score for virtually every group is little changed over the 18-month period. The mean score for the entire population increases only 0.1 percent. However, 17 percent of individuals experienced a credit-score increase of 10 points or more, and 17 percent experienced a decrease of 10 points or more. Significant changes in scores are relatively rare and not symmetric; 2.3 percent of individuals experienced a decline of 30 points or more, but only 1.6 percent of individuals experienced an increase of 30 points or more.

Some evidence suggests that, over time, scores tend to migrate toward the middle of the distribution. For example, the scores of 71 percent of the individuals in the lowest score decile in June 2003 rose over the performance period, whereas the scores of only 23 percent of individuals in the top decile rose. The pattern of migration of scores toward the middle varies by subpopulation. For example, only in the lowest decile did the majority of blacks experience an increase in score; the majority of non-Hispanic whites experienced an increase in all but the top three deciles. And borrowers younger than age 30 showed less of a tendency to experience increases in scores than individuals in other age groups: For each score decile, the percentage of younger individuals experiencing an increase was lower than for any of the other age groups.

Taken together as explanations for racial and age differences in scores, these data provide at most only a partial explanation for score differences across populations, or they suggest that, for certain populations, trigger events either are persistent or happen more often than they do to other populations.

Credit Scores and Performance

The Fact Act asks for an analysis of the statistical relationship, using a multivariate analysis, between credit scores and the "quantifiable risk and actual losses experienced

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[118] Assessments of the importance of trigger events and other factors influencing loan performance are in Scott Fay, Erik Hurst, and Michelle J. White (2002), "The Household Bankruptcy Decision," *American Economic Review*, vol. 92 (June) pp. 706-18; and Li Gan and Tarun Sabarwal (2005), "A Simple Test of Adverse Events and Strategic Timing Theories of Consumer Bankruptcy," NBER Working Paper Series 11763 (Cambridge, Mass.: National Bureau of Economic Research, November).

by businesses" for different populations. The credit-record data do not include direct information on losses. However, a common metric used by the industry as a proxy for losses is a measure of loan default. There are various ways to define default. Typically, they would include accounts that became 90 or more days delinquent or were in foreclosure or collection, or were otherwise in serious distress or loss. This is the approach used here. We define five measures of credit-account performance for the 18-month performance period contained in our data. These five performance measures are compared with credit scores at the beginning of the performance period.

Four of the credit-account measures (numbered 1–4 below), are commonly used in the industry. The fifth measure is one developed specifically for this study.

1. any-account
2. new-account
3. existing-account
4. random-account
5. modified new-account

We used the any-account measure to estimate the FRB base score. The any-account measure is based on the performance of new or existing accounts and measures whether individuals have been late 90 days or more on one or more of their accounts or had a public record item or a new collection agency account during the performance period.

New-account performance is defined in the same way as that for the any-account measure, but the accounts it covers are limited to those opened between July 2003 and December 2003. Unlike the any-account measure, the new-account measure does not consider public records or collection agency accounts.

Existing-account performance is limited to credit accounts that were opened before July 2003 and remained open during at least a portion of the performance period. The existing-account measure does not consider public records and classifies the performance of individuals with a collection account and no other bads as indeterminate rather than bad.

Random-account performance defines performance on each credit account in the same manner as the any-account measure, but instead of defining an *individual's* performance as good or bad, performance is defined as the percentage of the individual's *accounts* that have bad performance. Public records and collection accounts are not used in this calculation. This measure of performance is similar to the one used in developing the VantageScore.

The precise time when an account became bad often cannot be determined. Consequently, rules are developed to implement somewhat arbitrary decisions about how to determine whether an account was bad before the beginning of the performance period or whether it went bad subsequently. Errors in those decisions can create a spurious correlation between the performance measure and the score at the beginning of the performance period. Consequently, modelers generally validate performance using only unambiguously out-of-sample performance measures, such as accounts that are known to have been opened after the beginning of the performance period.

To address the concern that a seemingly new account in the present database may have actually existed and gone bad before the opening of the performance period, an additional measure of new-account performance, called the "modified new-account" measure, was constructed from the credit records. Under the modification, new accounts were eliminated if they appeared to have a high propensity to be reported only when performance is bad.

The accounts excluded to create the modified new-account measure consisted of student loans and utility, medical, and factoring accounts. Whenever any such account appears in the June 2003 data as new, it likely instead was already in existence but was not reported as opened until the later time. All these accounts were excluded regardless of their performance; doing so eliminated only about 10 percent of the new accounts but removed more than 50 percent of all bads. To better emulate industry out-of-sample performance measures, the modified new-account measure was computed at the account level rather than—as in the new-account measure—at the person level. Bad performance in the modified new-account measure is defined as it is in the other four performance measures (major derogatory or 90 or more days delinquent during the performance period).

The percentage of accounts that become bad varies greatly across the five performance measures and population groups (table 17). Twenty-eight percent of individuals exhibited bad performance using the any-account measure, compared with only 3.4 percent of modified new accounts. Performance across groups varied greatly, a topic examined in the next section.

Overall Performance

Regardless of the specific performance measure considered, each of the three credit scores used in this study predicts future loan performance: Figure 5 displays the actual average performance at each credit-score level for the three scores and for the five measures of performance. As shown, the percentage of bads consistently decreases as credit scores increase for all three scores and for all five measures of performance. The performance of those in the bottom 30 percent of the distribution differs substantially from those above that level. For example, for the TransRisk Score, 78.4 percent of the individuals with credit scores in the bottom three score deciles had at least one account go bad over the performance period, while only 1.8 percent of individuals in the top 30 percent of the score distribution had an account go bad.

Another way of illustrating the predictiveness of the scores is to plot the cumulative distribution of goods and bads by score (as shown earlier in figure 1). For each score and for each performance measure, the cumulative distribution of the bads is considerably to the left of that of the goods, a confirmation that the scores have considerable predictive power.

The poor performance of individuals in the lowest portion of the credit-score distribution warrants closer attention. The potential losses from extending credit to individuals in this credit-score region appear to be substantial. For example, the random-account performance measure indicates that 52.7 percent of new or existing accounts extended to individuals in the bottom 20 percent of the score distribution would be expected to go bad over an 18-month period. Not all of this poor performance necessarily reflects lender decisions on newly extended credit because it also potentially reflects deteriorating performance on existing accounts, which are those opened before the beginning of the performance period. However, credit-record data indicate that 17.9 percent of the individuals in the bottom two score deciles of our sample were extended credit in the last six months of 2003 (modified new account) and that about 16.1 percent of these accounts defaulted. Under the presumption that lenders screen for credit risk, the high incidence of bad performance in the two lowest deciles likely would have been even higher had more individuals in these low score deciles been extended credit.

Performance by Population Group

Credit scores appear to differentiate risk well within all population groups (figures 6.A–E; data given are only for the TransRisk Score, as the data for the other two scores are similar). The general shapes of the performance curves are similar across groups, as is the separation of the goods and bads (figures 7.A–E; again, data only for the TransRisk Score are shown). Within populations, the performance curves are not identical. Of particular interest for this study are performance curves for populations that are uniformly above or below that for others. A performance curve that is uniformly above (below) means that that group consistently underperforms (overperforms), which in turn means that the group performs worse (better) on their loans, on average, than would be predicted by the performance of individuals in the overall population with similar credit scores.

Another way of comparing performance across groups is to compute performance residuals. First, the mean performance for all individuals is computed at each score level (rounded to half a point). Residuals for each population group at each score level are derived as the difference between the mean performance of the population group at that score level and the mean performance of the full population at that score level. The group residual is calculated by averaging residuals over all score levels (results shown in tables 18.A–C). Consistently, across all three credit scores and all five performance measures, blacks, single individuals, individuals residing in lower-income or predominantly minority census tracts show consistently higher incidences of bad performance than would be predicted by the credit scores. Similarly, Asians, married individuals, foreign-born (particularly, recent immigrants), and those residing in higher-income census tracts consistently perform better than predicted by their credit scores.[119]

Results for age are mixed: For the TransRisk Score and FRB base score, individuals younger than age 30 consistently show higher incidences of bad performance than would be predicted by their credit scores. However, for the VantageScore, for some measures of performance, younger individuals perform better than would be predicted by this score. Differences in the results across scores are driven by the fact that the mean credit score for individuals younger than 30 is lower for the VantageScore than for the other two scores. As noted earlier, the primary reason for the relatively lower VantageScores for younger individuals is the choice of the random-account performance measure in estimating the model. The choice of this performance measure in estimation tends to lower scores for individuals with a small number of credit records (who are disproportionately younger) relative to those with many records.[120] Indeed, when the VantageScore performance residuals are calculated using the random-account performance measure, younger individuals perform about as predicted.

All the performance residual calculations are relative measures in that the mean performance residual for the whole population is normalized to zero for each credit-score measure and for each measure of performance. Thus, a positive average performance residual means that, on average, and controlling for credit score, the performance of the group was worse over the performance period used here than the average for the whole population.

For some of the population groups, the calculated underperformance or overperformance is not small, particularly for the new-account performance measure. The mean account performance data, shown earlier in table 17, together with the residuals shown in tables 18.A–C indicate how much of the performance can be predicted by score and how much is unexplained. For example, for the any-account performance measure, the mean bad rate for blacks is 65.9 percent; for the new-account measure, it is 21.7 percent. The TransRisk Score residual for these two performance measures for blacks are 5.6 percent and 3.4 percent respectively. We subtract the residual from the mean bad rate to find that the predicted performance for blacks based on the TransRisk score for the any-account measure would be 60.3 percent bad and for new accounts 18.3

[119] Prediction residuals for populations with extremely small sample sizes, such as the Native American group, and for those with unknown census tracts should be viewed with caution because the performance estimates have large standard errors.

[120] Consistent with this view, the major differences between the VantageScore and the other two scores are among the individuals on the FRB thin-file scorecard.

percent bad (derived from tables 17 and 18.A). Thus, the residual, or the component of average black performance that is unexplained, is not small: For example, the actual new-account percent bad is about one-sixth higher than would be predicted from the TransRisk Scores for blacks. At the other end of the spectrum, for recent immigrants the actual any-account percent bad is 5 percent lower than would be predicted, but for modified new accounts it is more than 25 percent lower.

One possible concern is that the performance measures may include performance on accounts that are not consistently reported. Three such items are student loans, noncredit-related collection agency accounts or public records such as those for medical or utility bills, and authorized user accounts (that is, accounts for which the individual is not responsible for repayment). The preceding analysis was repeated with any-account performance residuals adjusted to remove (1) student accounts, (2) noncredit collections and public records, and (3) authorized user accounts.

Not surprisingly, individuals younger than age 30 were the most affected by the removal of student loans or authorized user accounts; however, the effects were quite modest. The any-account TransRisk performance residual for the younger group fell from 1.5 to 1.3 when these account types were removed from the measurement of performance (results not shown in tables). Performance residuals for other populations were little changed when student loans or authorized user accounts were removed from the measurement of performance.

Removing collection and public record items had the largest effect on blacks, but the effect was very modest. Performance residuals for blacks fell about 0.1 point (or about 2 percent) for each score.

An Implication of Underperformance

Underperformance relative to the performance implied by the credit score has an implication for the groups involved, as it relates to the expected changes in credit-score levels over time. The score levels of groups that consistently underperform would be expected to deteriorate over time because payment performance is a significant factor in credit-scoring models. The deterioration would be particularly pronounced to the extent that new accounts without a performance history are in the credit records. Alternatively, groups that consistently overperform would be expected to experience an increase in credit scores over time as a result of their good performance. The fact that groups with the largest performance residuals—blacks, single individuals, those younger than age 30 (for the TransRisk Score and the FRB base score), and residents of lower-income and predominantly minority census tracts—have score levels that are consistently lower than average might be due to underperformance in the past. Similarly, the fact that groups that consistently overperform—married individuals, foreign-born individuals, and individuals residing in higher-income census tracts—have higher-than-average credit-score levels suggests that, over time, overperformance leads to higher scores for these groups.

Multivariate Analysis of Performance Residuals

In the preceding discussion, the performance residuals presented were univariate statistics. As was the case with the differences in credit-score levels across groups, the performance residuals for one population may reflect, at least partly, differences coming from other factors. To address that possibility, a multivariate analysis was conducted in a manner similar to that performed for score levels.

To identify the independent effect of race or ethnicity on differences in performance residuals, a regression model was fit to predict performance residuals using only non-Hispanic white individuals based upon their age (separated into five linear splines), sex, and marital status. The age splines were fully interacted with sex and marital status. For comparability with the score-level analysis and with the mean credit scores by census tract, the performance residual used for this analysis was based on the TransRisk Score. An additional advantage of using the TransRisk Score is that the performance residual is truly out-of-sample. The TransRisk Score was developed and available before June 2003, whereas both the VantageScore and the FRB base score were estimated using approximately the same performance period as that used here.

Predicted values from this equation were used to predict performance residuals for blacks, Hispanics, and Asians. Differences between individuals' actual performance residuals and their predicted performance residuals can be interpreted as unexplained racial or ethnic effects. The empirical estimation was then expanded to control for the census-tract estimate of the individual's income, the relative income of the individual's census tract, and the mean credit score of the individual's census tract. All regressions were conducted separately for individuals in the lowest TransRisk Score quintile, in the second-lowest quintile, and in the top three quintiles combined. The TransRisk Score and the TransRisk Score squared were also included in each regression. As with the analyses of score differences, the regressions were also run using only males, controls for age, and weights for the percentage of non-Hispanic whites in the census block.

The analysis was conducted with each of the five performance measures (tables 19.A–E). Unlike the case of the multivariate analysis of credit-score distributions, controlling for other personal demographic and census-tract factors appears to have only a modest effect on performance residuals across populations. For example, the performance residual for the any-account performance measure for blacks has a 5.6 percent bad rate, which is only reduced to 4.7 percent when other factors are taken into account. Thus, the performance residuals appear to largely reflect the group characteristic itself (or, as discussed below, other factors related to the group characteristic that were not included in the model) and not the confounding effect of other personal demographic factors.

Loan Terms and Performance

The preceding sections focus on explaining group differences in performance residuals that may be due to demographic characteristics. Another possible explanation for performance differences may be that different populations use different types of credit, borrow from different types of lenders, and receive different loan terms even when they have similar credit scores. The account details in the credit records allow for a limited assessment of these explanations.

The evaluation could technically be done for both existing credit accounts and for new accounts. The drawback to using existing accounts is that such accounts were opened at various times preceding the draw of sample credit records and thus may not reflect an individual's current credit circumstances. However, by focusing on accounts opened during the first six months of the performance period—July to December 2003—the credit records of June 2003 more credibly reflect the credit circumstances of the individuals when these loans were underwritten. Therefore, the analysis focuses on all accounts opened during that six-month period and contained in the December 2004 credit records. The analysis uses the modified new-account performance measure because of all the measures, the coverage of that one is the most likely to be truly new loans.

Data in the credit records allow for the classification of new loans along several dimensions: the type of lender—bank or thrift institution, finance company, credit union, and other (for example, retail stores); the type of loan—mortgage, auto, other installment, credit card, and other open-ended loans; largest amount owed; the month the loan was taken out; and, for mortgage loans and installment loans, the loan terms (loan maturity and monthly payment) and a derived estimate of the current interest rate.[121]

The analysis begins with simple univariate relationships describing differences in the types and terms of new loans for different population groups after controlling for credit scores. Tables 20.A–C present information on the distribution of loan type, interest rate, and subsequent performance for different groups of individuals in three segments of the TransRisk Score distribution: the lowest quintile; the second-lowest quintile; and the top three quintiles combined. On the basis of credit score alone, individuals in the lowest quintile would likely be in the subprime portion of the loan market. Those in the top three quintiles correspond roughly to individuals in the prime portion of the loan market, and those in the second-lowest quintile fall between these two groups.

[121] Interest rates are not included in credit-record data. However, for closed-end loans, one can estimate the current interest rate on the basis of items in the data, including the size of the monthly payment, the amount borrowed, and the term of the loan. Such estimates have been made for installment and mortgage loans and assume that the loans are fully amortizing.

The data indicate differences in the types of loans taken out by different population groups. For example, in all three score groups, the share of installment loans with finance companies is significantly larger among black and Hispanic borrowers than non-Hispanic white borrowers. Blacks and Hispanics are less likely to take out mortgages or other loans at banks than are non-Hispanic white borrowers. Not surprisingly, individuals younger than age 30 are less likely to take out mortgages but are more likely, at least in the upper four score quintiles, to have credit card accounts. Males are more likely to have mortgages than auto loans, but females are more likely than males to have "other" loans, primarily retail or store loans. Estimated interest rates also differ across populations after controlling for loan type and score quintile. Credit accounts of black borrowers have higher interest rates than those of non-Hispanic whites for each loan category in which rates can be determined, although differences were small for some loan products. This pattern is found across all the credit-score quintiles, including the top three score quintiles, where credit-risk differences, at least as measured by credit history, are smaller. Interest rate patterns for Asians differ, as interest rates paid by Asians are typically lower or about the same, on average, as those paid by non-Hispanic whites across all credit-score quintiles and all product categories for which rates could be estimated.

Very few consistent patterns emerge for interest rate by national origin or sex. Interest rates vary by age, although they exhibit different patterns across different products and credit-score quintiles.

The data also track the performance difference for each loan category by credit-score group. In almost every category, blacks show a higher incidence of default than non-Hispanic white borrowers, although differences are, in some cases, small. However, two product areas, auto loans from finance companies and credit card loans, show consistently higher and larger default rates for blacks than for non-Hispanic white borrowers for all credit-score quintiles.

For each credit-score quintile, younger individuals show higher default rates for bank-issued credit cards than older borrowers. Patterns for other products are inconsistent. For example, in the lowest quintile, the largest performance differences between young and old are for credit cards from finance companies, whereas for the second quintile, the largest performance gap is for auto loans from finance companies.

To better identify the possible effects of loan terms and interest rates on performance differences by race or ethnicity, a multivariate analysis similar to that presented in the previous section was conducted. A regression model was estimated using modified new accounts among non-Hispanic white individuals to predict performance residuals by type of loan and lender, the month the loan was taken out, the loan amount, and, when calculable, the interest rate. The empirical estimation was then expanded to taken into account age, marital status, sex, census-tract characteristics, and the census-tract-based estimate of the individual's income.

As before, all regressions were conducted separately for individuals in three TransRisk Score groupings: the lowest quintile, the second-lowest quintile, and the top three quintiles combined; the TransRisk Score and the TransRisk Score squared were also included in each regression. Also as before, the regressions were estimated using only males, with age controls, and weighted by the percentage of non-Hispanic white individuals in the census block.

Loan terms and interest rates explain virtually none of the differences in performance residuals by race, sex, or age (table 21). The results hold when loan terms and interest rates are considered without other controls or along with other demographic and location factors. Thus, differences in the kinds of loans used by different populations and the interest rates paid do not appear to be the source of differences in performance once credit score is taken into account.

Credit Scores and Credit Availability and Affordability

The credit-record data assembled for this study can be used to investigate the effects of credit scores on the availability and affordability of credit. However, there are a number of issues that need to be addressed in such an investigation. The first issue in using credit-record data for this purpose is that we observe an individual's credit score at a particular point in time. Unfortunately, the timing of new credit does not necessarily correspond to the same point in time at which the scores are calculated. As discussed in the previous section, some of the timing issues can be mitigated by focusing on new credit issued within a short period of time after the credit score was calculated.

The second issue is that we observe in credit bureau records only actual extensions of new credit. The incidence of new credit is effected by both demand and supply factors. Thus, some individuals do not receive new credit because they do not want or need it, others because they believe they will be turned down and are discouraged from applying, and others because they have applied but are denied. Ideally, one would like to isolate the latter two effects, which are direct reflections of the availability of credit. The credit-record data do not indicate direct denials; however, one method employed by the industry to proxy for denials is derived from a review of credit-inquiry patterns. Specifically, credit inquiries observed during a period when an individual does not receive credit are taken as indicators of loan denials. [122]

[122] Inquiries in the absence of new credit is obviously an imperfect proxy for denials, as the lack of new credit may reflect a decision by a prospective borrower not to borrow (for example, by withdrawing the loan application) rather than a denial of credit. Further, the inquiry might be associated with a loan taken out at a later time.

A third issue is that, as noted in the previous section, the credit-record data do not provide direct information on the pricing of credit. For open-ended credit, there is no loan term information provided at all in the credit records. For closed-ended credit, the credit records provide information on the loan terms at the time the credit report was drawn, which, as shown earlier, can be used to estimate interest rates. However, for variable-rate loans or for loans for which substantial upfront points or fees were charged, interest rates calculated in this way may not reflect the full pricing of credit.

Subject to these caveats, the approach taken to address affordability and availability parallels that used previously to address issues in loan performance. Specifically, we examine the relationship between our sample's TransRisk Scores, measured in June 2003, and three measures of availability and affordability of credit, as measured over the July 2003 to December 2003 period. The three measures are issuance of any new credit (evidence of availability), credit inquiries without the issuance of new credit (evidence of denial), and interest rates on new closed-end credit (evidence of affordability). These comparisons are made for different population groups and, when possible, for different loan types.

The credit-record data reveal relatively few differences across racial or ethnic groups in the incidence of new credit after controlling for credit-score quintile (shown earlier in tables 20.A–C). Black borrowers were somewhat less likely than others to take out new mortgages and automobile loans from banks and, in general, less likely to open credit card accounts, but they were more likely to take out new installment loans at finance companies. Differences were most pronounced in the lowest two credit-score quintiles. Not surprisingly, the incidence of new credit varied by age group. The general pattern shows younger and older individuals less likely to obtain new loans than middle-age individuals, a pattern consistent with the life-cycle theory of credit use.

For each credit-score quintile, black and Hispanic borrowers have a higher incidence of the denial proxy than non-Hispanic whites. Recent immigrants, younger individuals, single individuals, and individuals that live in low-income areas or areas with a high minority population also show a higher incidence of the denial proxy than do other groups.

Estimated interest rates also differ across populations after controlling for loan type and credit-score quintile. Black borrowers experienced higher interest rates than non-Hispanic whites for each loan category in which interest rates can be determined, although, as noted, some differences were small. Very few consistent patterns appear in the data regarding interest rates by national origin or sex. Interest rates vary by age, but they exhibit different patterns across different products and credit-score quintiles.

The data just presented may mask effects due to variation within credit-score quintiles. To provide a better measure of the continuous relationship between credit scores and the three measures of availability and affordability of credit, figures were constructed showing the continuous relationship between the TransRisk Score and the incidence of new credit, the incidence of the denial proxy, and the estimated interest rates.

For each demographic group, the relationship between credit scores and the incidence of new credit is in the shape of an inverted U (figure 8). The decline in incidence of new credit at higher credit-score levels is almost surely due to demand rather than supply: Individuals with higher scores are less likely to need or desire new credit. In the lower end of the credit-score range, the upward sloping incidence of new credit is much more likely to reflect differences in supply. The patterns for different demographic groups appear to be quite similar.

The incidence of denial, as proxied by the inquiry measure, uniformly declines in credit scores for each demographic group (figure 9). Moreover, both the shapes and levels of the curves appear to be quite similar, but older individuals show a somewhat lower incidence, and younger individuals show a somewhat higher inferred denial rate.

Similarly, estimated interest rates show a monotonically decreasing relationship with credit scores, again with the curves for different population groups exhibiting similar slopes and levels, although auto loan rates for black borrowers and individuals living in low-income census tracts appear to be somewhat higher than for individuals in other groups with similar credit scores (figures 10.A–C). The slopes of the curves do vary across loan products, with interest rates for mortgages showing a flatter pattern than those for automobile or other loans. The relationships for credit scores and other installment loan interest rates appear to be much less consistent than those for mortgage or automobile loans. This difference is likely due to the fact that the collateral for other installment loans is more heterogeneous and that the loan category incorporates a wider range of products.

To address whether population differences between these curves can be narrowed when other factors are controlled for, a multivariate analysis was conducted. The analyses are similar to those conducted for loan performance and include the same demographic characteristics and control factors, specifically, credit score and location.

The dependent variable for the first analysis is the incidence of new credit. Following the approach used for the performance residuals, a regression equation fitted for the non-Hispanic white population was used to predict the incidence of new credit for other racial or ethnic groups. The difference between the actual and predicted incidence of new credit is the unexplained residual. The multivariate analysis was also run for males only, with controls for age, and weighted by the percentage of non-Hispanic white individuals in the census block. The analysis reveals that differences in the incidence of new credit across racial or ethnic groups largely disappear once credit score and other factors are taken into account (table 22.A). Not surprisingly, differences by age are largely unaffected by control factors and remain significant.

A second multivariate analysis was conducted for the inquiry-based proxy for loan denial. Here, the higher incidences shown for black and Hispanic individuals are largely unaffected by controls for other factors (table 22.B). Differences by age, however, are reduced.

The third set of multivariate analyses focused on the interest rates for new mortgage and auto loans.[123] The multivariate regressions were virtually identical to those in the previous section, except that the dependent variable was the loan interest residuals rather than loan performance residuals, and, perforce, the sample for the interest rate analysis was limited to accounts for which interest rates could be calculated. Multivariate results suggest that some, but not all, of the difference in interest rates can be explained by loan type, lender, and amount and the demographic and location controls considered here (tables 22.C and D).[124] The gross mortgage interest rate difference between blacks and non-Hispanic whites was 0.39 percentage point after controlling for score; the difference was still 0.39 percentage point after loan terms and lender type were taken into account. (Auto loan rate differences across racial and ethnic groups widen when other factors are taken into account). The difference narrowed to 0.26 percentage point when demographic and location controls were taken into account. Both gross and conditional age differences in interest rates are much smaller and virtually disappear (or reverse sign) when credit score and other factors are considered.[125]

Accounting for Economic and Financial Factors Not Available in This Study

The multivariate analyses in the previous sections were, perforce, restricted to information contained in the credit records, the SSA file match, and factors based upon an individual's location. Thus, the data assembled for this study can provide only limited insights into the relationship between credit scores and credit performance, availability, and affordability (and essentially no insight into whether the relationship is one of cause and effect). The data do not contain key variables that would need to be taken into account. Missing data include other underwriting factors, such as loan-to-value ratios in the case of mortgages, and the weight given to credit scores relative to these other factors. Missing data also include underlying differences in socioeconomic factors such as employment experience and wealth; only a rough estimate of individual income is available. Moreover, the credit-record data used here cover only a brief period and

[123] Regressions for other new installment loans were estimated but are not presented. This loan category was quite heterogeneous, and estimation results were not robust.

[124] As noted, the interest rate analysis conducted here is limited to the data included in credit records and consequently does not account for all factors creditors consider in pricing credit (for example, debt-to-income ratios, loan-to-value ratios, and collateral status).

[125] An additional analysis was conducted using the amount borrowed, rather than the interest rate of the loan, as the dependent variable. All new loans could be used in that analysis because balances were reported for all loans. Results, not shown in the tables, indicate little difference across groups in the amounts borrowed once credit score and the type of loan and lender are taken into account.

therefore cannot reflect changes over time in the relationship between credit scores and the availability or affordability of credit.

The multivariate analysis discussed above highlighted unexplained differences in performance, denial rates and loan affordability across age groups as well as across racial and ethnic groups. In this section, we use information from the Federal Reserve Board's 2004 Survey of Consumer Finances (SCF) to explore the possibility that differences in, for example, wealth, employment history, and financial experience might help to explain the remaining differences in credit performance, affordability, and access across groups (tables 23–26).[126] Inferences from this analysis are only suggestive because the information cannot be linked to the individuals in the study sample and their credit-related performance or loan terms.

The financial literature on credit evaluation has traditionally pointed to several broad factors (termed "the five C's") that influence the likelihood that borrowers will repay their debts as scheduled: capacity, collateral, capital, conditions, and character.[127] Generally, *capacity* refers to the income flow that is available to service debts; *collateral* is the value of assets explicitly backing a loan; *capital* refers to assets that may be available to repay a loan but that do not explicitly back it; *conditions* refers to trigger events that may disrupt income flows or create unexpected expenses that affect the ability to make loan payments; and *character* corresponds to the financial experience, skills, or willingness of an individual regarding his or her ability to manage financial obligations. Differences in populations along any of these dimensions could potentially account for the performance differences found in this study and, to the extent they are used by loan underwriters, may affect pricing and loan availability as well.

Younger families differ substantially from older families over a wide variety of financial dimensions. Variation across age groups in income, wealth components, debt-payment burdens, and savings largely reflect the life-cycle pattern of income: Income rises as workers progress through their careers and falls sharply upon retirement. Thus, young families have comparatively low levels of income, wealth, and savings and are more likely to have high debt-payment burdens. Younger families are also more likely to have experienced a recent bout of unemployment. As age and income rise, families accumulate greater financial and nonfinancial assets, including homes, are less likely to suffer job loss, and are increasingly likely to save and reduce their debt burdens. None of these factors were explicitly accounted for in the multivariate performance analysis conducted with the credit-record data and thus could explain at least a portion of the underperformance of younger individuals and overperformance of older individuals.

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[126] Most of the data in the SCF are reported at the family level. Families are classified in the tables on the basis of the characteristics of the head of the family, except for race or ethnicity, which is reported by the survey respondent, who may not be the family head as defined by the SCF.

[127] Refer, for example, to Dev Strischek (2000), "The Quotable Five C's," *Journal of Lending and Credit Risk Management*, vol. 82 (April). pp. 47-49.

The SCF data show that income, wealth, and holdings of financial assets are substantially lower for black and Hispanic families than for non-Hispanic white families.[128] These racial patterns generally hold even after accounting for age, income, and household type, as shown in the bottom portion of the tables. Overall median net worth and financial assets among black or Hispanic households, for instance, are about 10 percent to 15 percent of the non-Hispanic white median. Black and Hispanic families are less likely than non-Hispanic white families to have any financial assets, so that the disparity in median financial assets for all families (rather than just those with financial assets) is even larger, with the overall medians for black and Hispanic families roughly 5 percent to 7 percent of the non-Hispanic white median. The likelihood of a recent unemployment spell are also higher for blacks and Hispanics. The median payment-to-income ratio for debtors is similar across the four racial and ethnic groups (blacks, Hispanics, non-Hispanic whites, and Asians), but nonwhite families are more likely to have payment-to-income ratios greater than 40 percent.

Finally, some argue that differences in educational attainment and credit-market experience among the four groups may be related to financial literacy. High-school and college graduation rates among Hispanics are below those for blacks, which, in turn, are lower than those for non-Hispanic whites. Each of these factors, none of which were included in the credit-record multivariate analysis, may at least partially explain remaining differences in loan performance and credit access and affordability across racial or ethnic groups.

Taken together, the SCF provides a more comprehensive picture of the varying economic circumstances of different populations than is available from the data in credit records. Differences across groups in these broad measures of economic and social well-being are consistent with the conjecture that disparities in the financial and nonfinancial characteristics of younger, single, nonwhite, and Hispanic families may at least partially explain both the underperformance of these groups for a given score and differences in availability and affordability of credit.

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[128] Differences in income across racial and ethnic groups are also evident in census data. Importantly for the present study, which shows that significant performance residual differences persist between blacks and non-Hispanic whites even when census-tract location is accounted for, the census data show that a substantial portion of the difference between blacks and non-Hispanic whites are *within* tract. Specifically, for black families, mean income in 2000 was $38,700; for non-Hispanic white families, $56,870; and for Hispanic families, $42,800. The dollar difference in mean income between blacks and non-Hispanic whites is reduced to $9,800 when census-tract location and age of family head are controlled for. The roughly $14,000 difference in mean incomes between non-Hispanic whites and Hispanics is reduced to $7,600 when census-tract location and age are taken into account.

FINDINGS ON DIFFERENTIAL EFFECT

This section provides an evaluation of whether credit scoring in general, and the factors included in credit-scoring models in particular, may result in negative or differential effects on specific subpopulations and, if so, whether such effects could be mitigated by changes in the model development process. As stated earlier, a credit characteristic in a credit-scoring model has a differential effect related to a particular demographic characteristic if the weights assigned to that credit characteristic differ from the weights that would be estimated in a demographically neutral environment. Thus, identifying such credit characteristics requires the estimation of both the FRB base model and models estimated in demographically neutral environments. These model estimations allow an evaluation of the differential effect for all credit characteristics that are included in the FRB base model. In addition, inferences about credit characteristics not included in the FRB base model can be gleaned by incrementally adding such characteristics one at a time to the existing model and determining their effect on the credit scores of different population groups.

Results in this section cover several different topics. First, descriptive information is provided on the univariate relationship between credit characteristics and both performance and demographics. Second, an assessment is made of the extent to which differences in mean credit scores across different population groups can be attributed to individual credit characteristics included in the FRB base model. Third, an assessment is made of the effect on different groups that would result from dropping each of the credit characteristics included in the FRB base model from the model. Fourth, a similar analysis of adding each excluded credit characteristic to the FRB base model is presented. Each of these four topics provides interesting descriptive information, but, as stated, the full assessment of differential effect requires the estimation of models in demographically neutral environments. Such analysis is provided in the next two subsections, but the focus is limited to race or ethnicity and age, which exhibited the highest potential propensity to experience a differential effect. (Sex was also tested, but the results showed little evidence of differential effect and are not presented). The final subsection discusses the implications of finding differential effects and ways in which they might be mitigated.

Correlations between Credit Characteristics and Both Performance and Demographics

As stated earlier, for a credit characteristic to have a differential effect for a particular demographic population, the credit characteristic at a minimum must be correlated with both the demographic characteristic and performance. Technically, such an assessment should be made in a multivariate environment controlling for other credit characteristics included in the model. However, univariate correlations of both of these relationships can provide useful insight into which credit characteristics are most likely to raise concerns regarding differential effects. In this section, we examine the correlations of each of the 312 credit characteristics provided by TransUnion both with subsequent credit performance and with each demographic characteristic considered in the study.

The first step of the analysis of correlations examines each of the credit characteristics to identify the degree to which they are correlated with performance and with demographic characteristics. Those that are found to have a high correlation with both are possible sources of a differential effect. Because performance and demographic characteristics have arbitrary signs, the correlations are expressed as positive values ranging from zero to 1. For those demographic characteristics that are categorical in nature and take on more than one value, such as race or ethnicity, multiple correlations are computed using a base group. For example, for race and ethnicity, non-Hispanic whites are the base, or comparison, group. Thus, the variable black versus non-Hispanic white is correlated with each credit characteristic as well as Asian versus non-Hispanic white and so on for each minority group.[129]

The twelve panels of figure 11 are scatter plots of the correlation of each credit characteristic with performance and with a demographic characteristic. Credit characteristics that appear above the 45-degree line are more correlated with performance than with the demographic characteristic, and credit characteristics below the line are more correlated with demographic characteristics than performance. For purposes of exposition, each credit characteristic is coded according to its assignment to one of the five distinct credit-characteristic groupings identified by Fair Isaac as discussed above. The twelve panels of figure 12 display the same correlations as those in figure 11, but for just the 19 credit characteristics that constitute the three scorecards of the FRB base model.

For race and ethnicity, almost all of the credit characteristics appear above the 45 degree line (that is, are more correlated with performance than with the demographic characteristic) regardless of the specific group considered. Indeed, most credit characteristics are only minimally correlated with race and ethnicity, many are not

[129] An additional difficulty in calculating correlations between credit characteristics and demographic characteristics is that some credit characteristics include missing information or take only categorical values. For example, those individuals who have never had a delinquent account would not have values for the characteristic "months since the most recent account delinquency." To account for these difficulties, a regression equation was estimated by regressing the demographic characteristic against two variables—a dichotomous indicator variable representing missing values for the credit characteristic and a continuous variable representing the credit characteristic when it was available. A similar approach was followed when the demographic characteristic had a small number of discrete categorical values, with the indicator variable used in the regression to represent the different values of the demographic characteristic. In both of these circumstances, the correlation coefficient was the square root of the *r*-squared of the regression.

correlated at all, and none are highly correlated. A virtually identical result is found when the census-tract proxy for race or ethnicity is used as a substitute for an individual's race and ethnicity.

For the comparison of performance on accounts held by blacks with the performance on accounts held by non-Hispanic whites, the characteristics that are most correlated with both performance and race are all related to past payment history. Each of these characteristics is also highly correlated with performance. With respect to the analysis for other racial or ethnic categories, most of the credit characteristics are not correlated at all, a few are only minimally correlated, and none are highly correlated.

The relationships for age differ significantly from those for race and ethnicity. Many credit characteristics are highly correlated with age. Most of the credit characteristics that appear to be highly correlated with age involve characteristics from the "length of credit history" group defined by Fair Isaac, such as "total number of months since the oldest account was opened," and several come from the four other credit characteristic groups. Some credit characteristics, such as "total number of months since the most recent account delinquency," which belongs in the payment history group, have aspects of credit history length in them. Other credit characteristics, however, such as one representing the ratio of revolving balance to high credit, which is in the "amounts owed" group, have no clear connection to length of credit history. These univariate results suggest that several credit characteristics are candidates for introducing differential effect across age groups.

Results for sex show that the vast majority of credit characteristics are much more highly correlated with performance than with sex. However, a significant number of credit characteristics, each involving a department store or retail trade account, exhibit correlations of more than 0.2 with sex, though each of these characteristics is only minimally related to performance. For marital status, the results are similar to those for race or ethnicity in that most credit characteristics are only minimally correlated with marital status.

The analysis of location characteristics finds that few credit characteristics are related to any significant degree to the proportion of minority population in the census tract, relative census-tract income, or degree of urbanization. Also, almost all of the credit characteristics show little or no correlation with foreign-born and recent immigrant populations. The few credit characteristics that are at least somewhat correlated with these demographic characteristics all involve characteristics related to the length of an individual's credit history.

The correlations for the characteristics included in the FRB base model exhibit patterns similar to those shown for the credit characteristics not included in the model. Regarding race and ethnicity, correlations between the demographic characteristics and credit characteristics are generally quite low. None of the correlations exceed 0.1, and nearly all are much smaller. The only racial group that appears to have any notable correlations between demographics and credit characteristics included in the model is blacks, but, even for this group, none of the correlations is substantial. Patterns for the race proxy, sex, marital status, and foreign-born status are similar to those for individual race and ethnicity. None of the credit characteristics included in the FRB base model is highly correlated with these demographic characteristics.

Findings regarding age, however, are notable. Several of the credit characteristics included in the FRB base model have relatively strong correlations with age, especially characteristics included in the "length of credit history" group or indirectly related to the individual's length of credit history. Such correlations are not surprising because younger individuals, by definition, have had only a relatively short time in which to establish credit histories.

Attributing Differences in Mean Credit Scores across Different Populations to Specific Credit Characteristics Included in the FRB Base Model

In this section we examine the extent to which differences in mean credit scores across populations can be attributable to the different credit characteristics in the model. We first decompose mean credit-score differences across populations into differences in the distribution of individuals in each population across the three scorecards used in the FRB base model (thin, clean, and major derogatory) and differences in the mean scores for each population within each scorecard. For the second decomposition, for each scorecard, we decompose differences in the mean score into differences in the predicative credit characteristics that are used in the scorecard.

The first decomposition has two stages. In the first stage, the portion of the mean credit-score differences that is attributable to disproportionate representation on the thin-file and major-derogatory scorecards is derived by calculating the change in the score that would have resulted if each population had the same mean score on each scorecard. Because mean scores are, on average, lower on the thin-file and major-derogatory scorecards than on the clean-file scorecard, population groups that have proportionately greater representation on these scorecards will have lower mean scores, even if all of the populations have the same mean scores on each individual scorecard. The second stage takes the remaining difference and attributes it to differences in population mean scores *within* each scorecard. The credit characteristics are sorted into five groups that are consistent with the groups of credit characteristics discussed above in the derivation of the FICO score. These calculations result in five sources of credit-score differences that will sum exactly to the total difference in mean scores across population groups.

Results are shown as a decomposition of the difference in scores between individuals in each population and a "base" group (table 27). For racial and ethnic groupings, the base group is non-Hispanic whites; for national origin, it is non-foreign-born; for sex, males; for marital status, married males; for age, individuals aged 62 or older; for census-tract income, middle-income tracts; for tract minority percentage, tracts with a minority population less than 10 percent; and for degree of urbanization, urban census tracts.

Looking across populations, the largest differences are between blacks and non-Hispanic whites and between individuals younger than age 30 and those aged 62 or older. The following discussion focuses on these two comparisons, although the tables present differences for all populations.

The difference in mean FRB base score between blacks and non-Hispanic whites, 28.3 points, is primarily due to the differences in the population distributions on the different scorecards. More than half of the point difference is attributable to the fact that blacks have the higher representation than non-Hispanic whites on the thin-file and major-derogatory scorecards combined, and most of that higher representation comes from the major-derogatory scorecard. Differences in mean scores within each scorecard are also substantial. A similar pattern is observed for the differences in scores between Hispanics and non-Hispanic whites.

Scorecard differences account for a portion of the differences in mean credit scores across age groups. However, patterns are different than those found for race or ethnicity. Young individuals are disproportionately represented on the thin-file scorecard, but that is not the major factor explaining score differences between those younger than age 30 and the base group. As noted below, differences in mean scores within scorecards is the source of most of the difference in overall mean scores between the young and the old.

For all comparisons among populations, differences in mean scores within scorecard play an important role. Mean differences across the three scorecards are generally of the same sign, although magnitudes vary. Groups that are disproportionately represented on the major-derogatory scorecard also have lower mean scores on the three scorecards, with one glaring exception: Recent immigrants are overrepresented on the clean-file scorecard but have much lower mean scores within the clean-file scorecard than either other foreign-born or non-foreign-born individuals.

The major-derogatory scorecard accounted for the largest portion of the difference in mean scores between blacks and non-Hispanic whites of the three scorecards. Differences in mean scores within the major-derogatory scorecard accounted for almost one-fifth of the total difference in mean scores between blacks and non-Hispanic whites.

For age differences, the largest portion of the difference between individuals younger than age 30 and those aged 62 or older derives from differences in mean scores between these two groups within the clean-file scorecard.

The second decomposition is scorecard specific and focuses on individual credit characteristics. For each scorecard, we attribute differences in the mean scores across demographic groups to specific individual credit characteristics (tables 28.A–C).

For the thin-file scorecard, a difference of 3 points in mean scores on this scorecard was found between non-Hispanic whites and blacks. More than 80 percent of this difference is accounted for by three credit characteristics ("the total number of public records and derogatory accounts with an amount owed greater than $100," "total number of months since the most recent account delinquency," and "percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months"). Almost two-thirds of the 6.8 point difference in mean scores on the thin-file scorecard between younger and older individuals is due to the same three credit characteristics. For all other groups, mean differences in credit scores across populations on the thin-file scorecard are small (at most a couple of points) and complex, as the effects of credit characteristics are often in different directions.

For the major-derogatory scorecard, three credit characteristics ("total number of public records and derogatory accounts with an amount owed greater than $100," "total number of months since the most recent account delinquency," and "percentage of accounts with no late payments reported") are found to account for more than 60 percent of the difference between blacks and non-Hispanic whites on that scorecard. All other credit characteristics played some role, but no other individual characteristic accounted for as much as 10 percent of the mean score difference within that scorecard. Some differences across age cohorts also appear on this scorecard The credit characteristic that accounts for the largest portion (about one-fifth) of the age difference is "average age of accounts on credit report."

The clean-file scorecard contains significant differences in mean scores across age cohorts. The credit characteristic that accounts for the largest portion of the difference in the mean scores between those younger than age 30 and those aged 62 or older is "average age of accounts on credit report." As noted above, recent immigrants had substantial differences in mean score within the clean-file scorecard. More than two-thirds of this difference can be attributed to differences in the credit characteristic "average age of accounts on credit report." The differences between blacks and non-Hispanic whites on the clean-file scorecard arise primarily from "total number of months since most recent account delinquency" and "percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months."

Differences in mean credit scores across populations can also be decomposed into the portions attributable to each of the five groups of credit characteristics designated by Fair Isaac: (1) types of credit in use, (2) payment history, (3) amounts owed, (4) length of credit history, and (5) new credit. The within-scorecard differences in mean credit scores across population groups can be aggregated across the three scorecards (table 29).

The results from these credit-characteristic-group decompositions are similar to those for individual credit characteristics. Of the 11.0 point difference in mean credit scores between blacks and non-Hispanic whites that is attributable to within-scorecard differences, 7.7 points, or 70.2 percent, of the difference derives from credit characteristics related to the group "payment history."

The within-scorecard difference in mean credit scores by age, which were as high as 22.1 points between those younger than age 30 and those aged 62 or older, are primarily attributable to differences in credit characteristics related to the group "payment history," which accounts for 10.9 point, or 49.5 percent, of this difference. That group of credit characteristics also explained an even higher share (about 60 percent) of the (smaller) within-scorecard differences in mean credit score between the other age groups and individuals aged 62 or older.

The final population with relatively large within-scorecard differences in mean credit scores was recent immigrants. The credit characteristic group that contributes the most to the difference in mean credit scores between recent immigrants and non-foreign-born individuals is "length of credit history," which accounts for 12.4 points. About half of the 12.4 point difference in mean credit scores between recent immigrants and non-foreign-born individuals is offset by higher mean scores for recent immigrants in the credit characteristic group "payment history." As a result, the overall within-scorecard difference in mean credit scores between recent immigrants and non-foreign-born individuals is 8.4 points.

Dropping Credit Characteristics from the FRB Base Model

The previous section examined the extent to which differences in mean credit scores across demographic groups could be attributed to specific credit characteristics. Another way of providing an inference about the potential for credit characteristics to have differential effects is to examine what the effect would be on the scores of each demographic group if each credit characteristic included in the model were dropped in turn. Also, the effects of dropping groups of related credit characteristics are evaluated. As in the preceding exercise, this evaluation must be conducted separately for each scorecard.

The analysis required two steps. First, each of the three scorecards of the FRB base model was reestimated (and renormalized to a rank-order scale of zero to 100) by dropping each included characteristic one at a time. Credit scores derived from each of the models that exclude an individual characteristic for each population are compared with scores from the original FRB base model to determine how the exclusion of that characteristic affects scores across demographic groups. If the excluded characteristic is highly correlated with a demographic characteristic, then the scores of individuals with that demographic characteristic should change substantially. This process is repeated for each of the credit characteristics on each of the three scorecards of the FRB base model.[130]

Results of this analysis indicate that, for most populations, dropping any single characteristic has only a slight effect on credit scores, typically 1 point or less (tables 30.A–C). Thus, such changes have little effect on differences in mean score between population groups. The small change in scores when a single characteristic is dropped reflects the high degree of correlation among the characteristics in the scoring model. The small effect of dropping a single characteristic holds across the three scorecards.

One exception to this pattern occurs on the clean-file scorecard and affects age groups and foreign-born individuals. Specifically, dropping the characteristic "average age of accounts on credit report" and reestimating the clean-file-scorecard model significantly raises mean credit scores for individuals on the clean scorecard younger than age 30 (5.4 points) and recent immigrants (6.7 points). The effect of dropping this credit characteristic is smaller for other groups and both raises and lowers scores. The net effect is to reduce the differences in mean score on the clean-file scorecard between individuals younger than age 30 and those aged 62 or older by about 7 points, or about one-fourth. Also, dropping the credit characteristic "average age of accounts on credit report" reduces the differences in mean score on the major-derogatory scorecard between individuals younger than age 30 and those aged 62 or older by about 2.5 points, or about one-fifth.

The analysis was extended to consider the effects of dropping groups of related credit characteristics as defined by Fair Isaac. The effects of dropping groups of credit characteristics were largely similar to the effects found when individual characteristics were dropped from the FRB base model. While changes in scores were somewhat larger when a group of characteristics was dropped, for the most part, the effects on credit scores were small for all populations. For example, for blacks, the group of credit characteristics whose exclusion had the largest effect on mean scores on the thin and major-derogatory scorecards were those related to "payment history" that raised the mean credit score for blacks by over 5 points on the thin-file scorecard and about 2 points on the major-derogatory scorecard (tables 31.A–C).

Large changes in mean credit scores by age and for recent immigrants were observed when the group of credit characteristics related to "length of credit history" was dropped from the clean scorecard or the major-derogatory scorecards. (Only one credit characteristic from this group appeared on these two scorecards, and it was the same characteristic). The largest differences for these two demographic groups were observed

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[130] Changing the characteristics on one scorecard can change the scores of individuals on other scorecards even though their estimated probability of going bad remains unchanged. The spillover effect occurs because the score, as we have used it here, is a rank-order score. Thus, a change of probability estimates on one scorecard can have effects on the rank-order of the whole population. In practice, the spillover effects are minor and are thus ignored in this presentation although not in the analysis.

on the clean-file scorecard where the exclusion of credit characteristics relating to “length of credit history” raised the mean credit scores of those younger than age 30 by 5.4 points and those of recent immigrants by 6.7 points. Notably, the net result of dropping the group of credit characteristics related to “length of credit history” is to narrow the difference between the mean credit scores of recent immigrants and non-foreign-born individuals on the clean-file scorecard from 14.6 points to 7.6 points (data for non-foreign-born individuals are not shown in tables).

Adding Credit Characteristics to the FRB Base Model

The analysis up to this point has been limited to credit characteristics in the FRB base model. In this section, we examine the effect on credit scores of adding other characteristics one by one to each scorecard. The model for each scorecard was reestimated (and renormalized) with the addition of a particular characteristic not in the base model for that scorecard, and the resulting credit scores were compared with those from the FRB base model.

Across population groups, credit scores change very little following the addition of a new credit characteristic. None of the additional credit characteristics changed the mean credit score for blacks on any of the three scorecards by more than 0.39 point (tables 32.A–C). In fact, on the major-derogatory scorecard, on which more than three-fifths of blacks are scored, the largest change in mean scores was a decrease of 0.1 point, which resulted when the characteristic “total number of finance installment accounts” was added to the model. For Hispanics, the results were largely the same, though the changes in mean scores on each of the three scorecards generally varied over a somewhat wider range than for blacks.

The changes in mean scores resulting from the above process were generally larger (both positive and negative) for age groups than for racial and ethnic groups. The range of changes was still small, however. The largest negative effect on the mean scores of any age group came from the inclusion of the credit characteristic "average balance of all open accounts reported in the past 12 months" on the thin-file scorecard, which produced a 1.78 point decline in the mean scores of individuals aged 62 or older. The largest positive effect came from the addition of the credit characteristic “total number of months consumer has had a credit report” to the thin-file scorecard, which raised the credit scores of individuals aged 62 and older by 1.24 points.

Although none of the credit characteristics that were omitted from the FRB base model was found to have a significant effect on mean credit scores for any demographic group, those credit characteristics that related specifically to finance company trades that were not in the model were identified to the extent possible and analyzed in detail because of concerns that have been raised publicly about their potential for a differential effect on blacks. Of the 312 credit characteristics included in the TransUnion data, 24 relate specifically to credit accounts involving finance companies (table 33). Both positive and negative changes in the mean credit scores of blacks result from the addition of each of the omitted credit characteristics related to finance companies, although the largest change was a decrease of only 0.1 point from the addition of the credit characteristic “total number of finance installment accounts” on the major-derogatory scorecard.[131] The largest positive change in mean scores for blacks was only 0.09 points, and came from the addition of either of two characteristics, “percentage of total remaining balance to total maximum credit for all open personal loan accounts” and “total number of finance installment accounts” on the clean-file scorecard.

Addressing Differential Effects Using Race-Neutral and Age-Neutral Credit-Scoring Models

In the previous sections, the potential for individual credit characteristics to have a differential effect was explored by dropping or adding such characteristics one by one from the FRB base model and, after each removal or addition, evaluating the change in credit scores for different populations and the overall fit of the model. Although inferential, these analyses do not provide a definitive assessment of differential effects for different populations and credit characteristics. As stated earlier, a definitive assessment requires a comparison of the weights credit characteristics receive in the FRB base model with those that would be estimated in a demographically neutral environment. These assessments can be made for individual credit characteristics. Assessments can also be made for the model as a whole by examining changes in mean credit scores for different populations using both the FRB base model and models estimated in demographically neutral environments. Assessments made for the model as a whole reflect the collective differential effect arising from all of the credit characteristics included in the model.

Because of the lack of evidence for sex-based differential effect, the detailed results are not presented here. The remaining analysis focuses on the protected populations—the racial or ethnic groups and the age groups—which, as discussed in the previous section, exhibited the highest potential propensity to experience a differential effect.[132] Consequently, additional estimations were conducted in a “race neutral” environment (meaning racially and ethnically neutral) and in an “age neutral” environment.

[131] These accounts include those assigned a code in the credit-record data indicating “finance company,” although they may also include some other types of creditors.

[132] Two additional attribute weight re-estimations were conducted in “sex-neutral” environments. One model was estimated using only the males in the sample and the other was estimated using only the females. The mean credit scores produced by these attribute weight re-estimations were very similar to those produced using the FRB base model for each demographic group, seldom varying by more than 0.25 points. These results confirm what the earlier analysis suggested, that the FRB base model does not embed a differential effect as a result of credit characteristics proxying for sex.

The general approach taken was the same for both race and age estimations. The credit characteristics and attributes of the FRB base model were frozen and the attribute weights reestimated (and scores recalculated) in demographically neutral environments. For each group, two different concepts of demographic neutrality were employed. The first way of creating neutrality was to restrict the estimating sample to a single demographic group. For the racial assessment the sample was restricted to non-Hispanic whites (the "white only" model).[133] For age, the estimating sample was limited to individuals aged 40 or older (the "older age" models).

Restricting the sample for the white-only and older-age models has the virtue of ensuring that the estimation of associated weights does not reflect correlations between credit characteristics and other racial, ethnic, or age groups. A disadvantage is that the estimated attribute weights reflect the relationship between performance and credit characteristics only for the population group used in the estimation. In the present case, another disadvantage is that the sample sizes are smaller.

In the second way of creating neutrality, the entire sample is used for the estimation, but in reestimating the attribute weights the estimations include shifts in the racial intercept (the "racial-indicator variable" model) or shifts in the age intercept (the "age-indicator variable" model). The shifts in the racial or age intercepts are used only in model estimation; they are not used in creating credit scores.

The race- and age-indicator-variable models have the advantage of using the full sample and of using all population groups in estimating the relationship between performance and credit characteristics. A disadvantage of this method is that race- and age-neutrality is defined very simply as a shift in mean credit scores in which everyone in the same racial or ethnic group or age group experiences an identical shift (up or down) in their scores. This common shift precludes accounting for the more-complex ways that age or race may affect model estimation.

Reestimating the attribute weights in demographically neutral environments is not a complete test of the potential for differential effect. It is possible that the presence of a large differential effect could mute the importance of a credit characteristic, and consequently that characteristic might not be included in a model estimated in a demographically neutral environment. To test for this possibility, each of the credit characteristics not included in the FRB base model was added, one at a time, to the race- and age-neutral versions of the model, and their effects on scores for different populations were evaluated. This process was identical to the process described earlier when the effects of adding credit characteristics to the FRB base model were evaluated.

[133] The choice of the population group (in this case non-Hispanic whites) was driven by sample size considerations alone. In principle, any group could serve as the base population for estimating a model. The non-Hispanic white population was the only population in the sample of sufficient size to provide a basis for model estimation

The interpretation of the results in this section focuses on the implications for a differential effect. As discussed above, if none of the credit characteristics in a scoring model impose a differential effect, then model results estimated in a demographically neutral environment would be nearly identical to those estimated with the entire sample or estimated without controls for personal demographics. That is, credit scores and the weights assigned to attributes should change little. Also, the overall predictiveness of the model should also be largely unaffected.

Alternatively, one or more of the credit characteristics included in the model might embody at least some element of differential effect for age, race, or ethnicity. In that event, two effects should be observed when the model is estimated in a demographically neutral environment: (1) The overall model predictiveness should weaken and (2) some change should appear in the relative scores across populations groups. The implication of this second item is that those groups whose scores rise are the groups that are hurt by differential effect; the groups that experience a decline in scores benefit from differential effect. Finally, if differential effect works by muting the effects of a credit characteristic, then adding the muted characteristic to the FRB base model in a demographically neutral environment should increase the predictiveness of the model and change mean scores of some groups.

Race-Neutral Models

As described previously, one aspect of differential effect is model fit or predictiveness. There are several different ways that the predictiveness of models can be compared. One is with the KS statistic and another is with the divergence statistic. A third way is to look at changes in the distribution of scores for individuals with good performance and for individuals with bad performance; these changes can be examined in different ways. Also, the performance measure and sample over which model fit is assessed must be defined. Here, we assess the predictiveness of each model for the full sample of 232,467 individuals using the five performance measures defined earlier.

A comparison of the KS statistics for different populations using the FRB base model reveals relatively small differences across groups (table 34). We present two different versions of KS statistics. The first column is the "raw" KS statistic for each population. The use of this statistic can be problematic in comparing fit across different groups since it is affected by the distribution of credit scores within a population group. The second column shows a normalized or "adjusted" KS statistic that displays what the KS statistic would be if each population group were reweighted to have the same overall score distribution as the population as a whole. The adjusted KS statistic is the more meaningful one to use in comparing model fit across different models.

A comparison of either KS statistics or mean score differences between goods and bads (the numerator in the calculation of the divergence statistic) between the FRB base model and the two racially neutral models shows virtually no difference in fit (table 35). Further, examining the mean scores for individuals with good or bad performance reveals that the mean scores are almost identical between the FRB base model and either of the two racially neutral models.

The second part of assessing differential effect is to look at changes in credit scores between the FRB base model and the racially neutral models. Descriptive statistics by racial group for the FRB base model and the two racially neutral models indicate that there is virtually no difference between the group mean and median scores or distribution by decile across the models (table 36). For example, mean scores for blacks are only 0.1 point higher for the white-only and racial-indicator-variable models. Score changes are also quite small when the population is segmented by credit-score quintile (table 37). Overall, only about 2 percent of individuals have a score change of 5 points or more (and virtually none of the individuals in the bottom 2 credit-score quintiles change scores by 5 points or more).

Another way of looking at differential effect is to examine changes in mean performance residuals for different population groups (table 38). Because performance residuals reflect the average difference between actual performances for each racial group and the predicted performance at each score level based upon the entire population, changes in these residuals can only occur if credit scores change for the population group when estimated in a demographically neutral environment, thus reflecting differential effect. Performance residuals are virtually unchanged for blacks or other racial groups in each of the two racially neutral models.

In contrast to race, it appears that mean credit scores and performance residuals for recent immigrants differ between the models estimated in a race-neutral environment and the FRB base model. Notably, mean credit scores for recent immigrants are 0.3 point higher in the two racially neutral models, and their overperformance declines also by about 0.3 percentage point. This result suggests that the FRB base model embeds a slight negative differential effect, as measured by the treatment of this group in a racially neutral environment. This pattern is found only for recent immigrants, as scores and performance measures for foreign-born individuals as a whole are unchanged.[134]

Tests of adding credit characteristics to the white-only and the racial-indicator-variable models showed no evidence of important excluded credit characteristics. Results are not presented since they are virtually identical to those presented in the previous section, where credit characteristics were added to the FRB base model in a non-demographically neutral environment.[135]

[134] In the sample used here, about 30 percent of recent immigrants are Asian and about 28 percent Hispanic. For the broader foreign-born population, the majority of individuals are non-Hispanic white.

[135] It is possible that this might not be a sufficient test for differential effect arising from excluded credit characteristics. The presence of a large differential effect could alter the way in which attributes are

Differential effects and race or ethnicity. There is little evidence from the analysis here that any of the credit characteristics included in the FRB base model embeds negative differential effects for any racial or ethnic group or that any important credit characteristic was left out of the model because a differential effect muted its predictiveness. Performance residuals and mean credit scores by group are virtually unchanged between those estimated using the FRB base model and either of the racially neutral models. Further, the lack of a differential effect is also evidenced by the lack of improvement in predictiveness in moving to the FRB base model from the racially neutral models. The lack of a differential effect for race or ethnicity appears to be driven mainly by the lack of correlation between credit characteristics and race or ethnicity.

These results strongly suggest that, in the aggregate, there is no differential effect for race or ethnicity in the FRB base model. Nonetheless, it may be possible that there may be offsetting effects among credit characteristics that go in different directions. To investigate this possibility, we compared the attribute weights assigned in the FRB base model with those estimated for the racially neutral models. The differences in the weights assigned to the attributes are minor.

For example, differences for the finance company credit characteristic, “total number of open personal finance installment accounts reported in the past 12 months,” a credit characteristic for which concerns have been raised, show virtually no difference for the three models (table 39). Further, dropping the finance company credit characteristic would have an adverse effect on model predictiveness. This can be seen by examining changes in the evaluation of good performers and bad performers between the FRB base model and the model dropping the credit characteristic, “total number of open personal finance installment accounts reported in the past 12 months.” The loss of predictiveness is shown by a comparison of the sum of the total percentage of bad performers that have score decreases plus good performers that have score increases with the sum of the

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defined or credit characteristics selected for a model. Consequently, as a robustness check, two more racially neutral models were estimated. Here, the entire process of model development—including attribute construction, selection of credit characteristics, and the estimation of attribute weights—was conducted using the white-only sample and separately with racial-indicator variables. Otherwise, the models were estimated using the same approach employed in the construction of the FRB base model.

Credit characteristics and attributes for these models developed in racially neutral environments did differ some from those selected for the FRB base model. However, this does not appear to arise from differential effect, but rather from differences in the sample and from the fact that controlling for race and ethnicity slightly alters the correlations among the credit characteristics. The high degree of correlation among credit characteristics implies that virtually any change in the model development process will affect the specific credit characteristics and attributes selected for the model. None of these changes, however, suggests evidence of differential effect or that a credit characteristic that would have appeared in a racially neutral model was left out of the FRB base model. The same process was followed for the age-neutral evaluations. Results were similar.

percentage of bad performers whose scores increase plus good performers whose scores decline: The greater the difference, the greater the loss in predictiveness. Results from dropping the characteristic “total number of open personal finance installment accounts reported in the past 12 months” from the clean scorecard are shown in table 40. For each racial or ethnic group, as well as for the total population, the percentage of individuals whose scores move 1 point or more in the direction of improved model predictiveness is significantly smaller than the percentage of individuals whose scores move 1 point or more in the direction that implies less model predictiveness.

Age-Neutral Models

A similar differential effect analysis was conducted for the age of individuals. A slight modification to the process had to be made, as age is a continuous rather than a categorical variable. The model was estimated using only individuals aged 40 or older as the restricted sample, an approach comparable to that for the restricted sample used to estimate the white-only models. However, even the restricted age sample still has some variation due to age and thus is not completely age neutral. To account for this age variation, the older-person model was estimated with age-indicator variables for each year from age 40 to age 75 and then in five-year intervals up to age 90, with a final indicator variable for those older than age 90. The full age-indicator-variable model was also estimated using the entire population with the same age-based indicator variables as used in the older-age model, but with additional indicator variables for each age between 18 and 39 and with an additional indicator variable for those younger than age 18.

There appears to be no change in overall predictiveness for the age-neutral models relative to the FRB base model (table 41). The result holds both when model predictiveness is measured by KS statistic or by the relative mean scores of individuals experiencing good or bad performance. Indeed, the KS statistics for the age-neutral models actually increase by 0.1 point over the FRB base model.

Although overall predictiveness does not change when credit scores are estimated in an age-neutral environment, mean scores of some groups do change (tables 42 and 43). For example, the mean score of individuals younger than age 30 falls 0.4 point when the age-indicator-variable model is compared with the FRB base model. However, the scores of individuals aged 62 or older increased by 1.5 points.[136] Changes in mean performance residuals are consistent with the score changes (table 44). For example, underperformance of individuals younger than age 30 falls from 0.4 point in the FRB base model to 0.1 point in the age-indicator-variable model. The slight underperformance of individuals aged 62 or older in the FRB base model widens from

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[136] Most of the changes in the scores for older individuals occur for those in the top three quintiles in the credit-score distribution. Score changes in this region of the score distribution imply very small differences in expected performance and are unlikely to effect access to credit.

0.1 to 0.3 point. Recent immigrants also show differences in mean scores and performance residuals between the FRB base model and the age-neutral models. Scores for this group are about 0.7 point lower with the age-neutral models compared with the FRB base model and the overperformance residuals are about 2 percentage points higher.

Results from adding credit characteristics to the age-neutral models showed little evidence of differential effect. As with the race-neutral models, results are not presented here since they are virtually unchanged from those found when characteristics were added to the FRB base model.

Differential effects and age. Unlike race and ethnicity (except as reflected by recent immigrant status), there is some evidence that the FRB base model credit characteristics may embed some disparate effects by age, but the effect appears small. Individuals younger than age 30 experience positive differential effect, and individuals aged 62 or older experience negative differential effect in the FRB base model. This is reflected in the fact that mean scores for individuals younger than age 30 are about 0.4 point higher in the FRB base model than in the age-neutral models, but scores for individuals aged 62 or older are about 1.5 points lower. As was the case with the racially neutral models, recent immigrants also appear to experience an age-related differential effect. However, it is in the opposite direction than was the case when comparisons were made in racially neutral environments. Mean scores of recent immigrants are about 0.7 points higher in the FRB base model than in models estimated in age-neutral environments.

To further understand a potential source of the differential effect, changes in the weights associated with each attribute and credit characteristic were examined. Much of the change in scores can be traced to changes in the attribute weights associated with the credit characteristic “average age of accounts on credit report.” The weights associated with the attributes for this characteristic have a wider range in the age-neutral models than in the FRB base model (table 45). Consequently, those individuals with shorter average account histories (for example, younger individuals and recent immigrants) have higher scores in the FRB base model, and individuals with longer average account histories (typically older individuals) have lower scores in the FRB base model.

The impact of these changes on the younger group is more complex than is apparent from the aggregate changes in mean scores and performance for this group. As shown in table 46, FRB base scores are lower than, or about the same as, those of the age-neutral models for individuals aged 19 and 20 and somewhat higher for individuals aged 21 through 29 [sentence corrected as of August 23, 2007]. In part these changes in different directions reflect the fact that individuals aged 19 though 22 underperform in the age-neutral environment, whereas individuals aged 23 through 29 overperform.

As noted, recent immigrants experience a positive differential effect in the FRB base model. However, it is also the case that this group overperforms, in part because their credit profile resembles those of younger individuals, though they perform like members of their own age cohort. The positive differential effect helps this group by increasing their average scores in the FRB base model, but the score increase is not sufficient to eliminate their overperformance. As noted, much of their overperformance stems from lower score levels as a consequence of having short credit histories, at least as represented in U.S. credit records. Mitigating the effects of a short credit history on recent immigrants would come at a cost. For example, dropping the credit characteristic “average age of accounts on credit report” from the clean-file and major-derogatory scorecards and dropping another length-of-credit-history characteristic, “total number of months since the most recent update on an account,” from the thin-file scorecard would lower the overall KS statistic for the model from 73.0 to 72.8.

Another way of looking at the effect of dropping credit characteristics related to length of credit history is to examine the changes in evaluation of good performers and bad performers when these characteristics when these characteristics are dropped from the FRB base model (table 47). For example, when the credit characteristic, “average age of accounts on credit report,” is dropped from the clean scorecard, 46 percent of sample individuals’ scores move by 1 point or more in the direction consistent with worse model performance. In contrast, 30 percent of individuals have scores that move by 1 point or more in the direction consistent with improved model predictiveness. On net, these changes imply a significant decrease in model predictiveness. Thus, to mitigate the fact that scores, even in an age-neutral environment, for recent immigrants are too low by dropping the characteristics related to length of credit history would result in a significant decrease in model predictiveness for other individuals.

Implications of Finding Differential Effects

The investigation of differential effects arising through individual credit characteristics was restricted to the FRB base model developed for this purpose, and thus these results are dependent upon the choices made in building this model and may not apply to other models used in the industry. Nevertheless, several generalizations are suggested by these findings.

First, there is little evidence that any of the credit characteristics included in the FRB base model embed negative differential effects for any racial or ethnic group, and there is no evidence that any important credit characteristic was excluded from the model because its predictiveness was muted by differential effect. Those results appear to be due mainly to the lack of correlation between credit characteristics and race or ethnicity. To the extent that the credit characteristics examined here are typical of those used in other generic credit history scoring models, the results presented here would likely apply to those models as well. A similar conclusion can be drawn about sex.[137]

Second, the analysis did find mild evidence of differential effects by age, with younger individuals and recent immigrants experiencing positive differential effects (higher scores) in the FRB base model, and older individuals experiencing negative differential effects (lower scores) in the FRB base model. These effects appear to be caused by credit characteristics related to length of credit history having somewhat more muted effects in the FRB base model than they would have in a model estimated in an age-neutral environment. The consequences of this more muted effect for these credit characteristics reduces scores of individuals with long credit histories and increases scores of individuals with short credit histories.

Mitigating the differential effect by dropping the credit characteristics related to length of credit history would be counterproductive because the characteristic is receiving too little weight in the FRB base model rather than too much. An alternative way of mitigating the effect would be to use the weights estimated in an age-neutral environment, although a choice must be made about which age-neutral environment to use for estimation since the resulting weights differ depending upon the way age-neutrality is achieved. For example, if the weights estimated for the attributes associated with the credit characteristic "average age of accounts on credit report" in the age-neutral age-indicator-variable model are substituted for the original weights for these attributes in the FRB base model (but all other attribute weights are left unchanged), the positive differential effect for recent immigrants and younger individuals is virtually eliminated. However, for individuals aged 62 or older, the fact that only about one-half of the negative differential effect is eliminated implies that other credit characteristics must be contributing to this effect. Predictiveness drops a small amount when the different weights are used; however, the reduction stems entirely from the elimination of the proxying effects in the characteristic weights.

In any event, if the effect is not mitigated, the size of the differential effect is relatively small. Mean scores of different age groups derived from the FRB base model and the age-neutral models differ by at most 1.5 points.

Recent immigrants appear to have somewhat lower FRB base model scores than would be appropriate given their performance. However, this is not due to a negative differential effect. Rather, it owes to the tendency of recent immigrants to have credit profiles similar to young people in terms of the lengths of their credit histories, as reflected in their U.S. credit records.

[137] Another indication that results regarding the absence of differential effects with respect to race or ethnicity and sex found in the FRB base model may generalize to other credit scores is the fact that performance residuals for race and sex as calculated with the FRB base model are virtually the same as those calculated with the VantageScore and the TransRisk Score.

The scores of recent immigrants might be made more consistent with performance by changes in the credit-reporting process. For example, it might be possible to gather information on the credit histories of recent immigrants from their home countries to supplement the credit records maintained by the three credit-reporting agencies in the United States More generally, ongoing industry efforts to incorporate into credit records items traditionally not collected, such as utility and rental payments, and experiences with nontraditional sources of finance, such as payday lenders and pawn shops, would broaden the information included in credit records and may serve to lengthen the period over which individuals will be recorded as having a credit record.

Limitations of the Analysis

Section 215 of the Fact Act asks for four related analyses regarding the use of credit scoring in credit markets. The first is the effect of credit scoring on the availability and affordability of financial products to consumers in general. The second is an analysis of the empirical relationship between credit scores and actual losses experienced by lenders. The third is an evaluation of the effect of scores on the availability and affordability of credit to specific population groups. Finally, the fourth is an evaluation of whether credit scoring in general, and the factors included in credit-scoring models in particular, may result in negative or differential effects on specific subpopulations and, if so, whether such effects could be mitigated by changes in the model development process.

Different approaches were taken to conduct each of these four analyses. The approach used to assess the general effect of credit scoring on the availability and affordability of credit was to rely on evidence from public comments and previous studies on the topic and to obtain indirect evidence from the Survey of Consumer Finances. The ideal way of addressing this question would have been to conduct a "before and after" study of the effects of the introduction of credit scoring on the availability and affordability of credit. Such an endeavor was not possible because credit scoring has been in use for many years, and it is difficult to distinguish the effects of scoring from economic and other changes that took place over the same time period. Also, the available public research is quite limited, perhaps because most analytical studies were proprietary and are not part of the public record. The approach taken here cannot conclusively address these concerns. Thus, our conclusions in this area can only be suggestive.

The approach taken to examine the empirical relationship between credit scores and actual losses experienced by lenders and to examine the effect of scores on the availability and affordability of credit to specific population groups relied on a nationally representative sample of individuals drawn from credit-reporting agency files. There are several limitations to this approach. First, the analysis was limited to credit history scores. Second, the data only included two commercially available credit scores. Third, the definition of performance was dictated by the time periods for which the samples were drawn. The resulting 18-month performance period is on the short end of the timeframes considered by many in the industry. Further, the time period used to evaluate performance represented a relatively favorable period of macroeconomic performance. Consequently, the absolute levels of performance observed here may overstate the performance one would expect in a less favorable economic climate.

The issues of loan performance and the availability and affordability of credit to different populations were addressed using multivariate analyses, which were restricted to information contained in the credit records as supplemented by demographic information from the SSA and data based on location. However, population groups differ widely along many financial and nonfinancial dimensions that are not reflected in credit records, and those other factors may affect credit performance and the conclusions one might draw about differences across populations. So, for example, the overperformance or underperformance of a demographic group may derive from financial or nonfinancial characteristics (such as wealth or employment experience) that bear on performance and that are correlated with the demographic characteristic but are not included in the credit records.

Another issue in this section of the analysis is the fact that performance and loan terms could be ascertained only for individuals receiving credit. It is reasonable to expect that individuals denied credit would have experienced both worse performance and higher interest rates; however, these outcomes are not included in the data as such individuals did not get loans. To the extent that individuals experiencing denials disproportionately have low credit scores, inclusion of these outcomes would likely have made the performance or interest rate curves steeper. The assessment of denial rates using the inquiry proxy is subject to the same limitation. Individuals who know that they have a low credit score, or believe that they do, may act under the assumption that they will be denied credit if they apply for it. If so, they are being “discouraged” from applying for credit, and the observed relationship between credit score and denial rate would then be less steep than it would be if everyone wanting credit applied for it. A final issue in this section is the fact that information on demographic characteristics had to be imputed for a portion of the sample. Tests suggest that the results here are generally robust. However, for some population segments, such as marital status, concerns may still remain.

The fourth analysis was conducted using a credit history scoring model developed by Federal Reserve staff. We attempted to emulate the process used by industry model developers in estimating credit-scoring models. However, our approach was inevitably approximate. For example, data restrictions forced a number of limitations to our approach, and there is no uniform industry methodology. In addition, the fact that industry modelers may have made different decisions or relied upon different samples clearly limits the generalizations that can be made from our results. This would be the case under any circumstances involving the construction of a new model.

Additional concerns are raised about our model development because of the relatively small sample used for estimation. The small sample size prevented evaluation of the FRB base model on an out-of-sample basis (that is, on a sample of individuals different from that used to develop it). Also because of the small sample, the FRB base model was developed with fewer scorecards than are typically used in the industry's credit history scoring models; consequently, the model has fewer credit characteristics than is typical in the industry. Having relatively few scorecards makes it difficult to identify credit characteristics that might have a differential effect on populations that could constitute other possible scorecards.

A limitation that runs through all four of the analyses is the decision to focus on credit history scoring models, as opposed to the broader class of scoring models. Much of the underwriting and pricing of credit relies upon credit-scoring models that incorporate factors not included in the records of the credit-reporting agencies. Further, the underwriting process may use other information that is judgmentally combined with credit scores in making final decisions on underwriting and pricing. The role of some of these other factors could mitigate or alter some of the conclusions reached in the present study.

APPENDIX A
SECTION 215 OF THE FAIR AND ACCURATE CREDIT TRANSACTIONS ACT OF 2003

Sec. 215. Study of Effects of Credit Scores and Credit-Based Insurance Scores on Availability and Affordability of Financial Products.

(a) STUDY REQUIRED.—The Commission and the Board, in consultation with the Office of Fair Housing and Equal Opportunity of the Department of Housing and Urban Development, shall conduct a study of—

(1) the effects of the use of credit scores and credit-based insurance scores on the availability and affordability of financial products and services, including credit cards, mortgages, auto loans, and property and casualty insurance;

(2) the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the Equal Credit Opportunity Act and other known risk factors, between credit scores and credit-based insurance scores and the quantifiable risks and actual losses experienced by businesses;

(3) the extent to which, if any, the use of credit scoring models, credit scores, and credit-based insurance scores impact on the availability and affordability of credit and insurance to the extent information is currently available or is available through proxies, by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, and creed, including the extent to which the consideration or lack of consideration of certain factors by credit-scoring systems could result in negative or differential treatment of protected classes under the Equal Credit Opportunity Act, and the extent to which, if any, the use of underwriting systems relying on these models could achieve comparable results through the use of factors with less negative impact; and

(4) the extent to which credit-scoring systems are used by businesses, the factors considered by such systems, and the effects of variables which are not considered by such systems.

(b) PUBLIC PARTICIPATION.—The Commission shall seek public input about the prescribed methodology and research design of the study described in subsection (a), including from relevant Federal regulators, State insurance regulators, community, civil rights, consumer, and housing groups.

(c) REPORT REQUIRED.—

(1) IN GENERAL.—Before the end of the 24-month period beginning on the date of enactment of this Act, the Commission shall submit a detailed report on the study conducted pursuant to subsection (a) to the Committee on Financial Services of the House of Representatives and the Committee on Banking, Housing, and Urban Affairs of the Senate.

(2) CONTENTS OF REPORT.—The report submitted under paragraph (1) shall include the findings and conclusions of the Commission, recommendations to address specific areas of concerns addressed in the study, and recommendations for legislative or administrative action that the Commission may determine to be necessary to ensure that credit and credit-based insurance scores are used appropriately and fairly to avoid negative effects.

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study

Row number	Code	Credit characteristic
1	AT01	Total number of accounts
2	AT03	Total number of open accounts in good standing
3	AT05	Total number of accounts opened in the past 3 months
4	AT06	Total number of accounts opened in the past 6 months
5	AT07	Total number of accounts opened in the past 12 months
6	AT08	Total number of accounts opened in the past 18 months
7	AT09	Total number of accounts opened in the past 24 months
8	AT10	Total number of open accounts with information confirmed in the past 3 months
9	AT11	Total number of open accounts with information confirmed in the past 6 months
10	AT12	Total number of open accounts with information confirmed in the past 12 months
11	AT13	Total number of open accounts with information confirmed in the past 18 months
12	AT14	Total number of open accounts with information confirmed in the past 24 months
13	AT20	Total number of months since the oldest account was opened
14	AT21	Total number of months since the newest account was opened
15	AT23	Total number of accounts in good standing, opened 3 or more months ago
16	AT24	Total number of accounts in good standing, opened 6 or more months ago
17	AT25	Total number of accounts in good standing, opened 12 or more months ago
18	AT26	Total number of accounts in good standing, opened 18 or more months ago
19	AT27	Total number of accounts in good standing, opened 24 or more months ago
20	AT28	Total maximum credit issued on open accounts reported in the past 12 months
21	AT29	Total number of open accounts reported in the past 12 months with remaining balance larger than zero
22	AT33	Total remaining balance from all open accounts reported in the past 12 months
23	AT34	Percentage of total remaining balance to total maximum credit for all open accounts reported in the past 12 months
24	AT35	Average balance of all open accounts reported in the past 12 months
25	AT36	Total number of months since the most recent account delinquency
26	AT99	Total remaining balances on open accounts updated in the past 12 months; not including mortgages
27	BR03	Total number of open bank revolving accounts in good standing
28	BR20	Total number of months since the oldest bank revolving account was opened
29	BR28	Total maximum credit on all bank revolving accounts reported in the past 12 months
30	BR33	Total remaining balances on all bank revolving accounts reported in the past 12 months
31	FR03	Total number of finance revolving accounts in good standing
32	FR33	Total remaining balances for all open finance revolving accounts reported in the past 12 months
33	FR35	Average remaining balance for all open finance revolving accounts reported in the past 12 months
34	RE03	Total number of open revolving accounts in good standing
35	RE10	Total number of open revolving accounts with information confirmed in the past 3 months
36	RE11	Total number of open revolving accounts with information confirmed in the past 6 months
37	RE12	Total number of open revolving accounts with information confirmed in the past 12 months
38	RE13	Total number of open revolving accounts with information confirmed in the past 18 months
39	RE14	Total number of open revolving accounts with information confirmed in the past 24 months
40	RE20	Total number of months since the oldest revolving account was opened
41	RE28	Total maximum credit on open revolving accounts reported in the past 12 months
42	RE32	Largest remaining balance on an open revolving account reported in the past 12 months
43	RE33	Total remaining balances from all open revolving accounts reported in the past 12 months
44	RE34	Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months
45	RE35	Average balance on all open revolving accounts reported in the past 12 months

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
46	BI01	Total number of bank installment accounts
47	BI03	Total number of open bank installment accounts in good standing
48	BI05	Total number of bank installment accounts opened in the past 3 months
49	BI06	Total number of bank installment accounts opened in the past 6 months
50	BI07	Total number of bank installment accounts opened in the past 12 months
51	BI08	Total number of bank installment accounts opened in the past 18 months
52	BI09	Total number of bank installment accounts opened in the past 24 months
53	BI20	Total number of months since the oldest bank installment account was opened
54	BI28	Total maximum credit on all bank installment accounts reported in the past 12 months
55	FI01	Total number of finance installment accounts
56	FI03	Total number of open finance installment accounts in good standing
57	FI05	Total number of finance installment accounts opened in the past 3 months
58	FI06	Total number of finance installment accounts opened in the past 6 months
59	FI07	Total number of finance installment accounts opened in the past 12 months
60	FI08	Total number of finance installment accounts opened in the past 18 months
61	FI09	Total number of finance installment accounts opened in the past 24 months
62	IN03	Total number of open installment accounts in good standing
63	IN05	Total number of installment accounts opened in the past 3 months
64	IN06	Total number of installment accounts opened in the past 6 months
65	IN07	Total number of installment accounts opened in the past 12 months
66	IN08	Total number of installment accounts opened in the past 18 months
67	IN09	Total number of installment accounts opened in the past 24 months
68	IN10	Total number of open installment accounts with information confirmed in the past 3 months
69	IN11	Total number of open installment accounts with information confirmed in the past 6 months
70	IN12	Total number of open installment accounts with information confirmed in the past 12 months
71	IN13	Total number of open installment accounts with information confirmed in the past 18 months
72	IN14	Total number of open installment accounts with information confirmed in the past 24 months
73	IN21	Total number of months since the newest installment account was opened
74	IN28	Total maximum credit on open installment accounts reported in the past 12 months
75	IN33	Total remaining balance from all open installment accounts reported in the past 12 months
76	IN34	Percentage of total remaining balance to total maximum credit for all open installment accounts reported in the past 12 months
77	MT01	Total number of mortgage accounts
78	MT02	Total number of open and active mortgage accounts reported in the past 3 months
79	MT03	Total number of open mortgage accounts in good standing
80	MT04	Total number of mortgage accounts that are too new to assess
81	MT20	Total number of months since the oldest mortgage account was opened
82	MT21	Total number of months since the newest mortgage account was opened
83	MT22	Total number of months since the newest open mortgage account was reported
84	MT28	Total maximum credit on open mortgage accounts reported in the past 12 months
85	MT29	Total number of open mortgage accounts reported in the past 12 months with remaining balance larger than zero
86	MT32	Largest remaining balance on an open mortgage account reported in the past 12 months
87	MT33	Total remaining balance from all open mortgage accounts reported in the past 12 months
88	MT34	Percentage of total remaining balance to total maximum credit for all open mortgage accounts reported in the past 12 months
89	MT35	Average remaining balances on all open mortgage accounts reported in the past 12 months

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
90	MT36	Total number of months since the most recent mortgage account delinquency
91	MT41	Total number of times a mortgage account had a past due payment of 30 days or more
92	MT42	Total number of times a mortgage account had a past due payment of 60 days or more
93	MT43	Total number of times a mortgage account had a past due payment of 90 days or more
94	MT44	Total number of times a mortgage account had a past due payment of 120 days or more
95	MT45	Total number of mortgage accounts that have been involved in bankruptcy, repossession, collections or charged-off
96	MT46	Total number of times a mortgage account had a past due payment of 30 days or more in the previous 6 months
97	MT47	Total number of times a mortgage account had a past due payment of 30 days or more in the previous 12 months
98	MT48	Total number of times a mortgage account had a past due payment of 30 days or more in the previous 24 months
99	MT49	Total number of mortgage accounts with payment currently 30 days or more past due
100	MT50	Total number of mortgage accounts with payment currently 30 days past due
101	MT51	Total number of mortgage accounts with payment currently 60 days past due
102	MT52	Total number of mortgage accounts with payment currently 90 days past due
103	MT53	Total number of mortgage accounts with payment currently 120 days past due
104	MT54	Total number of mortgage accounts with payment currently 150 days past due
105	MT55	Greatest amount of time a payment was late for any mortgage account
106	MT56	Largest past due balance on any mortgage account
107	MT57	Total past due balances on all open mortgage accounts reported in the past 12 months
108	PF02	Total number of open and active personal loan accounts reported in the past 3 months
109	PF03	Total number of open personal loan accounts in good standing
110	PF05	Total number of personal loan accounts opened in the past 3 months
111	PF06	Total number of personal loan accounts opened in the past 6 months
112	PF07	Total number of personal loan accounts opened in the past 12 months
113	PF08	Total number of personal loan accounts opened in the past 18 months
114	PF09	Total number of personal loan accounts opened in the past 24 months
115	PF33	Total remaining balance from all open personal loan accounts reported in the past 12 months
116	PF34	Percentage of total remaining balance to total maximum credit for all open personal loan accounts reported in the past 12 months
117	OF01	Total number of finance/credit union accounts
118	OF03	Total number of open finance/credit union accounts in good standing
119	OF20	Total number of months since the oldest finance/credit union account was opened
120	OF28	Total maximum credit on open finance/credit union accounts reported in the past 12 months
121	OF29	Total number of open finance/credit union accounts reported in the past 12 months with remaining balance larger than zero
122	OF33	Total remaining balance from all open finance/credit union accounts reported in the past 12 months
123	OF36	Total number of months since the most recent finance/credit union account delinquency
124	ON01	Total number of travel and gas card accounts
125	ON03	Total number of open travel and gas card accounts in good standing
126	ON20	Total number of months since the oldest travel and gas card account was opened
127	ON33	Total remaining balance from all open travel and gas card accounts reported in the past 12 months
128	ON34	Percentage of total remaining balance to total maximum credit for all open travel and gas card accounts reported in the past 12 months
129	BC01	Total number of bankcard accounts
130	BC02	Total number of open and active bankcard accounts reported in the past 3 months
131	BC03	Total number of open bankcard accounts in good standing
132	BC05	Total number of bankcard accounts opened in the past 3 months

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
133	BC06	Total number of bankcard accounts opened in the past 6 months
134	BC07	Total number of bankcard accounts opened in the past 12 months
135	BC08	Total number of bankcard accounts opened in the past 18 months
136	BC09	Total number of bankcard accounts opened in the past 24 months
137	BC10	Total number of open bankcard accounts with information confirmed in the past 3 months
138	BC11	Total number of open bankcard accounts with information confirmed in the past 6 months
139	BC12	Total number of open bankcard accounts with information confirmed in the past 12 months
140	BC13	Total number of open bankcard accounts with information confirmed in the past 18 months
141	BC14	Total number of open bankcard accounts with information confirmed in the past 24 months
142	BC21	Total number of months since the newest bankcard account was opened
143	BC29	Total number of open bankcard accounts reported in the past 12 months with remaining balance larger than zero
144	BC30	Percentage of bankcard accounts with a remaining balance to maximum credit ratio greater than 50%
145	BC31	Percentage of bankcard accounts with a remaining balance to maximum credit issued ratio greater than 75%
146	BC34	Percentage of total remaining balance to total maximum credit for all open bankcard accounts reported in the past 12 months
147	BC35	Average remaining balances on all open bankcard accounts reported in the past 12 months
148	BC36	Total number of months since the most recent bankcard account delinquency
149	BC98	Total available credit remaining on all bankcard accounts reported in the past 12 months
150	PB03	Total number of bankcard accounts with maximum credit greater than $7,500 in good standing
151	PB05	Total number of bankcard accounts with maximum credit greater than $7,500 opened in the past 3 months
152	PB06	Total number of revolving bank accounts with maximum credit greater than $7,500 opened in the past 6 months
153	PB07	Total number of revolving bank accounts with maximum credit greater than $7,500 opened in the past 12 months
154	PB08	Total number of revolving bank accounts with maximum credit greater than $7,500 opened in the past 12 months
155	PB09	Total number of revolving bank accounts with maximum credit greater than $7,500 opened in the past 24 months
156	PB10	Total number of bankcard accounts with maximum credit greater than $7,500 with information confirmed in the past 3 months
157	PB11	Total number of open bankcard accounts with maximum credit greater than $7,500 with information confirmed in the past 6 months
158	PB12	Total number of open bankcard accounts with maximum credit greater than $7,500 with information confirmed in the past 12 months
159	PB13	Total number of open bankcard accounts with maximum credit greater than $7,500 with information confirmed in the past 18 months
160	PB14	Total number of open bankcard accounts with maximum credit greater than $7,500 with information confirmed in the past 24 months
161	PB20	Total number of months since the oldest bankcard account with maximum credit greater than $7,500 was opened
162	PB21	Total number of months since the newest bankcard account with maximum credit greater than $7,500 was opened
163	PB33	Total remaining balance from all open bankcard accounts with maximum credit greater than $7,500 reported in the past 12 months
164	PB35	Average remaining balances on all open bankcard accounts with maximum credit greater than $7,500 reported in the past 12 months
165	RT01	Total number of retail store accounts
166	RT03	Total number of open retail store accounts in good standing
167	RT05	Total number of retail store accounts opened in the past 3 months
168	RT06	Total number of retail store accounts opened in the past 6 months
169	RT07	Total number of retail store accounts opened in the past 12 months
170	RT08	Total number of retail store accounts opened in the past 18 months

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
171	RT09	Total number of retail store accounts opened in the past 24 months
172	RT10	Total number of open retail store accounts with information confirmed in the past 3 months
173	RT11	Total number of open retail store accounts with information confirmed in the past 6 months
174	RT12	Total number of open retail store accounts with information confirmed in the past 12 months
175	RT13	Total number of open retail store accounts with information confirmed in the past 18 months
176	RT14	Total number of open retail store accounts with information confirmed in the past 24 months
177	RT20	Total number of months since the oldest retail store account was opened
178	RT21	Total number of months since the newest retail store account was opened
179	RT28	Total maximum credit on open retail store accounts reported in the past 12 months
180	RT29	Total number of open retail store accounts reported in the past 12 months with remaining balance larger than zero
181	RT33	Total remaining balance from all open retail store accounts reported in the past 12 months
182	RT34	Percentage of total remaining balance to total maximum credit for all open retail store accounts reported in the past 12 months
183	RT35	Average balance of all open retail store accounts reported in the past 12 months
184	RT36	Total number of months since the most recent reatil store account delinquency
185	UR03	Total number of open upscale retail store accounts in good standing
186	UR05	Total number of upscale retail store accounts opened in the past 3 months
187	UR06	Total number of upscale retail store accounts opened in the past 6 months
188	UR07	Total number of upscale retail store accounts opened in the past 12 months
189	UR08	Total number of upscale retail store accounts opened in the past 18 months
190	UR09	Total number of upscale retail store accounts opened in the past 24 months
191	UR10	Total number of open upscale retail store accounts with information confirmed in the past 3 months
192	UR11	Total number of open upscale retail store accounts with information confirmed in the past 6 months
193	UR12	Total number of open upscale retail store accounts with information confirmed in the past 12 months
194	UR13	Total number of open upscale retail store accounts with information confirmed in the past 18 months
195	UR14	Total number of open upscale retail store accounts with information confirmed in the past 24 months
196	UR20	Total number of months since the oldest upscale retail store account was opened
197	UR21	Total number of months since the newest upscale store account was opened
198	UR28	Total maximum credit on open upscale retail store accounts reported in the past 12 months
199	UR33	Total remaining balance from all open upscale retail store accounts reported in the past 12 months
200	UR35	Average balance of all open upscale retail store accounts reported in the past 12 months
201	DS02	Total number of open and active department store accounts reported in the past 3 months
202	DS03	Total number of open department store accounts in good standing
203	DS04	Total number of department store accounts that are too new to assess
204	DS05	Total number of department store accounts opened in the past 3 months
205	DS06	Total number of department store accounts opened in the past 6 months
206	DS07	Total number of department store accounts opened in the past 12 months
207	DS08	Total number of department store accounts opened in the past 18 months
208	DS09	Total number of department store accounts opened in the past 24 months
209	DS10	Total number of open department store accounts with information confirmed in the past 3 months
210	DS11	Total number of open department store accounts with information confirmed in the past 6 months
211	DS12	Total number of open department store accounts with information confirmed in the past 12 months
212	DS13	Total number of open department store accounts with information confirmed in the past 18 months
213	DS14	Total number of open department store accounts with information confirmed in the past 24 months
214	DS21	Total number of months since the newest department store account was opened
215	DS33	Total remaining balance on all department store accounts reported in the past 12 months

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
216	DS35	Average balance of all open department store accounts reported in the past 12 months
217	G001	Total number of times in payment history where payments were 30 days past due
218	G002	Total number of times in payment history where payments were 60 days past due
219	G003	Total number of times in payment history where payments were 90 days past due
220	G004	Total number of times in payment history where payments were 120 days past due
221	G005	Total number of times in payment history where payments were 150 days past due
222	G006	Total number of times in payment history where payments were 30 and 60 days past due
223	G007	Total number of times in payment history where payments were 30 days past due or more
224	G008	Total number of times in payment history where payments were 60 days past due or more
225	G009	Total number of times in payment history where payments were 90 days past due or more
226	G016	Total number of accounts with a past due payment equal to but not greater than 30 days past due in the past 3 months
227	G017	Total number of accounts with a past due payment equal to but not greater than 30 days past due in the past 6 months
228	G018	Total number of accounts with a past due payment equal to but not greater than 30 days past due in the past 12
229	G019	Total number of accounts with a past due payment equal to but not greater than 30 days past due in the past 18
230	G020	Total number of accounts with a past due payment equal to but not greater than 30 days past due in the past 24
231	G021	Total number of accounts with a past due payment equal to but not greater than 60 days past due in the past 3 months
232	G022	Total number of accounts with a past due payment equal to but not greater than 60 days past due in the past 6 months
233	G023	Total number of accounts with payments currently 60 days past due and reported in the past 12 months or payment history illustrates previous payments were 60 days past due in the past 6 months.
234	G024	Total number of accounts with a past due payment equal to but not greater than 60 days past due in the past 18
235	G025	Total number of accounts with a past due payment equal to but not greater than 60 days past due in the past 24
236	G026	Total number of accounts with a past due payment equal to but not greater than 90 days past due in the past 3 months
237	G027	Total number of accounts with a past due payment equal to but not greater than 90 days past due in the past 6 months
238	G028	Total number of accounts with a past due payment equal to but not greater than 90 days past due in the past 12 months
239	G029	Total number of accounts with a past due payment equal to but not greater than 90 days past due in the past 18 months
240	G030	Total number of accounts with a past due payment equal to but not greater than 90 days past due in the past 24 months
241	G041	Total number of accounts that have payments that were ever 30 or more days past due
242	G042	Total number of accounts that have payments that were ever 60 or more days past due
243	G043	Total number of accounts that have payments that were ever 90 or more days past due
244	G044	Total number of accounts that have payments that were ever 120 or more days past due
245	G045	Total number of accounts that have payments that were ever 150 or more days past due
246	G046	Total number of accounts that have payments that were never 30 or more days past due
247	G047	Total number of accounts that have payments that were never 60 or more days past due
248	G048	Total number of accounts that have payments that were never 90 or more days past due
249	G049	Total number of accounts that have payments that were never 120 or more days past due
250	G050	Total number of accounts that have payments that were never 150 or more days past due

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
251	G051	Percentage of accounts with no late payments reported
252	G057	Number accounts that have payments that are currently or previously 30 or more days past due within the past 3 months
253	G058	Number accounts that have payments that are currently or previously 30 or more days past due within the past 6 months
254	G059	Number accounts that have payments that are currently or previously 30 or more days past due within the past 12 months
255	G060	Number accounts that have payments that are currently or previously 30 or more days past due within the past 18 months
256	G061	Number accounts that have payments that are currently or previously 30 or more days past due within the past 24 months
257	G062	Number accounts that have payments that are currently or previously 60 or more days past due within the past 3 months
258	G063	Number accounts that have payments that are currently or previously 60 or more days past due within the past 6 months
259	G064	Number accounts that have payments that are currently or previously 60 or more days past due within the past 12 months
260	G065	Number accounts that have payments that are currently or previously 60 or more days past due within the past 18 months
261	G066	Number accounts that have payments that are currently or previously 60 or more days past due within the past 24 months
262	G067	Number accounts that have payments that are currently or previously 90 or more days past due within the past 3 months
263	G068	Number accounts that have payments that are currently or previously 90 or more days past due within the past 6 months
264	G069	Number accounts that have payments that are currently or previously 90 or more days past due within the past 12 months
265	G070	Number accounts that have payments that are currently or previously 90 or more days past due within the past 18 months
266	G071	Number accounts that have payments that are currently or previously 90 or more days past due within the past 24 months
267	G082	Total number of accounts currently past due 30 days or more in the past 2 months
268	G083	Total number of accounts currently past due 30 days in the past 2 months
269	G084	Total number of accounts currently past due 60 days in the past 2 months
270	G085	Total number of accounts currently past due 90 days in the past 2 months
271	G086	Total number of accounts currently past due 120 days in the past 2 months
272	G087	Total number of accounts currently past due 150 days in the past 2 months
273	G088	Total number of accounts currently less than 120 days past due in the past 2 months
274	G089	Greatest amount of time a payment was late ever on an account
275	G091	Total past due balances reported in the past 12 months
276	G093	Total number of dergoratory public records
277	G094	Total number of public records related to a bankruptcy
278	G095	Total number of months since the most recent occurrence of a derogatory public record
279	G096	Total number of inquiries for credit
280	G098	Total number of inquiries for credit in the past 6 months
281	G102	Total number of months since the most recent inquiry for credit

Appendix B
The 312 Credit Characteristics in the TransUnion Database of Credit Records Supplied for This Study--Continued

Row number	Code	Credit characteristic
282	G103	Total number of months since the most recent update on an account
283	G104	Total number of months consumer has had a credit report
284	S004	Average age of accounts on credit report
285	S008	Total number of finance accounts confirmed in the past 12 months
286	S009	Total number of bank, finance, personal, national or travel/entertainment revolving accounts
287	S010	Total number of bank, finance, personal, national or travel/entertainment revolving accounts in good standing
288	S011	Total number of open accounts
289	S012	Total number of open revolving accounts
290	S014	Total number of open finance installment accounts
291	S015	Total number of open bank revolving accounts with maximum credit greater than or equal to $5,000 reported in the past 12 months
292	S018	Total number of finance accounts opened in the past 12 months
293	S019	Total number of open personal finance installment accounts reported in the past 12 months
294	S020	Total number of open personal finance revolving accounts reported in the past 12 months
295	S027	Total number of months since the newest finance account was opened
296	S040	Largest maximum credit amount on all open retail store accounts reported in the past 12 months
297	S043	Total number of open non-installment accounts with a remaining balance to maximum credit issued ratio greater than 50% reported in the past 12 months
298	S046	Percentage of accounts that are open and active with a remaining balance greater than $0 reported in the past 12 months
299	S054	Total number of different credit issuers
300	S055	Total number of unique account numbers
301	S059	Total number of public records and derogatory accounts with an amount owed greater than $100
302	S060	Total number of accounts involved in bankruptcy, repossession, collections or charge off
303	S061	Total number of months since the most recent status on an account was 60 days or more past due
304	S062	Total number of months since the most recent status on an account was 90 days or more past due
305	S063	Total amounts held liable for all public records reported in the past 12 months
306	S064	Total the amount ever owed for all accounts sent to collection
307	S065	Total number of legal holds or claims against real estate for unpaid taxes
308	S066	Total number of accounts disputed by the consumer
309	S078	Percentage of total remaining balance to total maximum credit for all open personal finance revolving accounts reported in the past 12 months
310	S079	Percentage of total remaining balance to total maximum credit for all open department store and clothing store revolving accounts reported in the past 12 months
311	S114	Total number of credit inquiries made in the past 6 months not including auto or real estate credit inquiries
312	S115	Total number of credit inquiries made by a finance company

Appendix C
The 19 Credit Characteristics Selected from the TransUnion Database for Use in the FRB Base Model Scorecards

Row number from appen-dix B	Code	Credit characteristic
18	AT26	Total number of accounts in good standing, opened 18 or more months ago
20	AT28	Total maximum credit issued on open accounts reported in the past 12 months
25	AT36	Total number of months since the most recent account delinquency
44	RE34	Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months
76	IN34	Percentage of total remaining balance to total maximum credit for all open installment accounts reported in the past 12 months
146	BC34	Percentage of total remaining balance to total maximum credit for all open bankcard accounts reported in the past 12 months
251	G051	Percentage of accounts with no late payments reported
256	G061	Number accounts that have payments that are currently or previously 30 or more days past due within the past 24 months
273	G088	Total number of accounts currently less than 120 days past due in the past 2 months
274	G089	Greatest amount of time a payment was late ever on an account
278	G095	Total number of months since the most recent occurrence of a derogatory public record
279	G096	Total number of inquiries for credit
282	G103	Total number of months since the most recent update on an account
284	S004	Average age of accounts on credit report
293	S019	Total number of open personal finance installment accounts reported in the past 12 months
297	S043	Total number of open non-installment accounts with a remaining balance to maximum credit issued ratio greater than 50% reported in the past 12 months
298	S046	Percentage of accounts that are open and active with a remaining balance greater than $0 reported in the past 12 months
299	S054	Total number of different credit issuers
301	S059	Total number of public records and derogatory accounts with an amount owed greater than $100

Note. Tables 12.A–C show which of these characteristics were used on each of.three FRB base-model scorecards. Refer to appendix B for all characteristics in the TransUnion database.

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Table 1. National Distribution of FICO Credit Scores

FICO score	Percent of population[1]
Less than 499	2
500-549	5
550-599	8
600-649	12
650-699	15
700-749	18
750-799	27
800 or more	13
Total	100

1. For individuals with scoreable credit records.
Source. Fair Isaac Corp., www.myfico.com/CreditEducation/CreditScores.aspx.

Table 2. Default Rate on New Loans for the Two Years after Origination, by FICO Credit Score, October 2000 to October 2002

FICO score	Default rate (percent)
Less than 520	41.0
520-559	28.4
560-599	22.5
600-639	15.8
640-679	8.9
680-719	4.4
720 or more	1.0

Note. New accounts were those opened in the six months from October 2000 to April 2001. An account was in default if it had been delinquent for at least ninety days or had any other derogatory credit information within the two years starting in October 2000.
Source. Fair Isaac Corp.

Table 3. Average Interest Rate on Fixed-Rate, Thirty-Year Home Loans, by FICO Credit Score, June 5, 2007

FICO score	Interest rate
500-579	9.56
580-619	8.94
620-659	7.30
660-699	6.49
700-759	6.21
760-850	5.99

Note. Rates are national averages on new loans of $300,000.
Source. Fair Isaac Corp., www.myfico.com/LoanCenter/Refinance, accessed June 5, 2007.

Table 4. Proportion of Families Holding Debt and Credit or Charge Cards, by Type and by Race or Ethnicity of Family Head, 1983-2004

Item	Non-Hispanic white	Black	Hispanic	Asian or other	Difference relative to non-Hispanic whites (percentage points)								
					Unadjusted			Adjusted					
								With family characteristics for year shown			With family characteristics for 2004		
					Black	Hispanic	Asian or other	Black	Hispanic	Asian or other	Black	Hispanic	Asian or other
TYPE OF DEBT	Families holding debt (percent except as noted)												
Any													
1983	70.7	64.7	59.5	80.7	-5.9	-11.1	10.1	-0.7	-13.5	-3.1	1.0	-14.7	-4.0
1989	73.2	65.1	72.4	76.6	-8.1	-0.8	3.4	-1.2	-1.8	2.1	2.3	-3.8	0.2
1992	74.3	69.2	69.3	73.9	-5.1	-5.0	-0.4	-5.1	-11.4	-4.4	-2.3	-6.0	-6.8
1995	75.4	71.1	75.4	67.7	-4.3	0.0	-7.7	-4.5	-8.8	-13.4	-0.4	-4.4	-12.4
1998	74.9	68.6	72.3	78.0	-6.3	-2.5	3.2	-5.4	-11.1	-4.3	-2.7	-8.1	-5.4
2001	75.8	74.0	71.3	72.2	-1.9	-4.5	-3.6	-2.0	-10.2	-6.6	0.6	-8.7	-10.0
2004	78.0	71.7	71.0	80.4	-6.3	-7.0	2.4	-4.5	-12.6	-4.2	-4.5	-12.6	-4.2
Mean[1]	74.6	69.2	70.2	75.6	-5.4	-4.4	1.0	-3.3	-9.9	-4.8	-0.9	-8.3	-6.1
Trend	0.3	0.4	0.4	-0.1	0.1	0.1	-0.4	-0.2	-0.1	-0.2	-0.2	0.0	-0.2
Mortgage													
1983	39.2	25.4	23.9	42.9	-13.8	-15.4	3.6	-3.6	-11.7	-1.9	-1.5	-14.8	-6.8
1989	43.0	24.8	31.0	36.6	-18.2	-12.1	-6.4	-4.5	-4.1	-0.2	-1.4	-7.4	-3.3
1992	42.8	27.4	25.2	33.2	-15.4	-17.6	-9.6	-6.9	-12.8	-10.1	-7.4	-11.9	-12.2
1995	44.1	26.1	33.9	37.9	-18.0	-10.2	-6.2	-7.1	-10.2	-8.0	-4.2	-8.3	-12.0
1998	46.6	30.2	27.9	39.1	-16.5	-18.7	-7.6	-5.7	-17.7	-11.6	-4.6	-13.2	-17.4
2001	47.6	36.5	31.9	37.5	-11.1	-15.7	-10.2	-1.1	-9.9	-5.9	-0.6	-10.9	-15.6
2004	52.0	36.4	35.3	48.2	-15.6	-16.7	-3.8	-7.1	-13.9	-10.5	-7.1	-13.9	-10.5
Mean	45.1	29.6	29.9	39.3	-15.5	-15.2	-5.7	-5.1	-11.5	-6.9	-3.8	-11.5	-11.1
Trend	0.5	0.6	0.4	0.2	0.1	-0.1	-0.4	0.0	-0.2	-0.4	-0.1	0.0	-0.4
Installment[2]													
1983	43.9	43.9	42.0	57.2	0.0	-1.9	13.3	4.0	-4.6	2.6	6.0	-5.2	3.4
1989	46.9	41.5	47.3	47.4	-5.5	0.3	0.4	-1.2	-5.6	-2.4	2.6	-5.5	-3.8
1992	42.6	36.6	45.8	43.3	-6.0	3.2	0.7	-8.4	-3.6	-3.2	-7.2	1.0	-2.7
1995	41.4	37.8	39.8	35.1	-3.6	-1.6	-6.4	-2.0	-9.4	-11.2	1.2	-7.8	-12.2
1998	39.0	32.8	38.7	35.1	-6.3	-0.4	-3.9	-5.7	-8.3	-10.5	-4.1	-7.8	-11.1
2001	41.9	40.8	39.7	34.5	-1.0	-2.2	-7.4	-1.8	-9.5	-10.8	-0.8	-9.2	-11.3
2004	41.3	39.9	35.3	37.9	-1.4	-6.0	-3.3	2.8	-11.2	-9.0	2.8	-11.2	-9.0
Mean	42.4	39.0	41.2	41.5	-3.4	-1.2	-0.9	-1.8	-7.5	-6.4	0.1	-6.5	-6.7
Trend	-0.2	-0.2	-0.4	-1.0	0.0	-0.2	-0.8	-0.1	-0.3	-0.6	-0.2	-0.3	-0.7
Any credit or charge card balance[3]													
1983	37.9	32.9	32.8	36.5	-5.0	-5.0	-1.4	-0.5	-3.5	-7.4	3.8	-4.2	-7.4
1989	41.4	33.4	34.7	36.9	-8.1	-6.8	-4.5	-2.6	-4.2	-3.5	4.2	-6.7	-5.9
1992	42.1	35.9	35.0	40.9	-6.2	-7.1	-1.2	-5.7	-10.3	-3.9	-1.9	-6.2	-7.3
1995	44.0	42.3	50.6	42.6	-1.8	6.6	-1.4	0.2	3.2	-4.3	5.5	4.6	-5.3
1998	42.5	38.8	43.5	35.8	-3.6	1.1	-6.7	-3.6	-4.0	-12.0	-0.7	-2.1	-13.7
2001	41.5	49.3	39.6	34.4	7.8	-1.9	-7.2	4.5	-8.6	-10.6	6.1	-6.2	-12.5
2004	43.8	43.9	42.8	38.2	0.1	-0.9	-5.6	-0.7	-5.9	-10.2	-0.7	-5.9	-10.2
Mean	41.9	39.5	39.9	37.9	-2.4	-2.0	-4.0	-1.2	-4.8	-7.4	2.3	-3.8	-8.9
Trend	0.2	0.7	0.5	0.0	0.5	0.3	-0.2	0.1	-0.1	-0.3	-0.1	0.0	-0.3

Table continued on next page.

Table 4. Proportion of Families Holding Debt and Credit or Charge Cards, by Type and by Race or Ethnicity of Family Head, 1983-2004—Continued

Item	Non-Hispanic white	Black	Hispanic	Asian or other	Difference relative to non-Hispanic whites (percentage points)								
					Unadjusted difference			Adjusted difference					
								With family characteristics for year shown			With family characteristics for 2004		
					Black	Hispanic	Asian or other	Black	Hispanic	Asian or other	Black	Hispanic	Asian or other
TYPE OF CARD	Families owning a credit or charge card (percent except as noted)												
Any credit or charge card													
1983	70.3	41.9	38.9	60.7	-28.5	-31.4	-9.6	-14.3	-21.8	-9.4	-13.0	-22.1	-15.9
1989	76.8	43.0	48.4	61.8	-33.8	-28.4	-15.1	-15.5	-10.3	-6.1	-12.1	-16.6	-10.5
1992	79.1	45.0	43.2	73.3	-34.1	-36.0	-5.8	-22.5	-28.2	-4.1	-22.1	-25.2	-4.9
1995	79.4	48.8	59.5	72.6	-30.6	-19.9	-6.8	-19.8	-14.6	-5.6	-18.0	-13.6	-8.7
1998	77.9	50.3	53.7	67.5	-27.6	-24.1	-10.4	-16.1	-17.7	-7.5	-13.7	-20.2	-11.1
2001	81.8	58.7	52.4	66.9	-23.1	-29.5	-14.9	-13.4	-19.8	-8.3	-13.4	-19.0	-11.0
2004	81.8	52.2	55.6	79.7	-29.6	-26.2	-2.1	-19.7	-18.0	-0.6	-19.7	-18.0	-0.6
Mean	78.2	48.6	50.2	68.9	-29.6	-27.9	-9.2	-17.3	-18.6	-5.9	-16.0	-19.2	-9.0
Trend	0.5	0.7	0.8	0.7	0.2	0.3	0.2	-0.1	0.1	0.2	-0.2	0.1	0.4
Bank-type or travel and entertainment card													
1983	49.0	24.6	27.1	48.8	-24.4	-21.9	-0.2	-10.1	-11.4	0.9	-6.9	-11.4	-4.5
1989	64.7	29.0	32.9	51.6	-35.8	-31.9	-13.1	-15.8	-12.4	-4.9	-12.4	-18.0	-14.1
1992	70.9	34.4	33.4	62.1	-36.5	-37.5	-8.8	-23.2	-27.5	-7.0	-23.6	-25.6	-7.9
1995	72.9	40.8	50.1	67.5	-32.2	-22.8	-5.4	-20.0	-16.8	-4.7	-19.8	-16.1	-8.2
1998	73.9	43.1	48.1	62.7	-30.9	-25.9	-11.3	-18.7	-17.5	-8.0	-16.7	-19.6	-11.3
2001	79.0	55.8	48.9	64.3	-23.2	-30.1	-14.7	-12.6	-20.3	-8.2	-11.6	-19.3	-9.8
2004	79.1	49.1	51.7	78.8	-30.0	-27.4	-0.4	-19.8	-18.7	1.0	-19.8	-18.7	1.0
Mean	69.9	39.5	41.7	62.2	-30.4	-28.2	-7.7	-17.2	-17.8	-4.4	-15.8	-18.4	-7.8
Trend	1.4	1.4	1.3	1.2	0.1	-0.1	-0.1	-0.2	-0.3	-0.1	-0.4	-0.2	0.2
Store or gas card only													
1983	21.4	17.3	11.8	11.9	-4.1	-9.5	-9.4	-4.1	-9.4	-8.9	-3.6	-9.2	-13.9
1989	12.1	14.0	15.6	10.2	2.0	3.5	-1.9	2.1	3.7	-1.8	2.1	3.6	3.3
1992	8.2	10.6	9.7	11.2	2.4	1.5	3.0	2.6	1.6	3.2	3.0	1.8	5.0
1995	6.5	8.0	9.4	5.1	1.5	2.9	-1.4	1.8	3.5	-0.9	1.8	3.5	-0.3
1998	3.9	7.2	5.7	4.8	3.3	1.8	0.9	3.5	2.1	1.2	3.3	1.5	0.7
2001	2.8	2.9	3.5	2.6	0.1	0.7	-0.3	0.4	1.3	0.2	0.2	1.1	-0.9
2004	2.6	3.1	3.9	0.9	0.4	1.2	-1.7	0.5	1.5	-1.4	0.5	1.5	-1.4
Mean	8.2	9.0	8.5	6.7	0.8	0.3	-1.6	1.0	0.6	-1.2	1.0	0.6	-1.1
Trend	-0.9	-0.7	-0.5	-0.6	0.1	0.4	0.3	0.2	0.4	0.3	0.1	0.3	0.4

Note. For details, refer to text.

1. Average of the seven values shown.

2. Excludes education loans.

3. Credit and charge cards consist of bank-type cards, which routinely allow carrying a balance (such as Visa, MasterCard, and Discover, and Optima and other American Express cards that routinely allow carrying a balance), so-called travel and entertainment cards (such as American Express cards that do not routinely allow carrying a balance and Diners Club), cards issued by stores or gasoline companies, and miscellaneous other cards. Balances exclude purchases made after the most recent bill was paid.

Source. Federal Reserve Board, Survey of Consumer Finances for years shown.

Table 5. Proportion of Families Holding Debt and Credit or Charge Cards, by Type and by Thirds of Family Income Distribution, 1983-2004

Item	Bottom one-third	Middle one-third	Top one-third	Difference relative to middle one-third (percentage points)					
				Unadjusted		Adjusted			
						With family characteristics for year shown		With family characteristics for 2004	
				Bottom one-third	Top one-third	Bottom one-third	Top one-third	Bottom one-third	Top one-third
TYPE OF DEBT	Families holding debt (percent except as noted)								
Any									
1983	47.1	74.9	87.5	-27.8	12.6	-10.6	6.1	-9.5	6.5
1989	50.9	77.1	89.0	-26.2	11.9	-15.8	3.9	-14.7	3.2
1992	54.8	77.9	86.4	-23.1	8.5	-13.6	3.7	-13.7	3.9
1995	55.6	79.4	88.2	-23.8	8.8	-15.9	4.6	-16.4	3.6
1998	54.5	77.8	89.0	-23.3	11.2	-12.1	4.1	-12.5	4.1
2001	57.1	80.8	87.8	-23.7	7.0	-15.3	4.2	-15.5	4.3
2004	58.4	82.7	87.9	-24.4	5.2	-14.8	-1.0	-14.8	-1.0
Mean	54.0	78.7	88.0	-24.6	9.3	-14.0	3.7	-13.9	3.5
Trend	0.5	0.3	0.0	0.2	-0.3	-0.1	-0.2	-0.2	-0.2
Mortgage									
1983	12.8	35.2	63.5	-22.4	28.4	-9.9	16.6	-10.6	15.6
1989	12.1	38.6	68.0	-26.5	29.4	-15.3	17.2	-16.7	14.3
1992	13.4	36.7	66.5	-23.3	29.8	-13.4	19.4	-13.6	19.4
1995	15.8	39.1	67.3	-23.3	28.3	-12.9	18.0	-12.8	16.4
1998	15.5	41.1	71.6	-25.6	30.6	-12.7	18.0	-12.9	17.4
2001	19.0	43.5	71.8	-24.4	28.3	-12.8	19.1	-12.8	19.0
2004	19.7	51.1	72.7	-31.4	21.6	-20.3	10.8	-20.3	10.8
Mean	15.5	40.7	68.8	-25.3	28.0	-13.9	17.0	-14.2	16.1
Trend	0.4	0.6	0.4	-0.3	-0.2	-0.3	-0.1	-0.2	-0.1
Installment									
1983	28.7	47.3	56.4	-18.6	9.1	-4.5	4.2	-2.9	5.7
1989	30.5	51.2	57.4	-20.6	6.2	-10.1	-0.4	-10.2	0.6
1992	30.1	47.1	48.6	-16.9	1.5	-6.8	-4.4	-7.7	-5.2
1995	25.1	44.9	51.5	-19.7	6.6	-11.3	2.0	-12.2	0.4
1998	23.6	43.2	46.9	-19.6	3.7	-11.7	-1.1	-11.9	-1.6
2001	28.4	48.1	47.8	-19.8	-0.3	-10.8	-3.5	-10.7	-3.6
2004	24.5	46.8	49.4	-22.4	2.5	-14.4	-3.5	-14.4	-3.5
Mean	27.3	46.9	51.1	-19.7	4.2	-9.9	-1.0	-10.0	-1.0
Trend	-0.2	-0.1	-0.5	-0.1	-0.3	-0.4	-0.3	-0.4	-0.4
Any credit or charge card balance									
1983	16.9	43.4	51.3	-26.5	7.9	-16.5	0.1	-17.3	-2.1
1989	19.8	46.5	52.9	-26.7	6.4	-19.1	-0.4	-18.8	-4.2
1992	25.8	47.8	48.0	-22.0	0.2	-13.6	-5.1	-14.4	-6.3
1995	27.3	49.3	55.3	-22.1	6.0	-18.7	4.1	-20.0	1.4
1998	27.6	46.1	51.4	-18.5	5.3	-10.4	-1.2	-10.9	-1.9
2001	32.2	50.1	44.4	-17.9	-5.7	-11.3	-8.9	-11.5	-9.3
2004	30.5	50.5	49.1	-20.0	-1.3	-13.3	-6.6	-13.3	-6.6
Mean	25.7	47.7	50.4	-21.9	2.7	-14.7	-2.6	-15.2	-4.1
Trend	0.7	0.3	-0.2	0.4	-0.5	0.3	-0.3	0.3	-0.2

Table continued on next page.

Table 5. Proportion of Families Holding Debt and Credit or Charge Cards, by Type and by Thirds of Family Income Distribution, 1983-2004—Continued

Item	Bottom one-third	Middle one-third	Top one-third	Difference relative to middle one-third (percentage points)					
				Unadjusted		Adjusted			
						With characteristics for year shown		With characteristics for 2004	
				Bottom one-third	Top one-third	Bottom one-third	Top one-third	Bottom one-third	Top one-third
TYPE OF CARD	Families owning a credit or charge card (percent except as noted)								
Any credit or charge card									
1983	35.4	70.8	90.9	-35.4	20.1	-28.6	10.2	-28.2	8.7
1989	39.8	76.1	93.2	-36.3	17.1	-28.8	10.1	-28.0	8.1
1992	46.3	75.9	92.6	-29.6	16.7	-21.1	8.7	-21.7	8.0
1995	47.2	79.0	95.4	-31.8	16.4	-29.9	13.9	-30.8	12.5
1998	44.8	77.1	94.4	-32.3	17.3	-25.4	10.2	-25.3	9.9
2001	52.6	81.3	94.7	-28.6	13.4	-23.3	8.5	-23.2	8.0
2004	48.6	80.0	95.7	-31.5	15.6	-27.9	10.0	-27.9	10.0
Mean	45.0	77.2	93.8	-32.2	16.6	-26.4	10.2	-26.4	9.3
Trend	0.7	0.4	0.2	0.3	-0.2	0.1	0.0	0.1	0.1
Bank-type or travel and entertainment card									
1983	17.1	43.9	74.9	-26.8	31.0	-21.7	20.4	-22.5	19.8
1989	23.5	62.3	85.9	-38.8	23.6	-31.2	15.6	-30.7	13.2
1992	34.9	64.9	88.6	-30.1	23.6	-21.5	13.5	-21.2	12.6
1995	37.3	71.8	92.0	-34.5	20.2	-31.5	16.8	-32.1	15.1
1998	38.2	72.2	92.4	-34.0	20.2	-25.8	12.2	-25.4	11.9
2001	47.7	78.4	93.8	-30.8	15.4	-24.7	10.1	-24.4	9.7
2004	44.7	76.9	94.3	-32.3	17.4	-28.8	11.7	-28.8	11.7
Mean	34.7	67.2	88.8	-32.5	21.6	-26.4	14.3	-26.5	13.4
Trend	1.5	1.5	0.9	-0.1	-0.7	-0.2	-0.4	-0.1	-0.4
Store or gas card only									
1983	18.3	26.9	16.0	-8.6	-10.9	-8.8	-10.9	-8.7	-11.6
1989	16.4	13.8	7.3	2.5	-6.5	2.9	-6.6	3.2	-6.5
1992	11.4	11.0	4.0	0.4	-7.0	1.0	-6.9	0.8	-6.6
1995	9.9	7.2	3.4	2.7	-3.8	2.7	-3.8	2.6	-4.0
1998	6.6	4.9	2.0	1.7	-2.9	1.3	-2.8	1.3	-3.0
2001	5.0	2.8	0.9	2.1	-2.0	2.0	-2.0	2.0	-2.0
2004	3.9	3.1	1.3	0.8	-1.8	0.7	-1.8	0.7	-1.8
Mean	10.2	10.0	5.0	0.2	-5.0	0.3	-5.0	0.3	-5.1
Trend	-0.8	-1.1	-0.7	0.4	0.4	0.3	0.4	0.3	0.5

Refer to notes to table 4.

Table 6. Proportion of Families Holding Debt and Credit or Charge Cards, by Type and by Age of Family Head, 1983-2004

Item	Less than 35	35-44	45-61	62 or older	Adjusted difference relative to age 48 (percentage points)							
					With family characteristics for year shown				With family characteristics for 2004			
					Less than 35	35-44	45-61	62 or older	Less than 35	35-44	45-61	62 or older
TYPE OF DEBT	Families holding debt (percent except as noted)											
Any												
1983	79.2	87.2	76.7	34.8	-2.3	2.5	-5.9	-41.9	-2.8	1.3	-4.2	-47.2
1989	79.8	88.6	81.7	41.5	-4.2	0.2	-3.4	-39.4	-4.3	-0.2	-3.2	-42.6
1992	81.5	86.3	81.3	46.1	-1.2	0.8	-4.4	-35.0	-2.1	-0.6	-4.1	-35.9
1995	83.5	87.0	82.5	46.8	0.7	2.3	-2.6	-33.6	1.0	2.3	-2.7	-34.8
1998	81.2	87.6	83.8	42.4	-3.3	0.6	-3.3	-39.9	-3.2	1.3	-3.2	-39.7
2001	82.7	88.6	81.4	48.1	-0.2	3.4	-3.7	-32.9	-0.6	2.5	-4.4	-32.8
2004	79.8	88.6	84.5	52.7	-6.8	0.0	-4.6	-33.4	-6.8	0.0	-4.6	-33.4
Mean	81.1	87.7	81.7	44.6	-2.5	1.4	-4.0	-36.6	-2.7	1.0	-3.8	-38.1
Trend	0.1	0.1	0.3	0.7	-0.1	0.0	0.1	0.4	-0.1	0.0	0.0	0.6
Mortgage												
1983	32.6	58.1	45.8	15.2	-19.1	-0.4	-9.0	-29.5	-18.4	-1.7	-7.5	-34.5
1989	34.8	57.9	52.5	16.8	-20.8	-6.1	-7.0	-33.9	-21.3	-7.2	-6.3	-36.6
1992	30.9	55.5	55.0	17.7	-23.2	-4.4	-5.4	-32.4	-23.9	-4.9	-5.2	-34.5
1995	33.0	54.3	57.3	20.4	-18.5	-4.3	-3.0	-28.0	-19.9	-5.6	-3.4	-30.1
1998	33.2	58.7	56.5	21.5	-14.0	2.2	-1.0	-24.8	-14.8	3.0	-0.8	-25.8
2001	35.7	59.6	56.7	24.4	-16.2	-0.2	-4.2	-27.4	-16.7	-1.2	-4.4	-25.9
2004	37.7	62.8	60.3	28.3	-20.3	-1.3	-5.5	-29.3	-20.3	-1.3	-5.5	-29.3
Mean	34.0	58.1	54.9	20.6	-18.9	-2.1	-5.0	-29.3	-19.3	-2.7	-4.7	-31.0
Trend	0.2	0.2	0.6	0.6	0.1	0.1	0.2	0.2	0.1	0.2	0.2	0.5
Installment												
1983	55.4	59.5	45.4	14.8	3.8	5.1	-7.6	-33.2	1.8	3.4	-6.6	-36.7
1989	54.6	63.9	50.8	18.4	-2.3	4.5	-8.3	-39.3	-2.3	4.5	-7.9	-40.1
1992	52.6	53.5	46.3	17.8	2.4	3.1	-5.5	-33.4	2.5	1.7	-5.5	-33.8
1995	51.9	54.0	43.5	15.1	4.1	4.7	-6.5	-32.9	5.4	5.4	-7.6	-33.1
1998	48.1	47.3	43.0	13.9	1.7	-0.6	-4.8	-32.6	2.9	-1.0	-5.1	-31.6
2001	55.2	53.1	40.9	18.4	12.6	8.8	-3.4	-25.1	11.9	8.7	-3.7	-24.6
2004	48.3	50.3	41.9	22.7	6.8	5.9	-3.0	-18.5	6.8	5.9	-3.0	-18.5
Mean	52.3	54.5	44.6	17.3	4.2	4.5	-5.6	-30.7	4.1	4.1	-5.6	-31.2
Trend	-0.3	-0.6	-0.3	0.2	0.4	0.1	0.3	0.7	0.4	0.1	0.2	0.9
Any credit or charge card balance												
1983	38.4	51.5	43.1	16.7	-4.2	5.2	-1.5	-22.0	-4.8	4.1	-1.2	-27.3
1989	44.5	50.5	44.2	21.1	-1.8	-1.5	-4.8	-23.7	0.3	-3.2	-4.6	-26.9
1992	48.1	47.0	43.9	25.1	4.3	0.4	-3.5	-18.7	4.4	0.7	-3.3	-19.8
1995	49.0	52.9	50.0	25.7	-3.7	-1.3	-4.5	-26.5	-2.5	-0.2	-5.1	-26.9
1998	48.1	48.6	48.1	22.0	-2.2	-2.8	-2.7	-26.7	-0.9	-1.7	-2.9	-26.1
2001	46.9	51.5	45.5	25.3	-2.4	1.3	-3.8	-22.7	-3.0	0.4	-4.2	-21.9
2004	43.1	54.9	48.1	28.1	-8.6	3.0	-4.0	-22.8	-8.6	3.0	-4.0	-22.8
Mean	45.4	51.0	46.1	23.4	-2.7	0.6	-3.5	-23.3	-2.2	0.4	-3.6	-24.5
Trend	0.2	0.1	0.2	0.4	-0.2	-0.1	-0.1	-0.1	-0.2	0.0	-0.1	0.2

Table continued on next page.

Table 6. Proportion of Families Holding Debt and Credit or Charge Cards, by Type and by Age of Family Head, 1983-2004—Continued

Item	Less than 35	35-44	45-61	62 or older	Adjusted difference relative to age 48 (percentage points)							
					With family characteristics for year shown				With family characteristics for 2004			
					Less than 35	35-44	45-61	62 or older	Less than 35	35-44	45-61	62 or older
TYPE OF CARD	Families owning a credit or charge card (percent except as noted)											
Any credit or charge card												
1983	57.2	74.2	74.2	59.0	-12.5	-2.2	3.1	2.0	-12.9	-2.7	2.1	-1.7
1989	61.7	74.2	75.6	68.6	-11.2	-7.9	0.3	4.4	-10.5	-9.0	0.3	2.5
1992	67.0	72.1	78.0	70.4	-2.4	-3.2	3.0	4.3	-1.6	-1.9	2.9	5.0
1995	66.9	75.1	79.5	74.5	-4.5	-1.2	2.1	8.2	-3.4	0.8	2.3	6.6
1998	63.3	75.0	80.2	69.7	-5.1	-1.4	3.3	5.4	-5.6	-1.8	3.3	4.6
2001	67.0	79.1	81.6	74.8	-8.2	-3.1	-0.9	0.6	-8.3	-3.4	-1.2	0.8
2004	63.3	75.7	81.0	76.3	-10.5	-3.6	0.1	3.3	-10.5	-3.6	0.1	3.3
Mean	63.8	75.1	78.6	70.5	-7.8	-3.2	1.6	4.0	-7.5	-3.1	1.4	3.0
Trend	0.3	0.2	0.4	0.7	0.1	0.1	-0.1	0.0	0.1	0.1	-0.1	0.2
Bank-type or travel and entertainment card												
1983	36.7	56.2	53.4	37.3	-9.9	1.0	3.2	0.9	-9.9	0.9	2.3	-1.4
1989	48.8	63.4	66.1	52.2	-12.3	-9.9	0.0	-0.1	-12.8	-10.8	0.0	1.0
1992	56.5	65.7	70.9	59.8	-4.6	-3.0	3.4	4.2	-4.3	-1.2	3.1	4.3
1995	59.6	69.8	74.9	64.6	-6.3	-2.1	2.0	4.6	-5.9	-0.7	2.1	2.8
1998	58.4	72.0	76.2	63.6	-2.7	0.4	3.3	5.9	-3.8	-1.1	3.1	5.0
2001	64.5	77.3	79.2	69.8	-7.1	-2.1	-0.5	0.3	-7.1	-2.3	-0.6	0.6
2004	60.8	73.8	78.3	72.5	-8.8	-2.3	0.3	3.0	-8.8	-2.3	0.3	3.0
Mean	55.1	68.3	71.3	60.0	-7.4	-2.6	1.7	2.7	-7.5	-2.5	1.5	2.2
Trend	1.2	0.9	1.2	1.6	0.2	0.1	-0.1	0.1	0.2	0.0	-0.1	0.2
Store or gas card only												
1983	20.5	18.1	20.8	21.7	0.2	-2.6	0.3	0.7	0.5	-2.1	0.5	0.5
1989	12.9	10.8	9.5	16.4	3.6	1.7	0.4	7.3	3.5	1.4	0.3	7.0
1992	10.5	6.4	7.2	10.6	3.6	-0.5	0.2	3.6	3.9	-0.5	0.5	4.0
1995	7.2	5.3	4.6	9.9	2.9	1.0	0.3	5.6	3.1	1.2	0.4	6.1
1998	4.9	3.0	4.0	6.1	1.3	-0.5	0.5	2.7	1.4	-0.3	0.6	2.8
2001	2.5	1.8	2.4	5.0	-0.3	-1.0	-0.4	2.2	-0.2	-0.9	-0.4	2.1
2004	2.5	1.9	2.7	3.9	-0.8	-1.2	-0.2	1.2	-0.8	-1.2	-0.2	1.2
Mean	8.7	6.8	7.3	10.5	1.5	-0.4	0.2	3.3	1.6	-0.4	0.2	3.4
Trend	-0.9	-0.8	-0.8	-0.9	-0.1	0.0	0.0	-0.1	-0.1	0.0	0.0	-0.1

Refer to notes to table 4.

Table 7. Number and Proportion of Individuals with Records at Credit-Reporting Agencies, by Type of Information in Credit Record, as of June 30, 2003

Type of information	Number	Percent of sample
Sample size	301,536	100
Credit account	259,211	86.0
Public record	36,742	12.2
Collection agency account	109,964	36.5
Inquiry[1]	188,185	62.4
None of the above	15	*
MEMO		
Credit account only	63,781	21.2
Public record only	53	*
Collection agency account only	34,999	11.6
Inquiry only[1]	31	*
Credit account plus other entry, by entry		
Public record	34,715	11.5
Collection agency account	67,747	22.5
Inquiry[1]	182,149	60.4

1. Includes only inquiries made within two years of June 30, 2003, the date the sample was drawn.

* Less than 0.5 percent.

Table 8. Type of Information Provided on the Demographic and Location Characteristics of Study Sample, by Source of the Data

Characteristic	Social Security Administration	Credit reporting agency	Demographic information company	2000 Census
Race or ethnicity	X		X	
Date of birth	X	X	X	
Marital status			X	
Sex	X		X	
Citizenship status	X			
Place of birth	X		X	
Religion			X	
Language preference			X	
Location[1]				
Census block		X		X
Census tract		X		X

1. Location information provided by the credit-reporting agency was latitude and longitude of the Census blocks and tracts.

Table 9. Number of Selected Credit-Record Items in Full Sample and Their Proportion in the Scorable and Estimation Samples, by Selected Characteristics of Sample Population

Characteristic	Full sample (number)								
	Total	No score available		Score available		Score available without performance		Estimation sample	
		Total	Mean trades	Total	Mean trades	Total	Mean trades	Total	Mean trades
Race or ethnicity—SSA data									
Non-Hispanic white	162,932	14,364	10.2	148,568	16.4	15,403	13.8	133,165	16.7
Black	25,937	4,569	3.8	21,368	13.0	3,094	10.9	18,274	13.3
Hispanic	19,446	2,496	5.8	16,950	13.7	2,248	11.3	14,702	14.1
Asian	9,675	855	12.8	8,820	15.5	914	11.5	7,906	15.9
American Indian	441	32	11.2	409	15.8	43	13.3	366	16.1
Unknown race	83,106	46,754	1.0	36,352	9.7	10,328	6.5	26,024	11.0
Race or ethnicity—location-based distribution [1]									
Non-Hispanic white	218,053	43,966	4.1	174,087	15.3	22,856	11.4	151,230	15.9
Black	35,151	11,205	2.0	23,946	12.9	3,841	9.6	20,105	13.6
Hispanic	34,222	10,589	2.2	23,632	13.1	3,722	9.4	19,910	13.8
Asian	11,670	2,654	3.7	9,016	14.5	1,331	10.3	7,685	15.2
American Indian	1,875	502	2.6	1,373	13.9	204	10.3	1,169	14.5
National origin									
Foreign-born	28,407	2,810	9.5	25,597	14.5	3,000	11.3	22,597	14.9
Recent immigrant	4,746	485	5.8	4,261	10.1	499	7.7	3,762	10.5
Sex									
Male	114,074	12,013	7.2	102,061	15.4	11,687	12.3	90,374	15.8
Female	116,950	11,603	9.9	105,347	16.0	11,316	13.7	94,031	16.3
Unknown	70,512	45,453	0.8	25,059	7.0	9,027	5.6	16,032	7.8
Marital status									
Married male	58,192	3,686	13.3	54,506	17.6	5,195	15.6	49,311	17.9
Single male	32,612	3,564	6.5	29,048	13.8	3,662	10.7	25,386	14.3
Married female	59,197	4,071	15.1	55,126	18.0	5,111	16.6	50,015	18.1
Single female	36,581	3,793	9.4	32,788	14.7	3,867	12.2	28,921	15.0
Unknown	114,954	53,955	1.3	60,999	9.8	14,195	6.9	46,804	10.7
Age—SSA data (years)									
Younger than 30	39,043	6,032	3.8	33,011	9.1	3,833	7.3	29,178	9.3
30 to 39	45,431	4,946	8.9	40,485	17.0	4,837	14.1	35,648	17.4
40 to 49	51,330	4,923	9.8	46,407	18.6	5,236	15.9	41,171	18.9
50 to 61	47,341	3,867	12.6	43,474	18.9	4,248	17.0	39,226	19.1
62 or older	47,926	3,851	9.7	44,075	13.4	4,855	9.7	39,220	13.9
Unknown	70,465	45,450	0.8	25,015	7.0	9,021	5.6	15,994	7.8
Census tract characteristics									
Income ratio[2]									
Low	13,300	5,669	0.9	7,631	9.9	1,383	6.7	6,248	10.7
Moderate	61,782	19,880	1.9	41,902	12.4	6,624	9.0	35,278	13.1
Middle	150,967	30,983	3.7	119,984	14.8	16,181	11.1	103,803	15.3
High	74,770	12,344	6.4	62,426	17.0	7,748	12.9	54,678	17.6
Unknown	544	148	7.6	396	10.5	75	7.0	321	11.4
Minority population (percent)[3]									
Less than 10	114,678	19,227	5.0	95,451	15.7	11,641	11.8	83,810	16.3
10-49	124,616	28,922	3.6	95,694	14.9	13,485	11.2	82,209	15.6
50-79	33,322	10,671	2.1	22,651	13.0	3,592	9.7	19,059	13.6
80 or more	28,355	10,097	1.4	18,258	11.4	3,236	8.2	15,022	12.0
Urban	251,844	57,930	3.5	193,914	15.0	26,898	11.0	167,016	15.6
Rural	49,113	10,986	3.1	38,127	14.0	5,054	10.8	33,073	14.4
All	**301,536**	**69,069**	**3.5**	**232,467**	**14.8**	**32,030**	**10.9**	**200,437**	**15.4**

Table continued on next page.

Table 9. Number of Selected Credit-Record Items in Full Sample and Their Proportion in the Scorable and Estimation Samples, by Selected Characteristics of Sample Population—Continued

Characteristic	Scorable sample (percent)								Estimation sample (percent)							
	Revolving account	Installment account	Mortgage account	Public record	Medical collection	Other collection	Inquiry	Delinquency[1]	Revolving account	Installment account	Mortgage account	Public record	Medical collection	Other collection	Inquiry	Delinquency[1]
Race or ethnicity—SSA data [2]																
Non-Hispanic white	88.3	45.2	33.8	12.9	14.7	14.5	75.9	14.6	90.2	45.9	34.7	12.1	13.7	13.5	76.4	13.9
Black	65.8	46.6	21.1	27.1	35.4	47.9	86.1	34.9	68.4	48.9	21.4	27.1	35.7	47.7	87.3	36.0
Hispanic	80.6	45.5	28.0	14.9	21.5	28.9	84.0	22.8	83.4	46.8	28.9	14.4	20.9	27.7	84.7	22.7
Asian	91.6	35.4	31.3	9.1	7.5	11.6	77.1	12.5	93.5	36.5	32.9	8.4	7.1	10.4	79.0	12.0
American Indian	90.7	41.2	30.9	12.4	12.3	11.6	67.8	13.5	92.8	41.6	31.9	12.0	11.0	10.3	68.1	12.6
Unknown race	80.2	27.6	18.8	8.8	11.0	14.0	52.7	11.9	85.6	31.5	21.5	9.0	11.3	13.2	59.0	12.7
Race or ethnicity—location-based distribution [3]																
Non-Hispanic white	86.4	42.9	31.4	12.7	15.1	15.7	73.4	15.0	88.8	44.5	32.9	12.2	14.4	14.8	75.2	14.7
Black	74.3	41.0	22.9	19.8	24.9	32.5	76.4	25.1	77.6	43.5	24.0	19.8	25.0	31.8	78.8	25.7
Hispanic	80.5	40.3	25.2	14.1	18.1	25.1	75.5	19.6	84.0	42.5	26.7	13.8	17.8	23.9	77.9	19.7
Asian	87.5	37.1	29.7	12.0	10.8	16.2	72.6	14.7	90.2	38.8	31.7	11.5	10.4	15.1	75.2	14.5
American Indian	78.5	46.7	24.6	14.9	20.0	23.4	75.2	20.9	81.8	48.9	25.9	14.8	19.4	22.5	76.9	21.1
National origin																
Foreign-born	88.4	37.7	31.6	11.7	12.1	17.0	80.1	16.3	90.6	38.7	32.9	11.1	11.6	15.9	81.4	15.9
Recent immigrant	88.7	35.4	24.3	5.5	9.1	13.8	83.5	12.7	90.7	36.9	25.6	5.0	8.6	12.5	85.8	12.9
Sex																
Male	84.4	47.4	33.0	15.5	16.8	19.7	79.0	16.9	86.8	48.7	34.1	14.6	15.8	18.3	79.6	16.3
Female	86.4	42.2	30.7	13.4	17.4	18.6	76.6	18.0	88.2	42.9	31.4	12.8	16.7	17.7	77.2	17.5
Unknown	77.3	21.2	12.9	6.5	8.9	12.5	41.4	9.4	83.5	24.6	14.6	6.5	9.1	11.3	46.7	10.1
Marital status																
Married male	90.3	50.2	41.1	13.0	13.0	12.3	77.2	13.8	91.8	50.5	41.7	12.2	12.2	11.4	77.4	13.0
Single male	81.0	44.1	26.4	17.7	19.0	25.6	80.3	19.6	83.9	45.9	27.6	16.9	18.3	24.2	81.4	19.5
Married female	92.2	43.1	38.9	11.2	12.5	11.0	74.6	14.4	93.3	43.0	39.2	10.6	11.8	10.3	74.7	13.6
Single female	83.1	40.9	23.3	15.4	20.9	24.8	77.9	21.7	85.1	42.1	24.0	15.0	20.3	23.9	78.9	21.4
Unknown	75.0	34.2	16.5	13.2	18.6	23.9	64.9	16.7	78.9	38.4	18.3	13.5	19.3	23.9	70.5	18.0
Age—SSA data (years)																
Younger than 30	72.5	54.8	11.3	9.1	21.9	29.9	86.8	21.1	74.7	56.3	11.6	8.8	21.4	28.9	87.3	21.0
30 to 39	80.5	52.7	36.4	19.8	24.1	29.0	89.4	24.3	82.7	53.9	37.5	19.0	23.3	27.7	90.0	23.9
40 to 49	86.1	49.4	45.1	19.1	19.7	20.5	85.6	19.7	88.3	50.2	46.3	18.2	18.6	19.2	86.0	19.1
50 to 61	90.6	46.1	42.2	15.4	14.0	13.6	78.3	15.7	92.5	46.5	43.0	14.5	13.1	12.5	78.4	14.9
62 or older	93.8	23.9	18.7	7.5	7.4	6.2	51.5	7.7	95.8	24.9	19.6	6.9	6.6	5.4	53.0	7.1
Unknown	77.2	21.1	12.9	6.5	8.9	12.5	41.3	9.4	83.4	24.6	14.6	6.5	9.1	11.3	46.6	10.1
Census tract characteristics																
Income ratio[4]																
Low	68.3	33.7	12.8	19.7	25.3	39.6	77.5	25.2	72.9	36.9	13.7	19.7	25.6	38.7	80.5	26.6
Moderate	76.7	40.4	21.2	17.4	22.7	28.3	74.7	21.7	80.1	42.9	22.5	17.2	22.6	27.4	77.1	22.1
Middle	84.7	44.0	29.6	13.8	16.6	17.5	73.3	16.6	87.3	45.6	30.9	13.3	16.0	16.5	75.1	16.3
High	91.5	41.2	38.1	9.8	10.0	11.1	74.0	11.9	93.2	42.5	39.8	9.4	9.6	10.5	76.0	11.5
Unknown	82.8	47.5	16.4	4.3	6.6	13.4	56.3	19.9	82.6	50.5	18.1	4.7	6.5	13.4	58.9	20.6
Minority population (percent)[5]																
Less than 10	88.0	43.8	32.9	11.7	13.8	12.7	73.0	13.3	90.2	45.2	34.3	11.1	13.1	11.9	74.7	12.9
10-49	84.8	42.1	30.1	13.8	16.3	18.6	73.7	16.6	87.4	43.9	31.6	13.4	15.8	17.7	75.7	16.4
50-79	78.0	40.4	24.4	16.8	21.7	28.4	75.8	22.1	81.2	42.6	25.7	16.7	21.5	27.7	78.2	22.6
80 or more	73.0	36.9	18.8	18.3	22.2	35.7	77.0	26.2	77.0	39.7	19.9	18.2	22.5	34.8	79.9	27.2
Urban	85.3	41.5	30.8	13.5	15.5	18.5	74.4	16.5	87.9	43.2	32.3	13.1	15.0	17.6	76.5	16.3
Rural	80.8	46.1	24.9	13.9	20.0	18.1	71.0	16.9	83.7	48.1	26.0	13.4	19.2	16.9	72.5	16.6
All	**84.5**	**42.2**	**29.8**	**13.5**	**16.2**	**18.4**	**73.8**	**16.6**	**87.2**	**44.0**	**31.3**	**13.1**	**15.7**	**17.5**	**75.8**	**16.3**

1. At least 90 days, any account. • 2. "Asian" is Asian, Asian American, and Pacific Islander; "American Indian" is North American Indian and Alaskan Native. • 3. Refer to text note 99 for details of computation.
4. Median income of tract as percentage of median income of tract's MSA or, if a rural tract, of state's rural areas. Low, less than 50 percent; moderate, 50-79 percent; middle, 80-119 percent; high, 120 percent or more.
5. Minority refers to other than non-Hispanic white.

Table 10. Number and Proportion of Individuals in Full Sample, by State, and Population Aged 18 or Older in Each State as a Proportion of U.S. Population

State	Number in sample[1]	Percentage of sample (1)	Adults as percentage of U.S. population (2)	Difference (1 - 2)
Alabama	4,584	1.52	1.56	-0.04
Alaska	630	0.21	0.21	0.00
Arizona	5,491	1.82	1.87	-0.05
Arkansas	2,848	0.95	0.94	0.01
California	37,446	12.44	11.97	0.47
Colorado	4,929	1.64	1.56	0.08
Connecticut	3,484	1.16	1.22	-0.06
Delaware	901	0.30	0.28	0.02
District of Columbia	660	0.22	0.21	0.01
Florida	19,273	6.40	6.01	0.39
Georgia	8,570	2.85	2.93	-0.08
Hawaii	1,229	0.41	0.44	-0.03
Idaho	1,299	0.43	0.46	-0.03
Illinois	12,991	4.32	4.33	-0.01
Indiana	6,620	2.20	2.11	0.09
Iowa	2,859	0.95	1.03	-0.08
Kansas	2,805	0.93	0.93	0.00
Kentucky	4,290	1.43	1.43	0.00
Louisiana	4,574	1.52	1.52	0.00
Maine	1,362	0.45	0.47	-0.02
Maryland	5,793	1.92	1.90	0.02
Massachusetts	5,891	1.96	2.27	-0.31
Michigan	10,485	3.48	3.46	0.02
Minnesota	4,802	1.60	1.75	-0.15
Mississippi	2,931	0.97	0.97	0.00
Missouri	5,849	1.94	1.97	-0.03
Montana	953	0.32	0.32	0.00
Nebraska	1,672	0.56	0.60	-0.04
Nevada	2,517	0.84	0.76	0.08
New Hampshire	1,304	0.43	0.45	-0.02
New Jersey	8,917	2.96	2.99	-0.03
New Mexico	1,810	0.60	0.63	-0.03
New York	18,758	6.23	6.73	-0.50
North Carolina	8,862	2.94	2.90	0.04
North Dakota	596	0.20	0.22	-0.02
Ohio	12,293	4.08	3.96	0.12
Oklahoma	3,688	1.23	1.21	0.02
Oregon	3,977	1.32	1.24	0.08
Pennsylvania	13,075	4.34	4.38	-0.04
Rhode Island	1,043	0.35	0.38	-0.03
South Carolina	4,357	1.45	1.43	0.02
South Dakota	685	0.23	0.26	-0.03
Tennessee	5,936	1.97	2.04	-0.07
Texas	22,379	7.44	7.29	0.15
Utah	2,373	0.79	0.74	0.05
Vermont	623	0.21	0.22	-0.01
Virginia	7,531	2.50	2.57	-0.07
Washington	6,945	2.31	2.13	0.18
West Virginia	1,869	0.62	0.65	-0.03
Wisconsin	5,718	1.90	1.90	0.00
Wyoming	515	0.17	0.17	0.00

Note. For individuals whose credit record included a geographic location.

Table 11. Distribution of Selected Charactistics of the Sample in the U.S. Population, and Distribution by Status of Unknown Values
(Percent)

Characteristic	U.S. adult population[1]	Unknown values excluded				Unknown values imputed			
		Full sample	No score available	Score available	Estimation sample	Full sample	No score available	Score available	Estimation sample
Race or ethnicity [2]									
Non-Hispanic white	68.7	74.6	64.4	75.8	76.4	72.5	63.9	75.0	75.6
Black	12.4	11.9	20.5	10.9	10.5	12.5	17.7	10.9	10.5
Hispanic	13.9	8.9	11.2	8.6	8.4	10.2	13.9	9.1	8.9
Asian	4.2	4.4	3.8	4.5	4.5	4.6	4.3	4.7	4.7
American Indian	0.8	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2
Total	100	100	100	100	100	100	100	100	100
Sex									
Male	49.2	49.4	50.9	49.2	49.0	50.5	54.6	49.3	49.0
Female	50.8	50.6	49.1	50.8	51.0	49.5	45.4	50.7	51.0
Total	100	100	100	100	100	100	100	100	100
Marital status									
Married male	n.a.	31.2	24.4	31.8	32.1	29.1	23.4	30.8	31.2
Single male	n.a.	17.5	23.6	16.9	16.5	21.4	31.2	18.5	17.8
Married female	n.a.	31.7	26.9	32.1	32.6	28.4	20.2	30.8	31.4
Single female	n.a.	19.6	25.1	19.1	18.8	21.1	25.2	19.9	19.6
Total	n.a.	100	100	100	100	100	100	100	100
Age (years) [3]									
Younger than 30	22.1	16.9	25.5	15.9	15.8	20.4	32.4	16.8	16.4
30 to 39	19.3	19.7	20.9	19.5	19.3	19.7	21.1	19.3	19.2
40 to 49	20.5	22.2	20.8	22.4	22.3	21.1	18.9	21.7	21.8
50 to 59	16.0	17.7	14.3	18.1	18.4	16.3	12.0	17.6	18.0
60 or older	22.1	23.5	18.4	24.1	24.2	22.6	15.6	24.6	24.6
Total	100	100	100	100	100	100	100	100	100
Census tract characteristics [4]									
Income ratio (percent)									
Low	3.9	4.3	8.0	3.2	3.0	*	*	*	*
Moderate	26.4	20.9	29.3	18.4	17.9	*	*	*	*
Middle	47.0	49.9	44.8	51.5	51.6	*	*	*	*
High	22.7	24.9	18.0	27.0	27.4	*	*	*	*
Total	100	100	100	100	100	*	*	*	*
Minority population (percent)									
Less than 10	30.5	32.3	22.9	35.1	35.8	*	*	*	*
10-49	47.8	44.6	43.6	44.9	44.9	*	*	*	*
50-79	10.8	12.2	16.7	10.9	10.7	*	*	*	*
80 or more	10.8	10.9	16.8	9.1	8.7	*	*	*	*
Total	100	100	100	100	100	*	*	*	*
Urban	82.7	83.7	84.1	83.6	83.5	*	*	*	*
Rural	17.3	16.3	15.9	16.4	16.5	*	*	*	*
Total	100	100	100	100	100	*	*	*	*

Note. For details of imputation, refer to text.
1. Age 18 or older.
2. For U.S. population, as defined by the Census Bureau; for the distributions in the sample population, as defined by SSA data.
3. Final two age ranges used in other tables have been modified here to conform with Census data for the U.S. population.
4. For definitions, refer to notes to table 9.
n.a. Not available.
* Data not available to support imputation.
Source. For distribution of the U.S. population by race, sex, and age, U.S. Census Bureau, Current Population Reports, 2006.

Table 12. Credit Points and Distribution of the Sample Population, by Credit Characteristic, for the Three Scorecards in the FRB Base Model

A. Thin-file scorecard

Characteristic and code	Credit points	Population distribution (percent)
Total number of public records and derogatory accounts with amount owed greater than $100 (S059)		
0	0	68.8
1	-269	9.1
2-3	-361	11.1
4	-400	3.2
5 or more	-425	7.9
Total number of months since the most recent account delinquency (AT36)		
Missing	407	69.2
0-1	0	4.9
2	54	1.4
3 or more	179	24.5
Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months (RE34)		
Missing	-96	47.3
0-10.5	0	36.1
10.6-24.3	-6	3.3
24.4-31.9	-16	1.3
32-64.9	-66	4.4
65-94.1	-87	4.0
94.2-100	-152	1.6
100.1-103.4	-199	0.5
103.5-106.3	-200	0.3
106.4-172.4	-233	1.1
172.5 or more	-295	0.2
Total number of accounts in good standing, opened 18 or more months ago (AT26)		
0	0	48.9
1 or more	73	51.1
Total maximum credit issued on open accounts reported in the past 12 months (AT28) (dollars)		
0-999	0	49.1
1,000-1,999	43	10.2
2,000-134,999	71	39.8
135,000-249,999	175	0.8
250,000 or more	240	0.2

Characteristic and code	Credit points	Population distribution (percent)
Total number of inquiries for credit (G096)		
0	0	56.7
1	-19	15.3
2	-44	9.0
3	-48	5.8
4	-73	3.7
5-12	-74	8.4
13 or more	-134	1.0
Total number of months since the most recent update on an account (G103)		
0	0	37.2
1	-17	37.4
2-3	-63	8.1
4-12	-105	9.4
13 or more	-114	7.9
Percentage of total remaining balance to total maximum credit for all open installment accounts reported in the past 12 months (IN34)		
Missing	11	83.2
0-64.08	0	4.7
64.09-100.8	-42	11.7
100.9 or more	-146	0.5
Memo: Scorecard Statistics		
Scorable sample		
Number in scorecard	29,656	
Percent in scorecard	12.8	
Estimation sample		
Number in scorecard	19,847	
Percent in scorecard	9.9	
Scorecard percent bad	34.8	
Scorecard KS statistic	72.4	

Note. A complete list of the credit characteristics in the TransUnion sample and their codes is in appendix B; the characteristics used for the three scorecards are listed in appendix C.

KS Kolmogorov-Smirnov.

Table 12. Credit Points and Distribution of the Sample Population, by Credit Characteristic, for the Three Scorecards in the FRB Base Model

B. Clean-file scorecard

Characteristic and code	Credit points	Population distribution (percent)
Total number of months since the most recent account delinquency (AT36)		
Missing	485	71.4
0	0	1.5
1	143	1.6
2	214	0.9
3-4	279	1.8
5	310	0.7
6-9	366	2.3
10-12	389	1.4
13-18	418	2.6
19-31	443	5.1
32-43	461	3.7
44 or more	474	7.1
Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months (RE34)		
Missing	-67	2.2
0-6.7	0	47.0
6.8-11.4	-1	9.3
11.5-14.9	-3	4.7
15-20.9	-4	6.3
21-26.2	-5	4.4
26.3-35.3	-12	5.7
35.4-44.5	-16	4.6
44.6-54	-19	3.7
54.1-62.6	-45	2.8
62.7-73.1	-63	3.0
73.2-78.9	-66	1.4
79-91.6	-99	2.9
91.7 or more	-172	2.1
Greatest amount of time a payment was late ever on an account (G089) [1]		
Missing	-24	71.1
Less than 60 days	0	16.4
60 days or more	-61	9.2
Other	-121	3.4
Total number of inquiries for credit (G096)		
0	0	28.2
1	-6	17.5
2	-8	13.1
3	-14	9.8
4-5	-16	13.3
6-7	-22	7.7
8	-32	2.5
9-11	-36	4.3
12-13	-44	1.4
14-16	-62	1.1
17-24	-77	0.9
25 or more	-102	0.2
Total number of open personal finance installment accounts reported in the past 12 months (S019)		
0	0	87.8
1	-23	10.4
2	-67	1.5
3 or more	-107	0.4

Characteristic and code	Credit points	Population distribution (percent)
Total number of open non-installment accounts with a remaining balance to maximum credit issued ratio greater than 50% reported in the past 12 months (S043)		
0	0	58.0
1	-6	21.2
2	-20	9.3
3	-50	4.8
4	-63	2.6
5	-81	1.6
6-7	-119	1.5
8	-187	1.0
Total maximum credit issued on open accounts reported in the past 12 months (AT28) (dollars)		
0-2,999	0	4.0
3,000-5,999	32	3.3
6,000-14,999	35	9.4
15,000-23,999	35	8.6
24,000-44,999	40	15.2
45,000-92,999	47	18.1
93,000-172,999	61	19.0
173,000-327,999	76	16.3
328,000 or more	92	6.2
Average age of accounts on credit report (S004) (months)		
0-9	0	0.7
10-15	62	1.3
16-33	104	6.3
34-44	123	4.6
45-55	134	5.5
56-61	151	3.8
62-70	151	7.4
71-75	158	4.9
76-84	161	9.7
85-103	162	19.1
104-152	164	24.6
153-224	165	9.2
225 or more	169	2.9
Memo: Scorecard Statistics		
Scorable sample		
Number in scorecard	129,289	
Percent in scorecard	55.6	
Estimation sample		
Number in scorecard	118,061	
Percent in scorecard	58.9	
Scorecard percent bad	7.4	
Scorecard KS statistic	53.5	

Note. Refer to notes to table 12.A.

1. Late 60 days or more includes paying or paid under a wage-earner plan or similar arrangement. "Other" includes repossession, charge-off, and collection.

Table 12. Credit Points and Distribution of the Sample Population, by Credit Characteristic, for the Three Scorecards in the FRB Base Model

C. Major-derogatory scorecard

Characteristic and code	Credit points	Population distribution (percent)
Total number of public records and derogatory accounts with an amount owed greater than $100 (S059)		
0	0	13.1
1	-82	20.7
2	-149	13.1
3	-201	10.0
4	-231	8.4
5	-258	6.8
6	-258	5.7
7-8	-289	8.3
9	-299	3.0
10-16	-320	8.9
17 or more	-355	2.2
Percentage of accounts with no late payments reported (G051)		
Missing	-81	0.0
0-53.2	0	44.6
53.3-62.4	10	8.6
62.5-66.6	26	6.9
66.7-71.08	33	2.7
71.09-74.9	36	3.1
75-94.6	84	23.2
94.7 or more	113	11.0
Percentage of total remaining balance to total maximum credit for all open bankcard accounts reported in the past 12 months (BC34)		
Missing	-104	45.3
0-28.4	0	17.8
28.5-41.9	-15	3.8
42-53.3	-34	3.4
53.4-71.7	-58	6.1
71.8-84.9	-88	6.0
85-96.4	-113	7.4
96.5-99.2	-144	2.2
99.3 or more	-148	8.0

Characteristic and code	Credit points	Population distribution (percent)
Total number of months since the most recent occurrence of a derogatory public record (G095)		
Missing	-32	60.3
0-10	0	5.6
11-23	2	6.7
24-26	21	1.5
27-47	40	7.8
48-64	51	6.4
65-82	77	5.9
83 or more	81	5.7
Average age of accounts on credit report (S004) (months)		
0-44	0	22.5
45-54	11	10.5
55-64	21	12.4
65-69	27	6.4
70-73	33	5.0
74-82	36	10.5
83-88	37	6.3
89-97	56	7.5
98-101	70	2.6
102-114	91	6.3
115-146	91	6.7
147-326	116	3.4
327 or more	306	0.0
Number accounts that have payments that are currently or previously 30 or more days past due within the past 24 months (G061)		
0-1	0	49.3
2	-60	15.5
3	-81	10.8
4	-91	7.4
5 or more	-101	17.0
Total number of accounts currently less than 120 days past due in the past 2 months (G088)		
0	0	84.2
1	-58	11.2
2 or more	-87	4.7

Characteristic and code	Credit points	Population distribution (percent)
Percentage of accounts that are open and active with a remaining balance greater than $0 reported in the past 12 months (S046)		
Missing	-198	13.9
0-47.7	0	10.6
47.8-65.3	-2	10.6
65.4-78.7	-12	11.7
78.8-84.5	-18	5.1
84.6 or more	-31	48.2
Total number of different credit issuers (S054)		
0-4	0	16.1
5	44	6.7
6-8	64	18.4
9-10	77	10.7
11-13	92	13.5
14-17	99	13.1
18-21	106	9.0
22 or more	106	12.5
Total number of months since the most recent account delinquency (AT36)		
Missing	309	10.6
0	0	14.3
1	27	13.6
2	75	6.0
3-4	97	7.6
5	124	3.4
6-8	170	6.7
9-12	199	7.3
13-16	226	5.7
17-31	236	13.1
32-39	262	3.1
40-53	290	3.6
54-70	315	3.4
71 or more	338	1.6
Memo: Scorecard Statistics		
Scorable sample		
Number in scorecard	73,522	
Percent in scorecard	31.6	
Estimation sample		
Number in scorecard	62,529	
Percent in scorecard	31.2	
Scorecard percent bad	64.7	
Scorecard KS statistic	61.7	

Note. Refer to notes to table 12.A.

Table 13. Nonlinear Conversion of Credit Points (CP) in the FRB Base Model to FRB Base Score

CP range	FRB base score	CP range	FRB base score	CP range	FRB base score	CP range	FRB base score
Less than -110	1	472 – 497	26	878 – 885	51	982 – 982	76
-110 – -51	2	498 – 524	27	886 – 892	52	983 – 983	77
-50 – -28	3	525 – 550	28	893 – 899	53	984 – 985	78
-27 – -5	4	551 – 577	29	900 – 906	54	986 – 986	79
-4 – 16	5	578 – 601	30	907 – 912	55	987 – 987	80
17 – 36	6	602 – 623	31	913 – 917	56	988 – 988	81
37 – 55	7	624 – 645	32	918 – 922	57	989 – 989	82
56 – 74	8	646 – 666	33	923 – 927	58	990 – 990	83
75 – 94	9	667 – 688	34	928 – 932	59	991 – 991	84
95 – 113	10	689 – 707	35	933 – 937	60	992 – 992	85
114 – 133	11	708 – 722	36	938 – 940	61	993 – 994	86
134 – 153	12	723 – 737	37	941 – 944	62	995 – 995	87
154 – 173	13	738 – 752	38	945 – 947	63	996 – 996	88
174 – 193	14	753 – 767	39	948 – 951	64	997 – 998	89
194 – 216	15	768 – 780	40	952 – 954	65	999 – 999	90
217 – 240	16	781 – 791	41	955 – 958	66	1000 – 1002	91
241 – 265	17	792 – 802	42	959 – 961	67	1003 – 1004	92
266 – 289	18	803 – 813	43	962 – 965	68	1005 – 1006	93
290 – 314	19	814 – 824	44	966 – 968	69	1007 – 1009	94
315 – 339	20	825 – 834	45	969 – 971	70	1010 – 1012	95
340 – 366	21	835 – 843	46	972 – 973	71	1013 – 1016	96
367 – 392	22	844 – 852	47	974 – 975	72	1017 – 1020	97
393 – 418	23	853 – 861	48	976 – 977	73	1021 – 1032	98
419 – 444	24	862 – 869	49	978 – 979	74	1033 – 1043	99
445 – 471	25	870 – 877	50	980 – 981	75	1044 – 1192	100

Table 14. Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population

A. TransRisk Score

Characteristic	Memo Sample (number)	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
		Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
Race or ethnicity—SSA data															
Non-Hispanic white	148,568	54.0	55.0	28.7	7.8	8.5	8.7	9.9	10.1	10.0	9.7	10.6	12.7	12.0	100
Black	21,368	25.6	19.8	22.8	30.1	22.5	15.6	10.1	7.2	4.6	3.2	2.7	2.4	1.7	100
Hispanic	16,950	38.2	33.8	26.0	15.1	15.0	14.9	13.3	10.8	9.5	6.8	5.6	5.0	4.0	100
Asian	8,820	54.8	55.6	26.2	5.7	6.6	7.3	10.6	12.0	14.0	12.4	11.1	10.6	9.8	100
American Indian	409	57.6	60.6	28.8	5.6	8.5	7.7	9.2	9.7	9.1	8.6	11.8	14.7	15.1	100
Unknown race	36,352	52.7	56.0	26.1	6.6	7.6	9.5	8.9	10.7	11.8	16.6	13.2	7.5	7.6	100
Race or ethnicity—location-based distribution															
Non-Hispanic white	174,087	52.7	53.8	28.6	8.5	8.9	9.0	9.7	10.1	10.2	10.6	10.7	11.5	10.8	100
Black	23,946	37.6	31.2	28.1	19.3	16.2	13.3	10.4	9.0	7.6	7.0	6.5	5.6	5.1	100
Hispanic	23,632	43.1	39.8	27.9	13.4	12.6	12.7	11.7	10.5	9.6	8.8	7.7	6.9	6.2	100
Asian	9,016	52.1	53.0	28.1	8.3	8.7	8.9	10.4	10.7	11.2	11.1	10.4	10.3	10.2	100
American Indian	1,373	44.0	40.4	28.8	13.3	13.7	11.7	11.1	9.7	8.8	8.4	8.0	8.1	7.3	100
National origin															
Foreign-born	25,597	48.8	47.8	26.9	8.3	9.2	10.4	12.6	12.4	12.2	10.3	8.8	8.2	7.8	100
Recent immigrant	4,261	45.5	46.8	21.9	7.6	7.3	10.1	14.6	15.1	18.5	13.4	8.4	3.6	1.4	100
Sex															
Male	102,061	48.8	47.4	28.9	10.6	10.7	10.3	10.8	10.2	9.8	8.8	9.2	10.4	9.1	100
Female	105,347	50.4	50.0	29.8	10.8	10.2	9.5	9.8	9.8	9.3	8.9	9.5	11.2	11.1	100
Unknown	25,059	53.8	57.8	24.6	5.1	6.8	9.3	8.2	10.7	12.8	19.9	14.9	6.2	6.4	100
Marital status															
Married male	54,506	55.7	57.6	28.1	6.5	7.8	8.0	9.8	10.3	10.4	10.0	11.3	13.9	12.0	100
Single male	29,048	43.4	39.8	28.4	14.1	12.7	11.8	11.7	10.4	9.5	7.7	7.7	7.6	6.9	100
Married female	55,126	57.5	60.6	28.6	6.5	7.3	7.4	9.1	9.7	9.6	10.0	11.3	14.5	14.5	100
Single female	32,788	44.8	41.6	29.6	14.6	12.4	11.0	10.7	9.9	8.6	7.7	8.0	8.7	8.5	100
Unknown	60,999	44.4	43.8	27.2	12.4	12.1	12.0	10.1	10.1	10.6	12.5	9.7	5.6	5.1	100

Table continued on next page.

Table 14. Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population—Continued

A. TransRisk Score—Continued

Characteristic	MEMO	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
	Sample (number)	Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
Age—SSA data (years)															
Younger than 30	33,011	34.3	33.0	21.6	16.9	14.8	14.6	13.9	12.5	13.6	8.7	3.9	1.1	0.2	100
30 to 39	40,485	39.8	36.2	27.0	16.9	13.9	12.1	11.4	9.5	9.7	9.1	7.7	6.9	2.8	100
40 to 49	46,407	46.9	45.0	28.8	11.7	11.8	10.6	10.8	10.2	9.4	8.9	8.9	10.6	7.1	100
50 to 61	43,474	54.5	55.4	28.9	7.3	8.8	8.6	9.9	10.7	9.2	9.0	10.4	14.3	11.9	100
62 or older	44,075	68.1	76.8	26.5	2.9	4.3	4.9	6.5	7.6	6.8	8.6	14.4	18.5	25.6	100
Unknown	25,015	53.8	57.8	24.6	5.1	6.8	9.3	8.2	10.7	12.8	19.9	14.9	6.1	6.4	100
Census tract characteristics															
Income ratio															
Low	7,631	32.5	25.4	25.5	22.8	18.2	15.0	10.6	8.4	7.6	6.3	5.4	2.9	2.8	100
Moderate	41,902	40.7	36.0	28.2	16.1	14.2	13.0	11.0	9.6	8.6	8.1	7.2	6.3	6.0	100
Middle	119,984	50.4	50.2	28.8	9.7	10.0	9.9	10.1	10.1	9.9	10.1	10.1	10.5	9.7	100
High	62,426	57.9	60.6	27.2	5.4	6.5	6.9	9.2	10.5	11.0	11.8	12.2	13.7	13.0	100
Unknown	413	46.4	45.0	25.0	6.5	10.2	12.8	13.6	14.5	10.4	12.4	8.0	7.8	3.9	100
Minority population (percent)															
Less than 10	95,462	55.7	58.2	28.1	6.8	7.7	8.1	9.1	10.0	10.5	11.1	11.7	12.9	12.2	100
10-49	95,692	49.6	49.2	28.7	10.2	10.1	9.9	10.4	10.3	9.9	10.2	9.8	10.0	9.2	100
50-79	22,642	40.6	36.2	28.1	16.2	14.1	12.6	11.6	10.0	8.8	7.8	7.0	6.0	5.9	100
80 or more	18,258	34.6	28.4	26.1	20.2	17.2	14.9	11.2	9.3	8.0	6.6	5.3	3.8	3.4	100
Urban	193,939	50.2	50.2	28.9	10.1	10.0	9.7	10.2	10.1	10.0	10.1	10.0	10.3	9.8	100
Rural	38,132	49.4	49.2	29.0	10.4	10.6	10.5	9.5	10.0	9.5	9.9	9.9	10.5	9.2	100
All	232,467	50.1	50.0	28.9	10.1	10.1	9.8	10.1	10.1	9.9	10.0	10.0	10.3	9.7	100

Note. Scores are normalized to a scale of 0-100. Also, refer to notes to table 9.

Table 14. Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population

B. VantageScore

Characteristic	MEMO	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
	Sample (number)	Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
Race or ethnicity—SSA data															
Non-Hispanic white	148,568	54.5	56.6	28.7	7.5	8.3	9.0	9.6	9.3	9.4	10.3	11.7	12.5	12.2	100
Black	21,368	26.0	19.0	23.3	30.2	21.9	15.1	10.1	6.9	5.0	3.8	2.9	2.1	2.0	100
Hispanic	16,950	38.6	34.0	26.2	14.9	14.9	15.1	12.4	10.9	9.1	7.4	6.3	4.7	4.2	100
Asian	8,820	55.7	56.4	26.7	4.9	6.7	8.4	10.5	11.8	12.0	11.5	11.8	10.5	11.9	100
American Indian	409	58.2	63.0	27.7	5.7	6.2	9.0	8.2	8.9	9.5	10.4	13.9	15.2	13.1	100
Unknown race	36,352	49.3	50.8	25.4	8.1	8.3	8.4	10.6	13.4	15.4	14.4	8.5	6.9	6.0	100
Race or ethnicity—location-based distribution															
Non-Hispanic white	174,087	52.6	54.0	28.5	8.4	8.8	9.2	9.8	9.9	10.2	10.8	10.9	11.2	10.8	100
Black	23,946	37.3	31.6	27.9	19.8	15.9	12.8	10.5	9.1	8.4	7.2	6.2	5.4	4.8	100
Hispanic	23,632	42.8	39.8	27.8	13.5	12.9	12.5	11.4	10.8	9.9	8.6	7.6	6.6	6.2	100
Asian	9,016	52.4	53.0	28.5	8.3	8.6	9.2	10.1	10.8	11.0	10.7	9.9	9.5	12.0	100
American Indian	1,373	43.4	39.8	28.4	13.6	13.8	12.0	11.0	9.4	9.3	8.5	8.2	7.9	6.3	100
National origin															
Foreign-born	25,597	49.5	48.4	27.2	7.7	9.3	11.3	11.6	11.9	11.3	10.2	10.0	8.0	8.7	100
Recent immigrant	4,261	43.9	44.4	22.5	7.7	9.2	12.3	14.0	16.0	16.2	11.4	8.2	3.1	2.0	100
Sex															
Male	102,061	49.8	49.0	29.4	10.5	10.5	10.4	10.1	9.5	9.2	9.4	10.0	10.0	10.6	100
Female	105,347	50.6	50.6	29.4	10.3	10.1	10.0	9.8	9.2	8.9	9.5	10.6	11.2	10.3	100
Unknown	25,059	48.4	50.8	23.5	7.8	7.5	7.5	10.8	15.2	18.2	16.4	7.7	5.5	3.5	100
Marital status															
Married male	54,506	57.6	60.8	28.3	5.8	7.3	8.2	8.9	9.5	9.8	10.5	11.9	13.2	15.0	100
Single male	29,048	43.8	40.2	28.5	13.7	12.7	12.2	11.3	9.5	8.8	8.6	9.0	7.5	6.7	100
Married female	55,126	58.1	62.2	28.0	5.6	6.9	8.2	8.8	9.2	9.4	10.7	12.7	14.3	14.3	100
Single female	32,788	44.8	41.4	29.1	13.7	12.8	11.6	10.7	9.1	8.2	8.6	9.0	9.2	7.1	100
Unknown	60,999	41.6	41.0	26.2	14.5	12.5	11.0	11.2	11.8	12.3	11.1	6.9	5.1	3.7	100

Table continued on next page.

Table 14. Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population—Continued

B. VantageScore—Continued

Characteristic	MEMO Sample (number)	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
		Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
Age—SSA data (years)															
Younger than 30	33,011	31.1	28.8	21.1	19.6	16.9	15.6	15.5	11.8	9.5	6.8	3.1	1.0	0.2	100
30 to 39	40,485	40.5	36.8	27.4	15.7	14.1	12.7	11.0	10.0	9.3	8.8	8.1	5.8	4.5	100
40 to 49	46,407	49.0	47.8	29.4	10.8	11.0	10.9	10.0	9.6	9.1	9.4	9.6	9.1	10.7	100
50 to 61	43,474	57.1	60.0	29.0	6.3	7.8	8.6	9.2	9.2	9.1	9.9	11.5	12.2	16.3	100
62 or older	44,075	67.7	75.0	24.4	2.4	3.6	4.8	5.4	6.7	8.3	11.6	17.3	22.3	17.7	100
Unknown	25,015	48.4	50.8	23.5	7.8	7.5	7.5	10.8	15.2	18.2	16.4	7.7	5.5	3.5	100
Census tract characteristics															
Income ratio															
Low	7,631	30.7	24.4	25.0	25.7	18.5	13.0	10.4	9.8	7.6	5.8	4.5	2.7	2.1	100
Moderate	41,902	39.9	35.6	27.6	16.6	14.3	12.8	11.0	10.0	9.3	7.9	7.2	6.2	4.7	100
Middle	119,984	50.0	50.0	28.3	9.5	10.0	10.1	10.4	10.1	10.1	10.5	10.3	10.5	8.6	100
High	62,426	59.2	62.6	27.7	5.2	6.1	7.3	8.6	9.6	10.7	11.7	12.0	12.7	16.2	100
Unknown	413	43.1	40.6	23.2	7.3	10.7	12.4	18.4	17.2	10.4	8.5	8.0	4.6	2.7	100
Minority population (percent)															
Less than 10	95,462	55.6	58.4	27.9	6.7	7.6	8.2	9.3	9.8	10.3	11.5	12.1	12.9	11.7	100
10-49	95,692	49.8	49.6	28.8	10.0	10.0	10.2	10.3	10.1	10.2	10.1	9.7	9.4	10.0	100
50-79	22,642	40.4	36.5	27.9	16.1	14.2	12.8	10.9	10.3	9.1	8.1	6.9	6.0	5.6	100
80 or more	18,258	33.8	28.4	25.7	21.3	17.1	13.9	11.3	9.9	8.8	6.2	5.0	3.5	3.0	100
Urban	193,939	50.3	50.4	29.0	10.1	9.8	9.8	9.9	10.0	10.0	10.1	9.9	10.0	10.3	100
Rural	38,132	48.4	48.0	28.1	10.2	11.1	10.4	10.4	9.9	9.9	10.6	10.4	10.5	6.9	100
All	232,467	50.0	50.0	28.9	10.1	10.0	9.9	10.0	10.0	10.0	10.2	10.0	10.0	9.7	100

Note. Scores are normalized to a scale of 0-100. Also, refer to notes to table 9.

Table 14. Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population

C. FRB base score

Characteristic	MEMO Sample (number)	Score statistics: Mean	Median	Standard deviation	Sample population, grouped by characteristic and distributed by score decile (percent): 1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
Race or ethnicity—SSA data															
Non-Hispanic white	148,568	54.0	56.0	28.3	7.6	8.4	9.0	9.5	9.6	10.1	10.3	12.3	12.2	11.1	100
Black	21,368	25.8	18.6	22.9	30.3	22.6	15.2	9.9	6.9	4.9	3.4	2.7	2.2	2.0	100
Hispanic	16,950	38.3	34.0	26.3	15.5	14.7	14.7	13.2	10.9	9.4	6.9	5.4	4.6	4.7	100
Asian	8,820	54.8	55.2	25.9	5.1	6.1	8.1	10.5	12.4	15.2	13.0	10.0	8.3	11.3	100
American Indian	409	57.3	63.0	27.8	5.5	6.3	10.7	8.8	8.2	8.1	10.2	15.2	15.4	11.6	100
Unknown race	36,352	52.2	52.4	27.2	7.2	8.1	9.0	10.5	12.6	13.7	11.4	8.1	8.2	11.3	100
Race or ethnicity—location-based distribution															
Non-Hispanic white	174,087	52.6	54.0	28.4	8.4	8.8	9.3	9.6	9.9	10.6	10.3	11.3	11.0	10.7	100
Black	23,946	37.5	31.2	28.0	19.4	16.4	13.1	10.4	9.1	8.1	6.5	6.0	5.8	5.1	100
Hispanic	23,632	43.1	39.8	28.0	13.7	12.6	12.2	11.9	10.9	10.0	8.1	6.9	6.8	6.9	100
Asian	9,016	52.5	53.0	28.5	8.3	8.3	9.2	10.4	10.8	11.8	10.1	9.3	9.3	12.7	100
American Indian	1,373	44.0	40.6	28.7	13.5	13.3	12.2	10.7	9.8	8.6	8.3	8.5	8.0	7.1	100
National origin															
Foreign-born	25,597	48.7	48.0	26.6	8.2	8.9	10.6	12.5	12.8	13.1	10.2	8.3	7.1	8.4	100
Recent immigrant	4,261	44.3	46.2	20.9	8.0	7.0	9.1	14.8	18.7	21.5	12.4	4.4	2.0	2.1	100
Sex															
Male	102,061	49.1	48.4	28.9	10.5	10.8	10.4	10.2	9.8	9.9	9.4	9.8	9.8	9.6	100
Female	105,347	50.2	50.6	29.2	10.7	9.9	9.9	9.7	9.4	9.6	9.3	11.3	10.7	9.6	100
Unknown	25,059	53.0	53.4	26.4	6.2	7.3	8.4	10.5	13.6	15.2	12.5	7.2	7.6	11.6	100
Marital status															
Married male	54,506	56.3	59.0	28.1	6.2	7.6	8.7	9.1	9.4	10.1	10.6	12.1	13.1	13.1	100
Single male	29,048	43.5	40.6	28.0	13.5	12.9	11.9	11.3	10.1	9.8	8.8	8.1	7.2	6.3	100
Married female	55,126	57.6	61.8	28.1	6.0	7.0	8.3	8.9	8.8	9.7	10.2	13.7	13.9	13.6	100
Single female	32,788	44.4	42.4	28.5	14.1	12.2	11.2	10.3	9.9	9.4	8.7	9.7	8.5	5.9	100
Unknown	60,999	43.6	41.8	27.7	13.6	12.3	11.1	11.0	11.6	11.8	9.3	6.5	5.7	7.2	100

Table continued on next page.

Table 14. Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population—Continued

C. FRB base score

Characteristic	MEMO	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
	Sample (number)	Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
Age—SSA data (years)															
Younger than 30	33,011	33.2	34.0	21.0	18.6	14.5	12.4	14.3	15.6	14.8	6.9	1.8	0.6	0.6	100
30 to 39	40,485	40.8	36.8	28.0	16.1	14.4	12.5	10.4	9.3	9.5	9.7	7.1	4.6	6.4	100
40 to 49	46,407	48.2	46.2	29.6	11.2	11.7	11.3	10.1	9.2	8.9	9.0	9.2	8.0	11.5	100
50 to 61	43,474	55.4	57.6	28.9	6.9	8.3	9.6	9.7	8.8	8.9	9.9	11.8	11.7	14.4	100
62 or older	44,075	66.0	74.4	24.4	2.6	4.0	5.8	6.2	6.4	7.9	10.6	20.5	23.7	12.5	100
Unknown	25,015	52.9	53.4	26.4	6.2	7.3	8.4	10.5	13.6	15.2	12.5	7.2	7.6	11.7	100
Census tract characteristics															
Income ratio															
Low	7,631	31.5	25.0	25.1	24.7	18.2	13.6	10.7	9.3	8.4	5.2	4.2	3.2	2.5	100
Moderate	41,902	40.4	36.4	27.8	16.3	14.3	12.7	11.0	10.2	9.2	7.4	7.1	7.0	5.0	100
Middle	119,984	50.1	50.6	28.4	9.6	10.0	10.0	10.1	10.0	10.4	10.0	10.9	10.5	8.7	100
High	62,426	58.6	61.2	27.6	5.3	6.0	7.7	9.1	9.9	11.2	11.1	11.7	12.0	16.1	100
Unknown	413	45.6	44.4	24.2	6.3	9.7	12.4	14.8	17.4	11.6	9.2	9.0	4.8	4.8	100
Minority population (percent)															
Less than 10	95,462	55.5	58.4	27.7	6.6	7.7	8.4	9.0	9.7	10.8	11.0	13.1	12.5	11.2	100
10-49	95,692	49.8	49.4	28.8	10.1	9.9	10.2	10.3	10.2	10.5	9.6	9.3	9.5	10.4	100
50-79	22,642	40.6	36.2	28.2	16.3	14.0	12.7	11.4	10.2	9.2	7.5	6.2	6.3	6.3	100
80 or more	18,258	34.2	28.2	26.0	20.8	17.4	14.1	11.7	10.0	8.2	5.7	4.5	3.9	3.8	100
Urban	193,939	50.2	50.4	28.9	10.1	9.8	9.9	10.0	10.0	10.4	9.7	9.9	9.9	10.3	100
Rural	38,132	48.9	48.8	28.4	10.4	10.8	10.4	9.6	9.8	9.7	9.8	11.8	10.4	7.2	100
All	232,467	50.0	50.0	28.8	10.1	10.0	10.0	10.0	10.0	10.3	9.7	10.2	10.0	9.8	100

Note. Scores are normalized to a scale of 0-100 according to the nonlinear conversion shown in table 13. Also, refer to notes to table 9.

Table 15. Multivariate Estimates of TransRisk Score Differences, by Race, Sex, and Age

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean score (in regression sample)	54.0	25.6	38.2	54.8	
Deviation of mean score from that for non-Hispanic white					
Gross	0.0	-28.3	-15.7	0.9	
Net, after controls					
Age, sex, and marital status	0.0	-22.8	-9.6	6.8	
Above, plus tract income	0.0	-20.0	-7.8	6.4	
Above, plus estimated income	0.0	-18.7	-6.7	5.5	
Above, plus mean tract score	0.0	-13.4	-3.9	5.5	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean score (in regression sample)	52.3	36.6	42.4	51.7	
Deviation of mean score from that for non-Hispanic white					
Gross	0.0	-15.7	-9.9	-0.5	
Net, after controls					
Age, sex, and marital status	0.0	-13.0	-6.6	2.0	
Above, plus tract income	0.0	-9.3	-4.1	1.9	
Above, plus estimated income	0.0	-8.8	-3.6	0.9	
Above, plus mean tract score	0.0	-2.5	-0.2	1.0	
	C. Sex				
	Male	Female			
Mean score (in regression sample)	48.4	50.1			
Deviation of mean score from that for male					
Gross	0.0	1.6			
Net, after controls					
Age, race, and marital status	0.0	1.5			
Above, plus tract income	0.0	1.5			
Above, plus estimated income	0.0	1.5			
Above, plus mean tract score	0.0	1.5			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean score (in regression sample)	34.3	39.8	46.9	54.5	68.1
Deviation of mean score from that for 62 or older					
Gross	-33.9	-28.4	-21.2	-13.7	0.0
Net, after controls					
Race, sex, and marital status	-27.6	-24.0	-19.1	-12.8	0.0
Above, plus tract income	-27.3	-24.1	-19.4	-13.1	0.0
Above, plus estimated income	-27.2	-24.4	-19.8	-13.5	0.0
Above, plus mean tract score	-29.4	-25.8	-19.5	-12.3	0.0

1. For definitions, refer to notes to table 9.

Table 16. Changes in TransRisk Score, by Selected Characteristics of Sample Population, June 2003 to December 2004

Characteristic	2003 score	2004 score	2003 to 2004: Mean change in score	2003 to 2004: Percent of scores rising	Score change, by point range: Negative change of more than 30	-30 to -10	-10 to -5	-5 to 5	5 to 10	10 to 30	Positive change of more than 30	Percent of scores rising, by 2003 score decile: 1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Race or ethnicity—SSA data																					
Non-Hispanic white	54.1	54.3	0.2	50.9	2.3	14.3	10.2	42.9	12.7	16.1	1.6	72.8	57.4	56.7	57.5	56.0	56.4	53.6	48.8	41.5	23.0
Black	25.7	25.8	0.1	52.2	1.5	13.1	9.8	48.0	13.3	13.3	1.0	68.5	48.4	43.9	46.2	45.8	44.9	45.1	40.9	36.0	19.1
Hispanic	38.4	38.5	0.2	52.4	2.3	15.1	10.1	41.0	13.6	16.5	1.5	70.4	53.4	54.5	52.4	52.0	49.1	45.4	43.3	38.7	22.9
Asian	54.9	55.7	0.9	53.2	2.6	14.2	9.6	39.6	13.1	18.8	2.2	70.9	62.5	62.2	60.8	61.2	56.6	51.4	47.5	44.4	25.3
American Indian	57.7	58.1	0.4	51.5	2.8	12.1	10.1	44.5	12.8	15.7	2.1	77.4	64.9	63.8	60.5	58.4	58.5	55.9	49.3	43.1	21.7
Unknown race	52.8	52.3	-0.5	50.6	2.9	14.5	10.8	44.3	12.2	13.8	1.6	70.7	57.3	58.2	54.9	56.0	56.6	52.8	42.5	35.5	20.3
Race or ethnicity—location-based distribution																					
Non-Hispanic white	52.7	52.9	0.1	51.0	2.3	14.3	10.3	43.1	12.7	15.7	1.6	72.0	56.4	56.0	56.9	55.9	56.4	53.3	47.7	41.1	22.7
Black	37.7	37.7	0.0	51.5	2.0	13.9	9.9	45.8	12.8	14.2	1.3	68.8	51.1	49.4	50.2	50.9	51.0	48.9	45.0	38.5	21.6
Hispanic	43.2	43.3	0.1	51.9	2.4	14.4	9.9	42.7	13.0	15.9	1.6	70.4	54.2	54.5	53.0	53.5	52.0	50.0	44.4	38.5	22.8
Asian	52.2	52.5	0.3	51.8	2.5	14.2	10.0	42.4	12.5	16.7	1.8	71.4	57.7	58.1	58.3	57.5	55.6	51.9	45.8	41.9	24.2
American Indian	44.1	44.1	0.1	51.6	2.3	14.1	10.6	42.9	13.6	15.1	1.4	69.8	52.9	52.5	51.4	56.9	52.8	52.7	48.4	40.4	20.4
National origin																					
Foreign-born	48.9	49.6	0.6	53.1	2.5	14.6	9.8	40.2	12.8	18.1	2.1	71.6	58.5	58.6	58.3	56.5	54.4	50.7	46.9	42.9	24.4
Recent immigrant	45.6	46.4	0.8	54.6	2.3	16.1	10.0	36.2	13.7	19.8	1.8	69.0	54.5	57.8	56.8	58.2	56.1	49.6	41.5	41.2	31.0
Sex																					
Male	48.9	49.3	0.4	52.1	2.2	14.2	10.0	42.3	13.1	16.6	1.6	72.5	56.0	54.9	56.2	55.4	55.3	52.1	47.6	42.1	24.4
Female	50.5	50.5	0.0	50.4	2.3	14.3	10.1	44.0	12.6	15.2	1.5	69.9	54.0	54.1	55.3	54.7	55.0	53.0	48.8	40.6	22.1
Unknown	54.0	53.3	-0.7	50.6	3.1	14.5	11.2	44.9	11.9	12.9	1.6	70.3	58.5	59.8	55.2	56.8	57.5	52.9	40.6	32.2	17.2
Marital status																					
Married male	55.7	56.1	0.4	51.3	2.1	14.4	10.2	42.0	12.9	16.6	1.7	73.2	59.1	56.1	58.1	57.2	57.7	54.0	49.3	42.3	24.6
Single male	43.5	44.0	0.5	52.8	2.3	13.8	9.8	43.0	13.2	16.4	1.7	72.2	54.0	55.0	55.5	53.3	52.7	50.1	45.5	42.0	24.1
Married female	57.5	57.5	0.0	49.8	2.3	14.3	10.4	43.5	12.5	15.4	1.6	71.6	57.1	57.2	58.0	55.9	56.9	55.4	50.9	41.0	22.7
Single female	44.9	44.9	0.1	50.8	2.3	14.0	9.8	44.9	12.4	15.1	1.6	68.0	53.5	53.7	52.8	53.8	53.0	50.3	46.4	39.7	20.4
Unknown	44.0	43.9	-0.2	51.9	2.5	14.4	10.3	43.7	12.8	14.8	1.4	71.2	53.5	53.5	53.4	54.5	54.4	51.0	41.3	36.8	19.9
Age—SSA data (years)																					
Younger than 30	34.4	34.0	-0.4	51.8	2.3	16.8	10.2	39.2	13.7	16.9	0.8	69.1	48.1	49.5	52.9	51.9	49.6	40.3	33.7	31.7	14.5
30 to 39	40.0	40.7	0.7	54.5	2.0	14.2	10.1	40.8	13.8	17.6	1.5	71.0	54.8	53.6	55.8	54.6	55.9	50.1	46.3	37.9	24.7
40 to 49	47.1	47.4	0.4	52.4	2.1	14.9	10.3	40.9	13.5	16.6	1.7	72.6	56.2	54.2	55.9	54.3	55.5	52.9	46.9	39.7	23.8
50 to 61	54.7	55.1	0.4	51.6	2.2	14.0	10.5	42.4	12.8	16.3	1.8	71.4	59.2	58.2	57.7	56.3	58.0	56.2	51.5	41.6	24.1
62 or older	68.3	68.1	-0.2	46.2	2.6	11.7	9.2	51.5	10.8	12.5	1.8	74.2	61.9	62.2	57.3	59.0	58.3	60.1	50.7	43.6	22.3
Unknown	54.0	53.2	-0.7	50.5	3.1	14.5	11.2	44.9	11.9	12.9	1.6	70.3	58.5	59.7	55.2	56.8	57.5	52.9	40.6	32.0	17.2
Census tract characteristics																					
Income ratio																					
Low	32.5	32.4	-0.1	51.7	2.1	14.2	9.5	46.5	12.0	14.4	1.3	67.2	48.0	51.2	47.5	49.5	49.9	50.5	39.8	35.0	18.8
Moderate	40.8	40.8	0.0	51.7	2.3	13.9	9.9	44.7	12.9	15.0	1.3	70.3	53.1	52.2	51.5	52.3	51.1	48.7	44.7	38.3	22.2
Middle	50.4	50.5	0.1	51.0	2.3	14.3	10.2	43.4	12.8	15.5	1.6	71.8	56.3	54.5	55.4	54.8	55.3	52.4	47.4	40.3	21.6
High	57.9	58.2	0.3	51.3	2.4	14.3	10.5	42.0	12.7	16.4	1.8	72.3	57.8	60.4	61.0	58.4	58.4	55.1	48.2	42.4	24.6
Unknown	45.9	45.2	-0.7	51.0	3.3	18.0	9.0	39.7	13.1	15.1	1.8	75.0	60.5	56.9	52.7	60.0	52.4	28.2	22.6	45.2	46.7
Minority population (percent)																					
Less than 10	55.8	55.9	0.1	50.5	2.3	14.4	10.5	43.1	12.6	15.7	1.6	73.3	57.5	56.8	58.3	56.1	57.3	54.2	48.4	41.0	22.1
10-49	49.6	49.9	0.2	51.6	2.3	14.1	10.0	43.1	12.9	15.8	1.7	70.9	55.5	55.4	55.7	55.8	55.5	52.5	46.7	41.2	23.7
50-79	40.6	40.7	0.1	52.1	2.3	13.9	10.1	44.3	12.8	15.2	1.5	70.1	53.2	52.8	53.4	52.8	51.3	48.0	44.7	39.1	23.4
80 or more	34.5	34.5	-0.1	51.4	2.2	14.5	9.7	44.8	12.8	14.8	1.3	68.6	51.0	50.2	48.3	50.0	48.3	46.6	40.7	34.7	19.7
Urban	50.3	50.4	0.1	51.2	2.3	14.3	10.2	43.1	12.7	15.8	1.6	71.0	55.1	55.0	55.9	55.3	55.7	52.7	46.8	40.9	23.2
Rural	49.5	49.6	0.1	51.1	2.1	14.0	10.2	44.4	13.0	14.9	1.4	71.4	55.7	54.6	55.0	55.0	54.3	52.5	49.0	40.2	20.2
All	50.1	50.3	0.1	51.2	2.3	14.2	10.2	43.3	12.8	15.6	1.6	71.1	55.3	55.0	55.7	55.2	55.5	52.6	47.1	40.8	22.7

Note. Refer to note to table 14.A.

Table 17. Sample Size and Performance (Percent Bad) of Credit-Account Performance Measures, by Selected Characteristics of Sample Population, June 2003 to December 2004

Characteristic	Any account		New account		Existing account		Random account		Modified new account	
	Sample size (number)	Percent bad	Sample size (number)	Percent bad	Sample size (number)	Percent bad	Sample size (number)	Percent bad	Sample size (number)	Percent bad
Race or ethnicity—SSA data										
Non-Hispanic white	133,165	22.6	54,501	5.2	123,408	15.8	137,046	9.4	86,628	2.5
Black	18,274	65.9	6,144	21.7	13,965	54.1	17,151	33.4	9,430	10.5
Hispanic	14,702	42.0	6,050	10.7	12,682	31.9	14,965	18.4	10,194	4.7
Asian	7,906	18.2	3,551	4.8	7,505	13.1	8,138	7.7	6,062	2.3
American Indian	366	18.6	131	5.0	345	13.3	379	7.5	198	2.4
Unknown race	26,024	24.4	7,639	7.8	24,059	17.6	26,386	11.4	12,206	3.6
Race or ethnicity—location-based distribution										
Non-Hispanic white	151,230	24.5	59,991	5.9	139,183	17.3	154,983	10.4	95,853	2.8
Black	20,106	47.4	6,892	14.7	16,743	35.9	19,576	22.7	10,715	7.0
Hispanic	19,910	36.5	7,474	10.1	17,547	27.1	20,078	16.5	12,208	4.6
Asian	7,685	23.8	3,107	6.2	7,131	17.1	7,892	10.7	5,032	3.1
American Indian	1,169	35.4	439	10.4	1,037	26.3	1,180	16.8	718	4.7
National origin										
Foreign-born	22,597	26.3	9,620	5.9	20,804	19.2	23,362	10.9	16,281	2.7
Recent immigrant	3,762	24.8	1,697	5.2	3,490	18.2	3,871	11.0	3,104	2.3
Sex										
Male	90,374	28.6	35,643	7.0	81,619	20.1	91,772	12.4	56,835	3.4
Female	94,031	28.4	38,748	7.1	85,419	20.5	96,181	12.3	62,240	3.3
Unknown	16,032	22.5	3,624	8.9	14,926	16.3	16,112	11.2	5,644	4.0
Marital status										
Married male	49,311	20.2	20,625	4.4	46,327	14.3	51,321	8.1	32,824	2.1
Single male	25,386	35.4	9,359	9.8	22,242	25.3	25,292	16.1	15,099	4.5
Married female	50,015	19.5	21,936	4.4	47,240	14.2	52,425	7.8	35,469	2.1
Single female	28,921	35.7	11,117	10.0	25,545	26.4	29,132	16.1	17,747	4.6
Unknown	46,804	36.6	14,978	11.2	40,610	26.3	45,895	17.4	23,580	5.4
Age—SSA data (years)										
Younger than 30	29,178	43.9	12,455	12.5	24,487	32.6	28,458	21.5	18,871	6.3
30 to 39	35,648	38.4	16,188	8.3	31,001	28.3	35,858	17.6	27,443	4.0
40 to 49	41,171	30.4	19,013	6.3	37,106	21.8	42,466	12.7	31,689	2.8
50 to 61	39,226	22.3	16,589	4.5	36,605	15.8	40,939	8.5	26,637	2.0
62 or older	39,220	12.2	10,159	3.9	37,877	8.7	40,274	4.6	14,453	2.0
Unknown	15,994	22.5	3,611	8.9	14,888	16.4	16,070	11.3	5,626	4.1
Census tract characteristics										
Income ratio										
Low	6,248	55.5	1,881	19.6	4,934	42.8	5,791	28.7	2,768	8.9
Moderate	35,278	41.3	12,275	12.3	30,197	30.5	34,814	19.2	19,285	5.9
Middle	103,803	27.3	40,325	6.9	94,601	19.5	106,105	11.8	64,315	3.3
High	54,678	17.6	23,385	3.8	51,825	12.4	56,901	7.1	38,098	1.8
Unknown	337	27.9	112	8.0	325	24.3	357	13.8	193	3.1
Minority population (percent)										
Less than 10	83,817	20.7	33,595	4.5	78,139	14.4	86,301	8.5	53,414	2.2
10-49	82,210	28.1	32,415	7.4	74,692	20.2	83,866	12.3	52,161	3.5
50-79	19,051	41.3	6,972	12.2	16,454	31.0	18,979	19.4	11,090	5.9
80 or more	15,022	51.2	4,921	16.4	12,354	39.7	14,562	24.9	7,861	7.4
Urban	167,039	27.9	65,729	7.1	151,928	19.9	170,231	12.2	105,522	3.4
Rural	33,077	28.7	12,179	7.3	29,726	20.1	33,493	12.2	19,011	3.6
All	200,437	28.0	78,015	7.2	181,964	20.0	204,065	12.2	124,719	3.4

Table 18.A. Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Credit-Account Performance Measures and Selected Characteristics of Sample Population, June 2003 to December 2004

Characteristic	Any account	New account	Existing account	Random account	Modified new account
Race or ethnicity—SSA data					
Non-Hispanic white	-1.0	-0.6	-0.8	-0.6	-0.4
Black	5.6	3.4	4.7	2.9	2.6
Hispanic	1.7	0.8	1.2	0.3	0.1
Asian	-2.1	0.0	-1.5	-0.7	0.0
American Indian	-2.1	-0.7	-1.3	-1.3	-0.5
Unknown race	0.8	1.1	1.1	1.5	0.4
Race or ethnicity—location-based distribution					
Non-Hispanic white	-0.6	-0.4	-0.4	-0.4	-0.2
Black	3.4	2.3	2.8	2.1	1.6
Hispanic	1.2	0.8	0.9	0.7	0.3
Asian	-1.2	0.1	-0.8	-0.1	0.2
American Indian	0.3	1.2	0.1	0.8	0.1
National origin					
Foreign-born	-0.6	-0.3	-0.7	-0.7	-0.4
Recent immigrant	-1.2	-0.3	-1.0	0.2	-0.6
Sex					
Male	-0.3	0.0	-0.5	-0.1	0.0
Female	0.0	-0.2	0.2	-0.4	-0.1
Unknown	1.2	2.2	1.6	2.6	1.0
Marital status					
Married male	-1.2	-1.0	-1.0	-1.1	-0.7
Single male	0.4	0.9	0.1	0.7	0.5
Married female	-1.1	-1.0	-0.7	-1.2	-0.6
Single female	0.8	0.5	0.7	0.0	0.4
Unknown	1.7	1.8	1.5	2.2	1.1
Age—SSA data (years)					
Younger than 30	1.5	2.6	1.5	2.8	2.0
30 to 39	-0.2	-0.5	-0.2	0.0	-0.1
40 to 49	-0.4	-0.7	-0.6	-1.0	-0.5
50 to 61	-0.7	-1.1	-0.8	-1.5	-0.8
62 or older	-0.3	0.0	-0.1	-0.4	-0.1
Unknown	1.2	2.2	1.6	2.6	1.0
Census tract characteristics					
Income ratio					
Low	5.2	5.4	4.4	5.0	3.1
Moderate	2.0	1.4	1.4	1.3	1.0
Middle	-0.2	-0.2	-0.1	-0.2	-0.1
High	-1.5	-0.9	-1.0	-0.9	-0.6
Unknown	-1.0	2.8	1.8	1.6	0.6
Minority population (percent)					
Less than 10	-1.0	-0.9	-0.7	-0.6	-0.5
10-49	-0.2	0.1	-0.1	-0.1	0.0
50-79	1.8	1.5	1.3	1.1	1.2
80 or more	4.1	3.1	3.5	2.8	1.7
Urban	0.0	0.1	0.0	0.1	0.1
Rural	0.1	-0.6	-0.1	-0.3	-0.4
All	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**

Note. Refer to notes to table 9.

Table 18.B. Performance Residuals (Unexplained Percent Bad) for the VantageScore, by Credit-Account Performance Measures and Selected Characteristics of Sample Population, June 2003 to December 2004

Characteristic	Any account	New account	Existing account	Random account	Modified new account
Race or ethnicity—SSA data					
Non-Hispanic white	-0.7	-0.6	-0.6	-0.5	-0.3
Black	6.0	3.3	5.3	2.6	2.6
Hispanic	1.9	0.6	1.2	0.1	-0.1
Asian	-2.1	0.1	-1.6	-0.5	0.0
American Indian	-1.0	-0.3	-0.5	-0.6	-0.3
Unknown race	-0.8	0.8	-0.4	0.7	0.3
Race or ethnicity—location-based distribution					
Non-Hispanic white	-0.5	-0.4	-0.4	-0.3	-0.2
Black	3.4	2.3	2.8	1.8	1.6
Hispanic	1.1	0.7	0.7	0.5	0.2
Asian	-1.2	0.1	-0.9	-0.1	0.2
American Indian	-0.2	0.7	-0.3	0.4	-0.1
National origin					
Foreign-born	-0.4	-0.4	-0.7	-0.6	-0.4
Recent immigrant	-4.0	-1.2	-3.6	-1.4	-1.1
Sex					
Male	0.1	0.0	-0.2	0.0	0.0
Female	0.2	-0.2	0.3	-0.2	-0.1
Unknown	-1.7	1.5	-0.9	1.2	0.6
Marital status					
Married male	-0.2	-0.6	-0.2	-0.5	-0.5
Single male	0.7	0.9	0.1	0.6	0.5
Married female	-0.5	-0.7	-0.1	-0.7	-0.4
Single female	0.9	0.4	0.7	0.0	0.3
Unknown	-0.2	1.0	-0.2	0.9	0.7
Age—SSA data (years)					
Younger than 30	-3.3	0.5	-3.2	-0.5	1.0
30 to 39	0.3	-0.4	0.3	0.1	0.0
40 to 49	1.1	-0.2	0.7	-0.1	-0.3
50 to 61	1.0	-0.5	0.7	-0.4	-0.6
62 or older	0.7	0.5	0.9	0.3	0.2
Unknown	-1.7	1.5	-0.9	1.2	0.6
Census tract characteristics					
Income ratio					
Low	3.8	4.5	3.0	3.3	2.8
Moderate	1.7	1.2	1.1	1.0	0.9
Middle	-0.2	-0.2	-0.1	-0.2	-0.1
High	-1.1	-0.7	-0.7	-0.6	-0.5
Unknown	-2.1	2.2	0.8	1.1	0.2
Minority population (percent)					
Less than 10	-1.0	-0.9	-0.7	-0.6	-0.5
10-49	-0.1	0.2	-0.1	-0.1	0.1
50-79	2.0	1.5	1.4	1.1	1.1
80 or more	3.8	2.7	3.1	2.2	1.5
Urban	0.1	0.1	0.1	0.1	0.1
Rural	-0.2	-0.7	-0.3	-0.4	-0.5
All	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**

Note. Refer to notes to table 9.

Table 18.C. Performance Residuals (Unexplained Percent Bad) for the FRB Base Score, by Credit-Account Performance Measures and Selected Characteristics of Sample Population, June 2003 to December 2004

Characteristic	Any account	New account	Existing account	Random account	Modified new account
Race or ethnicity—SSA data					
Non-Hispanic white	-0.8	-0.6	-0.6	-0.5	-0.3
Black	4.7	3.2	4.0	2.6	2.7
Hispanic	1.4	0.6	0.8	-0.1	0.0
Asian	-1.6	0.1	-1.2	-0.4	0.0
American Indian	-1.6	-0.5	-0.8	-0.8	-0.5
Unknown race	0.4	1.0	0.6	1.3	0.4
Race or ethnicity—location-based distribution					
Non-Hispanic white	-0.5	-0.4	-0.4	-0.3	-0.2
Black	2.9	2.4	2.5	1.9	1.6
Hispanic	1.0	0.7	0.7	0.6	0.3
Asian	-0.9	0.1	-0.6	0.0	0.2
American Indian	0.1	1.0	0.0	0.7	0.1
National origin					
Foreign-born	-0.5	-0.4	-0.6	-0.7	-0.4
Recent immigrant	-1.3	-0.3	-1.2	-0.1	-0.6
Sex					
Male	-0.2	0.0	-0.4	-0.1	0.0
Female	0.1	-0.2	0.2	-0.3	0.0
Unknown	0.5	2.0	0.9	2.3	0.9
Marital status					
Married male	-0.9	-0.9	-0.8	-1.0	-0.7
Single male	0.6	1.0	0.3	0.9	0.6
Married female	-0.8	-0.9	-0.5	-1.1	-0.6
Single female	1.0	0.6	0.8	0.1	0.5
Unknown	0.9	1.6	0.8	1.7	1.0
Age—SSA data (years)					
Younger than 30	0.4	2.2	0.5	2.0	1.8
30 to 39	-0.2	-0.5	-0.2	0.0	0.0
40 to 49	-0.2	-0.6	-0.4	-0.9	-0.5
50 to 61	-0.3	-1.0	-0.4	-1.2	-0.8
62 or older	0.1	0.2	0.3	-0.1	0.0
Unknown	0.6	2.1	0.9	2.3	0.9
Census tract characteristics					
Income ratio					
Low	4.0	5.3	3.5	4.3	3.2
Moderate	1.8	1.4	1.3	1.3	1.0
Middle	-0.2	-0.2	-0.1	-0.2	-0.1
High	-1.2	-0.9	-0.9	-0.8	-0.6
Unknown	-1.5	2.4	1.2	1.5	0.5
Minority population (percent)					
Less than 10	-0.9	-0.8	-0.6	-0.6	-0.5
10-49	-0.1	0.1	-0.1	-0.1	0.1
50-79	1.6	1.4	1.2	1.1	1.2
80 or more	3.4	3.0	2.9	2.6	1.7
Urban	0.0	0.1	0.1	0.1	0.1
Rural	-0.1	-0.7	-0.3	-0.4	-0.5
All	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**

Note. Refer to notes to table 9.

Table 19.A. Any-Account Performance Measure—Multivariate Estimates of Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Race, Sex, and Age

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-1.0	5.6	1.7	-2.1	
Deviation of mean residual from that for non-Hispanic white					
Gross	0.0	6.6	2.7	-1.1	
Net, after controls					
Age, sex, and marital status	0.0	6.9	2.7	-1.5	
Above, plus tract income	0.0	6.3	2.3	-1.4	
Above, plus estimated income	0.0	6.0	2.0	-1.3	
Above, plus mean tract score	0.0	4.7	1.4	-1.2	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.6	3.3	0.9	-1.4	
Deviation of mean residual from that for non-Hispanic white tract					
Gross	0.0	3.9	1.6	-0.8	
Net, after controls					
Age, sex, and marital status	0.0	3.9	1.4	-1.0	
Above, plus tract income	0.0	3.0	0.8	-1.0	
Above, plus estimated income	0.0	2.9	0.7	-0.8	
Above, plus mean tract score	0.0	1.3	-0.1	-0.8	
	C. Sex				
	Male	Female			
Mean of performance residuals (in regression sample)	-1.3	0.0			
Deviation of mean residual from that for male					
Gross	0.0	1.3			
Net, after controls					
Age, race, and marital status	0.0	0.0			
Above, plus tract income	0.0	0.0			
Above, plus estimated income	0.0	0.0			
Above, plus mean tract score	0.0	0.0			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean of performance residuals (in regression sample)	1.5	-0.2	-0.4	-0.7	-0.3
Deviation of mean residual from that for 62 or older					
Gross	1.7	0.0	-0.1	-0.4	0.0
Net, after controls					
Race, sex, and marital status	1.3	-0.1	-0.1	-0.3	0.0
Above, plus tract income	1.3	0.0	0.0	-0.2	0.0
Above, plus estimated income	1.1	0.3	0.6	0.3	0.0
Above, plus mean tract score	1.2	0.2	0.5	0.2	0.0

1. For definitions, refer to notes to table 9.

Table 19.B. New-Account Performance Measure—Multivariate Estimates of Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Race, Sex, and Age

Measure	A. Race or ethnicity—SSA data[1]			
	Non-Hispanic white	Black	Hispanic	Asian
Mean of performance residuals (in regression sample)	-0.6	3.4	0.8	-0.1
Deviation of mean residual from that for non-Hispanic white				
Gross	0.0	4.0	1.5	0.5
Net, after controls				
Age, sex, and marital status	0.0	4.5	1.5	0.3
Above, plus tract income	0.0	3.8	0.9	0.3
Above, plus estimated income	0.0	3.3	0.6	0.4
Above, plus mean tract score	0.0	2.1	0.3	0.3

Measure	B. Race or ethnicity—location-based distribution[1]			
	Non-Hispanic white	Black	Hispanic	Asian
Mean of performance residuals (in regression sample)	-0.5	2.0	0.6	0.0
Deviation of mean residual from that for non-Hispanic white tract				
Gross	0.0	2.5	1.1	0.5
Net, after controls				
Age, sex, and marital status	0.0	2.6	1.0	0.3
Above, plus tract income	0.0	1.8	0.5	0.2
Above, plus estimated income	0.0	1.6	0.3	0.3
Above, plus mean tract score	0.0	0.9	0.0	0.3

Measure	C. Sex	
	Male	Female
Mean of performance residuals (in regression sample)	0.0	-0.2
Deviation of mean residual from that for male		
Gross	0.0	-0.2
Net, after controls		
Age, race, and marital status	0.0	-0.4
Above, plus tract income	0.0	-0.4
Above, plus estimated income	0.0	-0.4
Above, plus mean tract score	0.0	-0.4

Measure	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean of performance residuals (in regression sample)	2.6	-0.5	-0.7	-1.1	0.0
Deviation of mean residual from that for 62 or older					
Gross	2.6	-0.5	-0.8	-1.2	0.0
Net, after controls					
Race, sex, and marital status	2.1	-0.7	-0.7	-1.1	0.0
Above, plus tract income	2.1	-0.6	-0.6	-1.0	0.0
Above, plus estimated income	1.8	-0.3	0.0	-0.4	0.0
Above, plus mean tract score	1.8	-0.3	0.0	-0.5	0.0

1. For definitions, refer to notes to table 9.

Table 19.C. Existing-Account Performance Measure—Multivariate Estimates of Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Race, Sex, and Age

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.8	4.7	1.2	-1.6	
Deviation of mean residual from that for non-Hispanic white					
Gross	0.0	5.5	2.0	-0.8	
Net, after controls					
Age, sex, and marital status	0.0	6.0	2.1	-1.0	
Above, plus tract income	0.0	5.6	1.7	-1.0	
Above, plus estimated income	0.0	5.3	1.5	-0.9	
Above, plus mean tract score	0.0	4.3	1.1	-0.9	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.5	2.5	0.6	-1.0	
Deviation of mean residual from that for non-Hispanic white tract					
Gross	0.0	3.0	1.1	-0.5	
Net, after controls					
Age, sex, and marital status	0.0	3.1	1.1	-0.6	
Above, plus tract income	0.0	2.5	0.6	-0.7	
Above, plus estimated income	0.0	2.4	0.6	-0.5	
Above, plus mean tract score	0.0	1.3	0.0	-0.5	
	C. Sex				
	Male	Female			
Mean of performance residuals (in regression sample)	-0.5	0.1			
Deviation of mean residual from that for male					
Gross	0.0	0.6			
Net, after controls					
Age, race, and marital status	0.0	0.4			
Above, plus tract income	0.0	0.4			
Above, plus estimated income	0.0	0.4			
Above, plus mean tract score	0.0	0.4			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean of performance residuals (in regression sample)	1.5	-0.2	-0.6	-0.8	-0.1
Deviation of mean residual from that for 62 or older					
Gross	1.5	-0.2	-0.5	-0.7	0.0
Net, after controls					
Race, sex, and marital status	1.3	-0.2	-0.4	-0.6	0.0
Above, plus tract income	1.3	-0.2	-0.4	-0.6	0.0
Above, plus estimated income	1.1	0.2	0.2	-0.1	0.0
Above, plus mean tract score	1.1	0.1	0.1	-0.1	0.0

1. For definitions, refer to notes to table 9.

Table 19.D. Random-Account Performance Measure—Multivariate Estimates of Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Race, Sex, and Age

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.6	2.9	0.2	10.7	
Deviation of mean residual from that for non-Hispanic white					
Gross	0.0	3.5	0.8	-0.4	
Net, after controls					
Age, sex, and marital status	0.0	2.4	0.6	0.0	
Above, plus tract income	0.0	1.6	0.1	-0.1	
Above, plus estimated income	0.0	1.5	0.1	0.0	
Above, plus mean tract score	0.0	0.9	-0.2	0.0	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.5	1.7	-0.2	-0.3	
Deviation of mean residual from that for non-Hispanic white tract					
Gross	0.0	2.2	0.3	0.2	
Net, after controls					
Age, sex, and marital status	0.0	2.4	0.2	-0.1	
Above, plus tract income	0.0	1.6	-0.4	-0.2	
Above, plus estimated income	0.0	1.5	-0.4	-0.2	
Above, plus mean tract score	0.0	1.2	-0.5	-0.2	
	C. Sex				
	Male	Female			
Mean of performance residuals (in regression sample)	-0.1	-0.4			
Deviation of mean residual from that for male					
Gross	0.0	-0.3			
Net, after controls					
Age, race, and marital status	0.0	-0.4			
Above, plus tract income	0.0	-0.4			
Above, plus estimated income	0.0	-0.4			
Above, plus mean tract score	0.0	-0.5			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean of performance residuals (in regression sample)	2.8	-0.1	-1.0	-1.5	-0.4
Deviation of mean residual from that for 62 or older					
Gross	3.2	0.4	-0.6	-1.1	0.0
Net, after controls					
Race, sex, and marital status	2.8	0.3	-0.4	-1.0	0.0
Above, plus tract income	2.8	0.3	-0.4	-0.9	0.0
Above, plus estimated income	2.5	0.6	0.1	-0.4	0.0
Above, plus mean tract score	2.5	0.6	0.1	-0.5	0.0

1. For definitions, refer to notes to table 9.

Table 19.E. Modified New-Account Performance Measure—Multivariate Estimates of Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Race, Sex, and Age

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.3	2.6	0.1	-0.1	
Deviation of mean residual from that for non-Hispanic white					
Gross	0.0	3.0	0.5	0.3	
Net, after controls					
Age, sex, and marital status	0.0	3.3	0.4	0.1	
Above, plus tract income	0.0	2.9	0.1	0.0	
Above, plus estimated income	0.0	2.6	-0.1	0.1	
Above, plus mean tract score	0.0	2.1	-0.3	0.0	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.3	1.4	0.1	0.2	
Deviation of mean residual from that for non-Hispanic white tract					
Gross	0.0	1.7	0.4	0.5	
Net, after controls					
Age, sex, and marital status	0.0	1.8	0.3	0.4	
Above, plus tract income	0.0	1.2	-0.1	0.3	
Above, plus estimated income	0.0	1.1	-0.2	0.3	
Above, plus mean tract score	0.0	0.8	-0.4	0.3	
	C. Sex				
	Male	Female			
Mean of performance residuals (in regression sample)	0.0	0.0			
Deviation of mean residual from that for male					
Gross	0.0	0.1			
Net, after controls					
Age, race, and marital status	0.0	-0.2			
Above, plus tract income	0.0	-0.2			
Above, plus estimated income	0.0	-0.2			
Above, plus mean tract score	0.0	-0.2			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean of performance residuals (in regression sample)	2.0	-0.1	-0.5	-0.8	-0.1
Deviation of mean residual from that for 62 or older					
Gross	2.1	0.0	-0.4	-0.7	0.0
Net, after controls					
Race, sex, and marital status	1.8	-0.1	-0.4	-0.7	0.0
Above, plus tract income	1.8	0.0	-0.4	-0.7	0.0
Above, plus estimated income	1.5	0.2	0.1	-0.3	0.0
Above, plus mean tract score	1.5	0.2	0.0	-0.3	0.0

1. For definitions, refer to notes to table 9.

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Table 20. Characteristics of New Loans for Borrowers in Selected Quintiles of TransRisk Score Distribution, and Distribution of Loans, by Selected Characteristics of Sample Population and Type of Loan, July-December 2003

A. Lowest quintile

Characteristic	Percent with loans	Estimated denial rate	Mortgage			Automobile loan					
						From bank			From finance company		
			Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad
Race or ethnicity—SSA data											
Non-Hispanic white	18.7	40.2	11.4	9.3	3.9	6.3	10.7	4.3	10.7	16.4	6.4
Black	17.9	44.9	7.9	9.4	4.8	3.7	14.1	4.6	11.4	17.6	11.2
Hispanic	17.9	43.4	8.2	9.6	1.9	3.9	11.1	10.8	9.1	16.4	8.6
Asian	19.1	41.9	10.2	9.0	3.6	4.7	10.9	7.5	7.6	15.3	4.9
American Indian	21.4	38.0	7.5	9.2	7.2	4.8	11.6	2.8	5.2	15.2	7.1
Unknown race	13.6	36.3	9.0	8.8	3.2	5.8	12.3	8.2	9.8	16.0	6.8
Race or ethnicity—location-based distribution											
Non-Hispanic white	18.6	40.4	10.5	9.3	4.0	5.9	11.0	4.5	10.6	16.6	6.9
Black	16.5	43.8	8.7	9.4	3.7	3.8	13.2	5.1	10.6	17.1	9.8
Hispanic	16.8	41.9	8.9	9.3	3.7	4.3	12.6	9.0	9.7	16.3	10.7
Asian	16.5	42.3	11.0	9.0	2.7	4.9	11.9	11.0	10.5	16.2	7.1
American Indian	18.4	39.0	5.5	9.6	3.9	5.3	11.7	23.7	11.5	16.9	7.0
National origin											
Foreign-born	16.7	45.3	11.0	9.4	2.4	5.5	10.4	4.9	7.7	15.0	3.5
Recent immigrant	14.5	45.8	6.6	9.8	0.0	6.6	13.7	0.0	5.9	12.6	11.1
Sex											
Male	17.4	41.5	11.2	9.3	4.5	6.5	11.4	4.2	10.8	16.8	8.0
Female	19.4	42.2	8.9	9.3	3.2	4.2	11.4	7.2	10.3	16.5	7.9
Unknown	9.9	33.1	10.7	9.0	2.2	6.0	12.2	3.9	8.8	15.6	5.3
Marital status											
Married male	21.0	40.1	14.0	9.5	3.3	7.5	11.5	1.7	10.4	16.2	4.4
Single male	16.0	43.1	8.7	9.3	5.6	5.4	10.7	7.1	10.9	17.2	10.0
Married female	23.2	40.0	11.1	9.3	3.5	4.4	11.5	4.3	11.6	16.3	7.3
Single female	18.1	43.2	7.2	9.6	1.8	3.5	11.9	10.0	9.7	16.4	6.3
Unknown	14.4	40.5	8.7	8.9	5.1	5.7	11.7	6.7	10.0	17.2	10.9
Age—SSA data (years)											
Younger than 30	14.9	45.5	5.8	8.9	7.8	6.7	11.5	10.2	11.6	17.8	14.8
30 to 39	19.1	43.1	10.5	9.2	3.8	5.3	11.5	3.8	11.4	16.5	7.0
40 to 49	20.1	41.1	11.5	9.4	3.8	5.0	11.4	3.1	10.3	16.3	6.0
50 to 61	20.7	38.6	11.8	9.6	3.2	4.6	11.4	5.1	9.5	15.9	3.0
62 or older	16.7	34.5	7.8	9.1	0.0	4.5	11.2	5.6	7.6	17.2	11.5
Unknown	9.9	33.0	10.7	9.0	2.2	6.0	12.2	3.9	8.8	15.6	5.3
Census tract characteristics											
Income ratio											
Low	12.1	46.2	6.7	8.8	5.9	3.3	15.6	17.7	9.0	17.7	17.4
Moderate	16.9	41.7	8.5	9.6	3.0	4.2	12.8	4.6	10.6	17.1	9.6
Middle	18.4	40.5	10.1	9.4	4.4	5.7	11.1	6.2	10.2	16.7	7.6
High	20.2	41.0	12.4	8.8	3.0	6.2	10.7	2.3	11.6	15.6	4.5
Unknown	5.8	40.6	0.0	n.a.	n.a.	40.0	10.5	0.0	20.0	17.1	0.0
Minority population (percent)											
Less than 10	18.9	40.6	11.4	9.3	3.7	7.1	10.5	3.0	10.3	16.9	5.6
10-49	18.4	39.9	9.7	9.3	3.7	5.0	11.4	6.1	10.8	16.4	7.9
50-79	17.4	42.8	8.8	9.6	5.3	3.3	14.4	7.0	11.1	17.2	8.9
80 or more	15.0	44.9	8.7	9.1	3.1	4.2	13.1	11.3	9.3	16.2	12.3
Urban	17.5	42.2	10.8	9.3	4.0	5.3	11.5	5.2	11.0	16.5	7.6
Rural	19.8	37.0	6.6	9.7	3.1	5.3	11.3	6.2	8.5	17.2	9.2
All	17.9	41.3	10.0	9.3	3.8	5.3	11.5	5.4	10.5	16.6	7.9

Table continued on next page.

Note. For definitions of characteristics, refer to notes to table 9.

n.a. Not available

Table 20. Characteristics of New Loans for Borrowers in Selected Quintiles of TransRisk Score Distribution, and Distribution of Loans, by Selected Characteristics of Sample Population and Type of Loan, July-December 2003—Continued

A. Lowest quintile—Continued

Characteristic	Installment loan						Credit card loan				Other loans	
	From bank			From finance company			From bank		From finance company			
	Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad	Percent of loans	Percent bad	Percent of loans	Percent bad	Percent of loans	Percent bad
Race or ethnicity—SSA data												
Non-Hispanic white	7.6	11.4	6.2	18.2	19.1	13.3	33.5	22.1	1.4	8.7	11.0	20.8
Black	5.7	14.6	6.0	28.2	20.5	14.8	31.0	35.5	1.4	27.6	10.7	29.4
Hispanic	3.7	12.4	3.9	32.4	22.5	17.6	28.3	20.2	2.7	19.7	11.6	14.8
Asian	5.0	9.8	7.1	10.9	19.9	25.9	45.5	17.5	2.6	2.0	13.6	11.2
American Indian	6.8	10.4	3.8	26.0	17.6	8.8	32.9	28.6	1.1	4.9	15.7	11.1
Unknown race	6.0	13.0	7.9	19.9	19.3	17.1	35.0	26.8	0.9	0.0	13.7	17.9
Race or ethnicity—location-based distribution												
Non-Hispanic white	7.2	11.8	5.9	20.5	19.8	14.4	32.8	23.8	1.4	11.9	11.1	20.0
Black	5.6	13.4	7.1	25.7	19.9	14.9	33.0	31.8	1.4	17.3	11.3	29.4
Hispanic	4.7	12.9	6.3	27.3	21.0	17.0	30.8	23.5	2.3	21.8	12.0	17.6
Asian	4.7	12.6	5.8	14.1	19.2	15.7	39.7	25.8	2.4	6.8	12.6	22.2
American Indian	7.0	15.4	4.8	36.3	18.9	12.6	25.3	31.1	1.6	7.2	7.5	26.4
National origin												
Foreign-born	2.7	11.0	3.3	16.6	19.2	17.3	39.8	14.9	3.1	14.7	13.7	11.1
Recent immigrant	2.0	10.0	0.0	19.1	15.8	10.3	38.2	8.6	4.6	0.0	17.1	0.0
Sex												
Male	7.2	11.4	6.2	21.0	19.6	16.4	33.7	24.5	1.4	18.0	8.3	14.3
Female	5.9	13.1	5.9	23.7	20.3	13.6	31.8	25.7	1.7	12.0	13.5	25.2
Unknown	6.0	8.7	7.7	16.7	19.0	15.3	33.6	28.3	0.7	0.0	17.4	22.7
Marital status												
Married male	5.9	10.8	5.0	20.3	19.9	13.0	31.7	22.9	1.1	16.0	9.1	16.1
Single male	8.2	11.4	5.3	22.0	18.6	15.2	35.7	25.5	1.9	22.9	7.2	9.9
Married female	5.9	12.9	3.9	21.6	21.7	10.8	30.4	22.3	1.9	14.3	13.1	24.6
Single female	6.0	13.7	7.3	23.7	19.2	14.7	34.0	27.6	1.3	10.3	14.8	23.8
Unknown	6.9	12.1	8.4	23.2	19.7	19.2	32.7	27.1	1.6	9.8	11.3	23.6
Age—SSA data (years)												
Younger than 30	6.8	12.4	6.0	24.6	16.7	21.7	31.4	30.4	2.1	17.0	11.1	24.4
30 to 39	6.1	11.7	6.1	21.8	18.5	17.9	32.5	27.2	1.8	14.5	10.7	22.0
40 to 49	7.1	11.9	5.7	20.6	21.5	10.4	33.3	25.0	1.4	15.6	10.8	18.7
50 to 61	6.4	13.0	6.6	21.7	21.7	9.8	33.1	19.7	1.2	11.5	11.6	19.6
62 or older	6.1	13.2	6.1	28.0	24.0	11.6	33.1	16.9	0.8	0.0	12.2	24.5
Unknown	6.0	8.7	7.7	16.7	19.0	15.3	33.6	28.3	0.7	0.0	17.4	22.7
Census tract characteristics												
Income ratio												
Low	4.9	14.0	4.0	24.5	17.9	22.4	38.4	30.6	2.9	26.7	10.2	36.5
Moderate	5.5	13.1	8.1	25.7	20.4	16.9	32.4	29.0	1.7	20.8	11.6	27.5
Middle	7.4	11.8	5.7	22.7	20.3	13.8	31.9	23.7	1.4	12.6	10.6	19.3
High	5.8	12.2	5.7	15.0	18.5	11.6	34.2	22.7	1.6	2.9	13.2	15.7
Unknown	0.0	n.a.	n.a.	0.0	n.a.	n.a.	20.0	0.0	0.0	n.a.	20.0	100.0
Minority population (percent)												
Less than 10	8.8	11.9	6.3	17.2	18.8	12.7	33.2	20.8	1.2	8.5	10.8	18.0
10-49	6.0	11.5	5.4	23.2	20.6	15.0	32.8	25.5	1.5	13.8	11.1	22.0
50-79	4.7	14.6	7.4	27.1	18.9	16.7	32.2	30.6	1.7	10.0	11.1	25.5
80 or more	4.6	13.8	7.4	25.9	20.8	16.1	32.0	29.2	2.2	28.1	13.3	22.2
Urban	5.4	12.3	5.5	19.0	19.6	16.0	34.7	25.1	1.7	15.0	12.2	21.4
Rural	11.2	11.9	7.3	35.1	21.0	12.5	24.6	25.5	0.9	9.1	7.8	21.1
All	6.5	12.2	6.1	22.2	19.9	14.9	32.7	25.2	1.5	14.3	11.3	21.4

Table 20. Characteristics of New Loans for Borrowers in Selected Quintiles of TransRisk Score Distribution, and Distribution of Loans, by Selected Characteristics of Sample Population and Type of Loan, July-December 2003

B. Second-lowest quintile

Characteristic	Percent with loans	Estimated denial rate	Mortgage			Automobile loan					
						From bank			From finance company		
			Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad
Race or ethnicity—SSA data											
Non-Hispanic white	42.0	19.4	16.4	8.3	1.4	8.7	7.6	1.5	4.2	12.2	2.3
Black	36.8	23.9	12.9	8.7	3.0	6.1	8.7	2.3	4.9	13.8	10.2
Hispanic	42.6	22.8	12.4	8.5	1.4	6.0	8.2	1.4	4.2	11.6	2.1
Asian	44.8	19.1	16.7	7.9	2.8	6.1	6.8	1.3	2.7	10.5	2.9
American Indian	36.5	16.1	14.3	8.2	0.4	7.8	7.1	0.2	5.8	8.8	1.2
Unknown race	27.2	16.3	15.0	8.4	2.2	7.0	8.1	2.4	4.7	13.0	2.1
Race or ethnicity—location-based distribution											
Non-Hispanic white	40.2	19.5	15.9	8.3	1.5	8.3	7.7	1.5	4.2	12.3	2.7
Black	35.4	21.4	13.7	8.7	2.9	6.3	8.4	2.3	4.7	13.3	6.2
Hispanic	38.4	20.3	13.8	8.4	2.0	6.4	7.8	1.8	4.3	12.0	3.5
Asian	40.3	19.4	16.9	8.0	1.1	6.8	7.3	1.3	4.0	11.8	3.7
American Indian	39.6	19.8	11.0	8.4	1.5	9.0	8.2	1.3	5.0	12.6	3.3
National origin											
Foreign-born	43.7	21.4	15.0	8.3	1.7	6.4	7.6	0.7	3.9	10.6	1.7
Recent immigrant	47.8	20.7	12.9	8.3	0.0	4.7	7.9	0.0	4.2	11.1	0.0
Sex											
Male	40.4	21.3	16.6	8.3	2.0	9.1	7.8	1.5	5.0	12.0	3.1
Female	42.3	19.5	14.3	8.4	1.2	6.7	7.7	1.6	3.6	12.7	3.4
Unknown	20.5	13.8	14.9	8.4	2.3	6.8	8.6	3.0	4.4	13.4	4.7
Marital status											
Married male	44.3	19.9	19.3	8.3	1.1	9.6	7.5	1.6	5.8	11.9	1.4
Single male	38.1	22.2	15.3	8.3	2.6	8.2	8.1	1.6	4.0	12.2	3.9
Married female	46.0	17.6	17.0	8.4	1.3	7.8	7.4	0.9	3.6	12.0	1.6
Single female	40.0	20.8	12.4	8.2	1.0	5.1	8.1	2.3	3.6	13.6	5.5
Unknown	31.7	19.5	12.1	8.4	2.9	7.6	8.2	2.0	4.2	12.6	5.6
Age—SSA data (years)											
Younger than 30	40.3	24.2	9.4	8.5	3.1	8.5	7.9	2.5	4.1	12.4	6.4
30 to 39	45.1	21.4	17.4	8.3	2.0	7.8	7.6	2.0	4.7	11.5	2.3
40 to 49	44.9	19.8	18.6	8.4	1.1	7.9	7.7	0.7	4.4	13.0	3.5
50 to 61	41.9	18.9	16.8	8.2	1.3	7.6	7.8	1.2	3.9	11.9	1.8
62 or older	28.7	15.4	12.3	8.0	1.1	6.5	7.9	0.7	3.8	13.4	0.0
Unknown	20.4	13.8	14.9	8.4	2.3	6.8	8.6	3.0	4.4	13.4	4.7
Census tract characteristics											
Income ratio											
Low	30.0	22.6	11.1	8.7	0.9	4.3	9.3	2.3	3.6	13.6	2.8
Moderate	35.4	21.0	13.0	8.6	3.2	6.8	8.0	2.9	4.2	12.3	2.7
Middle	40.4	19.4	14.9	8.4	1.5	8.4	7.9	1.4	4.2	12.9	3.9
High	42.9	19.2	19.2	8.0	1.1	7.8	7.2	1.2	4.6	11.1	2.6
Unknown	33.0	12.8	16.1	8.2	10.0	12.9	8.4	0.0	4.8	14.4	0.0
Minority population (percent)											
Less than 10	41.0	19.6	15.8	8.3	1.3	9.1	7.7	1.1	3.7	12.7	1.2
10-49	39.8	19.3	16.3	8.3	1.7	7.7	7.7	1.9	4.7	12.0	3.6
50-79	37.6	20.7	14.1	8.3	1.8	5.9	8.2	2.4	4.5	12.3	6.2
80 or more	34.5	21.7	11.7	8.7	3.2	5.2	8.2	2.0	4.1	13.2	5.0
Urban	39.5	20.3	16.3	8.4	1.6	7.6	7.7	1.7	4.3	12.2	3.3
Rural	38.8	17.7	10.8	8.2	2.6	9.0	8.2	1.1	4.0	13.3	3.5
All	39.4	19.8	15.4	8.3	1.7	7.8	7.8	1.6	4.3	12.4	3.3

Table continued on next page.

Note. For definitions of characteristics, refer to notes to table 9.

n.a. Not available

Table 20. Characteristics of New Loans for Borrowers in Selected Quintiles of TransRisk Score Distribution, and Distribution of Loans, by Selected Characteristics of Sample Population and Type of Loan, July-December 2003—Continued

B. Second-lowest quintile—Continued

Characteristic	Installment loan						Credit card loan				Other loans	
	From bank			From finance company			From bank		From finance company			
	Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad	Percent of loans	Percent bad	Percent of loans	Percent bad	Percent of loans	Percent bad
Race or ethnicity—SSA data												
Non-Hispanic white	6.4	10.4	1.8	8.9	19.7	6.1	29.2	7.2	2.4	5.4	23.8	3.9
Black	5.6	12.8	4.5	17.9	22.0	7.5	25.3	13.9	1.6	8.6	25.7	10.2
Hispanic	4.4	12.4	3.4	12.6	22.7	6.9	27.6	7.6	2.7	1.0	30.0	5.8
Asian	2.7	10.6	9.0	4.7	19.6	3.7	37.9	5.4	2.4	6.4	26.7	7.2
American Indian	9.4	10.9	0.9	12.2	21.0	3.8	26.7	4.0	2.5	1.0	21.2	2.6
Unknown race	6.2	10.1	2.7	10.6	20.0	8.7	30.5	7.8	2.1	6.4	24.0	5.2
Race or ethnicity—location-based distribution												
Non-Hispanic white	6.3	10.6	2.2	9.4	20.0	6.5	29.0	7.3	2.3	4.4	24.6	4.5
Black	5.7	11.4	3.1	14.6	21.6	6.9	27.7	11.7	1.9	10.4	25.5	8.4
Hispanic	4.4	11.5	3.8	12.9	21.8	7.0	29.8	8.3	2.7	5.4	25.7	5.5
Asian	4.0	11.3	4.3	7.0	19.6	7.9	32.3	8.0	2.3	6.2	26.8	5.8
American Indian	8.6	11.7	1.8	15.6	21.8	7.8	26.9	6.6	1.8	4.2	22.2	6.0
National origin												
Foreign-born	3.2	11.1	4.0	7.5	20.2	7.2	32.9	6.0	2.5	3.4	28.7	5.0
Recent immigrant	2.4	11.3	4.2	6.7	21.1	9.1	36.5	4.4	3.4	2.9	29.2	6.2
Sex												
Male	6.9	11.1	2.6	10.1	20.7	7.1	29.8	7.9	1.8	8.3	20.7	5.5
Female	5.0	10.5	2.4	10.5	20.5	6.0	28.2	7.7	2.8	3.1	28.9	5.0
Unknown	5.5	9.7	2.5	11.6	18.4	9.4	30.0	9.3	1.8	7.4	25.0	4.4
Marital status												
Married male	6.9	10.9	1.6	9.8	20.3	6.3	27.3	5.9	1.6	6.7	19.7	3.8
Single male	6.2	11.1	2.5	9.7	21.1	6.2	32.4	9.7	1.9	10.3	22.4	7.3
Married female	5.1	10.3	2.2	9.0	20.5	5.9	26.3	5.9	3.1	2.8	28.1	3.4
Single female	4.5	10.6	3.0	11.1	20.1	6.4	29.9	8.7	2.6	3.8	30.7	6.1
Unknown	6.6	10.9	3.4	12.1	20.6	8.1	30.9	9.6	2.2	5.6	24.3	6.2
Age—SSA data (years)												
Younger than 30	6.1	11.1	4.8	9.6	18.9	10.7	32.5	10.4	1.6	5.6	28.3	8.0
30 to 39	5.9	10.7	2.3	9.3	19.3	6.5	27.6	8.1	2.3	6.3	24.9	5.4
40 to 49	5.2	10.6	1.5	9.8	21.1	5.1	27.9	7.1	2.6	4.6	23.6	3.9
50 to 61	6.5	11.3	1.9	10.9	21.4	4.6	27.5	5.5	2.7	3.2	24.1	3.3
62 or older	6.7	10.1	1.3	15.9	22.9	5.7	31.6	6.6	2.3	7.6	21.1	4.1
Unknown	5.5	9.7	2.5	11.6	18.4	9.4	29.9	9.4	1.9	7.4	25.1	4.4
Census tract characteristics												
Income ratio												
Low	4.9	11.3	0.0	11.6	21.5	7.0	34.4	13.7	1.9	15.8	28.1	8.2
Moderate	5.9	11.4	3.6	13.4	21.2	7.3	29.7	9.2	2.3	5.6	24.8	6.8
Middle	6.5	10.7	2.4	10.6	20.4	6.3	29.2	8.0	2.2	4.7	24.0	5.4
High	4.7	10.2	2.0	7.1	19.8	7.0	27.5	5.3	2.6	4.6	26.5	2.9
Unknown	11.3	10.7	0.0	11.3	21.1	0.0	16.1	10.0	1.6	0.0	25.8	18.8
Minority population (percent)												
Less than 10	7.2	10.1	2.1	8.8	19.5	5.7	28.8	6.5	2.1	2.9	24.5	3.6
10-49	5.4	11.2	2.6	10.0	20.3	7.0	29.0	7.6	2.4	5.1	24.6	5.3
50-79	4.5	11.9	2.5	13.4	21.4	7.7	30.1	10.6	2.7	8.4	24.9	6.8
80 or more	4.8	11.2	4.3	14.6	22.9	7.1	29.8	10.9	2.2	9.4	27.5	8.1
Urban	4.8	10.9	3.1	9.2	20.6	7.1	29.7	8.0	2.5	5.1	25.6	5.0
Rural	11.6	10.5	1.2	16.5	20.3	5.6	25.7	7.1	1.3	5.9	21.1	5.7
All	5.9	10.8	2.5	10.4	20.5	6.7	29.1	7.9	2.3	5.2	24.9	5.2

Table 20. Characteristics of New Loans for Borrowers in Selected Quintiles of TransRisk Score Distribution, and Distribution of Loans, by Selected Characteristics of Sample Population and Type of Loan, July-December 2003

C. Top three quintiles

Characteristic	Percent with loans	Estimated denial rate	Mortgage			Automobile loan: From bank			Automobile loan: From finance company		
			Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad
Race or ethnicity—SSA data											
Non-Hispanic white	39.1	8.0	20.8	7.6	0.1	8.7	5.7	0.3	2.5	6.9	0.7
Black	39.0	11.4	17.3	8.4	0.2	7.1	6.6	1.4	2.2	7.9	0.0
Hispanic	43.3	10.4	18.7	7.8	0.3	7.7	6.4	0.5	2.4	9.2	1.6
Asian	42.2	9.9	20.9	7.0	0.2	6.5	5.6	0.4	1.7	6.9	0.0
American Indian	32.8	6.6	20.3	7.6	0.3	10.9	6.1	0.1	3.2	7.0	0.1
Unknown race	20.5	6.4	18.5	7.6	0.1	7.3	6.2	0.5	2.4	7.2	1.0
Race or ethnicity—location-based distribution											
Non-Hispanic white	36.5	7.9	20.4	7.6	0.1	8.5	5.8	0.3	2.5	7.0	0.7
Black	33.5	8.7	19.0	8.0	0.4	7.5	6.1	0.6	2.4	7.2	1.2
Hispanic	35.1	8.6	19.1	7.6	0.1	7.4	5.9	0.4	2.4	8.1	0.7
Asian	36.9	8.3	23.0	7.1	0.1	6.6	5.6	0.4	2.5	7.4	0.8
American Indian	35.8	7.8	18.7	7.6	0.2	10.0	6.2	2.8	2.6	7.6	0.7
National origin											
Foreign-born	41.1	10.1	20.5	7.4	0.5	6.4	6.0	0.3	2.3	8.0	1.3
Recent immigrant	43.0	10.8	16.1	7.4	0.3	6.1	6.0	0.0	2.1	8.7	0.0
Sex											
Male	38.8	9.3	22.6	7.6	0.1	10.1	5.8	0.4	3.1	7.1	0.7
Female	40.2	7.5	18.5	7.6	0.2	6.8	5.7	0.3	1.8	7.1	0.7
Unknown	13.4	5.3	17.7	7.6	0.2	6.9	6.3	0.8	2.6	7.6	1.0
Marital status											
Married male	39.6	8.6	23.2	7.6	0.1	10.7	5.6	0.2	3.2	7.1	0.3
Single male	36.8	10.2	22.6	7.6	0.2	8.5	6.0	0.8	2.9	7.2	1.6
Married female	41.5	7.0	19.5	7.6	0.1	7.2	5.6	0.2	1.9	6.9	0.4
Single female	37.5	8.3	16.7	7.6	0.4	5.9	6.0	0.2	1.8	8.0	0.5
Unknown	25.1	7.3	18.2	7.5	0.3	8.0	6.2	0.9	2.4	7.4	1.6
Age—SSA data (years)											
Younger than 30	46.2	12.2	12.0	7.8	0.1	8.6	6.4	0.7	2.2	8.2	2.3
30 to 39	51.6	10.1	25.1	7.7	0.3	8.3	5.6	0.4	2.6	6.8	0.2
40 to 49	48.6	9.4	23.7	7.7	0.1	8.9	5.7	0.2	2.5	7.2	0.6
50 to 61	41.5	8.5	21.6	7.5	0.2	8.5	5.6	0.1	2.5	6.8	0.4
62 or older	22.8	5.3	13.4	7.4	0.0	7.0	5.8	1.0	2.3	7.2	0.8
Unknown	13.3	5.3	17.6	7.6	0.2	6.9	6.3	0.8	2.6	7.6	1.0
Census tract characteristics											
Income ratio											
Low	30.8	9.9	12.4	7.6	0.0	7.4	6.0	0.0	1.6	8.4	0.0
Moderate	32.7	8.6	17.7	7.8	0.0	7.9	6.2	1.0	1.9	7.9	0.5
Middle	35.7	7.8	19.1	7.7	0.2	8.9	5.9	0.3	2.4	7.3	0.9
High	38.7	8.0	23.4	7.5	0.2	7.6	5.5	0.3	2.7	6.6	0.5
Unknown	30.6	7.2	15.1	7.2	0.0	15.9	7.7	0.0	4.0	8.6	0.0
Minority population (percent)											
Less than 10	36.6	7.9	20.0	7.6	0.1	8.9	5.8	0.3	2.3	7.0	0.8
10-49	36.6	7.8	21.2	7.6	0.1	8.1	5.7	0.4	2.6	7.1	0.7
50-79	34.7	8.9	20.0	7.5	0.4	6.7	6.1	0.5	2.5	7.7	0.0
80 or more	31.4	9.8	16.3	7.8	0.4	6.0	6.4	1.0	1.9	9.4	1.5
Urban	36.8	8.1	21.1	7.6	0.2	8.0	5.7	0.4	2.5	7.2	0.8
Rural	33.3	7.6	15.4	7.4	0.1	10.1	6.1	0.3	2.2	7.1	0.4
All	36.2	8.0	20.3	7.6	0.2	8.3	5.8	0.4	2.5	7.2	0.7

Table continued on next page.

Note. For definitions of characteristics, refer to notes to table 9.

n.a. Not available

Table 20. Characteristics of New Loans for Borrowers in Selected Quintiles of TransRisk Score Distribution, and Distribution of Loans, by Selected Characteristics of Sample Population and Type of Loan, July-December 2003—Continued

C. Top three quintiles—Continued

Characteristic	Installment loan						Credit card loan				Other loans	
	From bank			From finance company			From bank		From finance company			
	Percent of loans	Average interest rate	Percent bad	Percent of loans	Average interest rate	Percent bad	Percent of loans	Percent bad	Percent of loans	Percent bad	Percent of loans	Percent bad
Race or ethnicity—SSA data												
Non-Hispanic white	4.5	8.2	0.5	1.8	15.2	2.0	27.1	1.1	3.8	0.4	30.9	0.7
Black	4.6	10.6	2.2	4.4	19.9	5.3	29.1	4.2	2.9	2.3	32.4	1.7
Hispanic	3.2	9.1	2.5	3.3	18.0	2.5	27.3	2.1	3.3	1.2	34.2	1.6
Asian	2.5	8.3	0.0	1.2	15.0	0.1	33.9	0.8	2.7	1.7	30.6	1.2
American Indian	7.6	9.2	0.1	2.5	11.2	1.2	26.5	2.2	3.2	0.2	26.0	0.4
Unknown race	4.0	8.4	0.3	2.0	16.5	1.2	29.5	2.0	3.7	2.0	32.6	1.0
Race or ethnicity—location-based distribution												
Non-Hispanic white	4.3	8.3	0.5	1.8	15.2	1.9	27.5	1.2	3.8	0.6	31.2	0.8
Black	4.4	9.1	0.7	2.6	19.3	4.0	29.0	3.0	3.3	1.8	32.0	1.4
Hispanic	3.5	8.9	1.0	2.9	18.8	2.4	29.3	2.1	3.3	0.9	32.1	1.2
Asian	2.9	8.5	2.8	1.6	16.3	2.7	30.1	1.1	2.9	0.9	30.5	0.8
American Indian	6.9	10.1	0.2	2.9	17.4	1.1	28.4	1.7	3.1	0.6	27.6	0.9
National origin												
Foreign-born	2.5	8.6	0.8	1.9	17.0	2.5	31.7	1.2	3.1	1.5	31.6	0.9
Recent immigrant	2.1	8.3	2.4	1.4	21.8	0.0	36.7	1.5	2.8	3.7	32.8	0.9
Sex												
Male	5.1	8.3	0.7	2.1	16.1	3.0	29.0	1.4	2.4	0.8	25.6	0.8
Female	3.5	8.4	0.6	1.7	16.0	1.4	26.5	1.2	4.7	0.5	36.4	0.8
Unknown	3.9	8.6	0.0	2.9	15.9	1.8	30.5	3.0	3.9	2.7	31.6	1.8
Marital status												
Married male	5.2	8.1	0.3	1.9	15.8	1.6	28.0	0.8	2.5	0.3	25.4	0.6
Single male	4.5	8.5	1.3	2.4	17.5	4.9	30.7	1.8	2.3	1.5	26.1	1.0
Married female	3.4	8.1	0.3	1.5	15.7	1.6	25.3	0.9	5.2	0.2	36.0	0.5
Single female	3.4	8.7	1.1	2.2	17.3	0.4	28.9	1.5	4.1	1.4	37.0	1.0
Unknown	4.7	9.2	0.8	2.6	15.3	3.2	29.4	2.7	3.2	1.6	31.4	1.9
Age—SSA data (years)												
Younger than 30	4.7	9.3	1.9	2.7	11.9	3.3	34.0	2.8	2.8	2.1	32.9	2.5
30 to 39	3.7	8.0	0.7	1.9	15.5	3.2	25.7	1.0	3.4	0.4	29.4	0.7
40 to 49	4.0	8.5	0.2	1.9	17.6	1.3	25.1	1.3	3.5	0.4	30.5	0.6
50 to 61	4.5	8.0	0.5	1.8	17.4	1.8	27.0	0.5	3.5	0.5	30.6	0.4
62 or older	4.7	8.5	0.4	1.6	17.5	1.6	30.7	1.3	5.2	0.5	35.2	0.6
Unknown	3.9	8.6	0.0	2.9	16.1	1.9	30.5	3.0	3.9	2.7	31.7	1.8
Census tract characteristics												
Income ratio												
Low	4.0	9.3	0.0	3.8	21.8	6.3	32.7	6.1	1.7	4.6	36.5	1.7
Moderate	4.3	9.1	1.4	2.7	18.2	1.1	30.7	2.6	3.2	0.6	31.7	1.2
Middle	5.2	8.4	0.5	2.1	15.6	3.0	27.8	1.3	3.7	0.7	30.9	0.9
High	2.9	7.8	0.5	1.5	14.5	0.9	26.6	0.8	3.9	0.6	31.5	0.6
Unknown	11.9	10.6	0.0	1.6	n.a.	0.0	19.1	0.0	3.2	0.0	29.4	0.0
Minority population (percent)												
Less than 10	4.8	8.2	0.4	1.8	14.3	1.4	26.8	1.1	4.0	0.3	31.5	0.6
10-49	3.7	8.4	0.6	1.9	16.0	2.7	28.2	1.2	3.5	1.2	30.7	1.2
50-79	3.7	8.9	1.9	2.6	18.7	2.0	30.4	2.2	2.8	1.2	31.4	1.1
80 or more	3.4	10.4	1.7	3.8	21.8	4.5	31.0	4.1	2.6	1.1	35.0	1.2
Urban	3.5	8.3	0.7	1.8	15.9	2.5	27.9	1.4	3.7	0.7	31.4	0.9
Rural	8.5	8.6	0.5	2.8	16.8	1.2	27.1	1.3	3.3	1.1	30.5	0.8
All	4.2	8.4	0.6	2.0	16.1	2.2	27.8	1.4	3.6	0.7	31.3	0.9

Table 21. Modified New-Account Performance Measure, with Loan Terms--Multivariate Estimates of Performance Residuals (Unexplained Percent Bad) for the TransRisk Score, by Race, Sex, and Age

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.3	2.6	0.1	-0.1	
Deviation of mean residual from that for non-Hispanic white					
Gross	0.0	3.0	0.5	0.3	
Net, after controls					
Loan type, lender, and interest rate	0.0	3.2	0.4	0.0	
All controls in table 19.E	0.0	2.0	-0.3	0.0	
All controls	0.0	1.6	-0.5	-0.2	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Mean of performance residuals (in regression sample)	-0.3	1.4	0.1	0.2	
Deviation of mean residual from that for non-Hispanic white tract					
Gross	0.0	1.7	0.4	0.5	
Net, after controls					
Loan type, lender, and interest rate	0.0	1.6	0.3	0.3	
All controls in table 19.E	0.0	0.7	-0.4	0.3	
All controls	0.0	0.6	-0.6	0.2	
	C. Sex				
	Male	Female			
Mean of performance residuals (in regression sample)	0.0	-0.1			
Deviation of mean residual from that for male					
Gross	0.0	0.0			
Net, after controls					
Loan type, lender, and interest rate	0.0	-0.2			
All controls in table 19.E	0.0	-0.2			
All controls	0.0	-0.3			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Mean of performance residuals (in regression sample)	2.0	-0.1	-0.5	-0.8	-0.1
Deviation of mean residual from that for 62 or older					
Gross	2.1	0.0	-0.4	-0.7	0.0
Net, after controls					
Loan type, lender, and interest rate	2.0	0.3	-0.2	-0.6	0.0
All controls in table 19.E	2.0	0.3	0.0	-0.4	0.0
All controls	2.1	0.5	0.1	-0.4	0.0

1. For definitions, refer to notes to table 9.

Table 22.A. Multivariate Differences in the Incidence of New Loans
(Modified New Accounts)

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Incidence of new loans (percent)	18.7	17.9	17.9	19.1	
Deviation of incidence from that for non-Hispanic white after controls (percentage points)					
Score only	0.0	-2.3	0.4	1.8	
Age, sex, and marital status	0.0	-0.4	0.3	-0.2	
Above, plus tract income	0.0	0.6	0.9	-0.4	
Above, plus estimated income	0.0	0.8	1.2	-0.7	
Above, plus mean tract score	0.0	1.1	1.3	-0.7	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Incidence of new loans (percent)	18.6	16.5	16.8	16.5	
Deviation of incidence from that for non-Hispanic white tract after controls (percentage points)					
Score only	0.0	-2.9	-1.3	0.4	
Age, sex, and marital status	0.0	-1.4	-0.7	0.0	
Above, plus tract income	0.0	-0.3	-0.1	-0.1	
Above, plus estimated income	0.0	-0.3	0.0	-0.4	
Above, plus mean tract score	0.0	-0.4	0.0	-0.3	
	C. Sex				
	Male	Female			
Incidence of new loans (percent)	17.4	19.4			
Deviation of incidence from that for male after controls (percentage points)					
Score only	0.0	2.1			
Age, race, and marital status	0.0	2.5			
Above, plus tract income	0.0	2.5			
Above, plus estimated income	0.0	2.5			
Above, plus mean tract score	0.0	2.5			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Incidence of new loans (percent)	14.9	19.1	20.1	20.7	16.7
Deviation of incidence from that for age 62 or older after controls (percentage points)					
Score only	10.8	17.0	17.1	13.5	0.0
Race, sex, and marital status	12.2	17.9	17.4	13.6	0.0
Above, plus tract income	12.0	17.5	17.0	13.3	0.0
Above, plus estimated income	11.0	14.5	12.7	8.9	0.0
Above, plus mean tract score	10.9	14.1	12.3	8.6	0.0

1. For definitions, refer to notes to table 9.

Table 22.B. Multivariate Differences in the Incidence of Inquiries for the Sample Population That Had No New Loans (Proxy for Denial Rate), July-December 2003

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Inquiry-based denial rate (percent)	40.2	44.9	43.4	41.9	
Deviation of denial rate from that for non-Hispanic white after controls (percentage points)					
Score only	0.0	2.5	2.1	1.4	
Age, sex, and marital status	0.0	2.7	1.8	0.6	
Above, plus tract income	0.0	2.3	1.5	0.5	
Above, plus estimated income	0.0	2.6	1.7	0.3	
Above, plus mean tract score	0.0	2.6	1.7	0.4	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Inquiry-based denial rate (percent)	40.4	43.8	41.9	42.3	
Deviation of denial rate from that for non-Hispanic white tract after controls (percentage points)					
Score only	0.0	1.4	0.7	0.6	
Age, sex, and marital status	0.0	1.6	0.6	0.3	
Above, plus tract income	0.0	1.2	0.3	0.1	
Above, plus estimated income	0.0	1.2	0.3	0.0	
Above, plus mean tract score	0.0	1.2	0.3	0.0	
	C. Sex				
	Male	Female			
Inquiry-based denial rate (percent)	41.5	42.2			
Deviation of denial rate from that for male after controls (percentage points)					
Score only	0.0	-1.3			
Age, race, and marital status	0.0	-1.3			
Above, plus tract income	0.0	-1.3			
Above, plus estimated income	0.0	-1.3			
Above, plus mean tract score	0.0	-1.3			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Inquiry-based denial rate (percent)	45.5	43.1	41.1	38.6	34.5
Deviation of denial rate from that for age 62 or older after controls (percentage points)					
Score only	5.5	3.4	2.7	2.1	0.0
Race, sex, and marital status	5.1	3.1	2.6	2.0	0.0
Above, plus tract income	5.0	3.1	2.5	2.0	0.0
Above, plus estimated income	4.8	2.7	1.9	1.4	0.0
Above, plus mean tract score	4.8	2.7	2.0	1.4	0.0

1. For definitions, refer to notes to table 9.

Table 22.C. Multivariate Differences in Mortgage Interest Rates (Modified New Accounts)

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Interest rate residual (in the regression sample)	0.00	0.39	0.19	-0.58	
Deviation of interest rate residual from that for non-Hispanic white after controls					
Score only	0.00	0.39	0.19	-0.58	
Loan type, lender, and amount	0.00	0.39	0.19	-0.32	
Above, plus all controls in table 19.E	0.00	0.26	0.21	-0.30	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Interest rate residual (in the regression sample)	0.00	0.32	0.00	-0.45	
Deviation of interest rate residual from that for non-Hispanic white tract after controls					
Score only	0.00	0.32	0.00	-0.45	
Loan type, lender, and amount	0.00	0.27	0.04	-0.22	
Above, plus all controls in table 19.E	0.00	0.14	0.00	-0.21	
	C. Sex				
	Male	Female			
Interest rate residual (in the regression sample)	-0.01	0.02			
Deviation of interest rate residual from that for male after controls					
Score only	0.00	0.04			
Loan type, lender, and amount	0.00	0.02			
Above, plus all controls in table 19.E	0.00	0.04			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Interest rate residual (in the regression sample)	0.06	0.02	0.08	-0.06	-0.21
Deviation of interest rate residual from that for age 62 or older after controls					
Score only	0.27	0.24	0.29	0.15	0.00
Loan type, lender, and amount	0.30	0.42	0.46	0.27	0.00
Above, plus all controls in table 19.E	0.27	0.35	0.33	0.16	0.00

1. For definitions, refer to notes to table 9.

Table 22.D. Multivariate Differences in Auto Loan Interest Rates
(Modified New Accounts)

Measure	Demographic group				
	A. Race or ethnicity—SSA data[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Interest rate residual (in the regression sample)	-0.19	1.14	0.44	-0.56	
Deviation of interest rate residual from that for non-Hispanic white after controls					
Score only	0.00	1.47	0.68	-0.37	
Loan type, lender, and amount	0.00	1.33	0.60	-0.08	
Above, plus all controls in table 19.E	0.00	2.17	0.68	-0.01	
	B. Race or ethnicity—location-based distribution[1]				
	Non-Hispanic white	Black	Hispanic	Asian	
Interest rate residual (in the regression sample)	-0.10	0.60	0.13	-0.16	
Deviation of interest rate residual from that for non-Hispanic white tract after controls					
Score only	0.00	0.74	0.25	-0.05	
Loan type, lender, and amount	0.00	0.57	0.23	0.01	
Above, plus all controls in table 19.E	0.00	0.41	0.14	0.03	
	C. Sex				
	Male	Female			
Interest rate residual (in the regression sample)	-0.06	0.02			
Deviation of interest rate residual from that for male after controls					
Score only	0.00	0.08			
Loan type, lender, and amount	0.00	-0.02			
Above, plus all controls in table 19.E	0.00	-0.08			
	D. Age				
	Younger than 30	30-39	40-49	50-61	62 or older
Interest rate residual (in the regression sample)	0.16	-0.20	-0.01	-0.15	0.32
Deviation of interest rate residual from that for age 62 or older after controls					
Score only	-0.16	-0.52	-0.32	-0.47	0.00
Loan type, lender, and amount	0.14	-0.18	-0.03	-0.19	0.00
Above, plus all controls in table 19.E	0.23	-0.07	0.02	-0.16	0.00

1. For definitions, refer to notes to table 9.

Table 23. Financial Characteristics of Families, by Selected Characteristics of Families, 2004 Survey of Consumer Finances

(Thousands of 2004 dollars except as noted)

Characteristic	Percent of families	Median income	Median net worth	Home-ownership (percent)	Median home equity for home-owners	Families with financial assets		Families with debt				Percent of families with financial assets larger than desired buffer[1]	Percent of families that saved last year	Numnber of years with current checking account institution[2]
						Percent of all families	Median amount	Percent of all families	Median ratio of debt payments to income (percent)	Proportion with payments exceeding 40 percent of income (percent)	Percent with financial assets exceeding 3 months' debt payment			
All	**100**	**43.1**	**93.0**	**69.1**	**86.0**	**93.8**	**23.3**	**76.4**	**17.9**	**12.3**	**80.0**	**68.9**	**56.1**	**14.9**
Age of family head (years)														
Younger than 35	22.2	32.9	14.2	41.6	32.0	90.1	5.2	79.8	17.9	12.7	73.9	59.8	55.0	6.6
35-44	20.6	50.3	69.5	68.3	55.0	93.6	18.9	88.6	20.5	12.5	78.5	66.4	58.0	10.0
45-61	32.5	60.6	169.8	78.0	105.0	94.1	51.0	84.5	17.7	12.2	82.7	73.3	58.7	15.6
62 or older	24.7	30.8	184.0	82.6	125.0	96.9	43.5	52.7	14.3	11.6	84.8	73.3	52.0	24.6
Family income														
Bottom quartile	24.9	12.3	10.0	44.2	55.0	81.9	1.5	54.7	18.9	26.9	56.9	39.6	35.0	14.4
Second quartile	24.4	31.3	45.1	60.8	68.0	94.5	8.0	76.1	18.1	15.8	70.5	62.6	48.2	14.6
Third quartile	25.1	56.5	124.4	78.2	80.0	98.9	30.3	85.4	20.4	9.7	85.4	79.5	62.6	14.8
Top quartile	25.5	114.0	422.4	92.2	146.0	99.8	149.4	89.1	16.6	3.2	96.5	93.0	77.8	15.6
Marriage status and sex														
Married	50.6	65.7	181.3	83.9	100.0	97.4	49.5	84.0	18.4	10.3	85.3	76.9	64.7	15.6
Living with partner	7.4	40.0	25.3	46.8	55.0	84.1	7.2	76.1	13.6	11.3	73.3	59.5	50.9	9.1
Single male	14.7	30.8	57.9	56.2	69.2	92.5	14.5	68.1	19.0	12.5	80.3	65.4	57.0	14.1
Single female	27.3	22.6	32.9	54.4	70.0	90.5	6.2	67.1	17.2	17.1	69.6	58.4	41.0	15.2
Race or ethnicity of family head														
Non-Hispanic white	71.8	49.3	140.6	76.4	92.0	97.5	36.4	78.0	17.9	10.7	84.4	77.2	60.0	16.1
Black	13.4	28.8	20.6	50.6	45.0	86.4	4.0	71.7	18.1	16.0	68.0	49.8	43.3	12.7
Hispanic	11.1	28.8	18.8	47.8	70.0	78.7	4.5	71.0	17.6	18.0	62.8	39.8	43.4	9.0
Asian or other	3.7	51.3	142.0	57.5	175.0	95.3	23.0	80.4	17.9	16.1	81.1	64.2	64.3	10.8

1. Dollar size of desired buffer as defined by respondent.
2. For those with a checking account.
Source. Federal Reserve Board, Survey of Consumer Finances.

Table 24. Financial Characteristics of Families, by Race and Ethnicity of Family Head for Selected Characteristics of Families, 2004 Survey of Consumer Finances

(Thousands of 2004 dollars except as noted)

Characteristic and race or ethnicity	Percent of families	Median income	Median net worth	Home-ownership (percent)	Median home equity for home-owners	Families with financial assets		Families with debt				Percent of families with financial assets larger than desired buffer	Percent of families that saved last year	Number of years with current checking account institution
						Percent of all families	Median amount	Percent of all families	Median ratio of debt payments to income (percent)	Proportion with payments exceeding 40 percent of income (percent)	Percent with financial assets exceeding 3 months' debt payment			
All														
Non-Hispanic white	71.8	49.3	140.6	76.4	92.0	97.5	36.4	78.0	17.9	10.7	84.4	77.2	60.0	16.1
Black	13.4	28.8	20.6	50.6	45.0	86.4	4.0	71.7	18.1	16.0	68.0	49.8	43.3	12.7
Hispanic	11.1	28.8	18.8	47.8	70.0	78.7	4.5	71.0	17.6	18.0	62.8	39.8	43.4	9.0
Asian or other	3.7	51.3	142.0	57.5	175.0	95.3	23.0	80.4	17.9	16.1	81.1	64.2	64.3	10.8
Age (years)														
Younger than 35														
Non-Hispanic white	64.3	37.0	21.5	48.2	33.5	94.8	6.7	85.9	19.5	11.2	76.2	68.1	58.9	7.2
Black	15.6	27.7	8.8	29.2	25.0	84.3	2.9	71.2	16.7	14.8	72.8	49.6	47.4	5.7
Hispanic	16.0	25.7	6.8	27.9	22.0	75.1	2.2	62.7	15.6	19.8	57.7	32.9	44.7	4.8
Asian or other	4.1	47.2	51.0	37.9	. . .	97.6	18.0	82.6	10.1	9.2	87.5	73.5	62.8	5.4
35-44														
Non-Hispanic white	67.8	58.5	100.9	77.5	55.0	97.5	29.5	93.1	21.1	11.9	83.5	76.3	62.1	10.9
Black	13.0	35.9	14.1	45.1	30.0	84.7	4.2	77.1	16.7	12.2	61.9	50.3	41.6	8.0
Hispanic	15.7	37.0	27.3	50.3	82.0	84.7	5.3	78.2	21.8	16.5	66.0	42.5	50.9	7.8
Asian or other	3.4	51.3	74.7	56.3	. . .	91.7	12.2	89.6	13.9	9.2	80.1	40.8	72.5	7.5
45-61														
Non-Hispanic white	71.7	68.8	246.8	84.1	111.0	98.1	71.6	86.2	17.2	10.4	87.6	80.3	63.9	16.3
Black	13.8	35.9	40.0	61.9	50.0	85.7	8.2	79.3	19.2	14.6	69.6	54.2	41.5	13.8
Hispanic	9.2	35.9	46.6	59.2	100.0	75.6	14.2	79.7	17.8	19.5	61.5	48.1	42.3	11.5
Asian or other	5.3	61.6	214.1	69.4	249.0	94.6	56.2	84.3	24.3	19.3	80.5	71.8	61.2	13.8
62 or older														
Non-Hispanic white	82.1	34.9	226.9	86.6	127.0	98.6	74.8	52.5	13.7	8.9	88.9	80.6	54.9	25.2
Black	11.3	17.5	52.5	64.3	90.0	91.6	2.3	54.7	24.7	26.2	64.9	42.3	42.6	24.0
Hispanic	5.4	19.5	54.5	68.9	81.0	80.8	4.6	56.0	11.1	12.5	70.9	32.8	24.2	16.8
Asian or other	1.3	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Income quartile														
Bottom														
Non-Hispanic white	59.7	13.3	23.2	52.1	62.0	91.2	2.4	56.3	18.6	26.2	64.4	50.8	37.5	16.2
Black	20.9	11.3	3.0	37.5	39.0	72.7	1.0	53.0	20.6	28.6	47.7	29.2	32.8	12.9
Hispanic	15.9	14.4	3.5	28.6	40.0	56.5	0.3	48.5	16.6	23.5	33.2	10.6	27.0	7.4
Asian or other	3.5	12.3	3.0	19.0	. . .	91.4	1.5	65.9	23.5	39.1	70.2	42.7	40.4	8.4
Second														
Non-Hispanic white	66.1	31.8	72.5	68.5	70.0	97.5	13.9	76.5	18.3	13.9	75.4	70.5	50.4	16.8
Black	16.3	30.8	17.3	46.9	30.0	91.7	4.2	77.4	18.7	17.9	65.4	52.4	42.2	11.7
Hispanic	15.1	28.8	16.2	45.2	70.0	85.1	3.0	70.7	18.1	22.5	56.2	40.3	45.6	7.5
Asian or other	2.4	30.8	36.5	40.3	. . .	89.8	3.4	89.1	6.8	14.1	57.2	56.0	45.2	7.7

Table continued on next page.

Table 24. Financial Characteristics of Families, by Race and Ethnicity of Family Head for Selected Characteristics of Families, 2004 Survey of Consumer Finances—Continued
(Thousands of 2004 dollars except as noted)

Characteristic and race or ethnicity	Percent of families	Median income	Median net worth	Home-ownership (percent)	Median home equity for home-owners	Families with financial assets: Percent of all families	Families with financial assets: Median amount	Families with debt: Percent of all families	Families with debt: Median ratio of debt payments to income (percent)	Families with debt: Proportion with payments exceeding 40 percent of income (percent)	Families with debt: Percent with financial assets exceeding 3 months' debt payment	Percent of families with financial assets larger than desired buffer	Percent of families that saved last year	Number of years with current checking account institution
Income quartile--continued														
Third														
Non-Hispanic white	76.6	56.5	142.5	82.7	79.0	99.5	37.2	84.4	21.1	9.1	87.0	84.7	64.7	15.6
Black	10.5	53.4	60.1	64.5	50.0	97.8	16.6	85.5	18.3	7.4	77.7	63.5	51.8	12.3
Hispanic	9.1	56.5	75.9	64.0	93.0	95.9	13.0	96.5	20.1	15.0	81.1	63.1	53.2	11.0
Asian or other	3.8	55.5	149.8	58.9	. . .	96.0	22.0	79.3	15.5	12.7	84.4	58.8	72.8	13.9
Top														
Non-Hispanic white	84.3	116.0	453.6	93.4	150.0	99.9	169.7	88.2	16.6	3.0	96.8	93.8	78.6	16.1
Black	6.2	101.7	224.3	79.5	82.0	98.9	71.4	95.5	15.3	2.1	96.3	87.9	66.4	15.0
Hispanic	4.7	99.6	297.8	88.3	123.0	100.0	71.2	97.9	18.4	4.1	91.6	90.1	72.4	11.5
Asian or other	4.9	127.3	408.7	91.7	200.0	100.0	119.0	87.1	20.3	7.2	96.3	87.2	83.8	11.3
Marriage status and sex														
Married														
Non-Hispanic white	77.8	70.9	229.5	88.8	100.0	99.0	67.2	84.7	18.3	8.7	88.5	83.0	67.4	16.6
Black	6.8	55.5	61.5	71.0	82.0	96.6	13.7	83.4	17.8	10.2	77.3	61.5	52.9	14.3
Hispanic	10.9	40.0	50.3	63.0	85.0	86.4	8.9	80.2	18.6	19.2	68.9	46.0	47.4	10.7
Asian or other	4.6	71.9	184.7	69.7	175.0	97.1	39.5	80.3	20.8	17.4	79.2	69.9	78.4	10.5
Living with partner														
Non-Hispanic white	58.1	50.3	55.1	55.3	65.0	92.3	17.2	85.6	14.8	13.3	78.0	72.9	56.5	10.2
Black	14.6	35.9	10.0	27.5	. . .	83.1	3.5	62.3	9.3	7.3	71.3	55.2	46.7	7.1
Hispanic	24.5	25.7	10.4	37.3	30.0	63.4	1.9	60.6	14.6	8.9	54.1	30.6	38.5	6.2
Asian or other	2.8	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Single male														
Non-Hispanic white	70.2	32.9	84.4	62.8	75.0	96.2	22.0	69.2	19.5	12.2	80.6	71.9	59.8	15.8
Black	15.9	26.7	24.8	46.2	47.0	82.1	5.0	61.3	18.1	13.4	81.2	48.2	47.1	10.7
Hispanic	10.4	23.7	16.2	36.2	. . .	81.6	5.0	67.6	17.4	13.6	72.1	48.0	51.1	5.5
Asian or other	3.4	27.7	34.7	29.4	. . .	96.1	40.3	79.8	. . .	. . .	. . .	64.5	63.7	. . .
Single female														
Non-Hispanic white	65.3	24.6	58.7	61.9	79.0	96.0	11.5	66.3	16.6	14.3	77.2	68.5	44.8	16.6
Black	24.0	20.5	11.5	45.3	31.0	83.1	2.3	70.8	21.9	21.7	57.8	43.3	36.3	12.9
Hispanic	8.3	15.4	3.2	27.1	69.0	70.7	0.9	59.5	16.3	24.6	42.7	26.6	32.5	8.5
Asian or other	2.3	21.6	14.3	37.8	. . .	86.4	. . .	78.3	. . .	. . .	. . .	45.7	14.0	. . .

Note: Refer to notes to table 23.
. . . Fewer than 20 observations.

Table 25. Nonfinancial Characteristics of Families, by Selected Characteristics of Families, 2004 Survey of Consumer Finances

(Percent)

Characteristic	Percent of families	Head, spouse, or partner ever bankrupt	Opinion about purchasing on installment		Credit experience in past 5 years				Employment of head		Education of head	
					Application for credit							
			Good idea	Bad idea	Applied	Turned down	Approved for less than requested	Did not apply for fear of denial	Unem-ployed in past year	Mean number of years on job, if working	High-school degree	College degree
All	**100**	**11.0**	**31.3**	**31.7**	**68.7**	**25.5**	**4.9**	**15.8**	**12.4**	**9.3**	**85.6**	**36.6**
Age of family head (years)												
Younger than 35	22.2	5.6	35.9	29.5	76.5	37.1	7.3	27.6	23.6	3.4	88.7	34.2
35-44	20.6	14.6	33.7	33.0	79.8	30.5	6.0	21.9	16.6	7.1	87.8	38.4
45-61	32.5	15.1	30.8	32.6	74.9	21.1	4.4	13.1	9.9	13.3	90.2	42.5
62 or older	24.7	7.4	25.7	31.5	44.3	9.9	0.3	3.7	2.3	17.2	74.8	29.6
Family income												
Bottom quartile	24.9	9.9	28.9	32.9	45.2	39.2	3.1	20.0	20.3	5.0	65.7	15.4
Second quartile	24.4	13.8	32.9	28.8	64.3	35.8	5.9	22.5	14.7	7.6	84.8	22.3
Third quartile	25.1	13.6	29.7	31.8	79.5	26.1	5.1	15.3	8.8	9.6	93.2	38.6
Top quartile	25.5	6.8	33.6	33.3	85.2	10.5	4.8	5.8	6.2	12.5	98.2	69.0
Marriage status and sex												
Married	50.6	10.0	31.8	30.1	76.5	18.7	4.0	11.7	9.3	10.8	88.8	43.5
Living with partner	7.4	9.5	35.2	35.4	67.9	34.3	9.1	28.5	22.3	6.5	79.9	23.2
Single male	14.7	11.7	32.3	34.1	61.2	31.2	7.1	17.7	16.8	8.5	85.7	35.3
Single female	27.3	12.9	28.8	32.4	58.6	36.2	4.3	19.0	13.2	7.2	81.1	28.2
Race or ethnicity of family head												
Non-Hispanic white	71.8	10.7	29.4	33.1	72.2	21.5	4.0	11.7	10.8	10.1	90.6	41.1
Black	13.4	16.2	33.4	29.4	56.4	45.3	8.0	30.4	15.7	8.2	78.3	25.1
Hispanic	11.1	7.0	38.3	27.2	59.3	33.9	8.9	25.3	17.9	6.1	58.5	14.6
Asian or other	3.7	10.8	39.6	27.3	72.4	27.5	4.0	14.5	15.4	8.4	94.9	56.5

Source. Federal Reserve Board, Survey of Consumer Finances.

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Table 26. Nonfinancial Characteristics of Families, by Race and Ethnicity of Family Head for Selected Characteristics of Families, 2004 Survey of Consumer Finances
(Percent)

Characteristic and race or ethnicity	Percent of families	Head, spouse, or partner ever bankrupt	Opinion about purchasing on installment		Credit experience in past 5 years				Employment of head		Education of head	
					Application for credit							
			Good idea	Bad idea	Applied	Turned down	Approved for less than requested	Did not apply for fear of denial	Unem-ployed in past year	Mean number of years on job, if working	High-school degree	College degree
All												
Non-Hispanic white	71.8	10.7	29.4	33.1	72.2	21.5	4.0	11.7	10.8	10.1	90.6	41.1
Black	13.4	16.2	33.4	29.4	56.4	45.3	8.0	30.4	15.7	8.2	78.3	25.1
Hispanic	11.1	7.0	38.3	27.2	59.3	33.9	8.9	25.3	17.9	6.1	58.5	14.6
Asian or other	3.7	10.8	39.6	27.3	72.4	27.5	4.0	14.5	15.4	8.4	94.9	56.5
Age (years)												
Younger than 35												
Non-Hispanic white	64.3	6.0	35.2	32.4	83.6	34.5	5.7	22.7	22.4	3.6	94.3	39.6
Black	15.6	9.4	35.4	23.9	66.3	52.6	11.9	40.4	23.7	3.5	89.6	29.6
Hispanic	16.0	1.8	38.2	26.6	58.0	39.8	13.8	39.0	26.6	2.5	63.6	9.5
Asian or other	4.1	0.0	40.5	17.4	75.9	23.6	0.0	10.1	29.7	3.7	94.5	63.1
35-44												
Non-Hispanic white	67.8	13.6	31.8	33.4	87.3	24.0	5.4	17.0	15.2	7.7	93.7	44.2
Black	13.0	24.2	33.8	39.5	61.1	62.5	7.7	43.7	20.4	5.8	88.4	30.7
Hispanic	15.7	10.6	39.7	28.0	63.3	41.6	7.4	26.1	18.8	5.9	61.3	14.6
Asian or other	3.4	15.8	42.3	21.9	78.4	38.4	10.2	16.9	20.0	4.8	89.7	61.9
45-61												
Non-Hispanic white	71.7	14.7	28.7	33.8	78.7	17.4	3.9	9.9	8.9	13.8	94.8	47.5
Black	13.8	20.3	33.7	29.9	59.7	39.2	6.5	25.7	13.7	13.0	83.6	25.8
Hispanic	9.2	11.2	37.4	29.7	66.6	27.0	7.4	16.1	12.8	11.0	60.1	22.0
Asian or other	5.3	13.7	41.2	28.9	77.0	26.5	3.7	18.1	9.0	11.5	98.5	53.1
62 or older												
Non-Hispanic white	82.1	7.2	24.4	32.6	46.5	9.6	0.1	2.2	1.9	17.4	81.2	32.8
Black	11.3	10.2	30.2	25.6	34.4	15.5	3.0	12.8	4.5	...	46.1	13.1
Hispanic	5.4	2.6	37.2	20.8	36.9	5.0	0.0	6.7	4.1	...	34.3	11.9
Asian or other	1.3	...	...	...	...	...	...	...	...	...	...	...
Income quartile												
Bottom												
Non-Hispanic white	59.7	11.2	24.1	36.7	48.9	38.3	1.5	18.1	17.5	5.5	74.5	18.5
Black	20.9	11.6	32.2	28.9	39.8	46.6	8.1	23.4	22.1	4.1	60.0	10.2
Hispanic	15.9	3.1	41.3	24.2	36.0	36.1	5.2	23.1	24.2	4.5	34.5	4.5
Asian or other	3.5	8.0	35.4	32.3	56.4	30.8	0.0	18.0	39.8	...	90.3	42.7
Second												
Non-Hispanic white	66.1	12.5	30.1	29.3	65.9	30.6	4.2	16.4	13.6	8.3	89.4	25.7
Black	16.3	23.0	36.8	28.1	60.3	51.6	8.1	39.8	14.5	8.0	84.3	17.9
Hispanic	15.1	7.5	38.7	27.7	58.9	41.0	11.1	28.5	19.2	4.8	63.2	11.5
Asian or other	2.4	26.4	46.6	24.6	79.3	...	...	34.5	16.9	...	96.4	29.3

Table continued on next page.

Table 26. Nonfinancial Characteristics of Families, by Race and Ethnicity of Family Head for Selected Characteristics of Families, 2004 Survey of Consumer Finances—Continued

(Percent)

Characteristic and race or ethnicity	Percent of families	Head, spouse, or partner ever bankrupt	Opinion about purchasing on installment		Credit experience in past 5 years				Employment of head		Education of head	
			Good idea	Bad idea	Application for credit: Applied	Application for credit: Turned down	Application for credit: Approved for less than requested	Did not apply for fear of denial	Unem-ployed in past year	Mean number of years on job, if working	High-school degree	College degree
Income quartile--continued												
Third												
Non-Hispanic white	76.6	12.8	28.8	32.2	80.7	21.8	4.0	9.9	8.0	9.9	95.5	40.2
Black	10.5	22.5	29.3	30.2	69.9	49.1	8.2	39.7	10.3	9.0	93.7	41.6
Hispanic	9.1	9.7	33.7	30.3	83.6	34.3	11.9	33.9	12.5	7.9	73.5	18.4
Asian or other	3.8	15.2	38.9	32.9	72.0	36.8	4.1	12.0	10.1	9.1	91.8	44.4
Top												
Non-Hispanic white	84.3	7.0	33.0	34.3	85.6	9.3	4.8	5.2	6.6	12.8	98.4	69.2
Black	6.2	3.3	35.8	32.7	78.9	25.3	7.2	14.5	6.7	13.4	97.7	65.2
Hispanic	4.7	12.9	35.8	29.4	92.0	16.2	3.9	6.0	3.4	10.5	95.0	50.5
Asian or other	4.9	2.1	39.8	20.8	80.5	9.4	2.9	4.4	1.6	9.4	99.7	88.3
Marriage status and sex												
Married												
Non-Hispanic white	77.8	10.1	30.4	30.8	78.9	15.8	3.8	8.9	8.9	11.4	93.1	46.5
Black	6.8	11.5	30.0	36.6	66.4	34.5	7.5	28.9	8.6	10.6	82.7	35.0
Hispanic	10.9	7.5	39.4	23.5	67.9	30.9	5.3	20.6	13.4	7.8	59.0	15.9
Asian or other	4.6	11.1	40.1	24.9	70.8	22.4	0.0	12.4	7.8	8.8	95.7	69.6
Living with partner												
Non-Hispanic white	58.1	10.1	35.1	36.1	75.8	32.1	8.5	24.5	17.9	7.2	89.1	29.4
Black	14.6	13.8	36.5	26.8	52.2	40.1	16.8	25.5	33.9	7.9	87.3	17.0
Hispanic	24.5	5.5	34.4	40.2	57.6	35.8	5.6	43.0	25.4	4.5	52.9	11.3
Asian or other	2.8	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Single male												
Non-Hispanic white	70.2	11.1	27.2	38.1	64.6	27.5	3.5	11.6	13.8	9.4	90.3	40.3
Black	15.9	16.3	42.4	28.7	45.8	49.6	14.0	31.9	16.9	7.8	74.5	24.6
Hispanic	10.4	9.0	48.8	17.6	57.1	36.9	26.1	36.2	33.6	3.6	70.0	14.7
Asian or other	3.4	11.3	39.1	27.8	73.9	. . .	. . .	18.5	29.0	. . .	91.6	44.8
Single female												
Non-Hispanic white	65.3	11.8	27.1	34.6	61.1	30.7	3.3	14.8	11.7	7.6	85.8	32.5
Black	24.0	19.0	31.5	26.2	55.7	51.6	5.1	31.5	16.0	6.9	75.9	21.5
Hispanic	8.3	5.6	31.6	32.0	41.6	40.9	10.6	15.0	12.5	5.1	54.0	14.1
Asian or other	2.3	9.4	38.3	37.2	76.0	. . .	. . .	23.9	28.7	. . .	96.8	26.8

. . . Fewer than 20 observations.

Source. Federal Reserve Board, Survey of Consumer Finances.

Table 27. Decomposition of Mean Difference in the FRB Base Scores across and within Scorecards, by Selected Characteristics of the Sample Population and Scorecard

Characteristic	Mean score difference	Distribution		Differences within scorecards				Frequency percentage		
		Thin	Major derogatory	Total	Thin	Clean	Major derogatory	Thin	Clean	Major derogatory
Race or ethnicity—SSA data										
Non-Hispanic white (B)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.9	64.5	28.6
Black	-28.3	-1.9	-15.5	-11.0	-3.0	-3.2	-4.8	13.5	23.9	62.6
Hispanic	-15.7	-1.5	-7.4	-6.8	-1.2	-4.0	-1.6	12.1	43.0	44.9
Asian	0.7	-0.6	2.0	-0.7	0.8	-2.0	0.5	9.2	66.8	24.1
American Indian	3.3	0.4	0.8	2.2	0.6	0.9	0.7	5.4	67.7	27.0
Unknown race	-1.9	-8.6	3.3	3.5	4.8	-1.0	-0.3	37.4	41.1	21.5
Race or ethnicity—location-based distribution										
Non-Hispanic white (B)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.7	59.4	28.9
Black	-15.2	-1.1	-7.8	-6.3	-2.1	-2.1	-2.1	16.5	37.6	45.9
Hispanic	-9.6	-1.0	-4.3	-4.2	-1.2	-2.1	-0.9	16.5	45.3	38.2
Asian	-0.1	-0.4	0.3	0.0	0.2	-0.3	0.1	13.7	58.2	28.2
American Indian	-8.7	-0.3	-4.6	-3.8	-0.9	-1.7	-1.2	13.3	47.9	38.9
National origin										
Foreign-born	-1.5	0.6	-0.2	-1.9	-0.2	-2.4	0.7	10.6	57.5	32.0
Recent immigrant	-5.9	-1.1	3.6	-8.4	0.3	-8.5	-0.2	17.6	58.5	23.9
Sex										
Male (B)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.8	57.0	34.2
Female	1.2	0.4	0.6	0.1	0.1	0.3	-0.3	7.6	59.6	32.8
Unknown	3.9	-13.4	8.2	9.1	9.7	-0.6	0.0	50.6	33.2	16.2
Marital status										
Married male	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.5	66.9	27.6
Single male	-12.8	-1.2	-5.7	-5.9	-1.0	-3.2	-1.7	10.0	49.7	40.2
Married female	1.3	0.3	0.8	0.2	0.1	0.3	-0.2	4.4	69.7	25.9
Single female	-11.9	-0.8	-5.4	-5.8	-0.8	-3.0	-2.0	8.5	52.1	39.5
Unknown	-12.7	-6.5	-2.0	-4.1	0.8	-3.0	-1.9	30.4	37.5	32.1
Age—SSA data (years)										
Younger than 30	-32.8	-1.5	-9.2	-22.1	-6.8	-10.2	-5.1	20.9	41.4	37.7
30 to 39	-25.2	0.0	-12.2	-13.1	-2.7	-5.7	-4.7	7.0	48.5	44.5
40 to 49	-17.8	0.2	-9.5	-8.6	-1.9	-3.8	-2.9	5.1	56.5	38.4
50 to 61	-10.6	0.3	-6.1	-4.8	-1.1	-2.4	-1.3	4.0	65.0	31.0
62 or older (B)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.1	75.4	17.5
Unknown	-13.1	-4.9	0.6	-8.8	-4.5	-3.0	-1.3	50.7	33.1	16.2
Census tract characteristics										
Income ratio										
Low	-18.7	-2.6	-7.2	-8.9	-3.6	-2.9	-2.4	23.7	28.7	47.6
Moderate	-9.7	-1.1	-4.4	-4.3	-1.3	-1.8	-1.2	16.8	41.8	41.4
Middle (B)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.1	56.3	31.6
High	8.4	0.5	3.8	4.1	0.8	2.4	0.9	9.9	66.9	23.2
Unknown	-4.5	-2.3	1.8	-4.0	0.4	-4.2	-0.2	22.3	50.1	27.6
Minority population (percent)										
Less than 10 (B)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.6	63.9	25.5
10-49	-5.7	-0.4	-3.1	-2.2	-0.5	-1.1	-0.6	12.7	55.1	32.2
50-79	-14.9	-1.1	-7.6	-6.2	-1.7	-2.5	-2.0	16.0	41.9	42.1
80 or more	-21.3	-2.0	-10.1	-9.3	-3.2	-3.3	-2.8	20.2	32.2	47.6
Urban	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.7	55.9	31.4
Rural	-1.4	0.0	-0.7	-0.6	0.1	-0.4	-0.3	12.9	54.3	32.8

(B) Base population group from which the deviations were calculated.

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Table 28.A. Thin File—Decomposition of Mean Score Difference, by Selected Characteristics of Sample Population and Credit Characteristic

Characteristic	S059[1]		AT36		RE34		AT26		AT28		G096		G103		IN34		Total	
	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent
Race or ethnicity—SSA data																		
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-1.3	43.1	-0.9	29.1	-0.3	8.9	-0.2	5.3	-0.2	5.4	-0.1	3.8	-0.1	4.7	0.0	-0.3	-3.0	100
Hispanic	-0.4	33.4	-0.3	27.2	-0.2	13.5	-0.1	7.8	-0.1	6.0	-0.1	7.6	-0.1	4.7	0.0	-0.2	-1.2	100
Asian	0.4	50.8	0.2	22.2	0.1	8.8	0.0	1.9	0.0	6.0	0.0	2.1	0.1	7.1	0.0	1.1	0.8	100
American Indian	0.1	9.4	0.0	7.6	0.2	26.0	0.1	22.2	0.1	10.9	0.1	14.4	0.0	0.0	0.1	9.3	0.6	100
Unknown race	2.3	47.4	0.9	19.7	0.5	9.5	0.4	9.3	0.0	0.2	0.5	9.5	0.1	1.1	0.2	3.3	4.8	100
Race or ethnicity—location-based distribution																		
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.9	41.3	-0.6	29.1	-0.2	10.1	-0.1	5.8	-0.1	5.8	-0.1	3.8	-0.1	4.1	0.0	0.0	-2.1	100
Hispanic	-0.4	34.4	-0.4	29.2	-0.2	13.9	-0.1	8.1	-0.1	6.2	0.0	3.9	0.0	4.0	0.0	0.4	-1.2	100
Asian	0.1	53.3	0.0	21.5	0.0	7.6	0.0	-0.9	0.0	6.0	0.0	3.9	0.0	7.0	0.0	1.7	0.2	100
American Indian	-0.3	38.0	-0.2	27.5	-0.1	12.5	-0.1	7.9	0.0	3.5	0.0	3.6	0.0	5.4	0.0	1.6	-0.9	100
National origin																		
Foreign-born	-0.2	90.9	-0.1	58.3	0.0	-15.5	0.1	-42.3	-0.1	35.9	0.1	-63.3	-0.1	44.4	0.0	-8.3	-0.2	100
Recent immigrant	0.2	61.7	0.1	31.7	0.0	5.5	0.0	-11.3	0.0	9.8	0.0	-12.8	0.0	16.3	0.0	-0.9	0.3	100
Sex																		
Male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Female	0.0	17.5	0.0	38.4	0.0	23.0	0.0	13.2	0.0	-14.1	0.0	10.4	0.0	3.4	0.0	8.1	0.1	100
Unknown	4.3	44.6	2.2	22.6	1.0	9.9	0.9	8.8	0.1	1.2	0.8	8.6	0.2	1.9	0.2	2.5	9.7	100
Marital status																		
Married male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Single male	-0.5	45.7	-0.3	28.5	-0.1	8.6	0.0	4.3	-0.1	6.5	0.0	3.6	-0.1	5.3	0.0	-2.4	-1.0	100
Married female	0.0	41.9	0.0	24.6	0.0	11.0	0.0	6.1	0.0	-4.6	0.0	12.4	0.0	3.9	0.0	4.7	0.1	100
Single female	-0.4	48.4	-0.2	27.6	-0.1	7.0	0.0	3.0	-0.1	7.9	0.0	3.0	0.0	6.0	0.0	-3.0	-0.8	100
Unknown	0.4	47.3	0.0	2.3	0.1	13.6	0.2	22.9	-0.2	-23.5	0.3	34.7	-0.1	-16.4	0.2	19.1	0.8	100
Age—SSA data (years)																		
Younger than 30	-1.9	28.0	-1.5	22.3	-1.0	14.9	-0.9	13.0	-0.3	4.8	-0.6	9.2	-0.2	2.9	-0.3	5.0	-6.8	100
30 to 39	-1.1	40.5	-0.6	23.5	-0.3	10.9	-0.2	7.9	-0.1	4.7	-0.2	6.1	-0.1	5.2	0.0	1.2	-2.7	100
40 to 49	-0.8	41.5	-0.5	23.8	-0.2	10.9	-0.1	7.7	-0.1	4.5	-0.1	5.2	-0.1	5.3	0.0	1.0	-1.9	100
50 to 61	-0.4	39.8	-0.3	24.6	-0.1	12.1	-0.1	7.6	0.0	4.0	-0.1	5.7	-0.1	5.0	0.0	1.2	-1.1	100
62 or older (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Unknown	2.3	-50.1	-1.4	31.4	-1.8	40.1	-0.9	20.7	-1.4	31.4	0.2	-5.0	-1.1	25.1	-0.3	6.4	-4.5	100
Census tract characteristics																		
Income ratio																		
Low	-1.5	41.0	-1.0	28.2	-0.4	10.1	-0.2	6.1	-0.2	6.7	-0.1	3.9	-0.2	4.3	0.0	-0.2	-3.6	100
Moderate	-0.5	42.2	-0.4	27.3	-0.1	10.0	-0.1	6.2	-0.1	6.5	-0.1	4.1	-0.1	3.9	0.0	-0.3	-1.3	100
Middle (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
High	0.3	42.0	0.2	24.7	0.1	10.6	0.1	6.4	0.0	4.7	0.0	4.1	0.1	6.4	0.0	1.1	0.8	100
Unknown	0.3	74.0	0.0	-3.6	0.0	-0.7	0.0	4.0	0.0	9.6	0.0	10.4	0.0	9.0	0.0	-2.6	0.4	100
Minority population (percent)																		
Less than 10 (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
10-49	-0.2	35.7	-0.2	34.0	-0.1	11.8	0.0	7.6	0.0	4.9	0.0	3.3	0.0	3.1	0.0	-0.3	-0.5	100
50-79	-0.6	37.9	-0.5	31.3	-0.2	11.7	-0.1	6.8	-0.1	4.6	-0.1	3.7	-0.1	3.4	0.0	0.7	-1.7	100
80 or more	-1.2	38.3	-1.0	29.9	-0.4	11.3	-0.2	6.8	-0.2	6.3	-0.1	3.7	-0.1	3.8	0.0	-0.1	-3.2	100
Urban (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Rural	-0.1	-72.9	0.1	112.6	0.0	40.4	0.0	1.7	0.1	64.6	0.1	72.9	-0.1	-67.3	-0.1	-52.1	0.1	100

1. For translation of codes for credit chracteristics, refer to next page.
(B) Base population group from which the deviations were calculated.
. . . Not applicable

Translation of Codes for Credit Characteristics, Table 28.A

Code	Credit Characteristic
AT26	Total number of accounts in good standing, opened 18 or more months ago
AT28	Total maximum credit issued on open accounts reported in the past 12 months
AT36	Total number of months since the most recent account delinquency
G096	Total number of inquiries for credit
G103	Total number of months since the most recent update on an account
IN34	Percentage of total remaining balance to total maximum credit for all open installment accounts reported in the past 12 months
RE34	Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months
S059	Total number of public records and derogatory accounts with an amount owed greater than $100

Table 28.B. Clean File—Decomposition of Mean Score Difference, by Selected Characteristics of Sample Population and Credit Characteristic

Characteristic	AT36[1]		RE34		S004		G089		S043		AT28		G096		S019		Total	
	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent
Race or ethnicity—SSA data																		
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-1.2	37.2	-0.6	18.8	-0.3	8.4	-0.3	10.7	-0.4	12.8	-0.2	4.7	-0.1	3.5	-0.1	3.8	-3.2	100
Hispanic	-1.3	32.4	-0.5	12.2	-0.9	23.5	-0.3	6.9	-0.4	10.0	-0.2	5.1	-0.2	6.0	-0.2	3.8	-4.0	100
Asian	1.1	-55.3	0.4	-19.7	-3.1	157.2	-0.1	7.4	0.2	-8.9	0.0	-0.4	-0.7	37.3	0.4	-17.6	-2.0	100
American Indian	-0.7	-72.8	0.5	50.8	1.7	184.8	-0.6	-61.4	0.2	17.1	-0.9	-96.2	0.8	91.2	-0.1	-13.5	0.9	100
Unknown race	0.0	4.9	-0.2	15.0	-0.3	31.3	-0.1	9.9	0.1	-11.8	-0.7	70.1	0.1	-11.6	0.1	-7.8	-1.0	100
Race or ethnicity—location-based distribution																		
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.8	36.8	-0.4	16.9	-0.2	9.8	-0.2	10.6	-0.2	11.5	-0.2	10.5	0.0	0.6	-0.1	3.4	-2.1	100
Hispanic	-0.6	27.1	-0.3	13.8	-0.5	23.9	-0.2	8.7	-0.2	10.3	-0.2	9.8	-0.1	2.7	-0.1	3.7	-2.1	100
Asian	0.0	2.9	0.0	5.8	-0.3	109.3	0.0	14.6	0.0	15.8	0.1	-41.4	0.0	8.1	0.0	-15.1	-0.3	100
American Indian	-0.6	33.4	-0.3	17.3	-0.2	12.1	-0.2	11.6	-0.1	8.7	-0.2	12.2	0.0	-2.7	-0.1	7.4	-1.7	100
National origin																		
Foreign-born	-0.1	4.4	0.1	-3.0	-1.7	72.7	-0.1	5.6	-0.1	2.7	0.0	-0.2	-0.5	20.3	0.1	-2.4	-2.4	100
Recent immigrant	-0.1	1.3	-0.4	4.7	-5.8	68.6	0.0	-0.1	-0.4	4.7	-0.7	7.9	-1.2	13.8	0.1	-1.0	-8.5	100
Sex																		
Male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Female	0.0	13.2	0.2	51.2	0.1	18.6	0.0	12.9	-0.1	-36.9	-0.3	-107.2	0.3	95.5	0.2	52.8	0.3	100
Unknown	48.1	-8,011.2	-5.9	988.7	-5.5	921.8	0.6	-103.8	33.9	-5,648.5	-143.7	23,948.5	48.8	-8,128.1	23.2	-3,867.3	-0.6	100
Marital status																		
Married male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Single male	-0.7	21.5	-0.5	16.2	-0.9	27.0	-0.3	8.2	-0.1	4.6	-0.6	19.2	-0.2	5.1	0.1	-1.8	-3.2	100
Married female	0.0	-9.6	0.2	59.9	0.0	-15.2	0.0	13.4	-0.2	-63.0	-0.5	-169.7	0.5	165.8	0.4	118.4	0.3	100
Single female	-0.7	22.8	-0.4	12.6	-0.7	23.6	-0.3	8.4	-0.2	8.1	-1.0	33.2	0.1	-3.7	0.2	-5.2	-3.0	100
Unknown	-0.5	18.2	-0.5	16.7	-1.0	32.3	-0.2	6.3	0.0	0.1	-0.9	29.7	0.0	-0.7	0.1	-2.6	-3.0	100
Age—SSA data (years)																		
Younger than 30	-2.1	20.1	-1.8	17.8	-4.2	40.7	-0.2	1.8	-0.7	6.4	-0.2	2.3	-0.9	9.0	-0.2	1.9	-10.2	100
30 to 39	-2.1	36.2	-1.2	21.6	-1.2	21.6	-0.2	3.7	-0.8	14.9	1.3	-22.6	-1.1	19.4	-0.3	5.2	-5.7	100
40 to 49	-1.8	48.0	-0.8	22.0	-0.6	14.7	-0.1	1.8	-0.9	22.9	1.5	-38.7	-0.8	22.0	-0.3	7.3	-3.8	100
50 to 61	-1.2	51.2	-0.6	23.9	-0.3	11.0	0.0	1.9	-0.8	32.1	1.3	-53.4	-0.6	23.7	-0.2	9.6	-2.4	100
62 or older (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Unknown	-0.8	25.3	-0.7	22.7	-0.8	26.1	-0.1	2.4	-0.2	8.1	-0.1	3.9	-0.3	9.5	-0.1	1.9	-3.0	100
Census tract characteristics	0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0			
Income ratio																		
Low	-0.9	29.6	-0.4	13.6	-0.7	23.2	-0.2	8.4	-0.2	7.6	-0.4	15.0	-0.1	2.1	0.0	0.5	-2.9	100
Moderate	-0.5	26.2	-0.3	15.2	-0.4	20.1	-0.2	9.4	-0.2	9.2	-0.3	18.0	0.0	0.7	0.0	1.2	-1.8	100
Middle (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
High	0.4	16.1	0.4	18.6	0.4	15.6	0.2	7.0	0.1	2.8	1.0	43.3	-0.2	-7.3	0.1	4.1	2.4	100
Unknown	-2.0	47.5	-1.1	26.1	-0.4	8.6	-0.8	18.8	0.2	-3.7	-0.6	14.1	0.3	-8.1	0.1	-3.2	-4.2	100
Minority population (percent)																		
Less than 10 (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
10-49	-0.4	33.6	-0.2	19.7	-0.2	20.1	-0.1	9.2	-0.2	16.8	0.1	-5.4	0.0	2.0	0.0	3.9	-1.1	100
50-79	-0.8	31.8	-0.4	15.8	-0.5	20.3	-0.2	9.3	-0.3	11.3	-0.2	6.8	0.0	1.7	-0.1	3.0	-2.5	100
80 or more	-1.0	31.8	-0.5	14.0	-0.6	17.7	-0.4	10.9	-0.3	10.1	-0.4	11.4	0.0	1.2	-0.1	2.9	-3.3	100
Urban (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Rural	-23.1	5,765.7	-0.4	90.4	-19.7	4,935.0	-0.2	49.1	-54.3	13,571.9	142.4	-35,606.3	-60.7	15,169.5	15.5	-3,875.2	-0.4	100

1. For translation of codes for credit chracteristics, refer to next page.
(B) Base population group from which the deviations were calculated.
. . . Not applicable

Translation of Codes for Credit Characteristics, Table 28.B

Code	Credit Characteristic
AT28	Total maximum credit issued on open accounts reported in the past 12 months
AT36	Total number of months since the most recent account delinquency
G089	Greatest amount of time a payment was late ever on an account
G096	Total number of inquiries for credit
RE34	Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months
S004	Average age of accounts on credit report
S019	Total number of open personal finance installment accounts reported in the past 12 months
S043	Total number of open non-installment accounts with a remaining balance to maximum credit issued ratio greater than 50% reported in the past 12 months

Table 28.C. Major Derogatory: Decomposition of Mean Score Difference, by Selected Characteristics of Sample Population and Credit Characteristic

Characteristic	G051[1]		AT36		S059		S046		S004	
	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent
Race or ethnicity—SSA data										
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.6	12.1	-1.0	20.4	-1.4	28.6	-0.4	7.8	-0.3	5.5
Hispanic	-0.1	9.3	-0.4	24.4	-0.2	13.9	0.0	2.2	-0.3	15.8
Asian	0.1	13.3	0.1	14.5	0.1	28.8	0.1	13.0	0.0	-5.3
American Indian	0.0	6.2	0.1	18.4	0.2	21.6	0.0	5.9	0.1	18.9
Unknown race	0.0	12.1	-0.1	17.0	0.0	14.7	-0.1	17.1	0.0	-4.3
Race or ethnicity—location-based distribution										
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.3	12.7	-0.4	18.1	-0.6	29.7	-0.2	9.9	-0.1	4.1
Hispanic	-0.1	10.9	-0.2	18.2	-0.2	23.6	-0.1	7.0	-0.1	10.3
Asian	0.0	-20.2	0.0	4.4	0.0	15.1	0.0	15.6	0.0	15.7
American Indian	-0.2	13.0	-0.3	21.1	-0.1	8.6	-0.1	12.3	-0.1	8.9
National origin										
Foreign-born	0.1	16.0	0.1	12.7	0.2	32.1	0.1	18.3	-0.1	-8.0
Recent immigrant	0.6	-299.6	-0.3	170.4	2.0	-1012.9	0.8	-396.4	-2.3	1171.6
Sex										
Male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Female	0.0	12.7	-0.1	39.5	0.0	13.7	0.1	-18.1	0.0	7.4
Unknown	0.0	29.6	0.0	-160.7	0.0	-236.3	0.0	245.2	0.0	-232.4
Marital status										
Married male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Single male	-0.2	12.0	-0.1	6.0	-0.5	27.7	-0.3	17.3	-0.2	11.1
Married female	0.0	16.4	-0.1	45.6	0.0	5.0	0.0	-14.6	0.0	4.7
Single female	-0.2	11.8	-0.3	12.6	-0.5	24.7	-0.2	10.1	-0.2	10.5
Unknown	-0.2	11.8	-0.2	8.1	-0.4	22.4	-0.3	15.5	-0.2	10.7
Age—SSA data (years)										
Younger than 30	-0.6	11.7	-0.8	16.4	-0.6	11.9	-0.4	7.1	-1.0	20.5
30 to 39	-0.6	12.1	-0.9	19.0	-1.0	21.0	-0.3	7.0	-0.8	17.9
40 to 49	-0.3	11.9	-0.7	23.6	-0.6	22.3	-0.2	5.3	-0.5	17.6
50 to 61	-0.2	12.6	-0.3	26.4	-0.4	27.3	0.0	2.5	-0.2	18.9
62 or older (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Unknown	-0.2	12.2	-0.2	16.2	-0.2	15.5	-0.1	11.0	-0.2	15.6
Census tract characteristics										
Income ratio										
Low	-0.3	12.4	-0.3	11.7	-0.7	28.4	-0.3	14.4	-0.2	6.3
Moderate	-0.1	11.6	-0.1	11.6	-0.4	30.6	-0.1	12.4	-0.1	6.6
Middle (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
High	0.1	11.8	0.1	13.8	0.2	25.2	0.1	11.4	0.1	10.0
Unknown	-0.2	107.4	-0.4	224.3	1.0	-522.4	0.2	-77.9	-0.1	42.1
Minority population (percent)										
Less than 10 (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	
10-49	-0.1	11.7	-0.1	17.6	-0.2	35.1	0.0	7.1	0.0	5.6
50-79	-0.2	11.8	-0.4	19.2	-0.6	29.7	-0.2	7.6	-0.1	6.6
80 or more	-0.4	12.8	-0.5	18.8	-0.7	26.6	-0.2	8.6	-0.2	5.4
Urban (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Rural	0.0	-0.8	0.0	-14.5	0.0	8.1	-0.1	34.8	-0.1	22.2

Table continued on next page.

Code	Translation
AT36	Total number of months since the most recent account delinquency
G051	Percentage of accounts with no late payments reported
S004	Average age of accounts on credit report
S046	Percentage of accounts that are open and active with a remaining balance greater than $0 reported in the past 12 months
S059	Total number of unique account numbers

Table 28.C. Major Derogatory: Decomposition of Mean Score Difference, by Selected Characteristics of Sample Population and Credit Characteristic—Continued

Characteristic	BC34		G095		G061		S054		G088		Total	
	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent
Race or ethnicity—SSA data												
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.4	9.0	-0.1	3.0	-0.3	6.0	-0.3	6.6	-0.1	1.2	-4.8	100
Hispanic	-0.1	6.5	-0.2	13.0	-0.1	6.7	-0.1	7.3	0.0	0.9	-1.6	100
Asian	0.1	25.8	0.0	-9.7	0.0	4.9	0.0	8.8	0.0	5.8	0.5	100
American Indian	0.1	11.1	0.0	6.8	0.1	7.2	0.0	2.4	0.0	1.4	0.7	100
Unknown race	0.0	5.4	-0.1	16.8	0.0	1.0	-0.1	20.5	0.0	-0.2	-0.3	100
Race or ethnicity—location-based distribution												
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.2	8.9	-0.1	3.1	-0.1	4.9	-0.2	7.9	0.0	0.7	-2.1	100
Hispanic	-0.1	6.7	-0.1	10.0	0.0	4.6	-0.1	9.0	0.0	-0.3	-0.9	100
Asian	0.1	50.6	0.0	2.2	0.0	2.2	0.0	-6.3	0.0	20.7	0.1	100
American Indian	-0.1	10.9	-0.1	6.0	-0.1	5.5	-0.1	11.9	0.0	2.0	-1.2	100
National origin												
Foreign-born	0.1	19.8	-0.1	-8.1	0.0	6.3	0.1	8.0	0.0	2.9	0.7	100
Recent immigrant	0.9	-447.5	-1.6	790.9	0.0	-9.5	-0.3	151.9	0.0	-18.9	-0.2	100
Sex												
Male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Female	0.0	14.0	-0.1	20.0	-0.1	25.6	0.1	-22.0	0.0	7.2	-0.3	100
Unknown	0.0	12.5	0.0	302.3	0.0	-83.7	0.0	237.7	0.0	-14.2	0.0	100
Marital status												
Married male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Single male	-0.1	7.8	-0.1	5.8	0.0	0.6	-0.2	13.1	0.0	-1.4	-1.7	100
Married female	0.0	13.2	0.0	17.7	-0.1	27.3	0.0	-22.7	0.0	7.4	-0.2	100
Single female	-0.2	9.4	-0.2	8.2	-0.1	5.0	-0.2	7.5	0.0	0.2	-2.0	100
Unknown	-0.2	9.4	-0.1	7.4	0.0	1.4	-0.3	14.2	0.0	-0.9	-1.9	100
Age—SSA data (years)												
Younger than 30	-0.5	9.1	-0.4	7.7	-0.3	6.4	-0.4	8.2	-0.1	1.0	-5.1	100
30 to 39	-0.5	10.2	-0.1	1.8	-0.4	7.6	-0.1	1.8	-0.1	1.6	-4.7	100
40 to 49	-0.3	9.5	0.0	-1.2	-0.3	9.5	0.0	-1.0	-0.1	2.5	-2.9	100
50 to 61	-0.1	8.5	0.1	-5.0	-0.1	11.3	0.1	-5.5	0.0	3.0	-1.3	100
62 or older (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Unknown	-0.1	9.4	-0.1	5.9	-0.1	5.7	-0.1	7.3	0.0	1.2	-1.3	100
Census tract characteristics												
Income ratio												
Low	-0.2	7.9	-0.1	4.4	-0.1	2.1	-0.3	13.0	0.0	-0.6	-2.4	100
Moderate	-0.1	9.4	-0.1	4.5	0.0	2.5	-0.1	11.1	0.0	-0.4	-1.2	100
Middle (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
High	0.1	12.5	0.0	1.1	0.0	3.4	0.1	9.8	0.0	0.9	0.9	100
Unknown	0.1	-72.5	-0.4	201.0	-0.2	100.7	-0.2	91.1	0.0	6.2	-0.2	100
Minority population (percent)												
Less than 10 (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
10-49	0.0	8.0	0.0	4.4	0.0	5.7	0.0	4.8	0.0	-0.1	-0.6	100
50-79	-0.1	7.4	-0.1	4.7	-0.1	5.6	-0.1	7.1	0.0	0.4	-2.0	100
80 or more	-0.2	8.2	-0.2	5.8	-0.1	5.0	-0.2	8.5	0.0	0.4	-2.8	100
Urban (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Rural	-0.1	22.0	0.0	7.4	0.0	-11.1	-0.1	32.6	0.0	-0.7	-0.3	100

(B) Base population group from which the deviations were calculated.

Code	Translation
BC34	Percentage of total remaining balance to total maximum credit for all open bankcard accounts reported in the past 12 months
G061	Number of accounts that have payments that are presently or previously 30 or more days past due within the past 24 months
G088	Total number of accounts presently less than 120 days past due in the past 2 months
G095	Total number of months since the most recent occurrence of a derogatory public record
S054	Total number of different credit issuers

Table 29. All Scorecards: Decomposition of Mean Score Difference, by Selected Characteristics of Sample Population and Variable Groups

Characterisitc	Variable group: Types of credit in use		New credit		Length of credit history		Amounts owed		Payment history		Total	
	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent	Score	Percent
Race or ethnicity—SSA data												
Non-Hispanic white(B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.5	4.3	-0.2	1.9	-0.6	5.6	-2.0	18.0	-7.7	70.2	-11.0	100
Hispanic	-0.3	4.5	-0.2	3.0	-1.1	16.4	-1.2	17.9	-4.0	58.2	-6.8	100
Asian	-0.1	10.5	0.1	-10.5	0.3	-42.1	-0.3	36.8	-0.7	100.0	-0.7	100
American Indian	0.0	0.0	0.2	10.5	0.8	36.8	0.3	15.8	0.7	31.6	2.2	100
Unknown race	-0.1	-1.7	0.4	11.7	0.0	0.0	0.3	8.3	2.8	80.0	3.5	100
Race or ethnicity—location-based distribution												
Non-Hispanic white (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Black	-0.2	3.6	-0.1	1.2	-0.3	4.8	-1.4	21.4	-4.3	67.9	-6.3	100
Hispanic	-0.2	4.7	-0.1	2.3	-0.6	14.0	-0.9	20.9	-2.5	60.5	-4.2	100
Asian	0.0	0.0	0.0	0.0	0.0	-66.7	0.0	66.7	0.0	100.0	0.0	100
American Indian	-0.3	8.7	0.0	0.0	-0.3	8.7	-0.9	23.9	-2.2	58.7	-3.8	100
National origin												
Foreign-born	-0.3	14.3	0.8	-42.9	1.9	-100.0	-1.6	85.7	-2.7	142.9	-1.9	100
Recent immigrant	-0.4	5.3	-3.1	36.8	-12.4	147.4	0.0	0.0	6.2	-73.7	-8.4	100
Sex												
Male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Female	-0.1	-66.7	0.0	-33.3	0.0	0.0	0.0	33.3	0.2	166.7	0.1	100
Unknown	0.0	0.0	0.9	9.6	0.3	3.0	0.9	10.4	7.0	77.0	9.1	100
Marital status												
Married male (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Single male	-0.4	6.5	-0.2	3.2	-0.9	14.5	-1.5	25.8	-3.0	51.6	-5.9	100
Married female	-0.2	-100.0	-0.1	-50.0	0.0	0.0	0.1	50.0	0.4	200.0	0.2	100
Single female	-0.2	3.1	0.1	-1.5	-0.7	12.3	-1.5	26.2	-3.4	58.5	-5.8	100
Unknown	-0.5	12.2	0.3	-7.3	-1.0	24.4	-1.4	34.1	-1.5	36.6	-4.1	100
Age—SSA data (years)												
Younger than 30	-0.9	4.2	-1.1	5.2	-4.5	20.3	-4.8	21.7	-10.9	49.5	-22.1	100
30 to 39	-0.4	2.7	-0.7	5.4	-2.1	16.1	-2.1	16.1	-7.9	60.4	-13.1	100
40 to 49	-0.1	1.0	-0.5	6.1	-1.2	14.1	-1.1	13.1	-5.6	65.7	-8.6	100
50 to 61	-0.1	1.9	-0.5	9.4	-0.7	15.1	-0.5	9.4	-3.3	67.9	-4.8	100
62 or older (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Unknown	-0.3	3.9	0.0	0.0	-1.9	21.6	-3.8	43.1	-2.9	33.3	-8.8	100
Census tract characteristics												
Income ratio												
Low	-0.5	6.1	-0.2	1.7	-0.7	7.8	-1.9	21.7	-5.6	62.6	-8.9	100
Moderate	-0.3	5.9	-0.1	2.0	-0.4	9.8	-1.0	23.5	-2.5	58.8	-4.3	100
Middle (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
High	0.2	5.4	-0.1	-2.7	0.6	13.5	1.4	35.1	2.1	51.4	4.1	100
Unknown	-1.0	25.0	4.0	-100.0	-1.0	25.0	-5.0	125.0	-1.0	25.0	-4.0	100
Minority population (percent)												
Less than 10 (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
10-49	-0.1	3.8	0.0	0.0	-0.3	11.5	-0.4	19.2	-1.4	65.4	-2.2	100
50-79	-0.2	3.9	-0.1	1.3	-0.6	9.2	-1.2	19.7	-4.2	67.1	-6.2	100
80 or more	-0.5	5.2	-0.1	0.9	-0.6	6.9	-1.9	20.7	-6.2	66.4	-9.3	100
Urban (B)	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .	0.0	. . .
Rural	-0.2	40.0	0.1	-20.0	-0.1	20.0	-0.6	100.0	0.1	-20.0	-0.6	100

(B) Base population group from which the deviations were calculated.
. . . Not applicable

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Table 30.A. Thin File: Score Differences from the Elimination of Credit Characteristics, by Selected Characteristics of Sample Population and Credit Characteristic

Characteristic	Base score	G096	RE34	AT28	S059	AT36	G103	IN34	AT26
Race or ethnicity—SSA data									
Non-Hispanic white	40.7	0.34	-1.55	-0.76	0.48	-0.50	0.24	-0.05	-0.05
Black	18.6	0.16	0.14	0.17	1.36	0.49	0.04	-0.01	0.02
Hispanic	30.4	0.55	-0.04	-0.09	0.09	-0.34	0.13	-0.13	0.18
Asian	49.7	0.89	-2.30	-1.38	-1.11	-0.75	-0.20	-0.28	0.83
American Indian	51.5	0.30	-3.74	-2.74	2.76	-0.01	0.90	-0.69	-0.82
Unknown race	53.6	-0.66	-2.02	0.86	-0.67	-0.26	1.71	-0.16	-0.84
Race or ethnicity—location-based distribution									
Non-Hispanic white	46.7	-0.10	-1.84	0.01	-0.07	-0.40	0.98	-0.12	-0.41
Black	33.7	-0.13	-0.55	0.50	0.37	0.13	0.56	-0.06	-0.37
Hispanic	39.3	-0.09	-0.72	0.28	-0.11	-0.12	0.68	-0.10	-0.17
Asian	48.2	-0.09	-1.99	-0.29	-0.22	-0.58	0.81	-0.14	-0.19
American Indian	40.0	0.01	-1.09	-0.01	0.12	-0.15	0.74	-0.09	-0.36
National origin									
Foreign-born	42.7	1.01	-1.25	-0.90	-0.76	-0.76	-0.13	-0.32	0.49
Recent immigrant	45.9	1.44	-1.80	-0.67	-1.75	-1.07	-0.44	-0.40	1.30
Sex									
Male	35.5	0.50	-1.04	-0.69	0.31	-0.27	0.16	-0.10	0.08
Female	36.8	0.26	-1.21	-0.39	0.62	-0.36	0.16	-0.05	0.03
Unknown	54.6	-0.77	-2.05	0.97	-0.68	-0.25	1.84	-0.15	-0.93
Marital status									
Married male	44.1	0.75	-1.77	-1.20	-0.26	-0.52	0.16	-0.03	0.06
Single male	34.1	0.48	-0.98	-0.65	0.50	-0.23	0.10	-0.22	-0.07
Married female	46.3	0.19	-1.85	-0.88	0.12	-0.56	0.31	-0.03	0.06
Single female	35.0	0.30	-1.15	-0.23	0.74	-0.24	0.10	-0.13	-0.29
Unknown	46.6	-0.43	-1.57	0.61	-0.21	-0.23	1.30	-0.11	-0.54
Age—SSA data (years)									
Younger than 30	31.3	0.67	-0.41	0.32	-0.66	-0.32	-0.13	0.42	0.75
30 to 39	24.9	0.49	-0.24	-0.32	1.22	-0.27	0.11	-0.17	0.07
40 to 49	26.9	0.20	-0.24	-0.49	1.70	-0.25	0.27	-0.26	-0.08
50 to 61	36.5	0.39	-0.64	-1.36	1.02	-0.06	0.37	-0.47	-0.58
62 or older	63.6	-0.17	-4.39	-2.27	0.97	-0.53	0.64	-0.73	-1.03
Unknown	54.6	-0.77	-2.06	0.97	-0.68	-0.25	1.84	-0.15	-0.93
Census tract characteristics									
Income ratio									
Low	30.0	-0.04	-0.26	0.70	0.28	0.03	0.57	-0.07	-0.21
Moderate	37.1	-0.08	-0.85	0.33	0.24	-0.15	0.60	-0.10	-0.24
Middle	45.0	-0.09	-1.62	-0.01	-0.10	-0.32	1.01	-0.11	-0.38
High	53.5	-0.17	-2.44	-0.09	-0.24	-0.50	0.98	-0.12	-0.51
Unknown	46.6	-0.94	0.05	1.23	-1.89	3.14	1.15	0.07	0.04
Minority population (percent)									
Less than 10	48.9	-0.10	-2.13	-0.04	-0.15	-0.59	1.15	-0.14	-0.50
10-49	45.0	-0.11	-1.62	0.06	0.00	-0.27	0.85	-0.10	-0.35
50-79	38.0	-0.08	-0.75	0.17	0.07	0.05	0.58	-0.09	-0.23
80 or more	33.1	-0.12	-0.29	0.55	0.15	0.06	0.49	-0.07	-0.18
Urban	43.9	-0.09	-1.48	0.16	-0.04	-0.31	0.85	-0.11	-0.37
Rural	44.6	-0.19	-1.75	-0.22	0.09	-0.25	1.00	-0.10	-0.32
All	44.0	-0.10	-1.52	0.10	-0.03	-0.29	0.88	-0.11	-0.36

1. For translation of codes for credit chracteristics, refer to next page.

Translation of Codes for Credit Characteristics, Table 30.A

Code	Credit Characteristic
AT26	Total number of accounts in good standing, opened 18 or more months ago
AT28	Total maximum credit issued on open accounts reported in the past 12 months
AT36	Total number of months since the most recent account delinquency
G096	Total number of inquiries for credit
G103	Total number of months since the most recent update on an account
IN34	Percentage of total remaining balance to total maximum credit for all open installment accounts reported in the past 12 months
RE34	Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months
S059	Total number of public records and derogatory accounts with an amount owed greater than $100

Table 30.B. Clean File: Score Differences from the Elimination of Credit Characteristics, by Selected Characteristics of Sample Population and Credit Characteristic

Characteristic	Base score	S019	G096	S004	RE34	AT28	G089	S043	AT36
Race or ethnicity—SSA data									
Non-Hispanic white	69.0	-0.16	0.04	-0.25	-0.05	-1.37	-0.15	-0.14	-0.09
Black	55.8	0.04	0.01	-0.02	0.32	-0.19	0.22	0.04	-0.26
Hispanic	59.8	-0.05	-0.07	1.25	-0.23	-0.92	-0.01	-0.01	-0.25
Asian	66.1	-0.53	0.14	2.22	-0.35	-2.01	0.08	-0.01	-0.26
American Indian	70.3	0.15	-0.06	-1.21	-0.03	-0.58	0.12	-0.06	0.21
Unknown race	66.7	-0.16	0.07	-0.44	-0.07	0.10	-0.20	0.04	-0.06
Race or ethnicity—location-based distribution									
Non-Hispanic white	68.4	-0.17	0.08	-0.17	-0.06	-1.21	-0.15	-0.11	-0.09
Black	62.8	-0.01	-0.10	0.02	-0.01	-0.40	0.02	0.02	-0.11
Hispanic	63.8	-0.09	-0.08	0.55	-0.12	-0.87	-0.03	-0.01	-0.23
Asian	68.0	-0.29	-0.05	0.61	-0.15	-2.13	-0.03	-0.09	-0.24
American Indian	64.9	0.08	-0.19	0.14	0.07	-0.70	0.00	-0.12	0.04
National origin									
Foreign-born	63.8	-0.35	0.06	1.96	-0.40	-1.57	0.05	0.03	-0.26
Recent immigrant	53.5	-0.39	-0.18	6.71	-0.87	-1.02	0.16	0.18	0.10
Sex									
Male	67.4	0.00	0.25	-0.09	0.05	-1.56	-0.13	-0.27	-0.19
Female	68.0	-0.31	-0.16	0.07	-0.18	-1.11	-0.11	0.03	-0.07
Unknown	65.8	-0.13	0.09	-0.87	0.03	1.37	-0.22	0.14	0.14
Marital status									
Married male	70.3	0.08	0.26	-0.56	0.00	-2.15	-0.18	-0.28	-0.23
Single male	63.9	-0.17	0.23	0.43	0.07	-0.67	-0.03	-0.21	-0.09
Married female	70.8	-0.32	-0.25	-0.22	-0.18	-1.91	-0.16	-0.02	-0.13
Single female	64.6	-0.33	0.02	0.16	-0.22	0.22	-0.02	0.16	-0.04
Unknown	62.4	-0.15	0.08	0.51	0.07	0.36	-0.11	-0.05	0.04
Age—SSA data (years)									
Younger than 30	50.0	-0.19	-0.32	5.44	-0.14	-0.26	0.01	-0.23	0.28
30 to 39	63.1	-0.29	0.17	0.87	0.30	-2.38	-0.12	-0.68	-0.06
40 to 49	68.0	-0.16	0.18	-0.34	0.11	-3.06	-0.29	-0.39	-0.15
50 to 61	71.0	-0.07	0.07	-0.79	-0.14	-2.40	-0.17	0.00	-0.46
62 or older	74.7	-0.15	-0.03	-1.86	-0.34	1.13	0.01	0.39	-0.03
Unknown	65.8	-0.12	0.09	-0.87	0.04	1.39	-0.22	0.14	0.14
Census tract characteristics									
Income ratio									
Low	57.3	-0.11	-0.05	1.07	-0.18	0.81	0.16	0.21	0.12
Moderate	63.0	-0.10	-0.10	0.26	-0.09	0.24	-0.05	0.07	-0.16
Middle	67.2	-0.14	-0.01	-0.06	-0.02	-0.68	-0.13	-0.08	-0.06
High	70.8	-0.21	0.20	-0.27	-0.12	-2.62	-0.17	-0.21	-0.19
Unknown	58.8	-0.32	-0.67	0.33	1.32	-0.13	0.74	-0.71	0.30
Minority population (percent)									
Less than 10	69.3	-0.20	0.17	-0.37	-0.07	-1.02	-0.18	-0.13	-0.01
10-49	67.3	-0.14	-0.05	0.09	-0.05	-1.51	-0.12	-0.10	-0.19
50-79	63.3	-0.09	-0.14	0.59	-0.09	-0.80	-0.01	0.01	-0.22
80 or more	59.2	-0.02	-0.15	0.65	-0.14	0.01	0.21	0.12	-0.19
Urban	67.7	-0.18	0.10	-0.07	-0.09	-1.40	-0.12	-0.11	-0.15
Rural	66.9	-0.06	-0.23	-0.07	0.05	0.13	-0.13	-0.02	0.07
All	67.6	-0.16	0.04	-0.07	-0.06	-1.16	-0.12	-0.10	-0.11

1. For translation of codes for credit chracteristics, refer to next page.

Translation of Codes for Credit Characteristics, Table 30.B

Code	Credit Characteristic
AT28	Total maximum credit issued on open accounts reported in the past 12 months
AT36	Total number of months since the most recent account delinquency
G089	Greatest amount of time a payment was late ever on an account
G096	Total number of inquiries for credit
RE34	Percentage of total remaining balance to total maximum credit for all open revolving accounts reported in the past 12 months
S004	Average age of accounts on credit report
S019	Total number of open personal finance installment accounts reported in the past 12 months
S043	Total number of open non-installment accounts with a remaining balance to maximum credit issued ratio greater than 50% reported in the past 12 months

Table 30.C. Major Derogatory: Score Differences from the Elimination of Credit Characteristics, by Selected Characteristics of Sample Population and Credit Characteristic

Characteristic	Base score	S046	S054	S059	G095	G061	G088	G051	AT36	S004	BC34
Race or ethnicity—SSA data											
Non-Hispanic white	23.5	0.09	-0.11	-0.48	-0.21	0.06	-0.01	0.06	-0.06	-0.12	-0.20
Black	15.9	-0.07	0.03	0.21	0.05	-0.02	-0.03	0.05	-0.03	0.02	-0.04
Hispanic	19.9	-0.03	-0.10	-0.11	0.15	-0.02	-0.04	0.04	0.00	0.32	-0.09
Asian	25.4	0.08	-0.19	-0.49	-0.15	0.02	-0.10	0.12	0.10	0.29	-0.33
American Indian	26.0	0.07	0.01	-0.37	-0.34	0.11	-0.01	0.07	-0.14	-0.65	-0.30
Unknown race	22.0	0.11	0.05	-0.26	0.01	0.06	-0.03	0.03	0.07	-0.29	-0.12
Race or ethnicity—location-based distribution											
Non-Hispanic white	22.6	0.06	-0.09	-0.40	-0.15	0.04	-0.02	0.05	-0.04	-0.08	-0.18
Black	18.1	0.01	0.02	0.04	0.03	0.01	-0.03	0.05	-0.01	-0.06	-0.08
Hispanic	20.2	0.02	-0.06	-0.05	0.05	0.01	-0.04	0.06	0.00	0.07	-0.11
Asian	22.9	0.06	-0.10	-0.39	-0.23	0.05	-0.06	0.12	0.01	-0.11	-0.22
American Indian	19.7	0.10	0.03	-0.45	-0.08	0.06	-0.03	0.04	-0.03	0.06	-0.13
National origin											
Foreign-born	23.5	0.01	-0.14	-0.24	-0.01	-0.01	-0.07	0.05	0.10	0.29	-0.25
Recent immigrant	20.7	0.04	-0.17	-0.33	0.37	-0.10	-0.06	0.01	0.22	1.25	-0.24
Sex											
Male	22.0	0.09	-0.05	-0.31	-0.18	0.03	-0.03	0.04	0.00	-0.10	-0.26
Female	21.2	-0.01	-0.11	-0.27	-0.05	0.04	-0.02	0.08	-0.07	0.03	-0.06
Unknown	21.8	0.18	0.09	-0.29	0.12	0.03	-0.03	0.04	0.09	-0.42	-0.09
Marital status											
Married male	24.9	0.04	-0.20	-0.55	-0.26	0.07	-0.01	0.05	-0.02	-0.34	-0.37
Single male	20.7	0.14	0.03	-0.12	-0.14	0.02	-0.03	0.01	0.00	0.01	-0.21
Married female	24.1	-0.05	-0.20	-0.61	-0.18	0.10	-0.01	0.11	-0.08	-0.18	-0.13
Single female	19.9	-0.01	-0.08	-0.09	0.03	0.03	-0.02	0.07	-0.06	0.10	0.00
Unknown	19.0	0.10	0.08	-0.10	0.03	-0.02	-0.04	0.04	0.00	0.10	-0.08
Age—SSA data (years)											
Younger than 30	16.0	-0.04	-0.03	-0.56	0.29	-0.07	-0.03	0.17	-0.21	0.86	-0.04
30 to 39	19.1	0.04	-0.11	-0.27	-0.07	-0.02	-0.02	0.08	-0.08	0.46	-0.03
40 to 49	22.0	0.06	-0.09	-0.31	-0.25	0.04	-0.03	0.05	0.01	0.02	-0.19
50 to 61	25.3	0.05	-0.14	-0.13	-0.34	0.06	-0.02	0.05	0.04	-0.60	-0.32
62 or older	29.5	0.09	0.04	-0.14	-0.13	0.28	0.00	-0.16	0.11	-1.79	-0.32
Unknown	21.8	0.18	0.09	-0.30	0.12	0.03	-0.03	0.04	0.09	-0.42	-0.09
Census tract characteristics											
Income ratio											
Low	16.7	0.07	0.16	0.18	0.09	0.00	-0.04	0.08	0.04	0.07	-0.06
Moderate	19.0	0.03	0.02	-0.02	0.00	0.00	-0.02	0.03	-0.05	0.03	-0.05
Middle	21.8	0.05	-0.07	-0.34	-0.12	0.05	-0.01	0.05	-0.04	-0.02	-0.15
High	25.6	0.06	-0.23	-0.60	-0.20	0.05	-0.05	0.12	0.00	-0.30	-0.33
Unknown	21.1	-0.20	0.04	-1.79	0.22	0.03	0.01	0.19	-0.16	-0.39	-0.49
Minority population (percent)											
Less than 10	23.7	0.07	-0.08	-0.58	-0.19	0.06	0.01	0.04	-0.04	-0.09	-0.20
10-49	21.9	0.06	-0.11	-0.26	-0.13	0.03	-0.04	0.06	-0.04	-0.08	-0.17
50-79	19.0	0.02	0.00	0.08	0.01	0.04	-0.02	0.05	0.02	0.07	-0.11
80 or more	17.8	-0.03	0.04	0.02	0.13	-0.01	-0.05	0.08	0.01	-0.04	-0.05
Urban	21.8	0.04	-0.10	-0.30	-0.12	0.03	-0.03	0.09	-0.02	-0.07	-0.16
Rural	20.9	0.11	0.09	-0.21	-0.01	0.07	0.01	-0.08	-0.06	0.01	-0.14
All	21.6	0.05	-0.07	-0.29	-0.10	0.03	-0.02	0.06	-0.03	-0.06	-0.16

1. For translation of codes for credit chracteristics, refer to next page.

Translation of Codes for Credit Characteristics, Table 30.C

Code	Credit Characteristic
AT36	Total number of months since the most recent account delinquency
BC34	Percentage of total remaining balance to total maximum credit for all open bankcard accounts reported in the past 12 months
G051	Percentage of accounts with no late payments reported
G061	Number of accounts that have payments that are presently or previously 30 or more days past due within the past 24 months
G088	Total number of accounts presently less than 120 days past due in the past 2 months
G095	Total number of months since the most recent occurrence of a derogatory public record
S004	Average age of accounts on credit report
S046	Percentage of accounts that are open and active with a remaining balance greater than $0 reported in the past 12 months
S054	Total number of different credit issuers
S059	Total number of unique account numbers

Table 31.A. Thin File: Score Differences from Group Elimination, by Selected Characteristics of Sample Population and Variable Groups

Characteristic	Base score	Variable group: New credit	Length of credit history	Amounts owed	Payment history
Race or ethnicity—SSA data					
Non-Hispanic white	40.7	0.34	0.24	-3.05	-0.17
Black	18.6	0.16	0.04	0.11	4.00
Hispanic	30.4	0.55	0.13	-0.71	0.00
Asian	49.7	0.89	-0.20	-4.80	-1.96
American Indian	51.5	0.30	0.90	-8.10	1.93
Unknown race	53.6	-0.66	1.71	-3.84	-3.36
Race or ethnicity—location-based distribution					
Non-Hispanic white	46.7	-0.10	0.98	-3.54	-1.69
Black	33.7	-0.13	0.56	-1.20	0.57
Hispanic	39.3	-0.09	0.68	-1.75	-0.76
Asian	48.2	-0.09	0.81	-3.96	-1.85
American Indian	40.0	0.01	0.74	-2.37	-0.76
National origin					
Foreign-born	42.7	1.01	-0.13	-3.06	-2.00
Recent immigrant	45.9	1.44	-0.44	-3.52	-2.98
Sex					
Male	35.5	0.50	0.16	-2.23	0.46
Female	36.8	0.26	0.16	-2.40	0.39
Unknown	54.6	-0.77	1.84	-3.91	-3.53
Marital status					
Married male	44.1	0.75	0.16	-3.60	-1.13
Single male	34.1	0.48	0.10	-2.21	0.69
Married female	46.3	0.19	0.31	-3.72	-0.99
Single female	35.0	0.30	0.10	-2.30	0.58
Unknown	46.6	-0.43	1.30	-3.03	-1.91
Age—SSA data (years)					
Younger than 30	31.3	0.67	-0.13	0.07	-0.15
30 to 39	24.9	0.49	0.11	-0.89	2.22
40 to 49	26.9	0.20	0.27	-1.34	2.44
50 to 61	36.5	0.39	0.37	-3.03	0.76
62 or older	63.6	-0.17	0.64	-9.19	-1.63
Unknown	54.6	-0.77	1.84	-3.91	-3.53
Census tract characteristics					
Income ratio					
Low	30.0	-0.04	0.57	-0.43	0.79
Moderate	37.1	-0.08	0.60	-1.71	-0.16
Middle	45.0	-0.09	1.01	-3.21	-1.51
High	53.5	-0.17	0.98	-4.75	-2.55
Unknown	46.6	-0.94	1.15	-0.38	0.78
Minority population (percent)					
Less than 10	48.9	-0.10	1.15	-3.98	-2.31
10-49	45.0	-0.11	0.85	-3.21	-1.23
50-79	38.0	-0.08	0.58	-1.79	-0.19
80 or more	33.1	-0.12	0.49	-0.83	0.39
Urban	43.9	-0.09	0.85	-2.93	-1.31
Rural	44.6	-0.19	1.00	-3.38	-1.08
All	44.0	-0.10	0.88	-2.99	-1.26

Note. Refer to notes to table 9.

Table 31.B. Clean File: Score Differences from Group Elimination, by Selected Characteristics of Sample Population and Variable Groups

Characteristic	Base score	Variable group				
		Types of credit in use	New credit	Length of credit history	Amounts owed	Payment history
Race or ethnicity—SSA data						
Non-Hispanic white	69.0	-0.16	0.04	-0.25	-0.78	-0.06
Black	55.8	0.04	0.01	-0.02	1.82	1.74
Hispanic	59.8	-0.05	-0.07	1.25	-0.82	0.80
Asian	66.1	-0.53	0.14	2.22	-3.09	-0.21
American Indian	70.3	0.15	-0.06	-1.21	0.86	0.84
Unknown race	66.7	-0.16	0.07	-0.44	1.25	0.21
Race or ethnicity—location-based						
Non-Hispanic white	68.4	-0.17	0.08	-0.17	-0.65	-0.04
Black	62.8	-0.01	-0.10	0.02	0.93	0.93
Hispanic	63.8	-0.09	-0.08	0.55	-0.22	0.45
Asian	68.0	-0.29	-0.05	0.61	-1.85	0.25
American Indian	64.9	0.08	-0.19	0.14	0.19	0.29
National origin						
Foreign-born	63.8	-0.35	0.06	1.96	-2.40	0.19
Recent immigrant	53.5	-0.39	-0.18	6.71	-3.23	-0.74
Sex						
Male	67.4	0.00	0.25	-0.09	-1.27	-0.02
Female	68.0	-0.31	-0.16	0.07	-0.37	0.17
Unknown	65.8	-0.13	0.09	-0.87	3.19	0.18
Marital status						
Married male	70.3	0.08	0.26	-0.56	-1.80	-0.13
Single male	63.9	-0.17	0.23	0.43	-0.31	0.18
Married female	70.8	-0.32	-0.25	-0.22	-1.16	0.08
Single female	64.6	-0.33	0.02	0.16	1.13	0.38
Unknown	62.4	-0.15	0.08	0.51	1.07	0.16
Age—SSA data (years)						
Younger than 30	50.0	-0.19	-0.32	5.44	-1.60	-1.03
30 to 39	63.1	-0.29	0.17	0.87	-2.96	-0.55
40 to 49	68.0	-0.16	0.18	-0.34	-2.94	-0.07
50 to 61	71.0	-0.07	0.07	-0.79	-1.59	0.26
62 or older	74.7	-0.15	-0.03	-1.86	3.15	0.87
Unknown	65.8	-0.12	0.09	-0.87	3.21	0.18
Census tract characteristics						
Income ratio						
Low	57.3	-0.11	-0.05	1.07	1.83	0.94
Moderate	63.0	-0.10	-0.10	0.26	1.35	0.42
Middle	67.2	-0.14	-0.01	-0.06	0.10	-0.02
High	70.8	-0.21	0.20	-0.27	-2.52	0.05
Unknown	58.8	-0.32	-0.67	0.33	1.80	2.75
Minority population (percent)						
Less than 10	69.3	-0.20	0.17	-0.37	-0.59	-0.24
10-49	67.3	-0.14	-0.05	0.09	-0.78	0.18
50-79	63.3	-0.09	-0.14	0.59	0.00	0.80
80 or more	59.2	-0.02	-0.15	0.65	1.11	1.33
Urban	67.7	-0.18	0.10	-0.07	-0.84	0.09
Rural	66.9	-0.06	-0.23	-0.07	0.95	0.06
All	67.6	-0.16	0.04	-0.07	-0.55	0.09

Note. Refer to notes to table 9.

Table 31.C. Major Derogatory: Score Differences from Group Elimination, by Selected Characteristics of Sample Population and Variable Groups

Characteristic	Base score	Variable group: Types of credit in use	Length of credit history	Amounts owed	Payment history
Race or ethnicity—SSA data					
Non-Hispanic white	23.5	-0.11	-0.12	-0.15	-2.18
Black	15.9	0.03	0.02	-0.05	0.65
Hispanic	19.9	-0.10	0.32	-0.18	-0.74
Asian	25.4	-0.19	0.29	-0.56	-2.00
American Indian	26.0	0.01	-0.65	-0.25	-2.35
Unknown race	22.0	0.05	-0.29	-0.09	-1.09
Race or ethnicity—location-based distribution					
Non-Hispanic white	22.6	-0.09	-0.08	-0.16	-1.81
Black	18.1	0.02	-0.06	-0.06	-0.05
Hispanic	20.2	-0.06	0.07	-0.13	-0.74
Asian	22.9	-0.10	-0.11	-0.27	-1.45
American Indian	19.7	0.03	0.06	0.04	-1.44
National origin					
Foreign-born	23.5	-0.14	0.29	-0.47	-1.40
Recent immigrant	20.7	-0.17	1.25	-0.56	-1.10
Sex					
Male	22.0	-0.05	-0.10	-0.18	-1.75
Female	21.2	-0.11	0.03	-0.12	-1.09
Unknown	21.8	0.09	-0.42	-0.01	-1.03
Marital status					
Married male	24.9	-0.20	-0.34	-0.29	-2.43
Single male	20.7	0.03	0.01	-0.13	-1.26
Married female	24.1	-0.20	-0.18	-0.23	-1.60
Single female	19.9	-0.08	0.10	-0.07	-0.72
Unknown	19.0	0.08	0.10	-0.02	-0.98
Age—SSA data (years)					
Younger than 30	16.0	-0.03	0.86	-0.12	-1.42
30 to 39	19.1	-0.11	0.46	0.04	-1.14
40 to 49	22.0	-0.09	0.02	-0.11	-1.07
50 to 61	25.3	-0.14	-0.60	-0.33	-1.56
62 or older	29.5	0.04	-1.79	-0.43	-2.64
Unknown	21.8	0.09	-0.42	-0.01	-1.04
Census tract characteristics					
Income ratio					
Low	16.7	0.16	0.07	-0.01	0.14
Moderate	19.0	0.02	0.03	-0.03	-0.73
Middle	21.8	-0.07	-0.02	-0.11	-1.52
High	25.6	-0.23	-0.30	-0.38	-2.28
Unknown	21.1	0.04	-0.39	-0.85	-0.39
Minority population (percent)					
Less than 10	23.7	-0.08	-0.09	-0.18	-2.28
10-49	21.9	-0.11	-0.08	-0.13	-1.53
50-79	19.0	0.00	0.07	-0.11	-0.27
80 or more	17.8	0.04	-0.04	-0.12	0.28
Urban	21.8	-0.10	-0.07	-0.17	-1.30
Rural	20.9	0.09	0.01	0.02	-1.88
All	21.6	-0.07	-0.06	-0.14	-1.40

Note. Refer to notes to table 9.

Table 32.A. Thin File: Biggest Changes in Scores Arising from the Addition of New Credit Characteristics

Characteristic	Base score	Largest positive effect		Largest negative effect	
		Character-istic	Difference	Character-istic	Difference
Race or ethnicity—SSA data					
Non-Hispanic white	40.7	IN21	0.52	AT35	-0.67
Black	18.6	IN21	0.28	G047	-0.15
Hispanic	30.4	AT10	0.25	AT20	-0.34
Asian	49.7	AT10	0.49	AT20	-1.18
American Indian	51.5	G104	0.99	AT35	-2.06
Unknown race	53.6	IN21	0.56	S040	-0.56
Race or ethnicity—location-based distribution					
Non-Hispanic white	46.7	IN21	0.56	S040	-0.38
Black	33.7	IN21	0.30	S040	-0.20
Hispanic	39.3	IN21	0.26	AT20	-0.23
Asian	48.2	IN21	0.58	AT35	-0.42
American Indian	40.0	AT34	0.36	AT35	-0.43
National origin					
Foreign-born	42.7	AT10	0.44	AT20	-0.74
Recent immigrant	45.9	AT10	0.54	AT20	-1.36
Sex					
Male	35.5	IN21	0.31	AT35	-0.56
Female	36.8	IN21	0.51	RT21	-0.47
Unknown	54.6	IN21	0.59	S040	-0.60
Marital status					
Married male	44.1	IN21	0.43	AT35	-0.79
Single male	34.1	IN21	0.29	AT35	-0.57
Married female	46.3	IN21	0.58	AT35	-0.69
Single female	35.0	IN21	0.52	RT21	-0.50
Unknown	46.6	IN21	0.50	S040	-0.42
Age—SSA data (years)					
Younger than 30	31.3	RT28	0.36	AT20	-0.53
30 to 39	24.9	RT28	0.48	AT20	-0.39
40 to 49	26.9	RT28	0.51	S004	-0.34
50 to 61	36.5	IN21	0.49	AT35	-0.44
62 or older	63.6	G104	1.24	AT35	-1.78
Unknown	54.6	IN21	0.59	S040	-0.60
Census tract characteristics					
Income ratio					
Low	30.0	AT10	0.17	AT20	-0.22
Moderate	37.1	IN21	0.31	S040	-0.23
Middle	45.0	IN21	0.51	S040	-0.35
High	53.5	IN21	0.72	S040	-0.47
Unknown	46.6	AT24	0.69	S004	-0.45
Minority population (percent)					
Less than 10	48.9	IN21	0.61	S040	-0.42
10-49	45.0	IN21	0.53	S040	-0.35
50-79	38.0	IN21	0.29	S040	-0.25
80 or more	33.1	AT10	0.21	AT20	-0.21
Urban	43.9	IN21	0.48	S040	-0.33
Rural	44.6	IN21	0.48	AT35	-0.39
All	44.0	IN21	0.48	S040	-0.33

Note. A complete list of the credit characteristics in the TransUnion sample and their codes is in appendix B; the characteristics used for the three scorecards are listed in appendix C. Refer also to notes to table 9.

Table 32.B. Clean File: Biggest Changes in Scores Arising from the Addition of New Credit Characteristics

Characteristic	Base score	Largest positive effect		Largest negative effect	
		Characteristic	Difference	Characteristic	Difference
Race or ethnicity—SSA data					
Non-Hispanic white	69.0	S015	0.11	MT35	-0.26
Black	55.8	AT26	0.14	RT33	-0.39
Hispanic	59.8	MT20	0.19	DS02	-0.29
Asian	66.1	AT29	0.35	BI20	-0.25
American Indian	70.3	RT03	0.27	AT07	-0.35
Unknown race	66.7	AT01	0.38	S010	-0.23
Race or ethnicity—location-based distribution					
Non-Hispanic white	68.4	DS09	0.10	MT35	-0.25
Black	62.8	MT34	0.10	MT35	-0.23
Hispanic	63.8	AT34	0.10	AT07	-0.25
Asian	68.0	S015	0.11	AT07	-0.25
American Indian	64.9	OF01	0.15	MT35	-0.25
National origin					
Foreign-born	63.8	AT29	0.30	AT07	-0.30
Recent immigrant	53.5	RE28	0.83	G006	-0.36
Sex					
Male	67.4	DS03	0.42	MT35	-0.24
Female	68.0	DS09	0.10	DS03	-0.54
Unknown	65.8	AT01	0.65	MT01	-0.35
Marital status					
Married male	70.3	RT03	0.38	MT35	-0.29
Single male	63.9	DS03	0.52	AT07	-0.20
Married female	70.8	AT08	0.12	DS03	-0.64
Single female	64.6	S046	0.18	DS03	-0.45
Unknown	62.4	AT01	0.28	MT01	-0.19
Age—SSA data (years)					
Younger than 30	50.0	BR28	0.58	G006	-0.32
30 to 39	63.1	RE20	0.42	RE33	-0.22
40 to 49	68.0	MT20	0.26	G051	-0.28
50 to 61	71.0	MT21	0.23	BR20	-0.41
62 or older	74.7	AT33	0.38	AT07	-0.52
Unknown	65.8	AT01	0.65	MT01	-0.35
Census tract characteristics					
Income ratio					
Low	57.3	BR28	0.32	MT01	-0.20
Moderate	63.0	PF02	0.11	MT35	-0.24
Middle	67.2	MT34	0.10	MT35	-0.29
High	70.8	DS09	0.11	AT07	-0.22
Unknown	58.8	DS03	0.49	BC21	-0.54
Minority population (percent)					
Less than 10	69.3	S015	0.11	MT35	-0.29
10-49	67.3	DS09	0.09	AT07	-0.20
50-79	63.3	AT34	0.09	AT07	-0.21
80 or more	59.2	AT34	0.14	BR20	-0.35
Urban	67.7	DS09	0.10	MT35	-0.21
Rural	66.9	BI20	0.27	MT35	-0.33
All	67.6	MT34	0.10	MT35	-0.23

Note. Refer to note to table 32.A.

Table 32.C. Major Derogatory: Biggest Changes in Scores Arising from the Addition of New Credit Characteristics

Characteristic	Base score	Largest positive effect		Largest negative effect	
		Character-istic	Difference	Character-istic	Difference
Race or ethnicity—SSA data					
Non-Hispanic white	23.5	PB35	0.17	RE28	-0.06
Black	15.9	AT09	0.03	FI01	-0.10
Hispanic	19.9	IN34	0.09	S009	-0.10
Asian	25.4	MT32	0.29	S114	-0.19
American Indian	26.0	G096	0.22	FI01	-0.21
Unknown race	22.0	PB35	0.13	G086	-0.06
Race or ethnicity—location-based distribution					
Non-Hispanic white	22.6	PB35	0.16	G086	-0.06
Black	18.1	BC29	0.05	FI01	-0.06
Hispanic	20.2	G006	0.09	DS13	-0.05
Asian	22.9	MT32	0.28	G098	-0.07
American Indian	19.7	G096	0.09	FI01	-0.18
National origin					
Foreign-born	23.5	MT32	0.16	G098	-0.12
Recent immigrant	20.7	IN34	0.31	AT20	-0.18
Sex					
Male	22.0	RT03	0.18	FI01	-0.11
Female	21.2	BC29	0.10	RT12	-0.12
Unknown	21.8	PB35	0.11	G104	-0.07
Marital status					
Married male	24.9	PB35	0.27	FI01	-0.20
Single male	20.7	RT03	0.14	G098	-0.05
Married female	24.1	PB35	0.18	DS14	-0.15
Single female	19.9	S014	0.11	RT12	-0.10
Unknown	19.0	G006	0.07	MT02	-0.05
Age—SSA data (years)					
Younger than 30	16.0	PF02	0.12	AT20	-0.16
30 to 39	19.1	RE12	0.12	G104	-0.09
40 to 49	22.0	MT21	0.18	G043	-0.08
50 to 61	25.3	BC98	0.22	RE13	-0.13
62 or older	29.5	G096	0.38	AT28	-0.21
Unknown	21.8	PB35	0.10	G104	-0.07
Census tract characteristics					
Income ratio					
Low	16.7	S019	0.11	AT28	-0.10
Moderate	19.0	G006	0.06	AT28	-0.08
Middle	21.8	PB35	0.12	FI01	-0.05
High	25.6	MT32	0.38	G098	-0.14
Unknown	21.1	G096	0.37	MT21	-0.42
Minority population (percent)					
Less than 10	23.7	PB35	0.19	G098	-0.06
10-49	21.9	PB35	0.13	RE28	-0.06
50-79	19.0	G006	0.08	DS13	-0.04
80 or more	17.8	IN34	0.09	RE12	-0.08
Urban	21.8	PB35	0.13	G098	-0.05
Rural	20.9	G096	0.15	FI01	-0.14
All	21.6	PB35	0.13	G086	-0.05

Note. Refer to note to table 32.A.

Table 33. Change in Mean Scores for Blacks, by Scorecard, from the Marginal Inclusion of Finance Company Tradeline Variables

Finance company variable (credit characteristic)		Thin	Clean	Major derogatory
FI01	Total number of finance installment accounts	0.01	0.09	-0.10
FI03	Total number of open finance installment accounts in good standing	0.00	-0.05	-0.04
FI05	Total number of finance installment accounts opened in the past 3 months	0.00	0.00	-0.01
FI06	Total number of finance installment accounts opened in the past 6 months	0.02	-0.07	-0.02
FI07	Total number of finance installment accounts opened in the past 12 months	-0.01	-0.07	-0.01
FI08	Total number of finance installment accounts opened in the past 18 months	-0.01	-0.04	-0.02
FI09	Total number of finance installment accounts opened in the past 24 months	-0.02	-0.06	-0.02
PF02	Total number of open and active personal loan accounts reported in the past 3 months	0.00	0.03	-0.05
PF03	Total number of open personal loan accounts in good standing	-0.01	-0.02	-0.04
PF05	Total number of personal loan accounts opened in the past 3 months	0.00	-0.02	0.00
PF06	Total number of personal loan accounts opened in the past 6 months	0.01	0.07	-0.01
PF07	Total number of personal loan accounts opened in the past 12 months	-0.01	0.02	-0.01
PF08	Total number of personal loan accounts opened in the past 18 months	0.00	0.01	-0.01
PF09	Total number of personal loan accounts opened in the past 24 months	0.00	0.04	-0.02
PF33	Total remaining balance from all open personal loan accounts reported in the past 12 months	-0.02	0.03	-0.01
PF34	Percentage of total remaining balance to total maximum credit for all open personal loan accounts reported in the past 12 months	-0.01	0.09	-0.04
S008	Total number of finance accounts confirmed in the past 12 months	0.00	-0.07	-0.06
S014	Total number of open finance installment accounts	-0.02	0.08	-0.02
S018	Total number of finance accounts opened in the past 12 months	-0.01	0.07	-0.01
S019	Total number of open personal finance installment accounts reported in the past 12 months	-0.01	. . .	-0.04
S020	Total number of open personal finance revolving accounts reported in the past 12 months	0.00	0.06	0.01
S027	Total number of months since the newest finance account was opened	-0.01	-0.04	-0.02
S078	Percentage of total remaining balance to total maximum credit for all open personal finance revolving accounts reported in the past 12 months	-0.01	-0.03	-0.01
S115	Total number of credit inquiries made by a finance company	-0.01	-0.03	0.00

Note. A complete list of the credit characteristics in the TransUnion sample and their codes is in appendix B; the characteristics used for the three scorecards are listed in appendix C.

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Table 34. FRB Base Score: Measures of Fit, by Selected Characteristics of the Sample Population and Performance Measure

Characteristic	Any account				New account				Existing account				Random account				Modified new account			
	KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean	
	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads
Race or ethnicity—SSA data																				
Non-Hispanic white	72.8	73.5	66.0	21.1	61.9	62.0	58.9	21.2	74.1	74.6	65.8	20.1	71.7	71.4	60.5	16.2	54.6	52.7	57.7	26.5
Black	69.4	68.0	49.4	14.4	48.2	56.4	37.2	14.8	69.2	69.3	48.9	14.0	56.1	66.0	37.6	11.9	38.9	49.5	36.7	18.9
Hispanic	66.2	68.2	54.7	18.8	52.3	55.9	46.9	19.7	67.9	70.4	54.5	17.8	61.8	67.3	47.0	14.9	39.6	45.9	45.4	25.3
Asian	66.9	73.4	63.1	25.0	57.4	62.6	58.5	26.0	71.1	75.9	63.0	22.6	68.8	72.0	59.4	19.0	56.3	56.1	57.4	31.3
American Indian	70.9	72.7	67.4	23.1	65.0	65.6	59.6	20.1	71.3	73.5	67.4	23.0	70.8	72.9	62.5	18.0	57.5	55.6	57.6	26.4
Unknown race	70.2	73.0	63.8	22.4	57.8	58.8	56.0	21.6	70.6	73.4	63.6	21.8	67.2	68.5	59.0	18.8	50.1	51.8	54.8	26.7
Race or ethnicity—location-based distribution																				
Non-Hispanic white	73.1	73.5	65.3	20.5	61.2	61.4	57.8	20.5	74.3	74.5	65.1	19.6	71.2	70.8	59.5	16.0	53.5	52.3	56.5	25.6
Black	73.1	71.3	58.4	16.6	56.1	58.2	47.5	16.9	73.1	72.5	58.1	16.2	64.8	68.1	49.0	13.6	45.3	50.3	46.1	21.8
Hispanic	69.5	70.3	59.2	19.0	56.7	58.5	50.4	18.8	70.1	71.5	59.0	18.2	65.2	67.7	52.0	15.2	46.0	51.5	48.9	24.2
Asian	70.4	72.4	64.5	21.2	60.2	61.6	58.2	21.6	72.3	73.9	64.3	20.1	69.9	70.3	59.3	16.7	53.3	54.1	57.2	27.4
American Indian	73.1	72.8	60.8	17.7	61.8	63.4	51.5	17.8	74.0	73.6	60.6	16.9	67.3	69.2	53.4	14.5	49.6	54.3	48.9	22.6
National origin																				
Foreign-born	66.1	71.2	59.9	22.6	54.4	59.8	53.8	23.4	69.8	73.9	59.8	20.5	67.6	70.4	54.6	16.6	44.1	48.7	52.5	30.7
Recent immigrant	61.3	71.0	52.1	23.7	43.0	59.8	48.5	27.7	67.3	74.3	52.0	20.9	66.5	70.5	48.8	17.2	35.7	47.5	47.5	35.6
Sex																				
Male	72.4	72.7	63.6	19.6	59.6	60.6	55.8	20.4	73.4	73.8	63.3	18.8	70.1	70.7	57.3	15.3	51.0	51.9	54.3	25.5
Female	74.3	73.4	64.9	19.1	63.7	62.7	56.9	18.5	75.3	74.4	64.8	18.4	71.1	70.5	58.1	14.8	54.6	53.8	55.6	23.5
Unknown	68.8	73.4	63.5	23.7	53.3	56.2	54.6	23.9	69.1	73.6	63.4	23.3	66.5	68.4	59.7	20.8	46.8	49.1	53.4	30.5
Marital status																				
Married male	72.9	74.1	67.3	22.2	62.3	62.4	59.9	21.9	75.1	75.5	67.1	20.4	73.0	72.5	61.7	16.3	56.4	55.4	58.4	25.8
Single male	70.9	71.3	59.5	18.8	57.1	59.3	51.3	19.7	71.3	72.4	59.3	18.3	67.1	69.2	52.9	15.1	45.8	49.5	49.9	25.7
Married female	74.1	74.6	68.5	21.8	65.3	64.5	61.3	20.7	76.7	76.2	68.4	20.0	73.8	72.5	62.7	16.0	60.5	56.1	60.0	25.1
Single female	72.7	71.8	61.0	18.2	61.0	61.4	51.8	17.3	73.2	72.6	60.7	17.6	67.8	68.8	53.4	14.2	51.1	52.6	50.8	23.0
Unknown	71.9	72.2	58.8	18.2	55.3	57.7	49.4	19.4	71.5	72.4	58.7	18.3	65.7	67.9	52.5	15.7	44.8	49.8	48.3	24.7

Table continued on next page.

Table 34. FRB Base Score: Measures of Fit, by Selected Characteristics of the Sample Population and Performance Measure—Continued

Characteristic	Any account				New account				Existing account				Random account				Modified new account			
	KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean	
	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads
Age—SSA data (years)																				
Younger than 30	69.4	73.7	47.5	16.8	52.3	61.0	43.3	19.7	69.0	75.2	47.5	16.8	62.2	68.7	42.2	14.7	43.8	55.3	43.4	25.3
30 to 39	74.2	72.9	58.5	16.7	63.3	63.6	52.4	17.4	75.2	74.3	58.4	16.1	69.1	72.2	50.8	13.2	55.5	54.9	51.6	22.1
40 to 49	74.0	73.5	64.2	18.7	64.3	64.0	57.5	18.7	75.3	74.9	63.9	17.6	71.0	72.2	56.6	14.1	55.5	54.5	56.0	23.1
50 to 61	72.2	73.0	67.7	22.0	65.6	65.3	61.0	19.6	74.8	74.5	67.5	20.2	72.0	71.7	61.3	15.9	57.9	55.9	59.5	24.5
62 or older	68.1	71.7	72.9	30.4	62.6	60.5	67.3	26.9	70.2	72.1	72.7	28.7	70.0	68.7	69.6	24.0	56.0	48.9	65.2	33.6
Unknown	68.8	73.4	63.5	23.7	53.3	56.1	54.6	23.9	69.1	73.6	63.4	23.3	66.5	68.4	59.7	20.8	46.8	49.0	53.4	30.5
Census tract characteristics																				
Income ratio																				
Low	71.5	68.7	53.1	15.6	56.0	55.6	42.7	16.7	70.6	69.4	52.9	15.7	62.5	66.3	44.4	13.4	45.7	48.4	42.2	21.4
Moderate	71.4	70.9	58.5	17.7	57.0	58.3	48.3	17.7	71.8	72.2	58.2	17.2	65.4	68.1	50.6	14.4	46.3	52.8	46.9	22.1
Middle	72.8	73.0	63.8	19.9	59.5	60.0	55.6	20.2	73.6	73.8	63.6	19.1	69.8	70.0	57.5	15.7	50.2	50.7	54.1	25.6
High	71.9	74.7	68.2	23.1	64.5	64.9	62.1	22.5	74.4	76.2	68.0	21.5	72.9	72.2	63.3	17.3	57.2	55.8	61.1	28.0
Unknown	64.6	73.0	55.3	23.3	74.8	80.3	52.3	24.9	64.8	74.0	55.1	23.3	58.3	67.5	50.5	21.3	74.9	80.0	54.4	29.4
Minority population (percent)																				
Less than 10	73.3	74.2	66.6	21.6	62.2	61.8	59.6	21.8	74.3	74.9	66.4	20.7	72.3	71.4	61.4	16.8	55.1	52.7	58.4	27.0
10-49	72.4	72.8	63.9	19.7	60.4	60.7	56.0	20.0	73.7	74.0	63.7	18.9	69.8	70.1	57.5	15.5	51.4	51.8	54.6	24.8
50-79	71.4	70.8	58.6	17.6	57.5	58.7	49.0	17.7	72.0	72.1	58.3	16.9	65.3	68.2	50.5	14.2	46.4	52.3	47.7	23.1
80 or more	69.6	67.9	54.1	16.9	54.4	56.8	43.5	16.9	69.4	69.4	53.8	16.6	61.2	66.3	45.4	14.0	43.3	48.0	42.5	22.3
Urban	73.1	73.1	64.4	19.7	61.2	61.2	56.7	19.7	74.0	74.1	64.2	18.9	70.3	70.3	58.1	15.5	52.8	52.7	55.4	25.0
Rural	73.6	73.2	63.3	19.4	60.5	60.4	53.9	19.3	74.4	74.1	63.2	18.7	69.6	69.9	56.8	15.5	51.7	50.9	51.9	23.3
All	73.0	73.0	64.2	19.6	61.0	61.0	56.3	19.7	74.0	74.0	64.0	18.9	70.2	70.2	57.9	15.5	52.4	52.4	54.9	24.8

Note. Refer to notes to table 9. KS Kolmogorov-Smirnov.

Table 35. Scores from the FRB Base Model and Race-Neutral Models: Measures of Fit, by Selected Characteristics of the Sample Population and Performance Measure

Characteristic	Any account				New account				Existing account				Random account				Modified new account			
	KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean	
	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads
	FRB base model																			
Race or ethnicity—SSA data																				
Non-Hispanic white	72.8	73.5	66.0	21.1	61.9	62.0	58.9	21.2	74.1	74.6	65.8	20.1	71.7	71.4	60.5	16.2	54.6	52.7	57.7	26.5
Black	69.4	68.0	49.4	14.4	48.2	56.4	37.2	14.8	69.2	69.3	48.9	14.0	56.1	66.0	37.6	11.9	38.9	49.5	36.7	18.9
Hispanic	66.2	68.2	54.7	18.8	52.3	55.9	46.9	19.7	67.9	70.4	54.5	17.8	61.8	67.3	47.0	14.9	39.6	45.9	45.4	25.3
Asian	66.9	73.4	63.1	25.0	57.4	62.6	58.5	26.0	71.1	75.9	63.0	22.6	68.8	72.0	59.4	19.0	56.3	56.1	57.4	31.3
American Indian	70.9	72.7	67.4	23.1	65.0	65.6	59.6	20.1	71.3	73.5	67.4	23.0	70.8	72.9	62.5	18.0	57.5	55.6	57.6	26.4
Unknown race	70.2	73.0	63.8	22.4	57.8	58.8	56.0	21.6	70.6	73.4	63.6	21.8	67.2	68.5	59.0	18.8	50.1	51.8	54.8	26.7
Race or ethnicity—location-based distribution																				
Non-Hispanic white	73.1	73.5	65.3	20.5	61.2	61.4	57.8	20.5	74.3	74.5	65.1	19.6	71.2	70.8	59.5	16.0	53.5	52.3	56.5	25.6
Black	73.1	71.3	58.4	16.6	56.1	58.2	47.5	16.9	73.1	72.5	58.1	16.2	64.8	68.1	49.0	13.6	45.3	50.3	46.1	21.8
Hispanic	69.5	70.3	59.2	19.0	56.7	58.5	50.4	18.8	70.1	71.5	59.0	18.2	65.2	67.7	52.0	15.2	46.0	51.5	48.9	24.2
Asian	70.4	72.4	64.5	21.2	60.2	61.6	58.2	21.6	72.3	73.9	64.3	20.1	69.9	70.3	59.3	16.7	53.3	54.1	57.2	27.4
American Indian	73.1	72.8	60.8	17.7	61.8	63.4	51.5	17.8	74.0	73.6	60.6	16.9	67.3	69.2	53.4	14.5	49.6	54.3	48.9	22.6
National origin																				
Foreign-born	66.1	71.2	59.9	22.6	54.4	59.8	53.8	23.4	69.8	73.9	59.8	20.5	67.6	70.4	54.6	16.6	44.1	48.7	52.5	30.7
Recent immigrant	61.3	71.0	52.1	23.7	43.0	59.8	48.5	27.7	67.3	74.3	52.0	20.9	66.5	70.5	48.8	17.2	35.7	47.5	47.5	35.6
All	73.0	73.0	64.2	19.6	61.0	61.0	56.3	19.7	74.0	74.0	64.0	18.9	70.2	70.2	57.9	15.5	52.4	52.4	54.9	24.8

Table continued on next page.

Table 35. Scores from the FRB Base Model and Race-Neutral Models: Measures of Fit, by Selected Characteristics of the Sample Population and Performance Measure—Continued

Characteristic	Any account				New account				Existing account				Random account				Modified new account			
	KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean	
	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads
	Non-Hispanic-white-only model																			
Race or ethnicity—SSA data																				
Non-Hispanic white	72.7	73.4	66.2	21.0	61.7	62.0	59.0	21.2	74.0	74.5	66.0	20.1	71.7	71.2	60.6	16.2	54.5	52.6	57.7	26.6
Black	69.3	67.7	49.5	14.5	48.1	56.1	37.3	15.0	69.2	68.9	49.0	14.2	55.8	65.9	37.7	12.1	38.9	47.7	36.8	19.1
Hispanic	66.1	68.0	54.9	18.9	51.9	55.4	47.1	19.9	67.8	70.2	54.7	17.9	61.4	67.0	47.1	15.1	38.6	45.2	45.6	25.6
Asian	66.4	72.9	63.3	25.0	56.4	62.0	58.6	26.2	70.6	75.6	63.2	22.6	69.0	71.1	59.5	19.1	57.3	55.9	57.5	31.6
American Indian	70.7	72.6	67.5	23.1	65.8	66.6	59.6	20.0	71.0	73.5	67.5	22.9	71.2	72.3	62.6	18.0	58.2	56.8	57.6	26.3
Unknown race	69.9	72.7	63.5	22.5	57.7	59.1	56.2	21.8	70.2	72.9	63.3	21.9	66.9	68.3	58.8	19.0	50.1	51.5	54.9	27.0
Race or ethnicity—location-based distribution																				
Non-Hispanic white	73.0	73.4	65.4	20.5	61.1	61.2	57.9	20.6	74.1	74.4	65.2	19.6	71.1	70.7	59.6	16.1	53.2	51.9	56.6	25.7
Black	72.9	71.2	58.5	16.7	55.9	57.9	47.6	17.1	72.9	72.3	58.2	16.3	64.6	68.1	49.1	13.7	45.0	50.6	46.2	22.0
Hispanic	69.3	70.2	59.3	19.1	56.2	58.0	50.6	18.9	69.9	71.3	59.1	18.3	64.9	67.5	52.1	15.3	44.7	50.9	49.1	24.5
Asian	70.1	72.2	64.6	21.3	59.6	61.5	58.3	21.8	71.9	73.6	64.4	20.2	69.9	70.1	59.4	16.8	52.4	53.2	57.3	27.7
American Indian	73.0	72.5	61.0	17.8	61.8	64.0	51.7	17.9	74.0	73.6	60.7	17.0	67.2	69.3	53.6	14.7	50.4	54.6	49.0	22.7
National origin																				
Foreign-born	65.9	70.8	60.1	22.7	54.2	59.3	53.9	23.5	69.7	73.4	59.9	20.6	67.4	69.8	54.7	16.7	44.8	48.5	52.6	31.0
Recent immigrant	61.2	70.5	52.5	24.0	43.8	60.2	48.9	28.0	67.0	72.9	52.4	21.2	66.4	70.1	49.2	17.6	36.3	49.8	47.9	36.0
All	72.9	72.9	64.3	19.7	60.8	60.8	56.4	19.8	73.9	73.9	64.1	18.9	70.1	70.1	57.9	15.6	52.0	52.0	55.0	24.9
	Racial-indicator-variable model																			
Race or ethnicity—SSA data																				
Non-Hispanic white	72.8	73.4	66.3	21.1	61.9	62.1	59.2	21.2	74.0	74.4	66.1	20.1	71.7	71.3	60.7	16.2	54.7	52.7	58.0	26.6
Black	69.4	67.8	49.6	14.4	48.3	56.0	37.4	14.8	69.2	69.2	49.1	14.0	56.1	66.1	37.8	11.9	38.8	50.0	36.9	18.9
Hispanic	66.3	68.2	55.0	18.8	52.3	55.4	47.2	19.7	68.0	70.4	54.8	17.8	61.7	67.3	47.2	14.9	39.7	44.7	45.7	25.4
Asian	66.4	73.3	63.4	25.0	56.3	62.8	58.9	26.1	70.5	75.7	63.3	22.6	68.8	71.5	59.6	19.0	55.9	56.3	57.8	31.6
American Indian	70.9	72.8	67.7	23.1	65.4	67.0	59.9	20.1	71.2	73.3	67.6	23.0	70.8	72.4	62.7	18.0	58.0	57.5	57.9	26.3
Unknown race	70.1	73.2	63.2	22.4	57.7	59.9	56.2	21.7	70.5	73.4	63.0	21.9	67.2	68.9	58.5	18.9	50.5	52.8	55.0	26.7
Race or ethnicity—location-based distribution																				
Non-Hispanic white	73.1	73.5	65.5	20.5	61.2	61.3	58.1	20.5	74.1	74.4	65.3	19.6	71.2	70.7	59.6	16.0	53.7	52.2	56.8	25.6
Black	73.0	71.3	58.5	16.6	56.1	57.9	47.7	16.9	73.0	72.4	58.2	16.2	64.5	68.2	49.1	13.6	45.2	50.3	46.3	21.8
Hispanic	69.5	70.3	59.3	19.0	56.6	58.4	50.7	18.8	70.1	71.4	59.1	18.2	65.0	67.8	52.2	15.2	45.4	51.1	49.2	24.3
Asian	70.4	72.3	64.7	21.3	60.1	61.6	58.5	21.7	72.1	73.7	64.5	20.1	69.9	70.1	59.4	16.7	53.1	53.7	57.5	27.6
American Indian	73.0	72.6	61.0	17.7	61.7	62.9	51.8	17.8	74.0	73.3	60.8	16.9	67.2	69.1	53.6	14.5	49.7	53.5	49.1	22.6
National origin																				
Foreign-born	66.1	71.1	60.2	22.6	54.1	59.7	54.1	23.4	69.8	73.8	60.0	20.5	67.6	70.3	54.8	16.6	44.3	48.6	52.8	30.9
Recent immigrant	61.2	70.7	52.5	23.9	43.2	58.9	49.0	27.9	66.9	74.6	52.4	21.0	66.5	71.2	49.2	17.3	35.9	46.4	48.0	36.0
All	73.0	73.0	64.3	19.6	60.9	60.9	56.5	19.7	73.9	73.9	64.2	18.9	70.1	70.1	58.0	15.5	52.2	52.2	55.2	24.8

Note. Refer to notes to table 34.

Table 36. Scores from the FRB Base Model and Race-Neutral Models: Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population

Characteristic	MEMO Sample (number)	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
		Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
	FRB base model														
Race or ethnicity—SSA data															
Non-Hispanic white	148,568	54.0	56.0	28.3	7.6	8.4	9.0	9.5	9.6	10.1	10.3	12.3	12.2	11.1	100
Black	21,368	25.8	18.6	22.9	30.3	22.6	15.2	9.9	6.9	4.9	3.4	2.7	2.2	2.0	100
Hispanic	16,950	38.3	34.0	26.3	15.5	14.7	14.7	13.2	10.9	9.4	6.9	5.4	4.6	4.7	100
Asian	8,820	54.8	55.2	25.9	5.1	6.1	8.1	10.5	12.4	15.2	13.0	10.0	8.3	11.3	100
American Indian	409	57.3	63.0	27.8	5.5	6.3	10.7	8.8	8.2	8.1	10.2	15.2	15.4	11.6	100
Unknown race	36,352	52.2	52.4	27.2	7.2	8.1	9.0	10.5	12.6	13.7	11.4	8.1	8.2	11.3	100
Race or ethnicity—location-based distribution															
Non-Hispanic white	174,087	52.6	54.0	28.4	8.4	8.8	9.3	9.6	9.9	10.6	10.3	11.3	11.0	10.7	100
Black	23,946	37.5	31.2	28.0	19.4	16.4	13.1	10.4	9.1	8.1	6.5	6.0	5.8	5.1	100
Hispanic	23,632	43.1	39.8	28.0	13.7	12.6	12.2	11.9	10.9	10.0	8.1	6.9	6.8	6.9	100
Asian	9,016	52.5	53.0	28.5	8.3	8.3	9.2	10.4	10.8	11.8	10.1	9.3	9.3	12.7	100
American Indian	1,373	44.0	40.6	28.7	13.5	13.3	12.2	10.7	9.8	8.6	8.3	8.5	8.0	7.1	100
National origin															
Foreign-born	25,597	48.7	48.0	26.6	8.2	8.9	10.6	12.5	12.8	13.1	10.2	8.3	7.1	8.4	100
Recent immigrant	4,261	44.3	46.2	20.9	8.0	7.0	9.1	14.8	18.7	21.5	12.4	4.4	2.0	2.1	100
All	232,467	50.0	50.0	28.8	10.1	10.0	10.0	10.0	10.0	10.3	9.7	10.2	10.0	9.8	100

Table continued on next page.

Table 36. Scores from the FRB Base Model and Race-Neutral Models: Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population—Continued

Characteristic	MEMO Sample (number)	Score statistics: Mean	Median	Standard deviation	Sample population, grouped by characteristic and distributed by score decile (percent): 1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
	Non-Hispanic-white-only model														
Race or ethnicity—SSA data															
Non-Hispanic white	148,568	54.1	56.6	28.4	7.7	8.3	9.0	9.4	9.7	9.4	10.8	12.5	11.9	11.3	100
Black	21,368	25.9	18.8	23.0	30.1	22.6	15.3	10.0	7.0	4.6	3.5	2.9	2.0	2.0	100
Hispanic	16,950	38.5	34.0	26.4	15.5	14.6	14.7	13.0	11.2	8.9	7.3	5.4	4.5	4.9	100
Asian	8,820	54.9	56.2	25.9	5.2	6.2	7.8	10.4	12.6	14.5	13.8	9.6	8.4	11.4	100
American Indian	409	57.4	63.2	27.9	5.5	6.5	10.6	8.7	8.3	7.4	10.7	15.1	15.6	11.6	100
Unknown race	36,352	51.9	53.0	27.1	7.2	8.1	9.1	11.0	11.9	14.9	10.9	7.5	10.1	9.5	100
Race or ethnicity—location-based distribution															
Non-Hispanic white	174,087	52.7	54.4	28.5	8.5	8.8	9.3	9.7	9.9	10.2	10.7	11.3	11.1	10.7	100
Black	23,946	37.5	31.2	28.0	19.3	16.4	13.1	10.5	9.2	8.0	6.5	6.1	6.0	5.0	100
Hispanic	23,632	43.1	40.0	28.0	13.7	12.6	12.2	11.7	11.0	9.9	8.3	6.9	7.0	6.7	100
Asian	9,016	52.6	53.6	28.4	8.3	8.2	9.3	10.3	10.8	11.5	10.6	9.2	9.7	12.2	100
American Indian	1,373	44.1	40.6	28.7	13.4	13.4	12.2	10.7	9.9	8.5	8.3	8.4	8.1	7.1	100
National origin															
Foreign-born	25,597	48.8	48.0	26.7	8.3	8.8	10.6	12.4	13.0	12.4	11.0	8.1	6.9	8.6	100
Recent immigrant	4,261	44.6	46.6	21.0	7.7	7.1	9.2	14.3	19.0	20.2	14.2	3.9	2.1	2.3	100
All	232,467	50.1	50.0	28.8	10.1	10.0	10.0	10.0	10.0	10.0	10.0	10.2	10.1	9.7	100
	Racial-indicator-variable model														
Race or ethnicity—SSA data															
Non-Hispanic white	148,568	54.2	56.8	28.4	7.7	8.3	9.0	9.4	9.7	9.4	10.9	12.3	12.0	11.3	100
Black	21,368	25.9	18.6	23.1	30.3	22.6	15.3	9.8	7.0	4.6	3.5	2.8	2.2	2.0	100
Hispanic	16,950	38.5	34.0	26.4	15.6	14.6	14.7	13.0	11.0	8.9	7.4	5.4	4.6	4.8	100
Asian	8,820	54.9	56.4	25.9	5.1	6.2	8.0	10.3	12.3	14.6	13.9	10.2	8.2	11.2	100
American Indian	409	57.4	63.4	27.9	5.5	6.3	10.8	8.5	8.5	7.5	10.6	15.5	15.1	11.6	100
Unknown race	36,352	51.5	52.2	26.8	7.1	8.2	9.0	11.2	12.1	15.0	10.6	8.0	9.5	9.3	100
Race or ethnicity—location-based distribution															
Non-Hispanic white	174,087	52.7	54.0	28.5	8.5	8.8	9.3	9.7	9.9	10.3	10.7	11.3	11.1	10.6	100
Black	23,946	37.5	31.2	27.9	19.4	16.4	13.2	10.4	9.2	8.0	6.6	6.0	5.9	5.0	100
Hispanic	23,632	43.1	39.8	28.0	13.7	12.6	12.2	11.8	10.9	9.8	8.4	6.9	7.0	6.7	100
Asian	9,016	52.6	53.2	28.5	8.3	8.2	9.2	10.4	10.8	11.5	10.6	9.2	9.6	12.3	100
American Indian	1,373	44.0	40.6	28.7	13.5	13.3	12.3	10.6	9.9	8.4	8.5	8.6	7.9	7.1	100
National origin															
Foreign-born	25,597	48.8	48.0	26.7	8.2	8.8	10.7	12.4	12.8	12.4	11.2	8.3	7.0	8.4	100
Recent immigrant	4,261	44.6	46.2	20.9	7.7	7.2	9.0	14.4	18.6	20.4	14.4	4.3	2.0	1.8	100
All	232,467	50.0	50.0	28.8	10.2	10.0	10.0	10.0	10.0	10.0	10.0	10.2	10.1	9.7	100

Note. Scores are normalized to a scale of 0-100 according to the nonlinear conversion shown in table 13. Refer also to notes to table 9.

Table 37. FRB Race-Neutral Models: Changes in FRB Base-Model Scores and in the FRB Base-Model Probability of Bad Performance, by Quintiles of the FRB Base Score

Characteristic	Lowest							Second lowest							Top three						
	Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance		Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance		Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance	
	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase
	Non-Hispanic-white-only model																				
Race or ethnicity—SSA data																					
Non-Hispanic white	0.0	0.0	0.6	55.9	100.0	-0.6	36.8	0.1	0.0	0.6	57.6	100.0	1.2	77.2	0.2	0.0	1.3	55.0	97.2	-0.2	29.1
Black	0.1	0.2	0.6	63.4	100.0	-0.4	39.6	0.1	0.2	0.6	62.1	99.9	1.3	78.1	0.1	0.2	1.4	57.0	97.4	0.1	45.5
Hispanic	0.1	0.0	0.6	61.8	100.0	-0.4	39.4	0.1	0.2	0.7	59.6	99.9	1.3	78.1	0.2	0.2	1.4	58.4	97.1	0.1	43.2
Asian	0.0	0.0	0.6	53.2	100.0	-0.6	35.8	0.1	0.0	0.7	56.2	99.9	1.1	75.5	0.2	0.0	1.4	54.9	95.9	-0.1	36.7
American Indian	-0.1	-0.2	0.6	46.2	100.0	-0.6	34.8	-0.1	0.0	0.7	51.7	100.0	0.9	71.0	0.1	0.0	1.4	53.2	97.2	-0.3	24.7
Unknown race	0.0	0.0	0.7	55.2	99.9	-0.5	37.2	-0.1	0.0	0.8	50.9	99.8	0.9	68.0	-0.4	0.0	2.2	51.8	88.5	-0.4	32.1
Race or ethnicity—location-based distribution																					
Non-Hispanic white	0.0	0.0	0.6	56.8	100.0	-0.5	37.2	0.0	0.0	0.7	57.0	99.9	1.1	76.0	0.1	0.0	1.5	54.6	95.8	-0.2	30.0
Black	0.1	0.0	0.6	61.6	100.0	-0.4	39.4	0.1	0.0	0.7	58.2	99.9	1.1	75.5	0.0	0.0	1.5	55.3	95.3	-0.1	36.6
Hispanic	0.1	0.0	0.6	60.1	100.0	-0.5	38.2	0.1	0.0	0.7	57.8	99.9	1.2	75.6	0.1	0.0	1.6	55.6	95.2	-0.1	37.3
Asian	0.0	0.0	0.6	58.3	100.0	-0.5	37.4	0.1	0.0	0.7	56.7	99.9	1.1	75.7	0.0	0.0	1.6	53.4	94.7	-0.2	32.4
American Indian	0.1	0.0	0.6	59.6	100.0	-0.4	38.6	0.1	0.0	0.7	59.3	99.9	1.3	77.7	0.1	0.0	1.5	56.4	96.0	-0.1	34.0
National origin																					
Foreign-born	0.0	0.0	0.6	56.7	100.0	-0.5	36.8	0.1	0.0	0.7	57.0	99.9	1.2	76.1	0.2	0.0	1.4	56.2	96.3	0.0	39.4
Recent immigrant	0.2	0.2	0.6	66.5	100.0	-0.2	43.7	0.2	0.2	0.8	61.3	99.8	1.5	80.3	0.5	0.4	1.7	62.7	94.9	0.4	59.9
All	0.0	0.0	0.6	58.2	100.0	-0.5	37.8	0.1	0.0	0.7	57.2	99.9	1.1	75.9	0.1	0.0	1.5	54.7	95.7	-0.2	31.2

Table continued on next page.

Table 37. FRB Race-Neutral Models: Changes in FRB Base-Model Scores and in the FRB Base-Model Probability of Bad Performance, by Quintiles of the FRB Base Score—Continued

Characteristic	Lowest							Second lowest							Top three						
	Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance		Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance		Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance	
	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase
	Racial-indicator-variable model																				
Race or ethnicity—SSA data																					
Non-Hispanic white	-0.1	-0.2	0.3	47.8	100.0	0.6	81.7	0.0	0.0	0.3	62.4	100.0	0.1	51.6	0.3	0.4	0.9	75.1	98.4	-0.2	27.3
Black	0.0	0.0	0.3	54.0	100.0	0.8	88.2	0.0	0.0	0.3	62.5	100.0	0.1	52.7	0.3	0.4	0.9	75.3	98.3	-0.1	41.5
Hispanic	0.0	0.0	0.3	52.3	100.0	0.8	86.5	0.1	0.0	0.3	62.7	100.0	0.1	52.1	0.3	0.4	1.0	76.3	98.1	-0.1	41.0
Asian	-0.1	-0.2	0.3	47.2	100.0	0.6	82.7	0.1	0.0	0.4	59.8	99.9	0.1	50.9	0.2	0.4	1.0	72.7	97.3	-0.1	34.1
American Indian	-0.1	-0.2	0.3	44.2	100.0	0.6	74.7	0.0	0.0	0.3	62.0	100.0	0.1	51.0	0.2	0.4	0.9	72.3	98.2	-0.2	22.2
Unknown race	0.1	0.0	0.4	56.0	100.0	1.0	85.0	-0.1	0.0	0.5	54.3	99.9	-0.1	46.1	-1.1	0.0	2.1	54.6	84.0	-0.8	24.5
Race or ethnicity—location-based distribution																					
Non-Hispanic white	0.0	-0.2	0.3	49.2	100.0	0.7	82.8	0.0	0.0	0.3	61.2	100.0	0.0	50.8	0.1	0.4	1.1	71.7	96.1	-0.3	27.3
Black	0.0	0.0	0.3	54.2	100.0	0.8	87.2	0.0	0.0	0.3	60.9	100.0	0.1	51.2	0.0	0.4	1.2	70.3	94.9	-0.3	32.6
Hispanic	0.0	0.0	0.3	53.2	100.0	0.8	86.5	0.0	0.0	0.4	60.8	100.0	0.1	50.6	0.0	0.4	1.2	70.9	95.1	-0.3	33.1
Asian	0.0	0.0	0.3	51.8	100.0	0.7	85.0	0.0	0.0	0.4	60.6	100.0	0.1	51.3	0.0	0.4	1.2	71.8	95.0	-0.3	29.6
American Indian	0.0	0.0	0.3	51.1	100.0	0.7	84.1	0.0	0.0	0.3	63.0	100.0	0.1	51.9	0.1	0.4	1.1	72.0	95.9	-0.3	31.2
National origin																					
Foreign-born	0.0	-0.2	0.3	48.5	100.0	0.7	83.4	0.1	0.0	0.4	60.8	100.0	0.1	50.5	0.2	0.4	1.0	73.2	97.4	-0.1	36.5
Recent immigrant	0.1	0.0	0.3	57.9	100.0	0.9	88.4	0.2	0.2	0.4	67.9	99.9	0.3	60.3	0.4	0.6	1.3	78.5	95.6	0.0	58.4
All	0.0	0.0	0.3	50.8	100.0	0.7	84.2	0.0	0.0	0.3	61.1	100.0	0.0	50.9	0.1	0.4	1.1	71.5	95.9	-0.3	28.3

Note. Refer to notes to table 9.

Table 38. Scores in the FRB Base and Race-Neutral Models: Performance Residuals (Unexplained Percent Bad)

Characteristic	Any account	New account	Existing account	Random account	Modified new account
	FRB base score				
Race or ethnicity—SSA data					
Non-Hispanic white	-0.8	-0.6	-0.6	-0.5	-0.3
Black	4.7	3.2	4.0	2.6	2.7
Hispanic	1.4	0.6	0.8	-0.1	0.0
Asian	-1.6	0.1	-1.2	-0.4	0.0
American Indian	-1.6	-0.5	-0.8	-0.8	-0.5
Unknown race	0.4	1.0	0.6	1.3	0.4
Race or ethnicity—					
Non-Hispanic white	-0.5	-0.4	-0.4	-0.3	-0.2
Black	2.9	2.4	2.5	1.9	1.6
Hispanic	1.0	0.7	0.7	0.6	0.3
Asian	-0.9	0.1	-0.6	0.0	0.2
American Indian	0.1	1.0	0.0	0.7	0.1
National origin					
Foreign-born	-0.5	-0.4	-0.6	-0.7	-0.4
Recent immigrant	-1.3	-0.3	-1.2	-0.1	-0.6
All	0.0	0.0	0.0	0.0	0.0
	Non-Hispanic-white-only score				
Race or ethnicity—SSA data					
Non-Hispanic white	-0.8	-0.6	-0.6	-0.6	-0.4
Black	4.8	3.4	4.1	2.7	2.8
Hispanic	1.5	0.6	0.9	0.0	0.0
Asian	-1.5	0.2	-1.2	-0.4	0.0
American Indian	-1.7	-0.5	-0.9	-0.9	-0.5
Unknown race	0.3	1.0	0.5	1.2	0.3
Race or ethnicity—					
Non-Hispanic white	-0.5	-0.4	-0.4	-0.3	-0.2
Black	3.0	2.4	2.5	2.0	1.6
Hispanic	1.0	0.7	0.8	0.6	0.3
Asian	-0.9	0.1	-0.6	0.0	0.2
American Indian	0.2	0.9	0.1	0.8	0.1
National origin					
Foreign-born	-0.4	-0.4	-0.6	-0.7	-0.4
Recent immigrant	-1.0	-0.2	-1.0	0.0	-0.6
All	0.0	0.0	0.0	0.0	0.0
	Racial-indicator-variable score				
Race or ethnicity—SSA data					
Non-Hispanic white	-0.8	-0.6	-0.6	-0.6	-0.3
Black	4.7	3.3	4.0	2.6	2.7
Hispanic	1.4	0.6	0.9	0.0	0.0
Asian	-1.5	0.2	-1.1	-0.4	0.0
American Indian	-1.6	-0.5	-0.8	-0.8	-0.5
Unknown race	0.3	1.0	0.5	1.3	0.3
Race or ethnicity—					
Non-Hispanic white	-0.5	-0.4	-0.4	-0.3	-0.2
Black	3.0	2.4	2.5	2.0	1.6
Hispanic	1.0	0.7	0.7	0.6	0.3
Asian	-0.9	0.1	-0.6	0.1	0.2
American Indian	0.1	1.0	0.0	0.7	0.2
National origin					
Foreign-born	-0.4	-0.4	-0.6	-0.7	-0.4
Recent immigrant	-1.1	-0.2	-1.1	0.0	-0.6
All	0.0	0.0	0.0	0.0	0.0

Note. Refer to notes to table 9.

Table 39. Credit Points Assigned to Attributes of Credit Characteristic S019, Number of Open Finance Trades: Comparison of the Clean Scorecards in the FRB Base and Race-Neutral Models and Distribution of the Sample Population by Attribute

S019, number of finance trades	Model			Population distribution (percent)
	FRB base	White-only	Racial-indicator-variable	
0	0	0	0	87.8
1	-23	-18	-21	10.4
2	-67	-56	-63	1.5
3 or more	-107	-118	-104	0.4

Note. Credit characteristic S019 is "Total number of open personal finance installment accounts reported in the past 12 months."

The data shown here for the FRB base model are also reported in table 12.B.

Table 40. Effect on Scores and Predictiveness when Credit Characteristic S019, Number of Open Finance Trades, Is Dropped from the Clean-File Scorecard of the FRB Base Model, by Selected Characteristics of Race, Ethnicity, and National Origin of the Sample Population and Performance Measure

Characteristic	Any-account performance					New-account performance					Existing-account performance				
	Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness	
	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point
Race or ethnicity—SSA data															
Non-Hispanic white	1.6	12.8	46.6	1.3	37.8	0.3	14.3	40.6	0.3	44.5	1.0	13.0	46.5	0.9	38.5
Black	3.9	13.7	50.3	4.3	27.7	0.6	18.8	46.6	1.2	33.0	2.8	14.7	49.8	3.2	29.5
Hispanic	2.8	12.9	49.7	3.1	31.5	0.7	17.8	44.9	0.8	35.9	2.0	13.6	49.2	2.2	32.9
Asian	1.8	7.9	51.8	1.0	37.5	0.5	9.2	46.4	0.3	43.6	1.1	8.2	51.4	0.8	38.6
American Indian	1.3	15.5	48.5	0.9	33.9	0.3	17.5	40.1	0.2	41.8	0.9	15.7	48.5	0.7	34.3
Unknown race	1.9	13.6	53.3	1.4	29.9	0.5	13.3	47.3	0.4	38.6	1.4	13.9	53.1	1.0	30.6
Race or ethnicity—location-based distribution															
Non-Hispanic white	1.7	12.6	47.2	1.3	37.3	0.4	14.0	41.3	0.3	44.1	1.1	12.9	47.0	0.9	38.1
Black	2.5	13.8	50.6	2.6	30.4	0.5	16.5	44.9	0.8	37.4	1.7	14.4	50.3	2.0	31.6
Hispanic	2.2	13.1	50.3	2.3	32.1	0.6	16.7	44.6	0.7	37.5	1.5	13.6	49.9	1.7	33.2
Asian	1.8	11.2	52.0	1.2	33.8	0.4	12.6	46.6	0.4	40.1	1.2	11.5	51.8	0.9	34.6
American Indian	1.8	14.8	46.8	2.3	34.4	0.4	18.2	41.6	0.4	39.4	1.2	15.2	46.8	1.5	35.3
National origin															
Foreign-born	2.2	9.7	51.3	1.6	35.1	0.5	12.3	46.5	0.4	40.2	1.4	10.1	51.0	1.1	36.4
Recent immigrant	2.0	8.6	59.2	1.5	28.6	0.7	11.4	57.9	0.3	29.8	1.2	9.1	58.8	1.2	29.8
All	1.8	12.7	47.8	1.5	36.2	0.4	14.3	42.0	0.4	42.9	1.2	13.0	47.7	1.1	37.1

Table continued on next page.

Table 40. Effect on Scores and Predictiveness when Credit Characteristic S019, Number of Open Finance Trades, Is Dropped from the Clean-File Scorecard of the FRB Base Model, by Selected Characteristics of Race, Ethnicity, and National Origin of the Sample Population and Performance Measure—Continued

Characteristic	Random-account performance					Modified new-account performance				
	Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness	
	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point
Race or ethnicity—SSA data										
Non-Hispanic white	0.4	13.9	47.0	0.4	38.4	0.2	14.7	39.7	0.2	45.2
Black	1.0	17.1	50.7	1.2	30.0	0.4	19.6	46.9	0.9	32.2
Hispanic	0.8	15.5	50.2	1.0	32.5	0.4	18.7	46.2	0.7	34.1
Asian	0.4	9.0	51.8	0.4	38.5	0.3	10.0	45.2	0.2	44.3
American Indian	0.4	15.9	48.9	0.2	34.5	0.2	17.5	39.0	0.1	43.2
Unknown race	0.6	14.5	53.7	0.5	30.7	0.3	13.3	47.4	0.3	38.7
Race or ethnicity—location-based distribution										
Non-Hispanic white	0.4	13.7	47.5	0.4	37.9	0.2	14.4	40.5	0.2	44.6
Black	0.6	15.8	51.0	0.8	31.8	0.3	17.4	44.4	0.5	37.3
Hispanic	0.6	15.0	50.7	0.8	33.0	0.3	17.4	45.1	0.6	36.7
Asian	0.5	12.2	52.2	0.4	34.7	0.2	13.1	45.8	0.3	40.6
American Indian	0.5	16.4	47.4	0.8	34.9	0.3	18.4	41.6	0.3	39.5
National origin										
Foreign-born	0.5	11.3	51.5	0.5	36.3	0.4	13.1	46.3	0.3	39.9
Recent immigrant	0.5	10.1	59.2	0.5	29.7	0.6	11.7	58.8	0.1	28.8
All	0.4	13.9	48.2	0.5	37.0	0.2	14.8	41.4	0.3	43.2

Note. Credit characteristic S019 is "Total number of open personal finance installment accounts reported in the past 12 months."

Table 41. Scores from the FRB Base Model and Age-Neutral Models: Measures of Fit, by Selected Characteristics of the Sample Population and Performance Measure

Characteristic	Any account				New account				Existing account				Random account				Modified new account			
	KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean		KS statistic		Score mean	
	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads	Raw	Adjusted	Goods	Bads
	FRB base model																			
Age—SSA data (years)																				
Younger than 30	69.4	73.7	47.5	16.8	52.3	61.0	43.3	19.7	69.0	75.2	47.5	16.8	62.2	68.7	42.2	14.7	43.8	55.3	43.4	25.3
30 to 39	74.2	72.9	58.5	16.7	63.3	63.6	52.4	17.4	75.2	74.3	58.4	16.1	69.1	72.2	50.8	13.2	55.5	54.9	51.6	22.1
40 to 49	74.0	73.5	64.2	18.7	64.3	64.0	57.5	18.7	75.3	74.9	63.9	17.6	71.0	72.2	56.6	14.1	55.5	54.5	56.0	23.1
50 to 61	72.2	73.0	67.7	22.0	65.6	65.3	61.0	19.6	74.8	74.5	67.5	20.2	72.0	71.7	61.3	15.9	57.9	55.9	59.5	24.5
62 or older	68.1	71.7	72.9	30.4	62.6	60.5	67.3	26.9	70.2	72.1	72.7	28.7	70.0	68.7	69.6	24.0	56.0	48.9	65.2	33.6
Unknown	68.8	73.4	63.5	23.7	53.3	56.1	54.6	23.9	69.1	73.6	63.4	23.3	66.5	68.4	59.7	20.8	46.8	49.0	53.4	30.5
National origin																				
Foreign-born	66.1	71.2	59.9	22.6	54.4	59.8	53.8	23.4	69.8	73.9	59.8	20.5	67.6	70.4	54.6	16.6	44.1	48.7	52.5	30.7
Recent immigrant	61.3	71.0	52.1	23.7	43.0	59.8	48.5	27.7	67.3	74.3	52.0	20.9	66.5	70.5	48.8	17.2	35.7	47.5	47.5	35.6
All	73.0	73.0	64.2	19.6	61.0	61.0	56.3	19.7	74.0	74.0	64.0	18.9	70.2	70.2	57.9	15.5	52.4	52.4	54.9	24.8
	Older-age model																			
Age—SSA data (years)																				
Younger than 30	69.1	73.8	46.2	16.9	52.0	57.3	42.2	19.8	68.8	75.2	46.1	16.8	61.6	68.4	41.1	14.7	43.9	48.1	42.3	25.6
30 to 39	74.1	73.3	57.1	16.7	63.1	63.8	51.0	17.4	75.1	74.9	56.9	16.0	68.8	72.3	49.7	13.2	55.3	55.3	50.3	22.1
40 to 49	74.1	73.4	63.4	18.7	64.2	63.6	56.5	18.6	75.3	74.8	63.1	17.5	70.9	72.1	55.9	14.0	55.9	54.6	55.1	23.0
50 to 61	72.4	72.7	67.8	22.0	65.7	65.2	60.7	19.5	74.8	74.2	67.5	20.1	71.9	71.3	61.4	15.8	57.8	55.6	59.1	24.4
62 or older	68.1	71.1	75.2	30.7	62.8	59.4	68.2	27.0	70.3	71.5	75.1	29.0	70.1	67.9	71.7	24.3	56.3	48.0	65.9	33.5
Unknown	68.5	73.6	63.1	23.6	52.8	55.2	53.9	24.0	68.8	73.9	63.0	23.1	66.6	68.7	59.4	20.7	42.3	46.2	52.8	31.0
National origin																				
Foreign-born	66.0	71.1	59.3	22.5	53.4	58.9	52.9	23.3	69.7	73.6	59.2	20.3	67.4	69.9	54.1	16.5	42.4	47.6	51.6	30.9
Recent immigrant	60.9	69.1	50.6	23.4	43.7	56.4	47.4	27.6	66.9	73.5	50.5	20.5	66.2	68.4	47.5	17.0	36.1	46.1	46.5	35.6
All	73.1	73.1	64.2	19.7	60.9	60.9	55.6	19.7	74.0	74.0	64.0	18.8	70.0	70.0	57.8	15.5	52.6	52.6	54.2	24.8
	Age-indicator-variable model																			
Age—SSA data (years)																				
Younger than 30	69.3	73.1	46.8	16.7	52.3	59.2	42.6	19.6	69.0	75.1	46.7	16.7	62.1	68.3	41.5	14.6	43.5	53.4	42.7	25.2
30 to 39	74.1	73.4	57.4	16.6	63.3	63.9	51.3	17.3	75.1	74.9	57.3	16.0	69.0	72.3	49.9	13.1	55.6	55.1	50.6	22.0
40 to 49	74.1	73.5	63.6	18.7	64.4	64.1	56.7	18.6	75.4	75.0	63.3	17.6	71.0	72.3	56.0	14.1	55.7	54.4	55.3	23.0
50 to 61	72.2	72.9	67.7	22.1	65.7	65.4	60.7	19.6	74.7	74.5	67.5	20.2	72.0	71.7	61.3	15.9	57.7	55.7	59.1	24.4
62 or older	68.2	71.4	74.6	30.7	62.7	60.5	68.0	27.0	70.3	71.8	74.4	29.0	70.0	68.5	71.1	24.3	56.1	49.3	65.7	33.6
Unknown	68.8	73.5	63.7	23.7	53.2	55.4	54.2	23.9	69.2	73.7	63.5	23.3	66.5	68.4	59.9	20.8	45.8	49.5	53.0	30.5
National origin																				
Foreign-born	66.0	71.3	59.5	22.5	54.0	59.7	53.1	23.3	69.8	73.9	59.4	20.4	67.7	70.3	54.2	16.6	44.9	49.5	51.8	30.5
Recent immigrant	61.5	68.5	51.1	23.5	42.1	58.0	47.6	27.6	67.7	73.2	51.0	20.7	67.0	70.2	47.9	17.1	35.3	45.4	46.6	35.4
All	73.1	73.1	64.2	19.6	61.1	61.1	55.8	19.6	74.1	74.1	64.0	18.8	70.1	70.1	57.9	15.5	52.5	52.5	54.3	24.7

Note. Refer to notes to table 34.

Table 42. Scores from the FRB Base Model and Age-Neutral Models: Credit-Score Statistics, and Distribution of Sample Population by Score Decile, by Selected Characteristics of Sample Population

Characteristic	MEMO Sample (number)	Score statistics			Sample population, grouped by characteristic and distributed by score decile (percent)										
		Mean	Median	Standard deviation	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Total
	FRB base model														
Age—SSA data (years)															
Younger than 30	33,011	33.2	34.0	21.0	18.6	14.5	12.4	14.3	15.6	14.8	6.9	1.8	0.6	0.6	100
30 to 39	40,485	40.8	36.8	28.0	16.1	14.4	12.5	10.4	9.3	9.5	9.7	7.1	4.6	6.4	100
40 to 49	46,407	48.2	46.2	29.6	11.2	11.7	11.3	10.1	9.2	8.9	9.0	9.2	8.0	11.5	100
50 to 61	43,474	55.4	57.6	28.9	6.9	8.3	9.6	9.7	8.8	8.9	9.9	11.8	11.7	14.4	100
62 or older	44,075	66.0	74.4	24.4	2.6	4.0	5.8	6.2	6.4	7.9	10.6	20.5	23.7	12.5	100
Unknown	25,015	52.9	53.4	26.4	6.2	7.3	8.4	10.5	13.6	15.2	12.5	7.2	7.6	11.7	100
National origin															
Foreign-born	25,597	48.7	48.0	26.6	8.2	8.9	10.6	12.5	12.8	13.1	10.2	8.3	7.1	8.4	100
Recent immigrant	4,261	44.3	46.2	20.9	8.0	7.0	9.1	14.8	18.7	21.5	12.4	4.4	2.0	2.1	100
All	232,467	50.0	50.0	28.8	10.1	10.0	10.0	10.0	10.0	10.3	9.7	10.2	10.0	9.8	100
	Older-age Model														
Age—SSA data (years)															
Younger than 30	33,011	32.6	33.8	20.0	18.4	14.6	12.6	15.3	15.3	16.7	5.3	1.2	0.4	0.2	100
30 to 39	40,485	40.0	36.8	26.8	16.1	14.3	12.6	10.2	9.9	9.0	12.0	8.0	4.5	3.5	100
40 to 49	46,407	47.7	46.6	28.9	11.3	11.7	11.3	9.6	9.4	7.9	11.3	10.7	8.6	8.2	100
50 to 61	43,474	55.5	59.6	28.8	7.0	8.3	9.5	9.1	8.8	7.7	11.5	12.6	12.3	13.2	100
62 or older	44,075	68.1	77.2	25.5	2.7	3.9	5.7	5.8	6.3	6.6	9.6	15.7	22.3	21.3	100
Unknown	25,015	52.5	53.6	26.3	6.1	7.4	8.3	12.2	12.8	17.1	8.2	9.5	7.9	10.6	100
National origin															
Foreign-born	25,597	48.3	47.8	26.3	8.3	8.8	10.6	12.3	13.1	13.8	10.5	8.0	7.2	7.4	100
Recent immigrant	4,261	43.2	45.6	19.7	8.1	6.9	9.4	15.2	18.6	25.6	10.2	3.6	1.5	0.9	100
All	232,467	50.0	50.0	28.8	10.1	10.0	10.0	10.0	10.0	10.1	9.9	10.1	9.9	9.9	100
	Age-indicator-variable model														
Age—SSA data (years)															
Younger than 30	33,011	32.8	33.8	20.4	18.5	14.7	12.4	15.3	15.1	15.8	5.9	1.6	0.5	0.3	100
30 to 39	40,485	40.2	36.8	27.1	16.1	14.4	12.6	10.6	9.4	9.8	10.3	8.1	4.4	4.4	100
40 to 49	46,407	47.8	46.4	29.2	11.2	11.7	11.3	10.2	9.1	8.8	9.7	10.6	7.8	9.7	100
50 to 61	43,474	55.4	58.0	28.9	6.8	8.3	9.6	9.7	8.7	8.7	10.2	12.5	11.4	14.2	100
62 or older	44,075	67.5	76.2	25.3	2.6	3.9	5.7	6.1	6.1	7.5	9.9	15.9	23.8	18.4	100
Unknown	25,015	53.0	53.8	26.3	6.2	7.2	8.3	10.7	13.5	14.9	11.8	8.5	9.0	9.8	100
National origin															
Foreign-born	25,597	48.4	47.8	26.4	8.2	8.9	10.6	12.7	12.8	13.5	10.2	8.2	7.0	7.8	100
Recent immigrant	4,261	43.6	45.8	20.1	8.0	7.1	9.2	15.1	19.1	23.1	11.4	4.5	1.6	1.1	100
All	232,467	50.1	50.0	28.9	10.1	10.0	10.0	10.2	9.8	10.4	9.6	10.0	10.0	9.9	100

Table 43. FRB Age-Neutral Models: Changes in FRB Base-Model Scores and in the FRB Base-Model Probability of Bad Performance, by Quintiles of the FRB Base Score

Characteristic	Lowest							Second lowest							Top three						
	Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance		Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance		Change in score			Percent of sample with a change in score, by type of change		Change in probability of bad performance	
	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase	Mean	Median	Mean absolute value	Increase	Change of less than 5 points	Mean	Percent of sample with an increase
	Older-age model																				
Age—SSA data (years)																					
Younger than 30	0.2	0.0	0.9	52.4	99.6	0.5	49.3	0.1	-0.2	1.3	46.7	96.3	0.5	52.3	-1.9	-1.6	3.1	28.9	79.7	-1.6	16.9
30 to 39	0.0	0.0	0.8	51.2	99.9	0.2	48.6	0.1	0.0	0.9	53.7	99.3	0.7	60.4	-1.8	-1.0	3.3	38.1	77.4	-0.7	28.8
40 to 49	0.0	-0.2	0.8	50.0	99.9	0.1	48.0	0.2	0.0	0.9	56.3	99.6	0.8	62.8	-1.0	-0.2	3.0	47.1	79.7	-0.3	38.0
50 to 61	-0.1	-0.2	0.8	48.4	99.9	0.1	47.0	0.2	0.0	0.9	57.1	99.8	0.8	63.5	0.1	0.2	2.8	57.4	81.5	0.0	49.6
62 or older	-0.2	-0.2	0.8	45.9	100.0	0.0	45.8	0.3	0.2	0.9	60.3	99.7	1.0	65.4	2.6	1.8	4.2	72.7	63.8	0.5	72.3
Unknown	0.3	0.0	1.0	58.0	99.6	0.9	57.4	-0.2	-0.2	1.3	45.6	98.5	0.1	50.7	-0.7	-1.4	4.4	41.4	64.8	-0.8	35.9
National origin																					
Foreign-born	-0.1	-0.2	0.9	44.4	99.8	0.0	42.7	0.2	0.0	1.1	51.3	97.6	0.7	57.0	-0.7	-0.4	3.3	45.7	75.7	-0.5	36.7
Recent immigrant	-0.1	-0.2	0.8	45.4	99.8	-0.1	41.8	0.2	-0.2	1.5	46.4	94.6	0.6	50.4	-1.9	-1.6	3.6	30.2	74.4	-1.3	19.5
All	0.1	0.0	0.8	51.0	99.8	0.3	48.9	0.1	0.0	1.0	53.5	98.9	0.7	59.5	0.0	0.0	3.5	52.2	73.9	-0.3	45.7
	Age-indicator-variable Model																				
Age—SSA data (years)																					
Younger than 30	0.0	0.0	0.2	61.4	100.0	0.0	28.6	-0.1	0.0	0.3	58.1	100.0	-0.4	18.8	-1.0	-0.8	1.3	23.0	97.6	-0.7	12.0
30 to 39	0.0	0.0	0.1	69.4	100.0	0.0	41.9	0.0	0.0	0.2	73.5	100.0	-0.2	37.3	-1.3	-0.6	1.8	33.4	91.1	-0.4	26.1
40 to 49	0.0	0.0	0.1	74.4	100.0	0.1	50.5	0.0	0.0	0.2	80.4	100.0	-0.1	49.6	-0.8	-0.2	1.6	47.8	92.7	-0.1	46.1
50 to 61	0.0	0.0	0.1	77.9	100.0	0.1	55.4	0.1	0.0	0.2	84.2	100.0	-0.1	56.9	0.0	0.4	1.6	61.1	94.4	0.1	65.6
62 or older	0.0	0.0	0.1	79.0	100.0	0.1	60.9	0.1	0.2	0.2	88.3	100.0	0.1	67.4	1.9	1.4	2.7	77.0	82.6	0.6	83.0
Unknown	0.0	0.0	0.2	76.1	100.0	0.1	56.6	0.1	0.0	0.3	76.9	100.0	-0.1	51.7	0.0	-0.2	2.1	49.4	84.2	-0.1	37.6
National origin																					
Foreign-born	0.0	0.0	0.1	68.8	100.0	0.0	40.2	0.0	0.0	0.2	71.6	100.0	-0.2	38.5	-0.4	-0.2	1.7	45.8	92.1	-0.2	41.3
Recent immigrant	-0.1	0.0	0.2	62.1	100.0	-0.1	28.0	-0.1	0.0	0.3	55.7	100.0	-0.4	20.6	-1.1	-0.8	1.6	25.0	95.4	-0.7	15.4
All	0.0	0.0	0.1	71.0	100.0	0.1	44.9	0.0	0.0	0.2	76.0	100.0	-0.2	44.9	0.1	0.0	1.9	53.9	89.7	0.0	52.6

Table 44. Scores in the FRB Base and Age-Neutral Models: Performance Residuals (Unexplained Percent Bad)

Characteristic	Any account	New account	Existing account	Random account	Modified new account
	FRB base score				
Age—SSA data (years)					
Younger than 30	0.4	2.2	0.5	2.0	1.8
30 to 39	-0.2	-0.5	-0.2	0.0	0.0
40 to 49	-0.2	-0.6	-0.4	-0.9	-0.5
50 to 61	-0.3	-1.0	-0.4	-1.2	-0.8
62 or older	0.1	0.2	0.3	-0.1	0.0
Unknown	0.6	2.1	0.9	2.3	0.9
National origin					
Foreign-born	-0.5	-0.4	-0.6	-0.7	-0.4
Recent immigrant	-1.3	-0.3	-1.2	-0.1	-0.6
All	0.0	0.0	0.0	0.0	0.0
	Older-age score				
Age—SSA data (years)					
Younger than 30	0.1	2.1	0.2	1.9	1.8
30 to 39	-0.3	-0.5	-0.2	0.0	0.0
40 to 49	-0.1	-0.6	-0.4	-0.9	-0.5
50 to 61	-0.1	-1.0	-0.3	-1.2	-0.8
62 or older	0.3	0.3	0.5	-0.1	0.0
Unknown	0.4	2.0	0.8	2.2	0.9
National origin					
Foreign-born	-0.6	-0.4	-0.7	-0.8	-0.4
Recent immigrant	-1.7	-0.4	-1.6	-0.3	-0.7
All	0.0	0.0	0.0	0.0	0.0
	Age-indicator-variable score				
Age—SSA data (years)					
Younger than 30	0.2	2.1	0.3	1.9	1.8
30 to 39	-0.3	-0.5	-0.3	-0.1	0.0
40 to 49	-0.1	-0.6	-0.4	-0.8	-0.5
50 to 61	-0.2	-1.0	-0.4	-1.2	-0.8
62 or older	0.3	0.3	0.4	-0.1	0.0
Unknown	0.6	2.1	1.0	2.3	0.9
National origin					
Foreign-born	-0.5	-0.4	-0.7	-0.7	-0.4
Recent immigrant	-1.5	-0.4	-1.4	-0.2	-0.7
All	0.0	0.0	0.0	0.0	0.0

Table 45. Credit Points Assigned to Attributes of Credit Characteristic S004, Average Age of Accounts: Comparison of the Clean Scorecards in the FRB Base and Age-Neutral Models and Distribution of the Sample Population by Attribute

S004, average age of accounts (months)	Model			Population distribution (percent)
	FRB base	Older-age	Age-indicator-variable	
0-9	0	0	0	0.7
10-15	62	-81	64	1.3
16-33	104	4	102	6.3
34-44	123	-3	116	4.6
45-55	134	27	131	5.5
56-61	151	50	152	3.8
62-70	151	57	155	7.4
71-75	158	71	164	4.9
76-84	161	72	168	9.7
85-103	162	76	172	19.1
104-152	164	79	176	24.6
153-224	165	86	181	9.2
225 or more	169	92	188	2.9

Note. Credit characteristic S004 is "Average age of accounts on credit report."

The data shown here for the FRB base model are also reported in table 12.B.

Table 46. Scores and Performance Residuals: FRB Base Model and Age-Neutral Models, by Selected Ages and Status of National Origin of the Sample Population

Charac-teristic	FRB base		Older-age		Age-indicator-variable	
	Mean score	Mean per-formance residual	Mean score	Mean per-formance residual	Mean score	Mean per-formance residual
Age	33.2	0.4	32.5	-0.3	32.8	0.1
19	38.7	1.5	38.6	0.5	38.9	1.6
20	37.0	3.3	37.0	2.7	37.1	3.3
21	35.4	3.9	35.1	3.4	35.2	3.7
22	33.1	2.1	32.9	1.5	32.9	1.9
23	31.3	0.3	30.8	-0.4	31.0	0.0
24	31.3	-0.5	30.6	-1.3	30.8	-0.8
25	30.8	-0.3	29.9	-1.1	30.2	-0.7
26	31.6	-0.3	30.6	-1.1	31.1	-0.6
27	33.2	-0.7	32.1	-1.4	32.5	-1.0
28	33.6	-1.1	32.6	-1.7	33.0	-1.4
29	34.3	-1.5	33.4	-2.1	33.6	-1.7
62 or older	66.0	0.1	68.1	0.3	67.5	0.3
Recent immi-grants	44.3	-1.3	43.2	-1.6	43.6	-1.5

Table 47. Effect on Scores and Predictiveness when Credit Characteristics Related to Length of Credit History Is Dropped from the FRB Base Model, by Scorecard, Selected Age and National Origin Characteristics of the Sample Population, and Performance Measure

Characteristic	Any-account performance					New-account performance					Existing-account performance				
	Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness	
	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point
	Thin-file														
Age—SSA data (years)															
Younger than 30	14.9	8.1	40.9	12.3	23.9	4.9	13.1	45.7	3.1	33.2	7.3	10.7	44.1	4.6	33.4
30 to 39	18.4	7.1	30.8	24.2	19.5	7.0	17.2	33.5	5.8	36.4	10.9	10.5	36.8	9.1	32.6
40 to 49	18.6	9.0	30.0	21.2	21.2	8.7	19.4	29.9	6.3	35.8	9.5	13.9	34.9	7.2	34.4
50 to 61	13.6	12.6	27.1	16.0	30.8	7.6	17.6	34.8	5.7	34.3	7.1	17.2	28.5	4.4	42.9
62 or older	4.6	22.9	17.8	3.2	51.6	2.8	22.0	22.1	2.8	50.3	2.4	24.2	16.9	1.0	55.6
Unknown	5.4	19.9	25.8	4.9	44.1	4.1	24.4	30.5	2.3	38.8	3.4	21.0	25.8	2.7	47.0
National origin															
Foreign-born	9.1	11.9	31.4	8.1	39.5	3.8	12.7	34.7	1.2	47.6	4.6	13.5	31.9	3.6	46.4
Recent immigrant	7.4	9.9	29.0	6.7	47.1	3.3	11.7	29.6	0.4	55.0	3.8	10.7	29.2	3.9	52.4
All	11.1	14.1	30.2	10.9	33.7	5.3	17.0	38.2	3.7	35.8	5.5	17.3	31.0	3.9	42.4

Table continued on next page.

Table 47. Effect on Scores and Predictiveness when Credit Characteristics Related to Length of Credit History Is Dropped from the FRB Base Model, by Scorecard, Selected Age and National Origin Characteristics of the Sample Population, and Performance Measure—Continued

Characteristic	Any-account performance					New-account performance					Existing-account performance				
	Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness	
	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point
	Clean-file														
Age—SSA data (years)															
Younger than 30	1.6	67.2	14.3	9.9	7.1	0.3	74.7	14.6	2.9	7.5	1.2	69.8	14.0	7.6	7.4
30 to 39	2.7	33.3	22.4	2.8	38.8	0.6	34.7	23.0	0.7	41.1	1.8	34.2	22.3	1.8	39.9
40 to 49	2.5	22.9	24.8	1.8	48.0	0.5	23.6	25.2	0.4	50.4	1.7	23.4	24.7	1.2	49.1
50 to 61	2.4	19.9	25.5	1.2	51.1	0.4	20.2	26.1	0.3	53.0	1.5	20.3	25.3	0.7	52.1
62 or older	2.5	15.4	23.2	0.6	58.3	0.7	18.2	25.3	0.3	55.6	1.7	15.6	23.2	0.4	59.1
Unknown	3.0	24.0	18.2	2.9	52.0	0.6	34.4	21.6	1.1	42.2	2.0	24.7	18.2	1.9	53.2
National origin															
Foreign-born	2.2	40.8	20.7	4.2	32.2	0.5	47.7	19.5	1.2	31.2	1.4	42.1	20.6	2.7	33.3
Recent immigrant	1.0	73.2	11.4	7.9	6.5	0.2	81.4	10.0	2.0	6.4	0.9	76.6	11.2	4.7	6.6
All	2.4	26.6	22.7	2.4	45.8	0.5	31.5	23.4	0.8	43.9	1.6	27.2	22.6	1.7	46.8
	Major-derogatory														
Age—SSA data (years)															
Younger than 30	0.8	13.1	63.3	22.6	0.2	0.1	37.1	54.4	7.8	0.5	0.5	17.8	61.5	19.9	0.3
30 to 39	7.1	11.6	64.6	12.7	4.0	1.6	29.9	56.2	4.4	8.0	5.9	15.4	62.7	10.9	5.1
40 to 49	12.5	11.3	55.4	10.5	10.3	2.4	26.5	49.7	3.2	18.2	10.3	14.6	53.5	8.5	13.2
50 to 61	16.2	10.0	46.6	8.6	18.6	2.6	21.9	42.5	2.5	30.6	13.0	12.3	45.1	6.8	22.8
62 or older	19.6	7.3	36.5	5.5	31.2	3.5	16.3	39.3	2.2	38.7	15.4	8.6	34.8	4.3	36.9
Unknown	14.0	9.0	51.8	12.3	12.8	4.3	25.6	46.3	5.0	18.8	12.1	11.7	50.0	9.8	16.3
National origin															
Foreign-born	8.2	16.7	50.6	14.7	9.7	1.2	36.1	43.9	4.2	14.7	6.7	20.5	48.7	12.3	11.9
Recent immigrant	0.5	24.2	50.7	24.3	0.4	0.0	55.5	38.4	6.1	0.0	0.4	29.6	48.9	20.7	0.4
All	10.6	10.9	55.3	12.4	10.7	2.0	27.2	49.6	4.1	17.1	8.8	14.1	53.2	10.2	13.7

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Table 47. Effect on Scores and Predictiveness when Credit Characteristics Related to Length of Credit History Is Dropped from the FRB Base Model, by Scorecard, Selected Age and National Origin Characteristics of the Sample Population, and Performance Measure—Continued

Characteristic	Random-account performance					Modified new-account performance				
	Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness	
	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point
	Thin-file									
Age—SSA data (years)										
Younger than 30	6.0	12.0	44.2	4.1	33.7	3.1	12.6	47.4	1.6	35.3
30 to 39	9.4	13.5	35.6	8.6	32.9	4.0	16.4	38.1	3.1	38.5
40 to 49	8.3	15.5	34.6	6.8	34.7	4.2	19.4	33.6	2.2	40.6
50 to 61	5.9	18.3	28.6	4.4	42.7	3.6	17.1	37.8	2.6	38.9
62 or older	2.2	24.2	17.3	1.1	55.2	2.3	20.5	27.0	1.4	48.8
Unknown	2.8	21.6	25.9	2.4	47.3	2.5	23.0	34.5	1.1	38.9
National origin										
Foreign-born	3.9	14.6	33.0	3.2	45.4	2.3	12.6	35.9	0.5	48.8
Recent immigrant	3.4	11.7	29.9	3.4	51.5	1.5	11.1	32.4	0.2	54.8
All	4.7	17.9	31.6	3.7	42.1	3.2	16.4	41.0	1.8	37.7

Table continued on next page.

Table 47. Effect on Scores and Predictiveness when Credit Characteristics Related to Length of Credit History Is Dropped from the FRB Base Model, by Scorecard, Selected Age and National Origin Characteristics of the Sample Population, and Performance Measure—Continued

Characteristic	Random-account performance					Modified new-account performance				
	Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness		Increase in predictiveness		No change in predictiveness (percent whose score changed less than 1 point)	Decrease in predictiveness	
	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point	Bad performers, percentage whose score decreased more than 1 point	Good performers, percentage whose score increased more than 1 point		Bad performers, percentage whose score increased more than 1 point	Good performers, percentage whose score decreased more than 1 point
	Clean-file									
Age—SSA data (years)										
Younger than 30	0.7	73.1	14.8	3.5	7.9	0.2	71.6	18.6	2.1	7.5
30 to 39	0.8	34.6	23.8	0.8	40.1	0.3	34.4	25.4	0.5	39.3
40 to 49	0.6	23.6	26.0	0.5	49.3	0.3	23.3	26.8	0.3	49.5
50 to 61	0.5	20.5	26.5	0.3	52.2	0.2	19.9	27.6	0.2	52.1
62 or older	0.7	15.7	23.7	0.2	59.7	0.4	18.3	26.6	0.2	54.5
Unknown	1.0	26.1	19.0	1.0	53.0	0.3	32.5	25.5	1.0	40.8
National origin										
Foreign-born	0.6	43.6	21.2	1.1	33.5	0.3	48.0	20.8	0.9	30.2
Recent immigrant	0.5	79.3	11.6	1.8	6.8	0.2	80.7	12.3	1.1	5.7
All	0.7	28.1	23.6	0.8	46.9	0.3	31.1	25.5	0.6	42.6
	Major-derogatory									
Age—SSA data (years)										
Younger than 30	0.4	27.4	60.9	11.0	0.4	0.1	42.6	52.4	4.5	0.4
30 to 39	3.7	20.5	63.1	5.5	7.1	0.7	33.7	55.5	2.4	7.8
40 to 49	5.7	18.4	54.1	4.1	17.7	1.1	29.7	50.7	1.9	16.6
50 to 61	6.3	15.8	45.6	3.1	29.2	0.8	25.4	43.9	1.4	28.5
62 or older	7.6	11.3	35.6	1.9	43.7	1.2	19.9	41.6	1.2	36.1
Unknown	7.1	16.6	50.7	5.1	20.6	2.1	30.3	46.6	2.4	18.6
National origin										
Foreign-born	3.4	26.8	49.2	5.8	14.9	0.4	40.6	42.8	2.1	14.0
Recent immigrant	0.3	40.4	48.9	10.0	0.3	0.0	61.3	35.9	2.8	0.0
All	4.7	19.0	53.7	5.2	17.4	0.8	30.9	49.9	2.2	16.2

Note. Credit characteristic G103, "Total number of months since the most recent update on an account," is dropped from the thin-file scorecard. Credit characteristic S004, "Average age of accounts on credit report," is dropped from the clean-file and major-derogatory scorecards.

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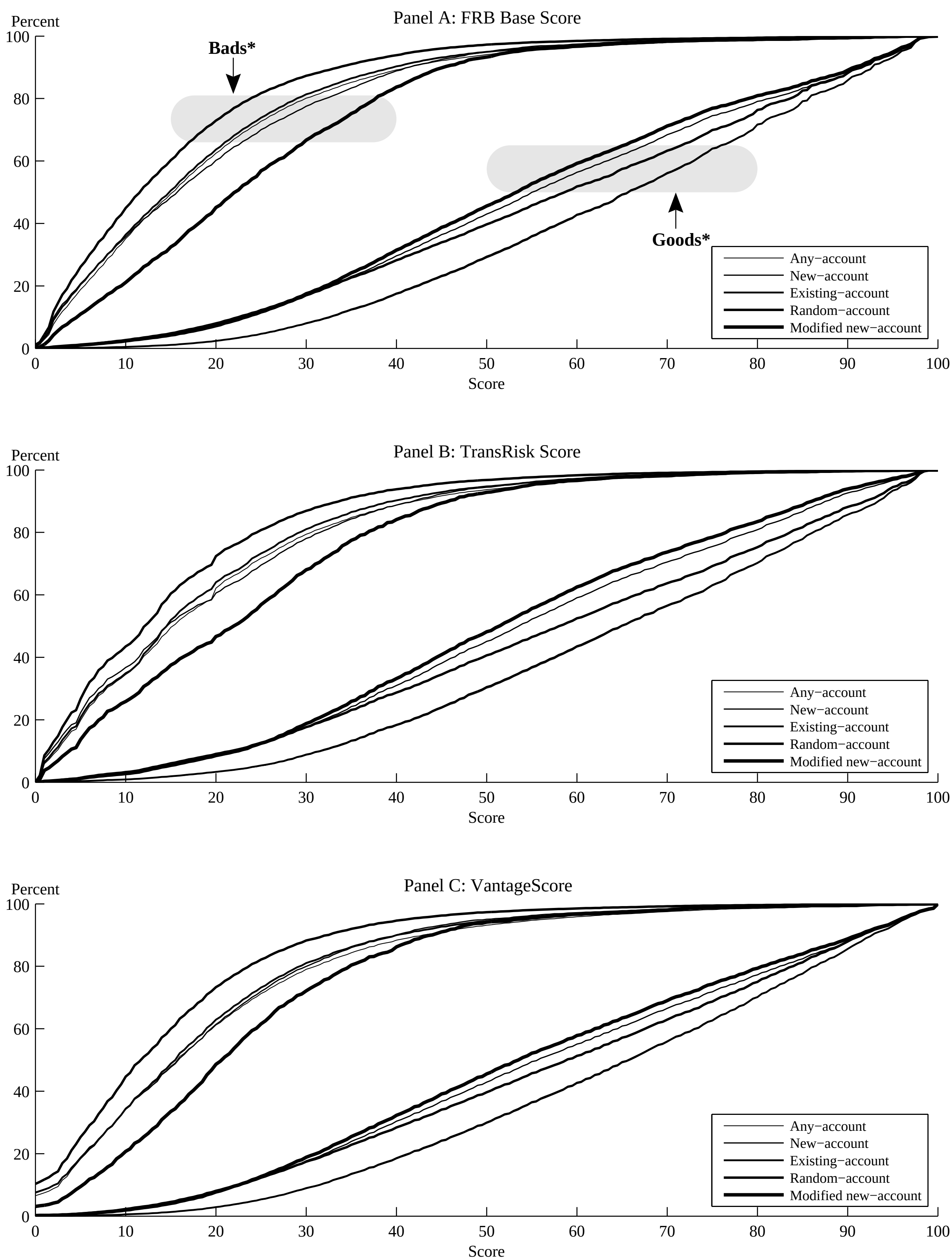
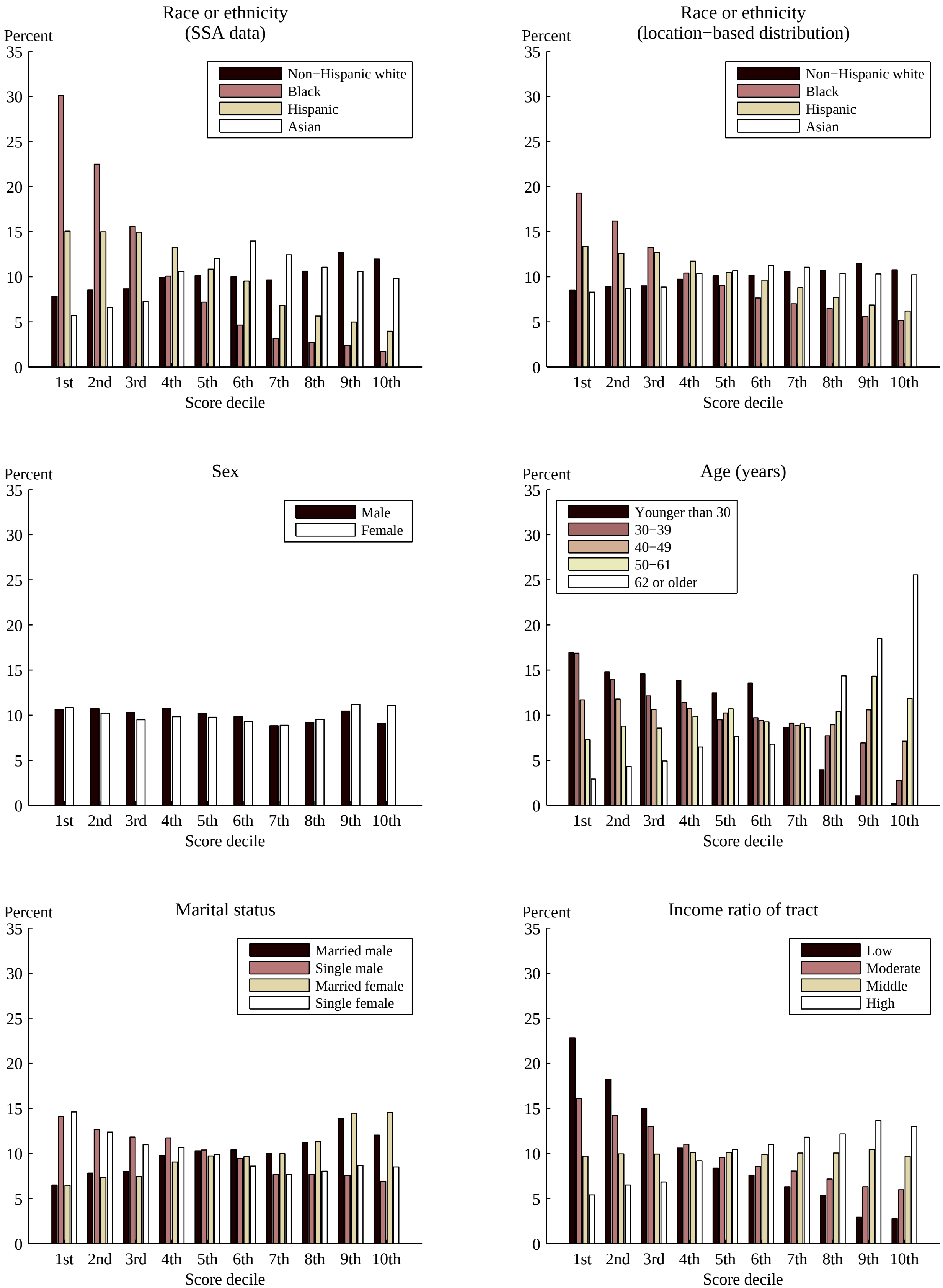
[Figure 1 corrected as of Jan. 25, 2008]

Figure 1. Cumulative Percentage of Goods and Bads, All Individuals



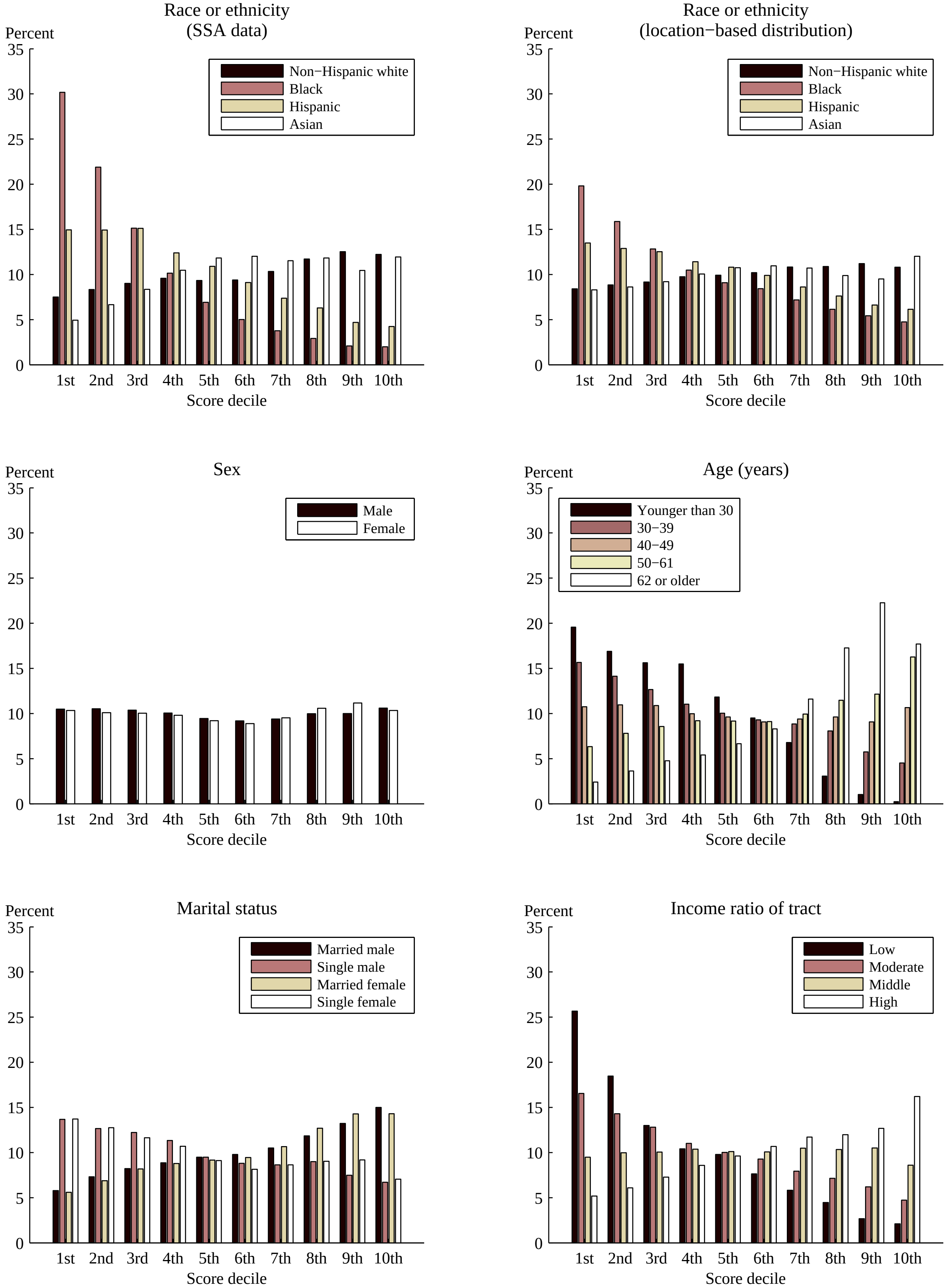
* Curves encompassed by the ellipses are the data for goods and bads respectively.

Figure 2.A. TransRisk Score: Sample Population, Grouped by Demographic Characteristic and Distributed by Score Decile



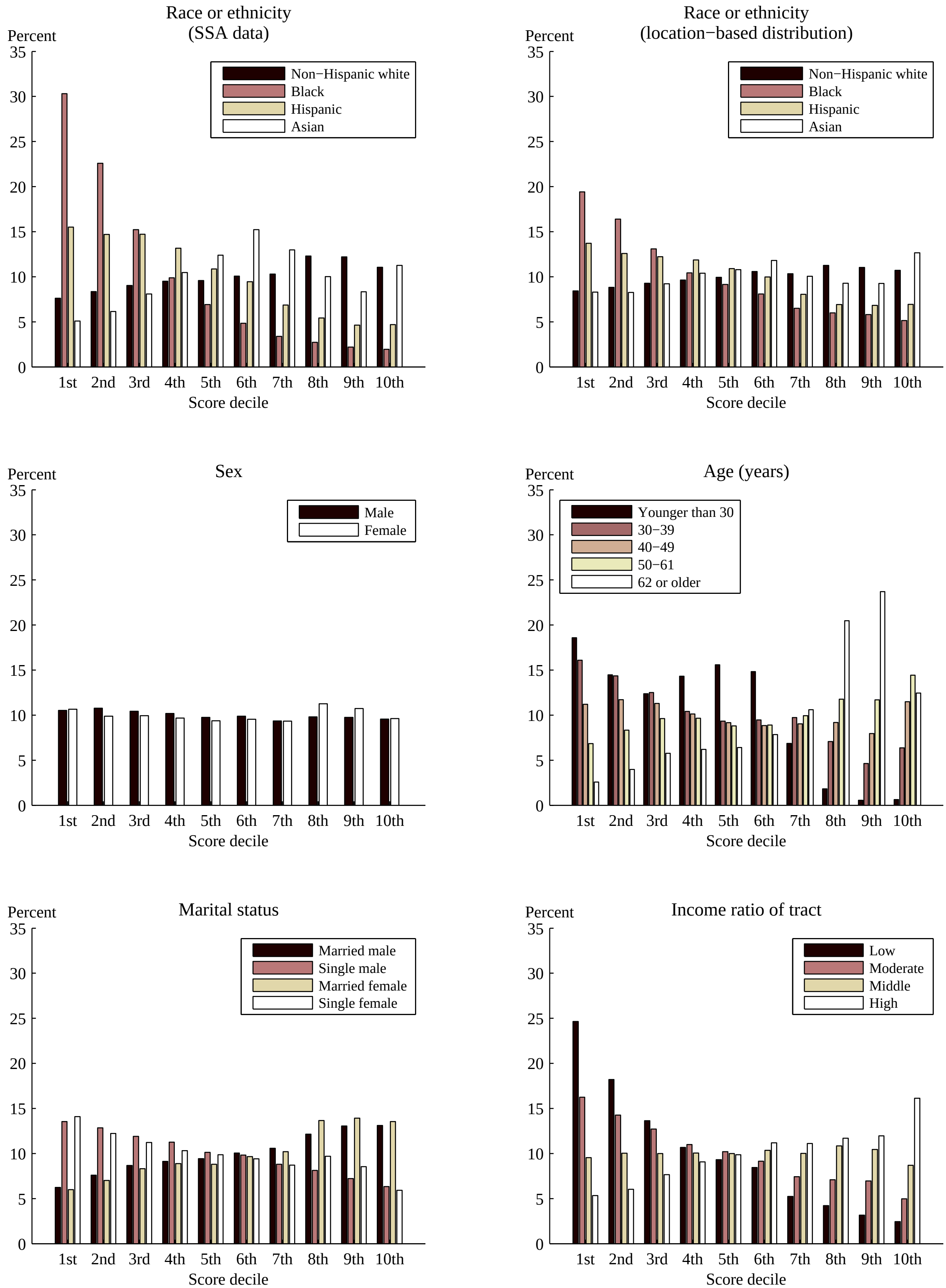
Note. For definition of characteristics, refer to notes to table 9.

Figure 2.B. VantageScore: Sample Population, Grouped by Demographic Characteristic and Distributed by Score Decile



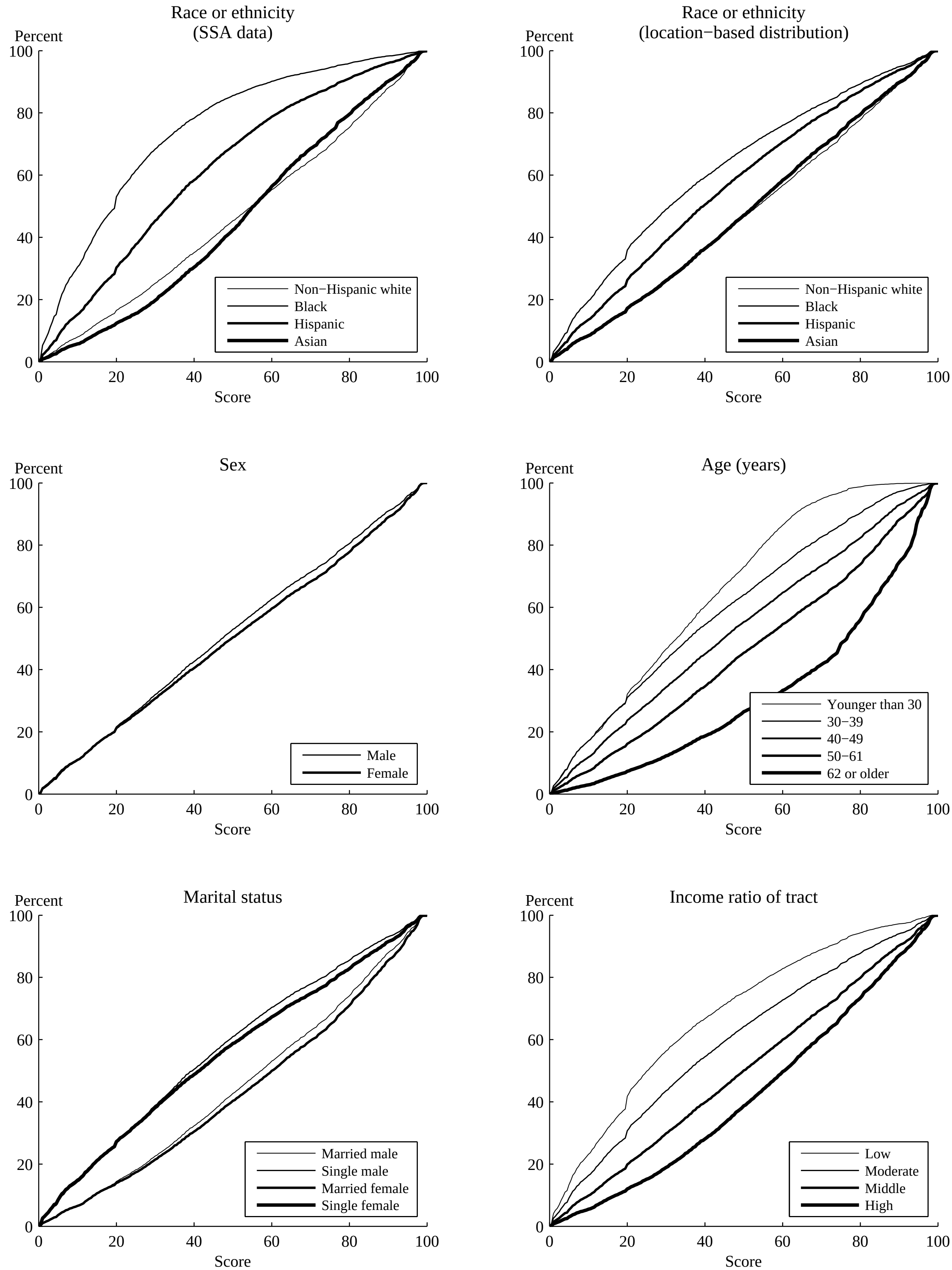
Note. For definition of characteristics, refer to notes to table 9.

Figure 2.C. FRB Base Score: Sample Population, Grouped by Demographic Characteristic and Distributed by Score Decile



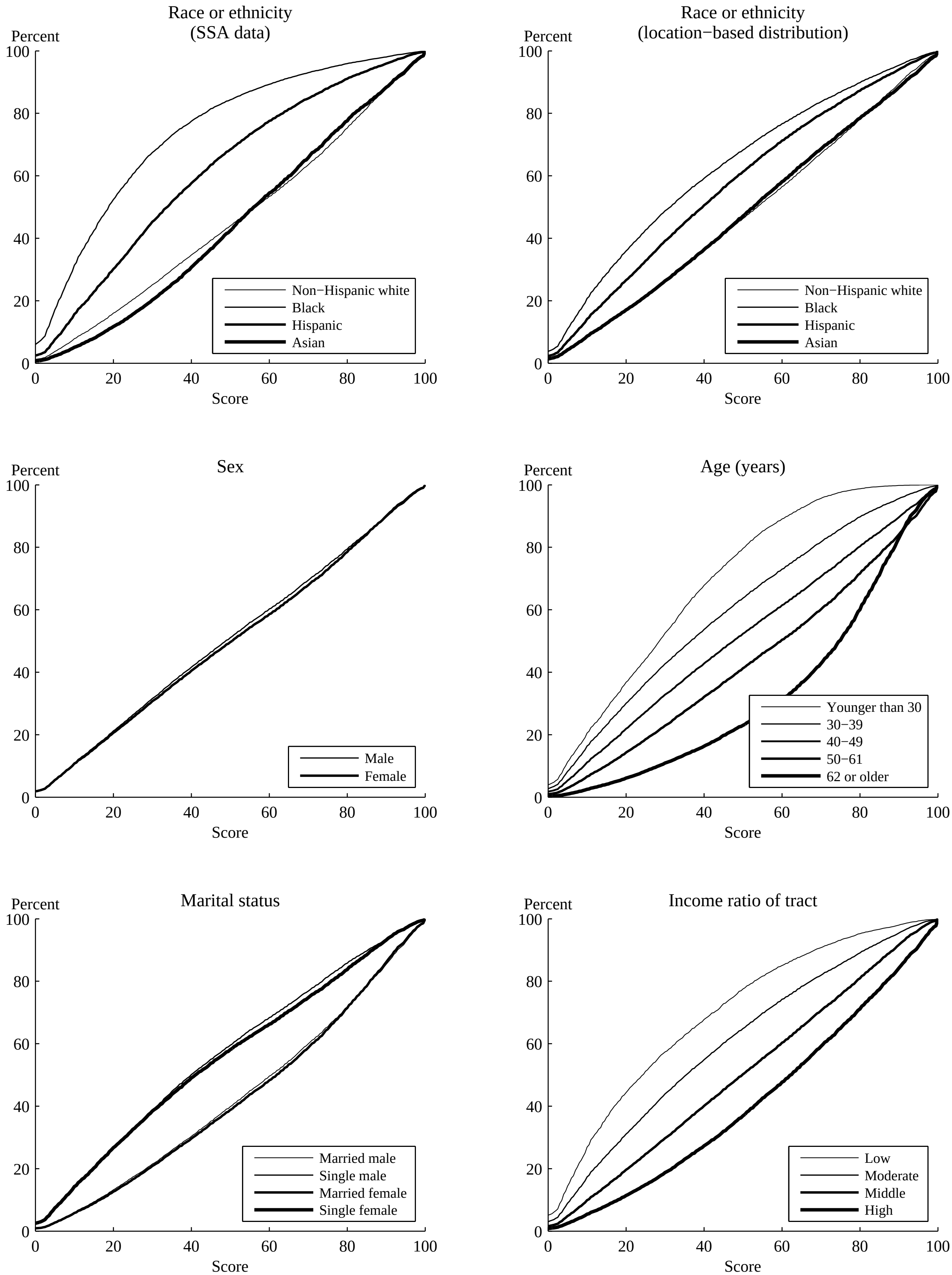
Note. For definition of characteristics, refer to notes to table 9.

Figure 3.A. TransRisk Score: Cumulative Percentage, by Demographic Group



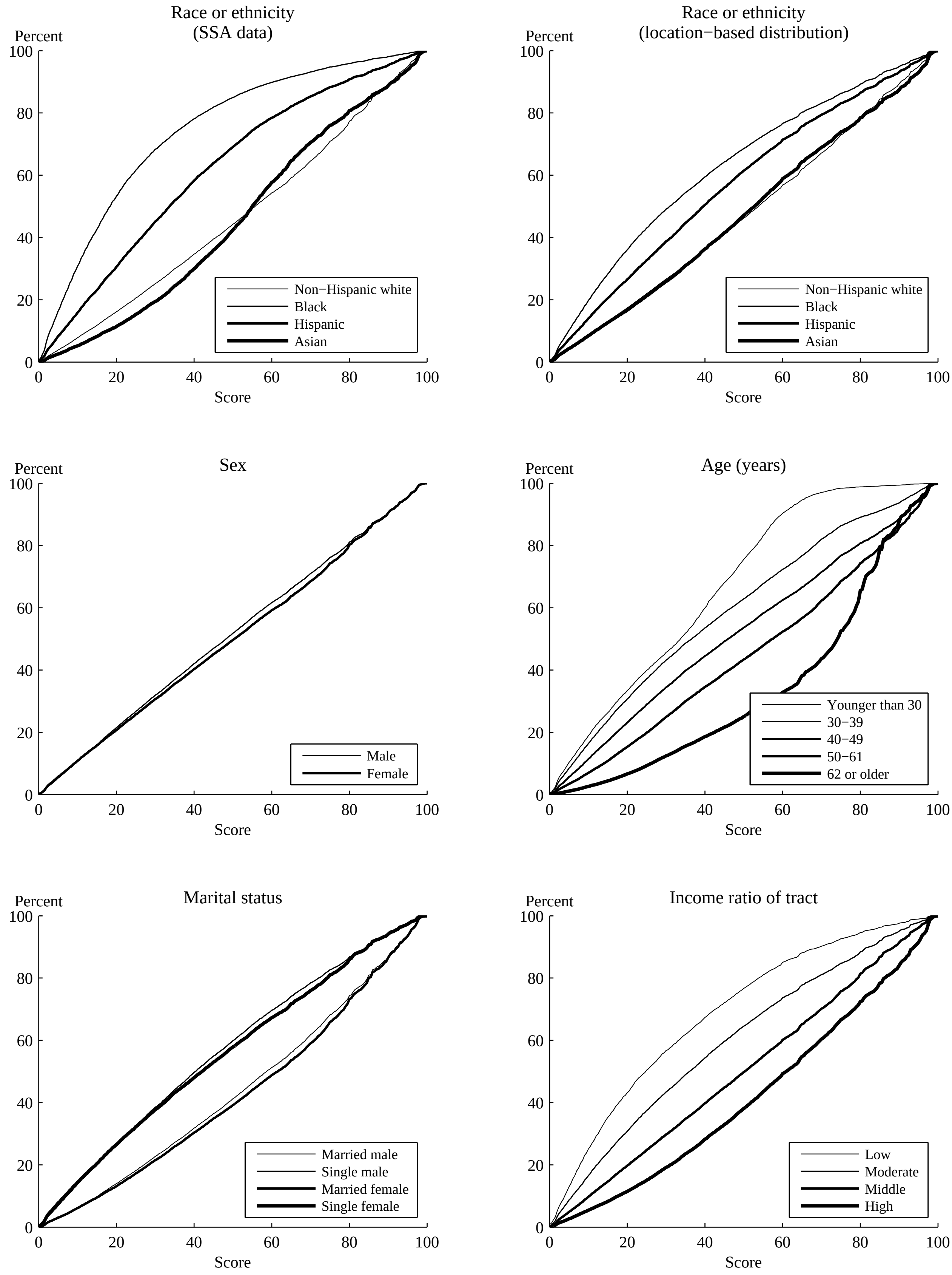
Note. For definition of characteristics, refer to notes to table 9.

Figure 3.B. VantageScore: Cumulative Percentage, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

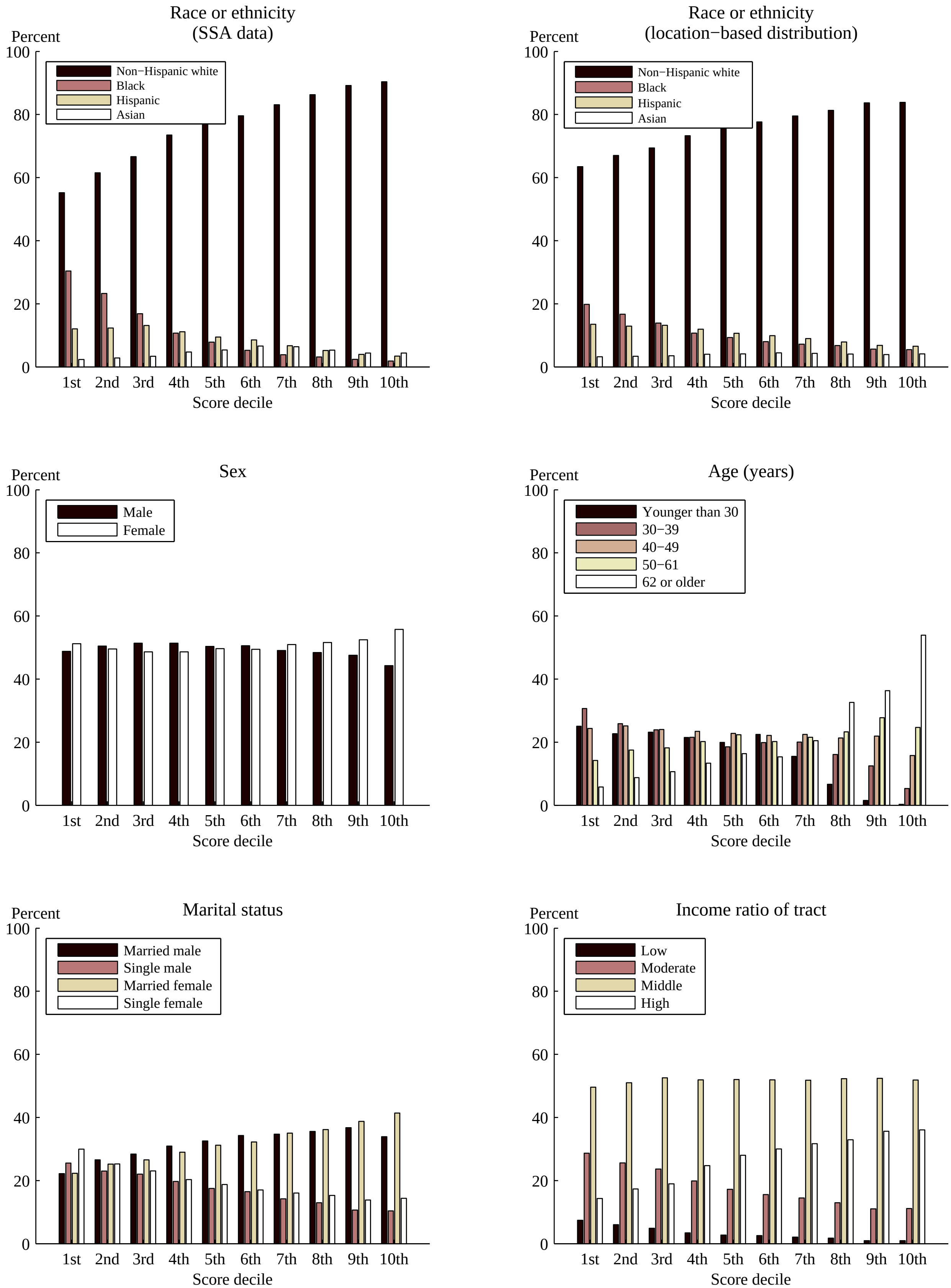
Figure 3.C. FRB Base Score: Cumulative Percentage, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

[Figures 4.A and 4.B corrected as of Jan. 25, 2008]

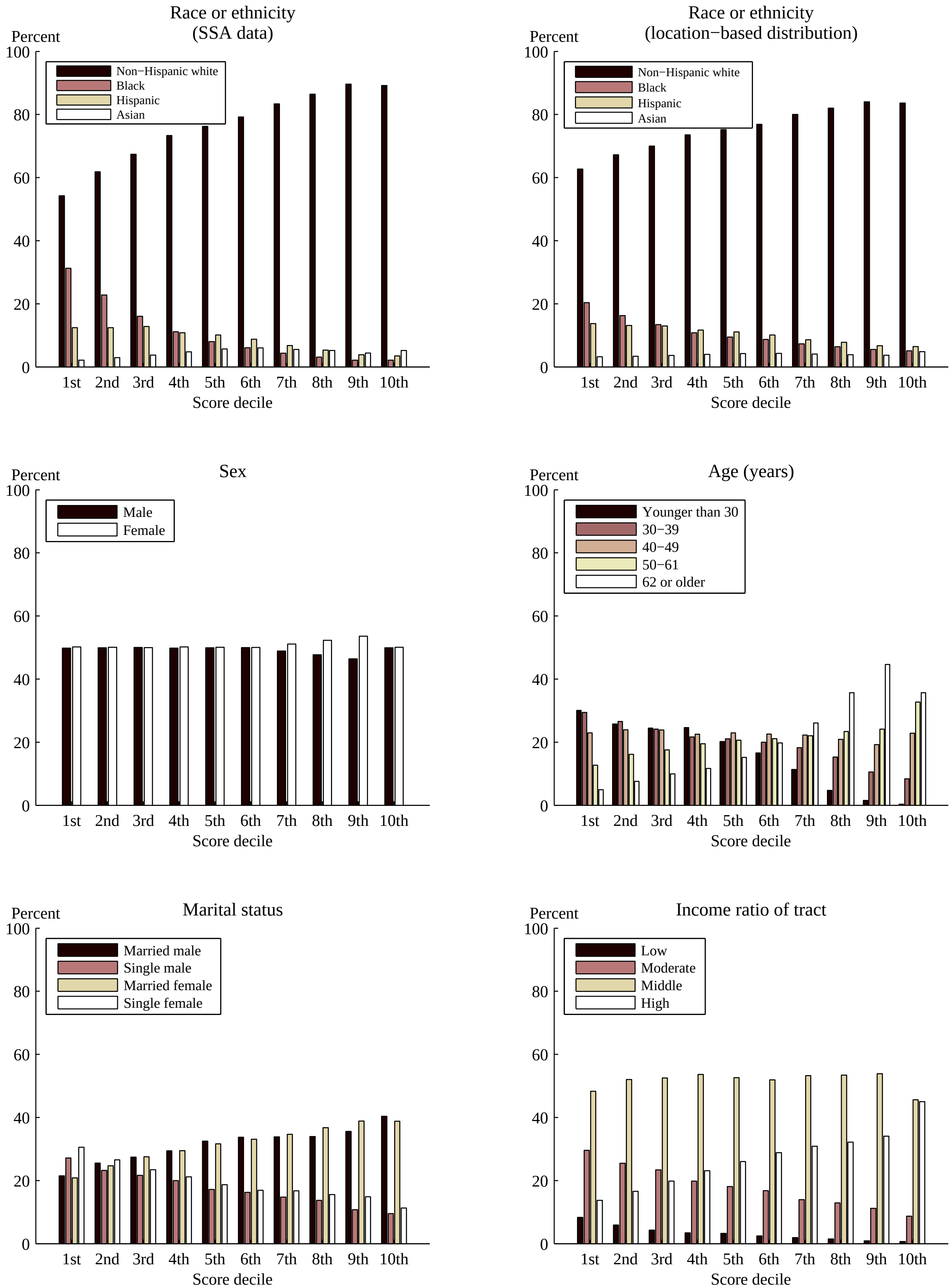
Figure 4.A. TransRisk Score: Percent of Score Decile, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

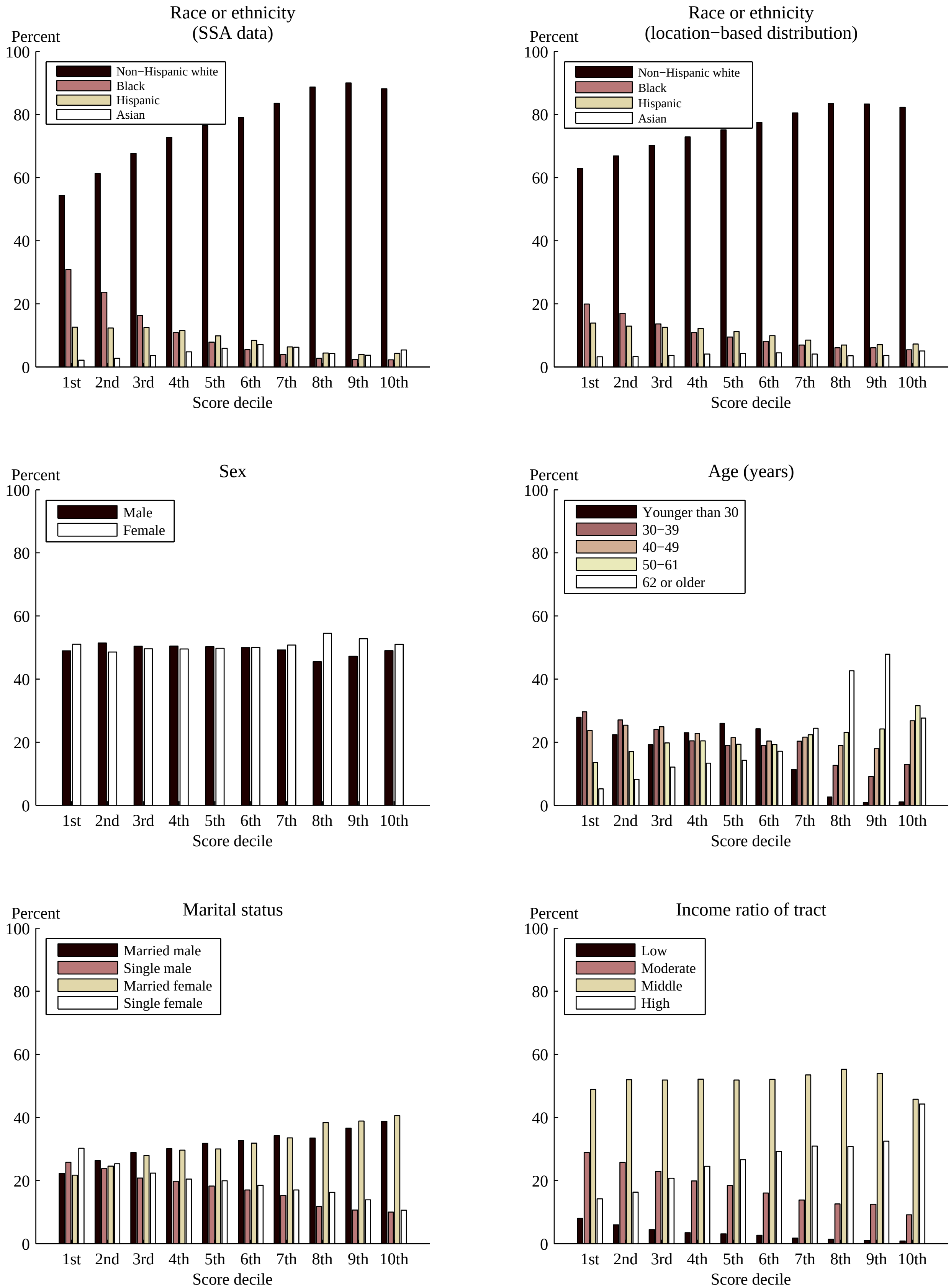
[Figures 4.A and 4.B corrected as of Jan. 25, 2008]

Figure 4.B. VantageScore: Percent of Score Decile, by Demographic Group



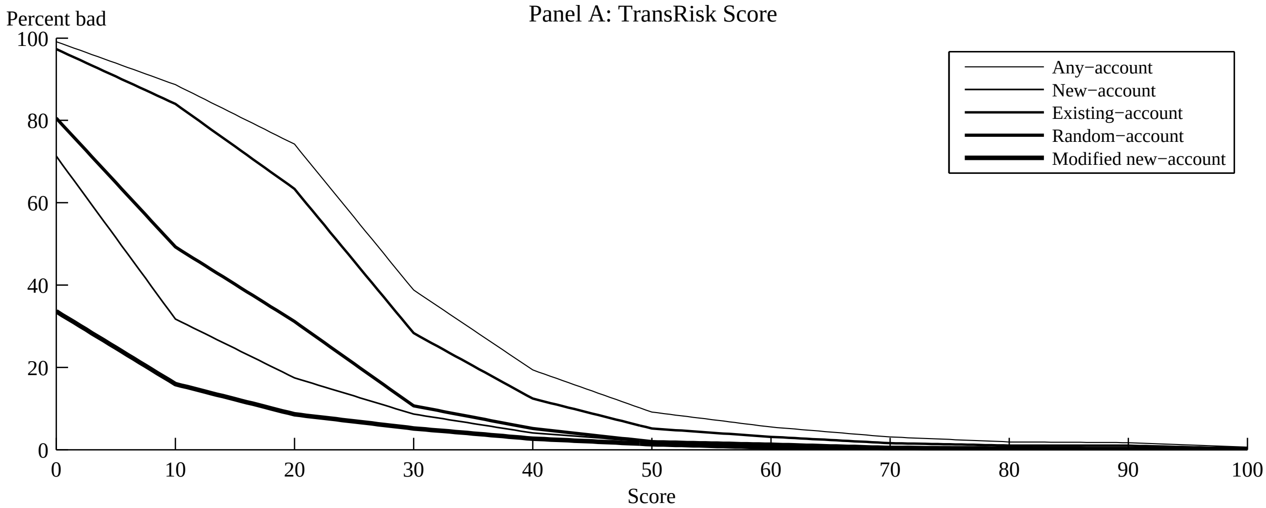
Note. For definition of characteristics, refer to notes to table 9.

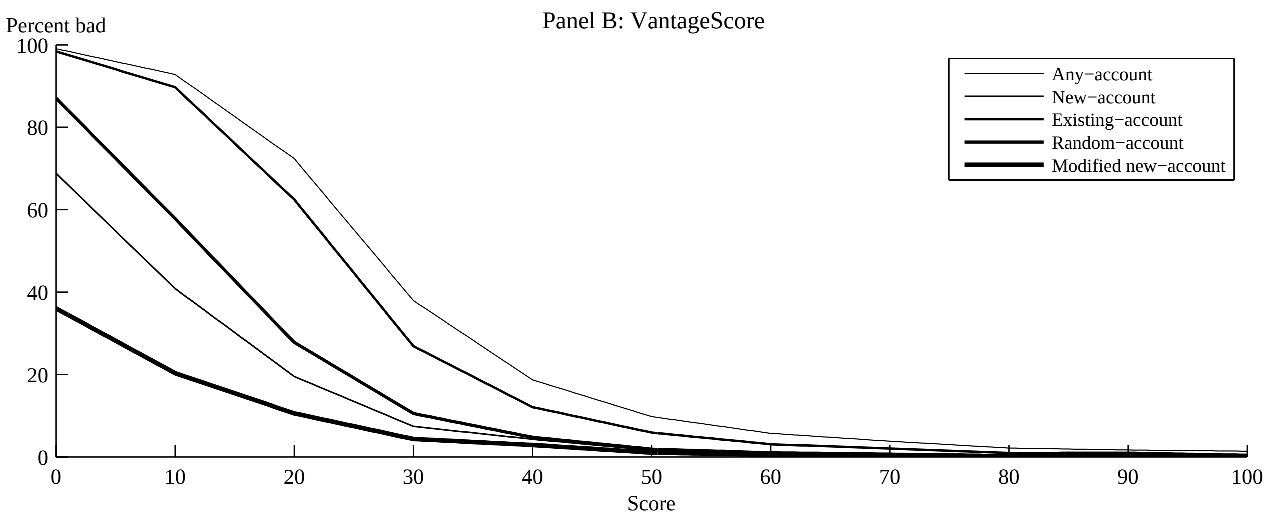
Figure 4.C. FRB Base Score: Percent of Score Decile, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

Figure 5. Performance, All Individuals





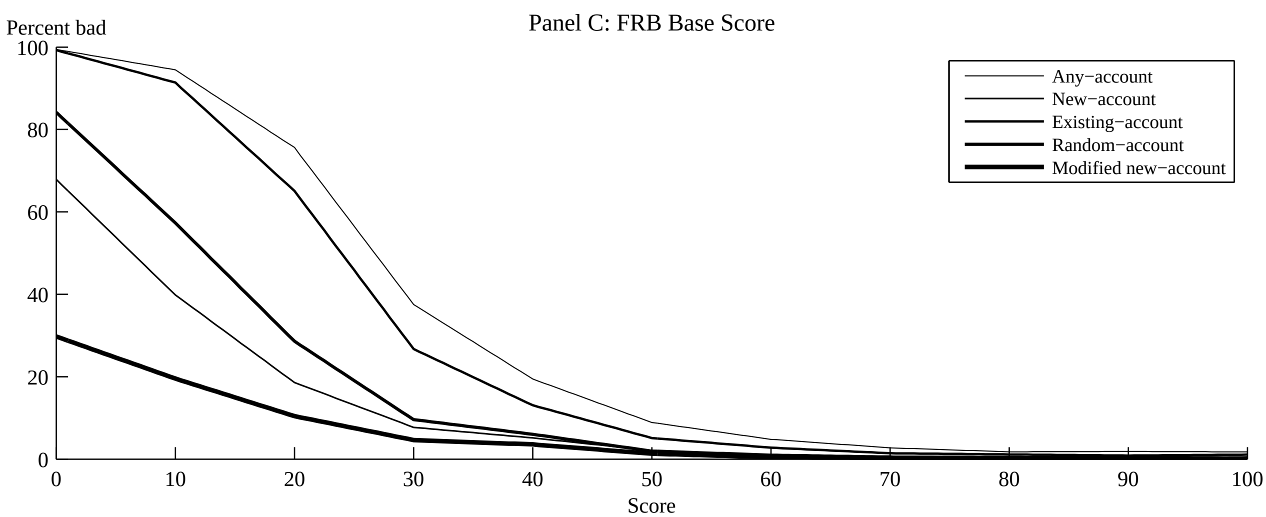
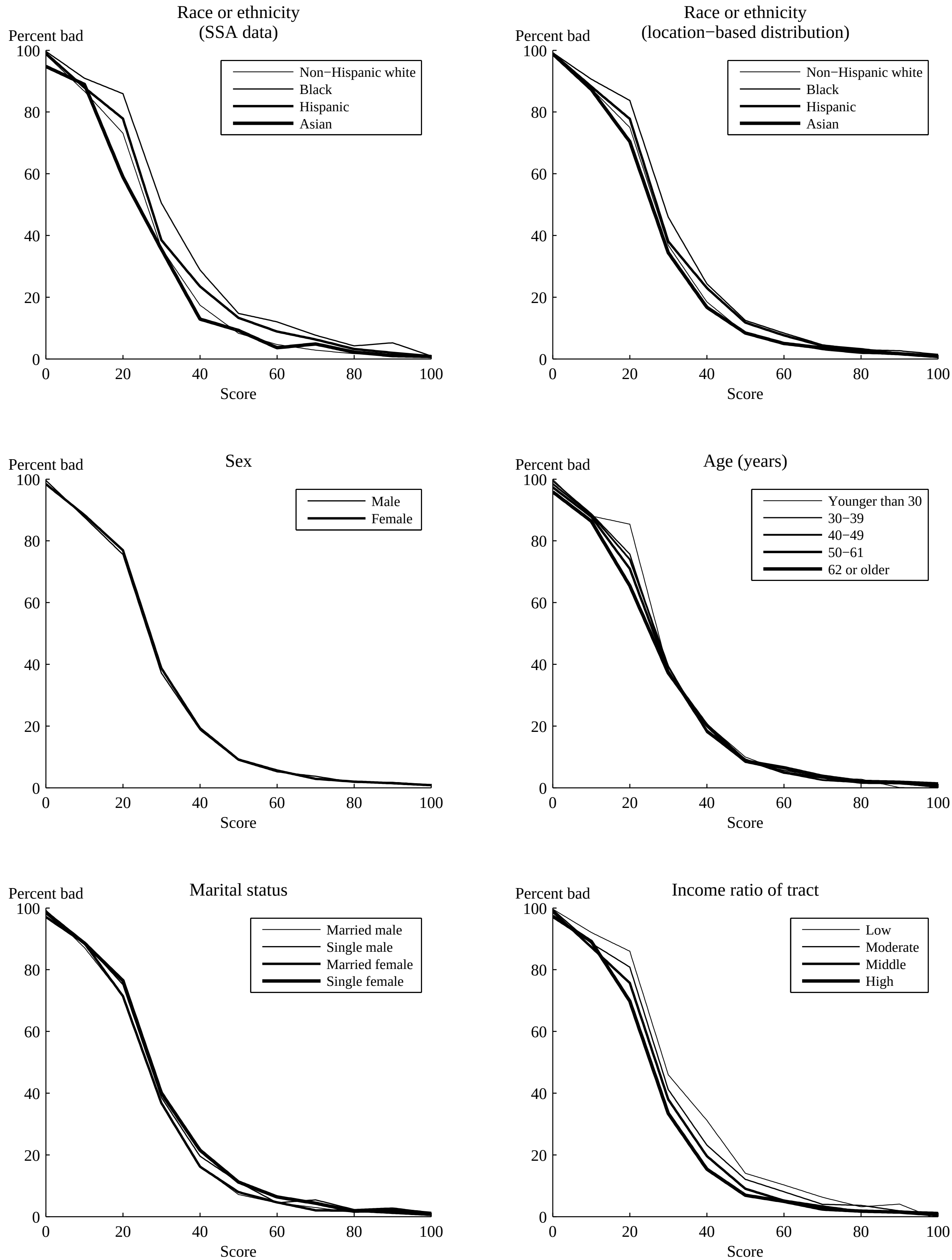
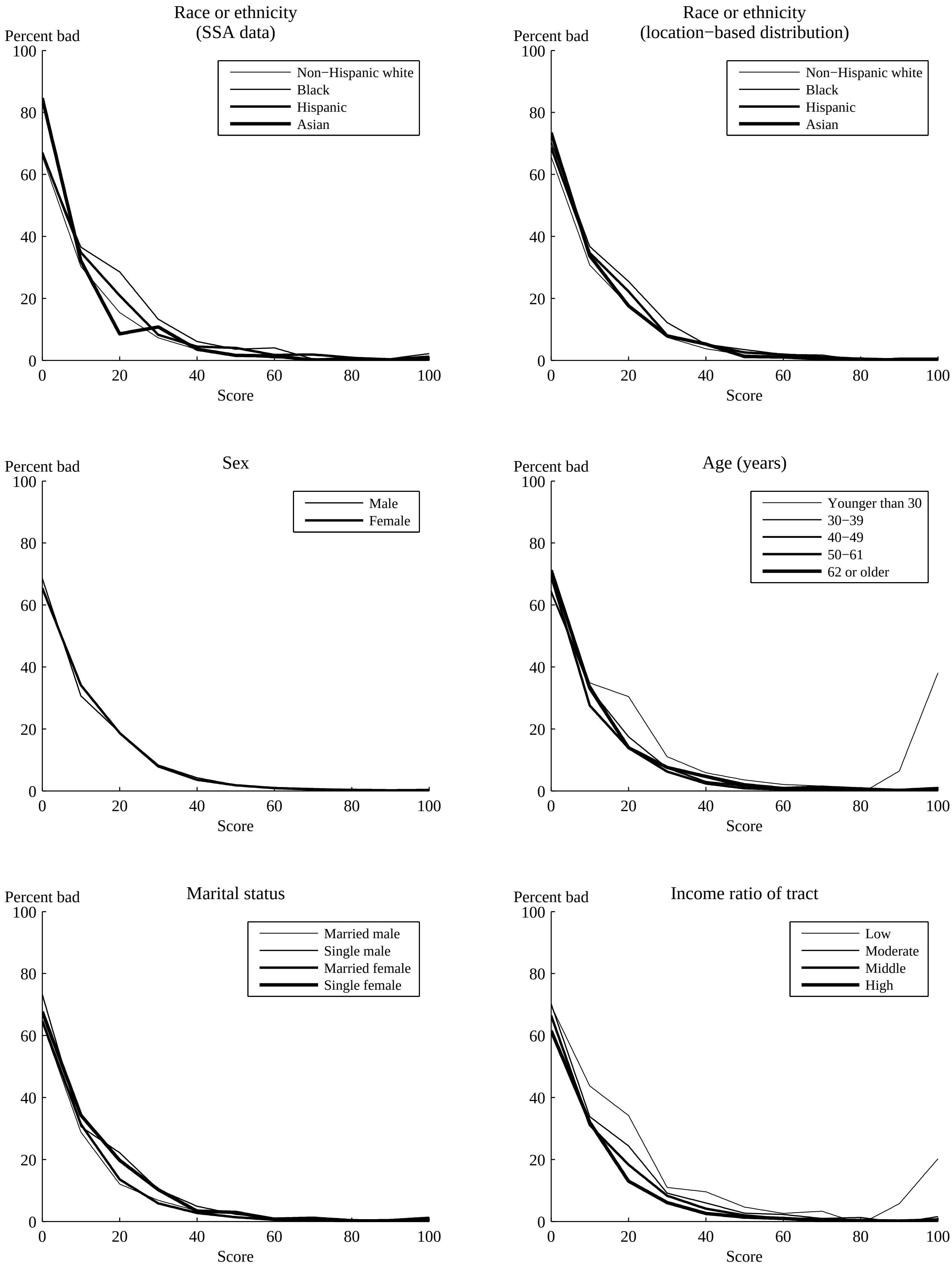


Figure 6.A. TransRisk Score: Any−Account Performance (Percent Bad), by Demographic Group



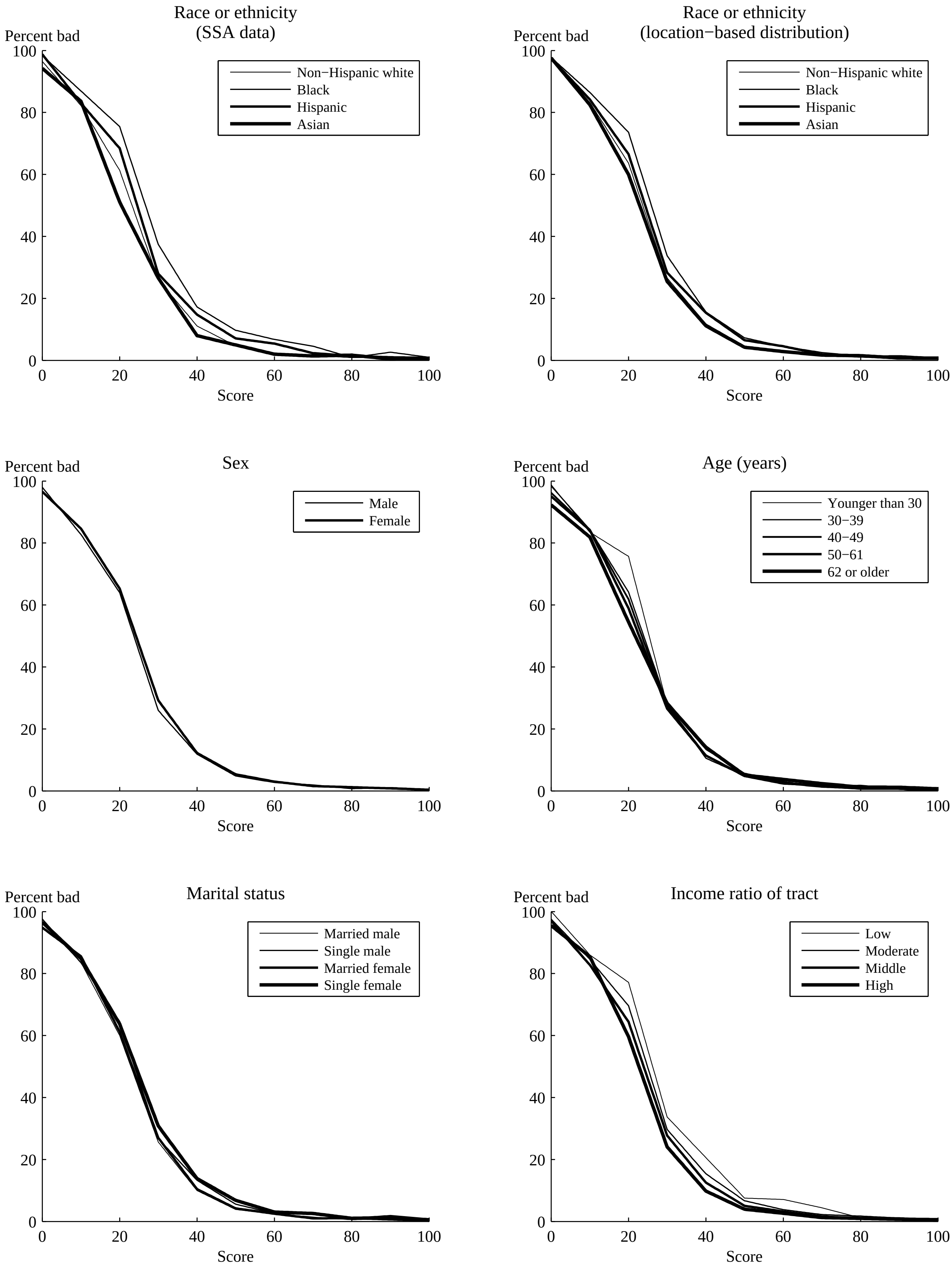
Note. For definition of characteristics, refer to notes to table 9.

Figure 6.B. TransRisk Score: New−Account Performance (Percent Bad), by Demographic Group



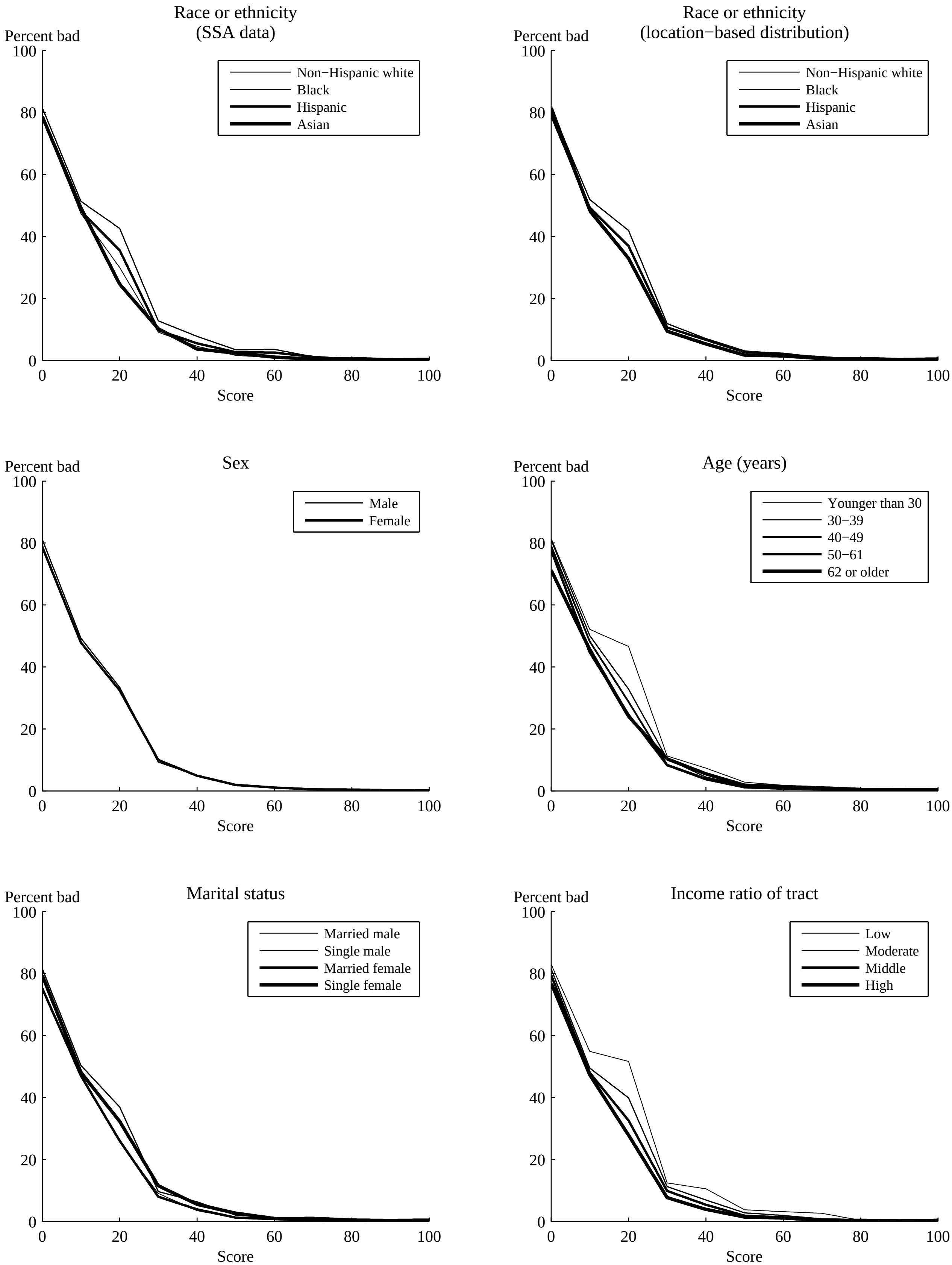
Note. For definition of characteristics, refer to notes to table 9.

Figure 6.C. TransRisk Score: Existing−Account Performance (Percent Bad), by Demographic Group



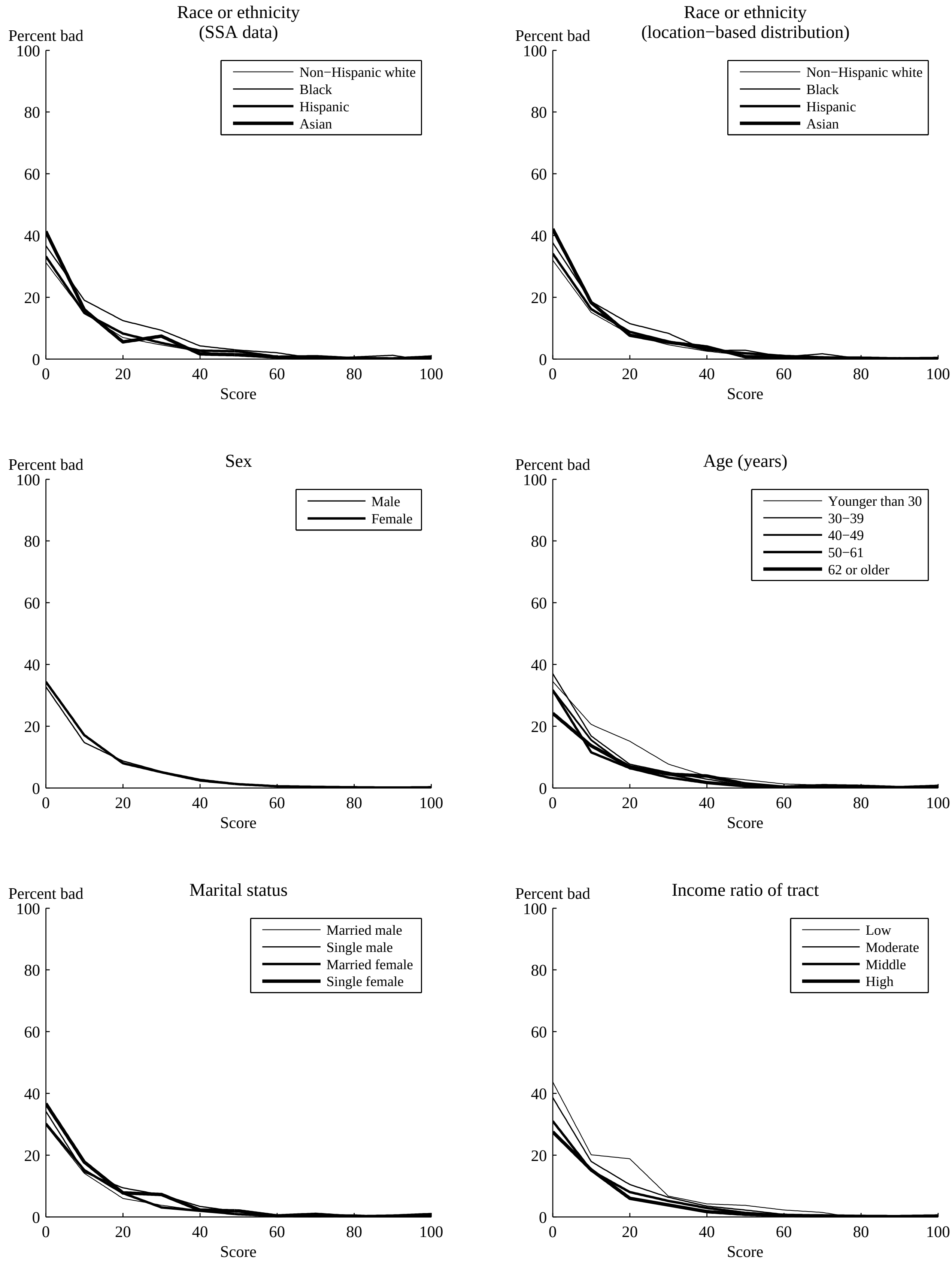
Note. For definition of characteristics, refer to notes to table 9.

Figure 6.D. TransRisk Score: Random−Account Performance (Percent Bad), by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

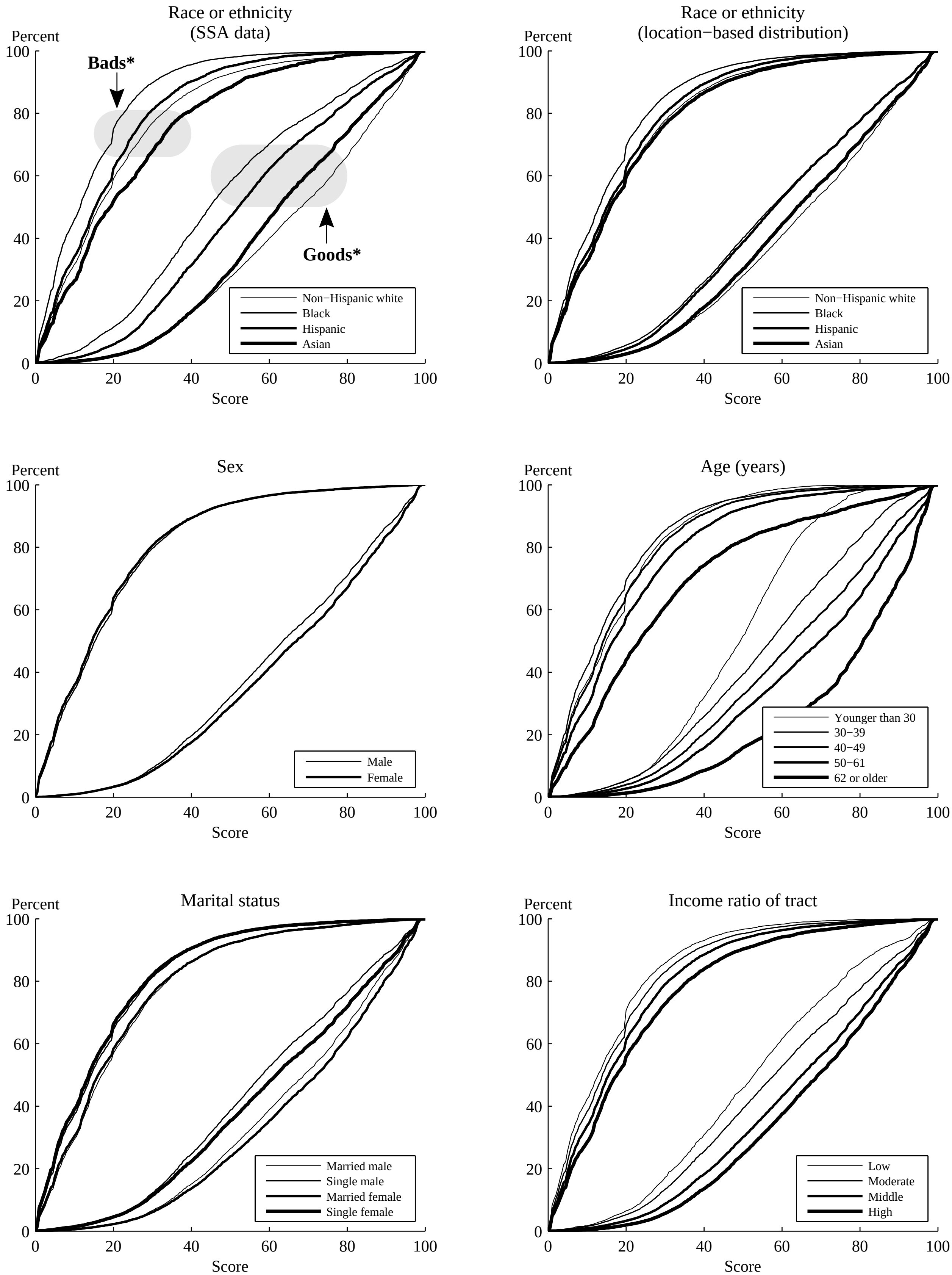
Figure 6.E. TransRisk Score: Modified New−Account Performance (Percent Bad), by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

[Figures 7.A-E corrected as of Jan. 25, 2008]

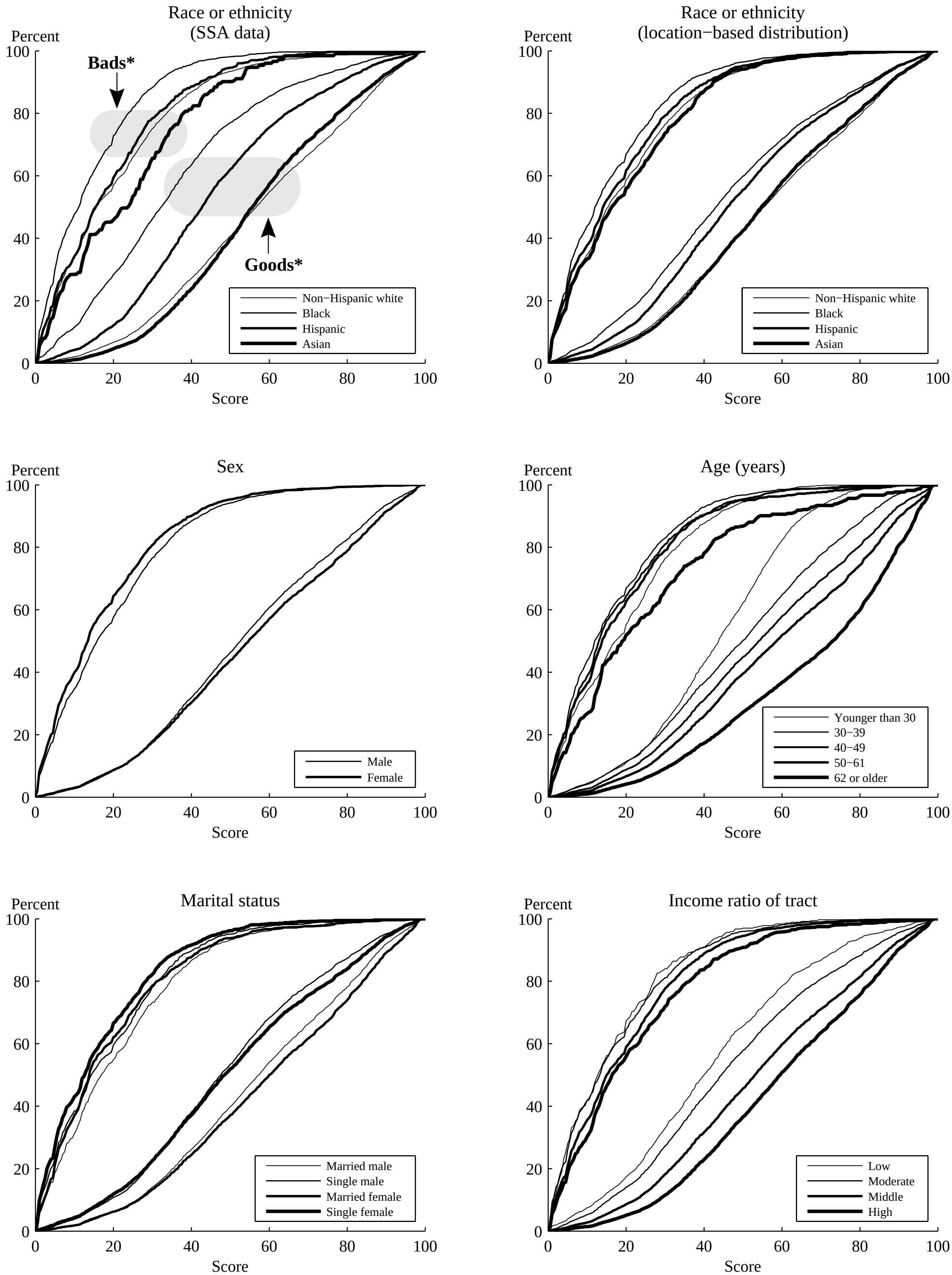
Figure 7.A. TransRisk Score: Cumulative Percentage of Goods and Bads, by Demographic Group (Any−Account Performance)



Note. For definition of characteristics, refer to notes to table 9.
* Curves encompassed by the ellipses are the data for goods and bads respectively.

[Figures 7.A-E corrected as of Jan. 25, 2008]

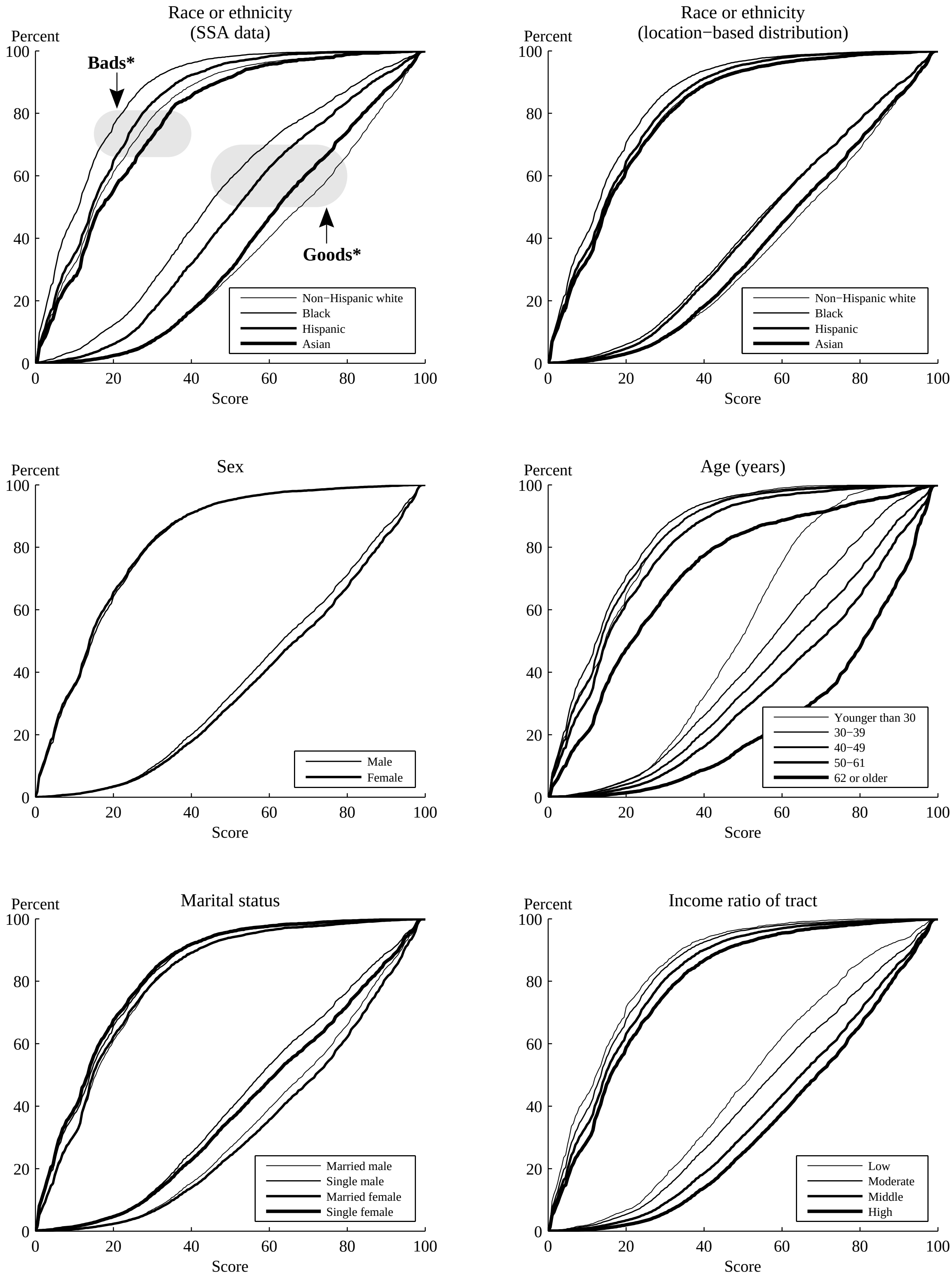
Figure 7.B. TransRisk Score: Cumulative Percentage of Goods and Bads, by Demographic Group (New−Account Performance)



Note. For definition of characteristics, refer to notes to table 9.
* Curves encompassed by the ellipses are the data for goods and bads respectively.

[Figures 7.A-E corrected as of Jan. 25, 2008]

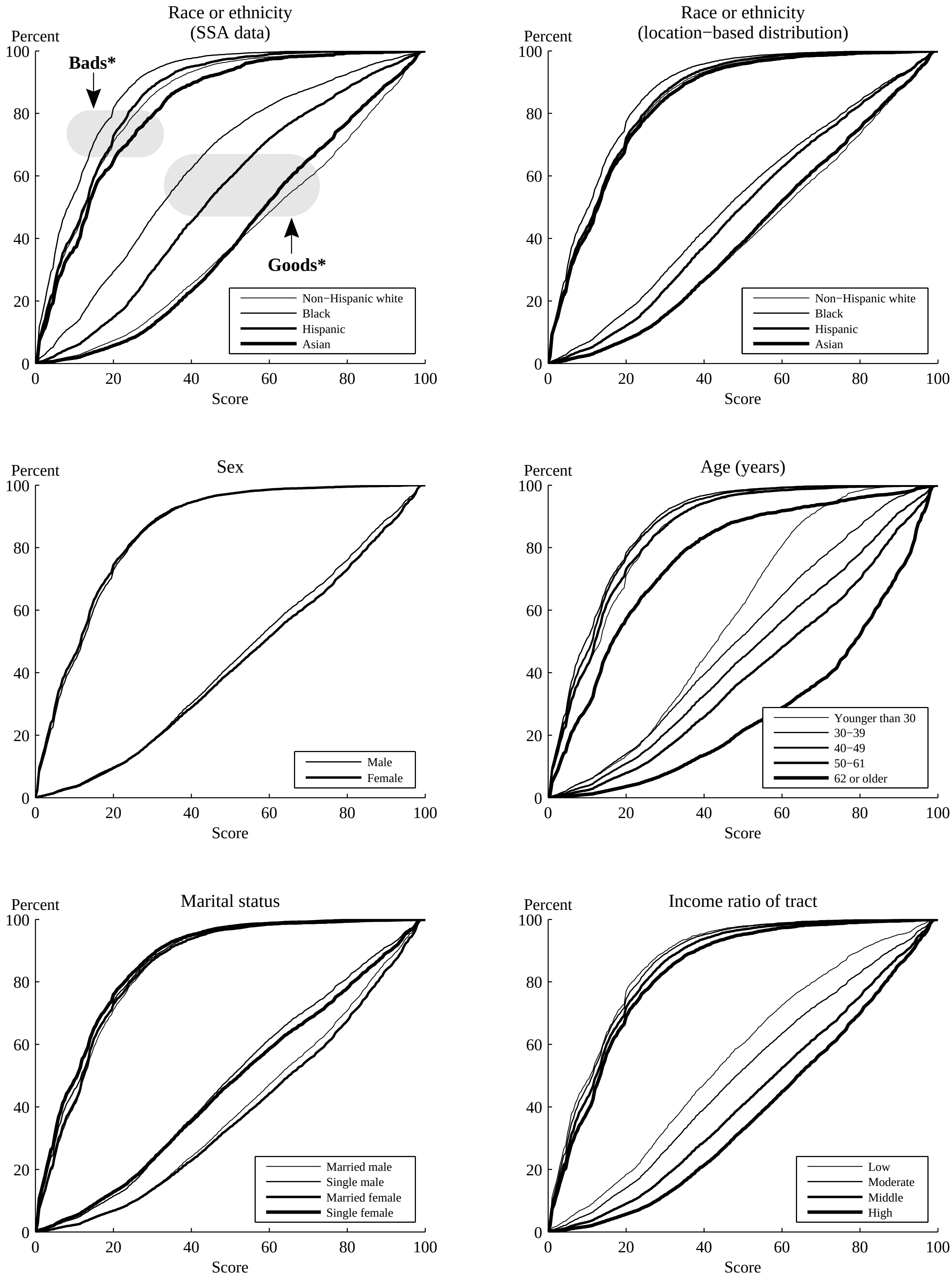
Figure 7.C. TransRisk Score: Cumulative Percentage of Goods and Bads, by Demographic Group (Existing−Account Performance)



Note. For definition of characteristics, refer to notes to table 9.
* Curves encompassed by the ellipses are the data for goods and bads respectively.

[Figures 7.A-E corrected as of Jan. 25, 2008]

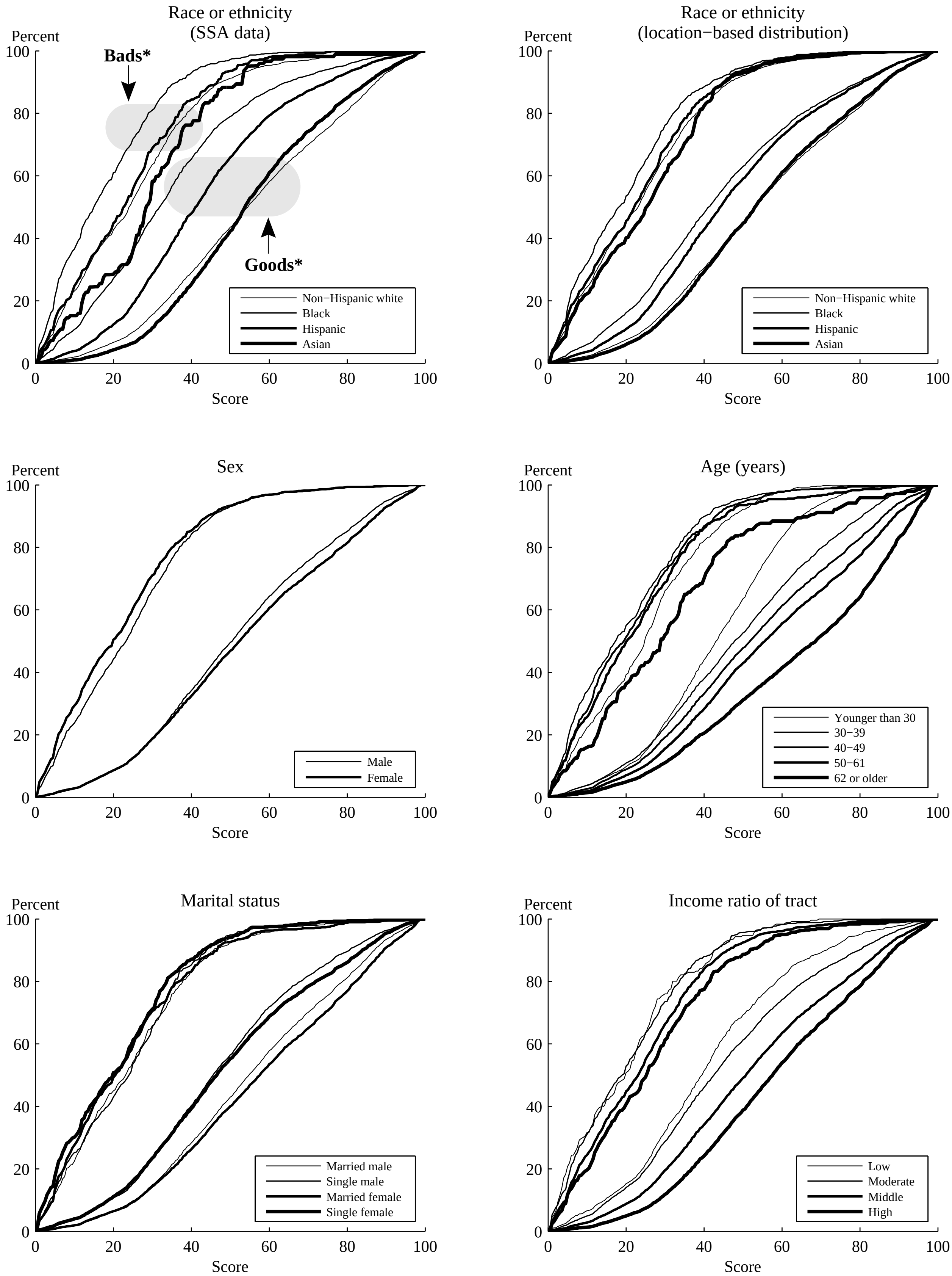
Figure 7.D. TransRisk Score: Cumulative Percentage of Goods and Bads, by Demographic Group (Random−Account Performance)



Note. For definition of characteristics, refer to notes to table 9.
* Curves encompassed by the ellipses are the data for goods and bads respectively.

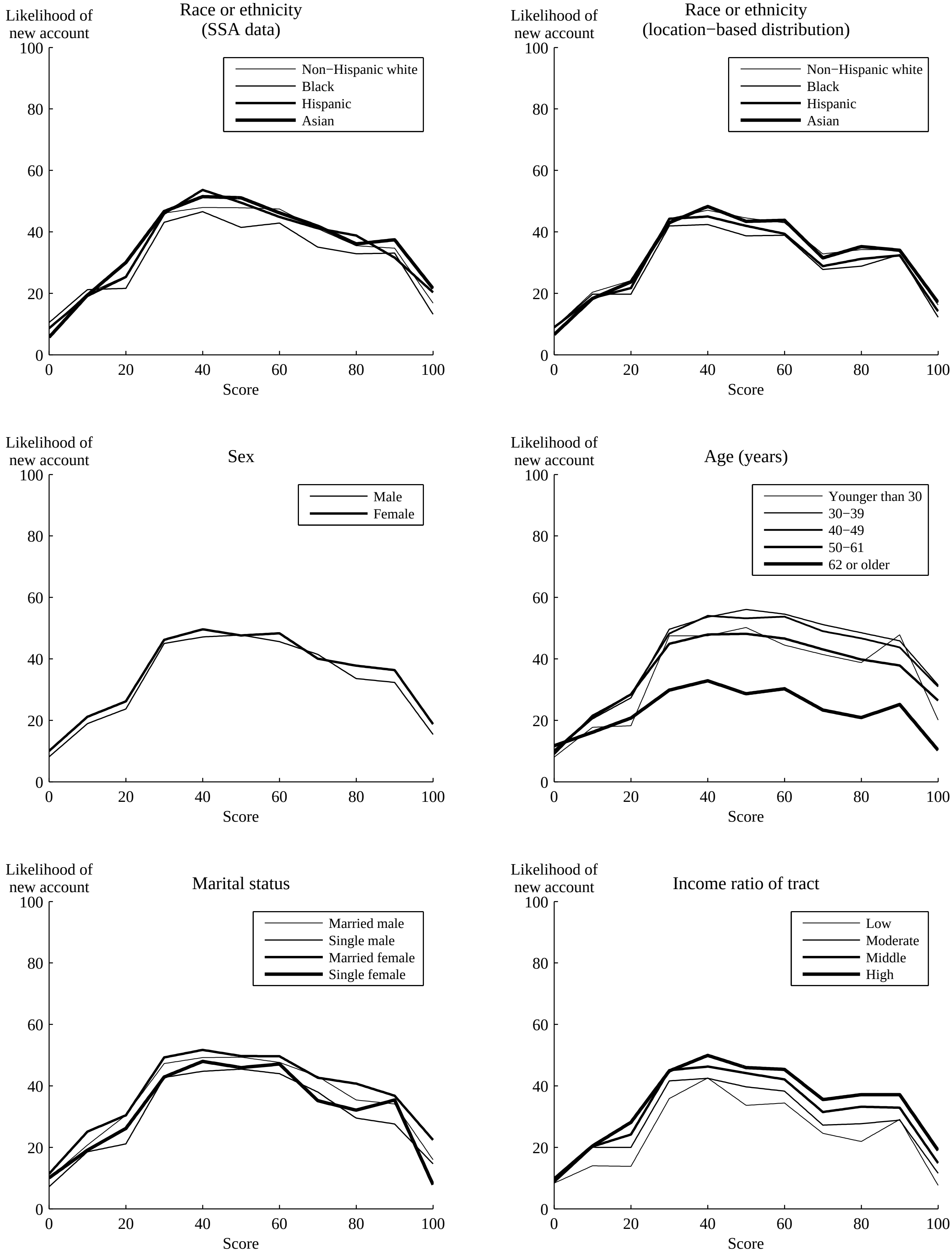
[Figures 7.A-E corrected as of Jan. 25, 2008]

Figure 7.E. TransRisk Score: Cumulative Percentage of Goods and Bads, by Demographic Group (Modified New−Account Performance)



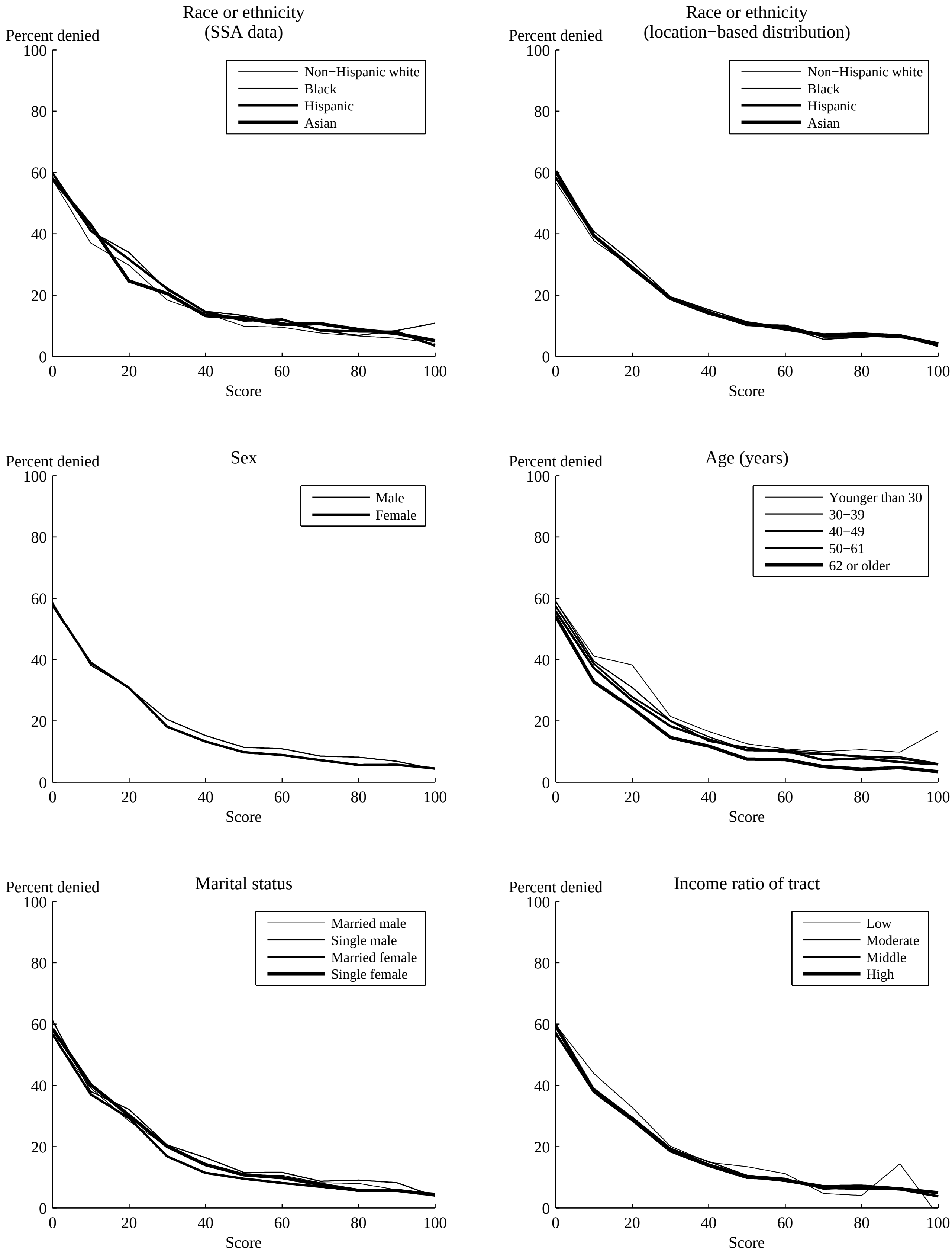
Note. For definition of characteristics, refer to notes to table 9.
* Curves encompassed by the ellipses are the data for goods and bads respectively.

Figure 8. TransRisk Score: New Account Acquisition, by Demographic Group



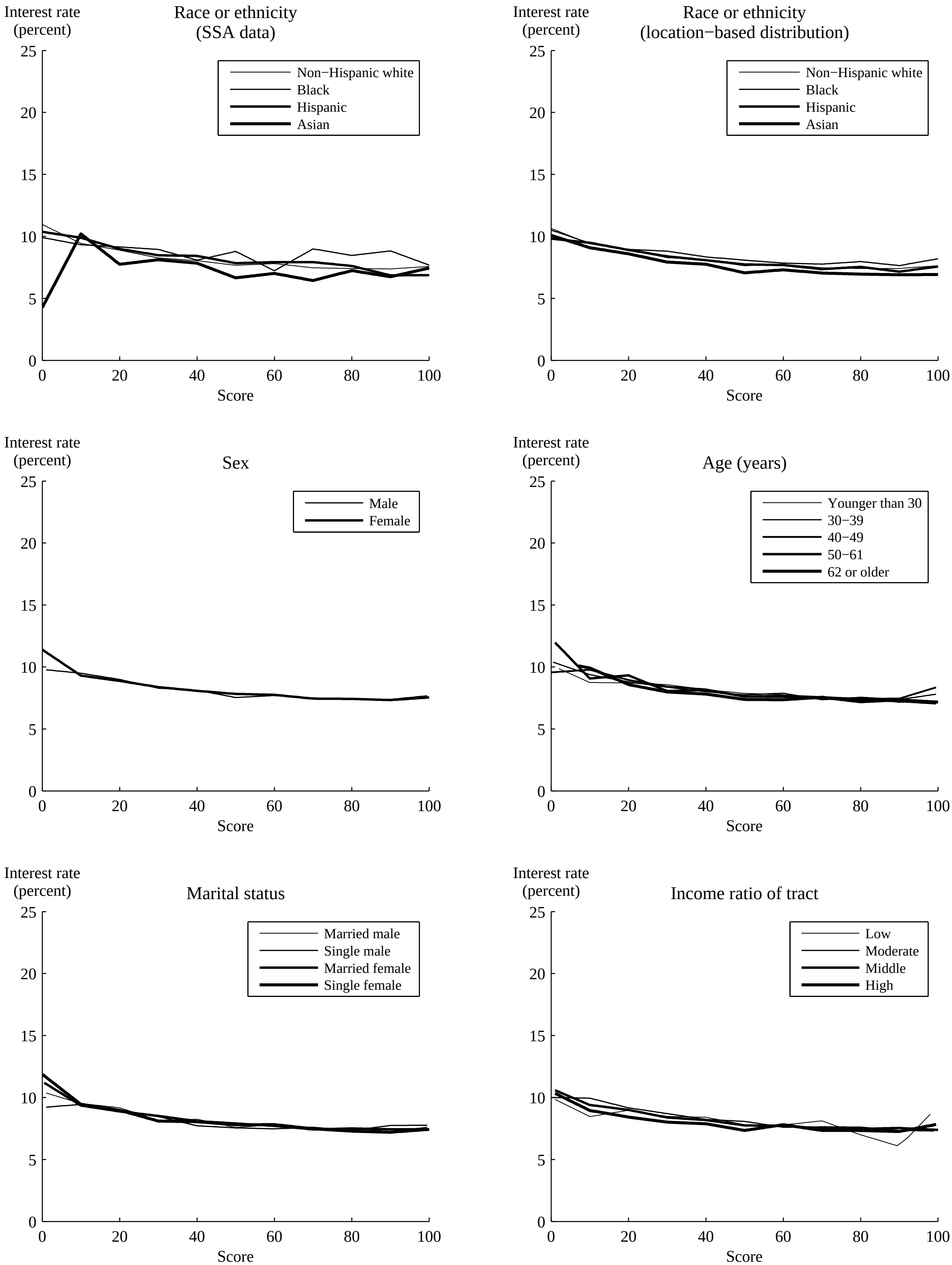
Note. For definition of characteristics, refer to notes to table 9.

Figure 9. TransRisk Score: Inquiry−Based Proxy for Denials, by Demographic Group



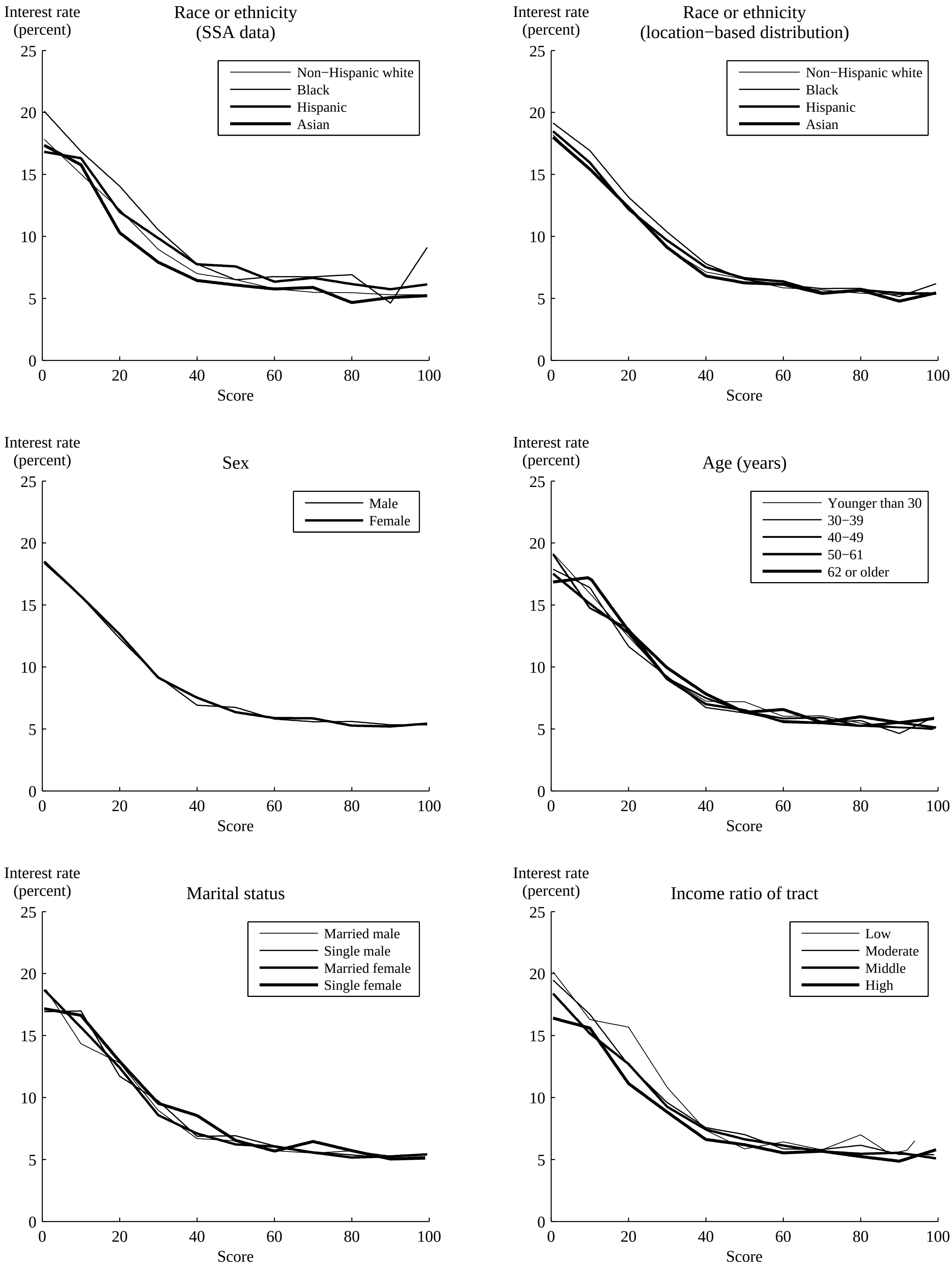
Note. For definition of characteristics, refer to notes to table 9.

Figure 10.A. TransRisk Score: Mortgage Interest Rate, by Demographic Group



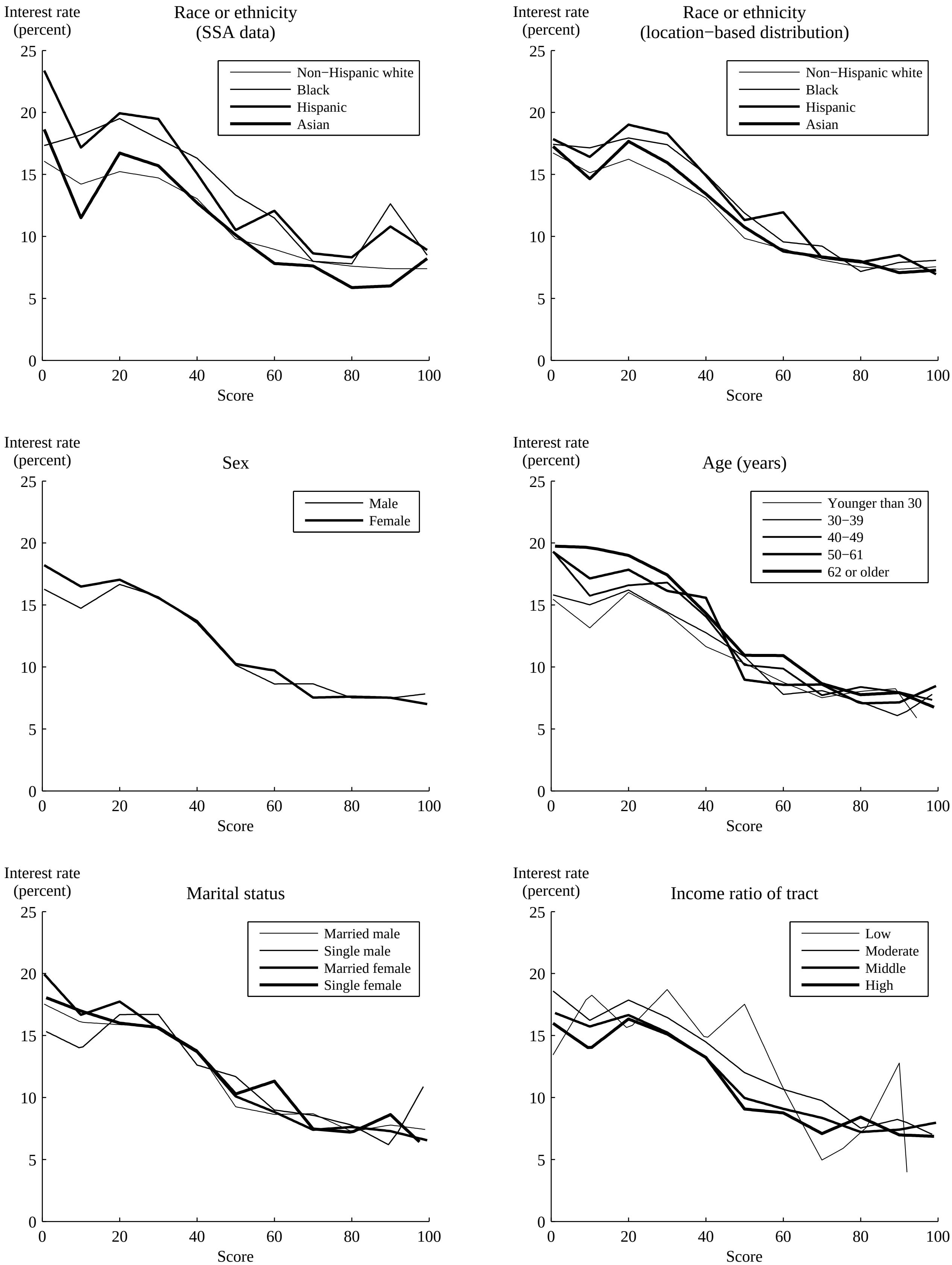
Note. For definition of characteristics, refer to notes to table 9.

Figure 10.B. TransRisk Score: Auto Loan Interest Rate, by Demographic Group



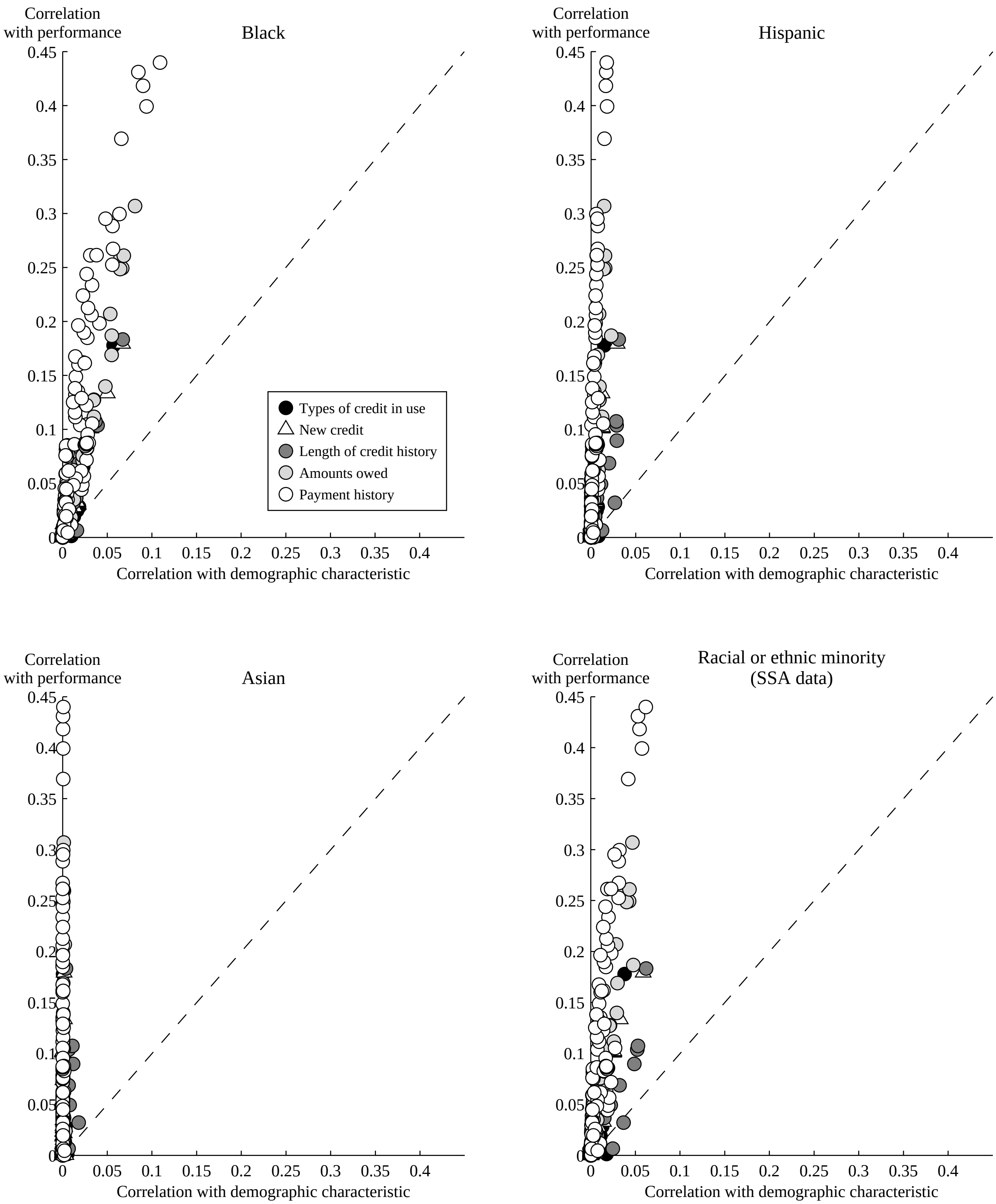
Note. For definition of characteristics, refer to notes to table 9.

Figure 10.C. TransRisk Score: Other Installment Interest Rate, by Demographic Group



Note. For definition of characteristics, refer to notes to table 9.

Figure 11. Correlations of the 312 Credit Characteristics in the TransUnion Database with Any−Account Performance and with Selected Demographic Characteristics



Note. The list of 312 credit characteristics is in appendix B. The correlation measure shown is the R−squared coefficient from the regression of each credit characteristc on any−account performance and on the demographic characteristic. For credit characteristics with missing values, two regressors were used: (1) an indicator variable with a value of 1 if the characteristic is missing and a value of zero otherwise and (2) a variable that takes a value of zero if the characteristic value is missing and the value of the credit characteristic otherwise. Generally, the demographic characteristic is an indicator variable that takes a value of 1 if the individual is a member of a specific nonbase demographic group and a value of zero if the individual is a member of the base group (refer to table 27 for the identity of the base groups). For these calculations, no base group is used for age; instead, age (expressed in years) is a continuous variable.

Figure 11. Correlations of the 312 Credit Characteristics in the TransUnion Database with Any−Account Performance and with Selected Demographic Characteristics − Continued

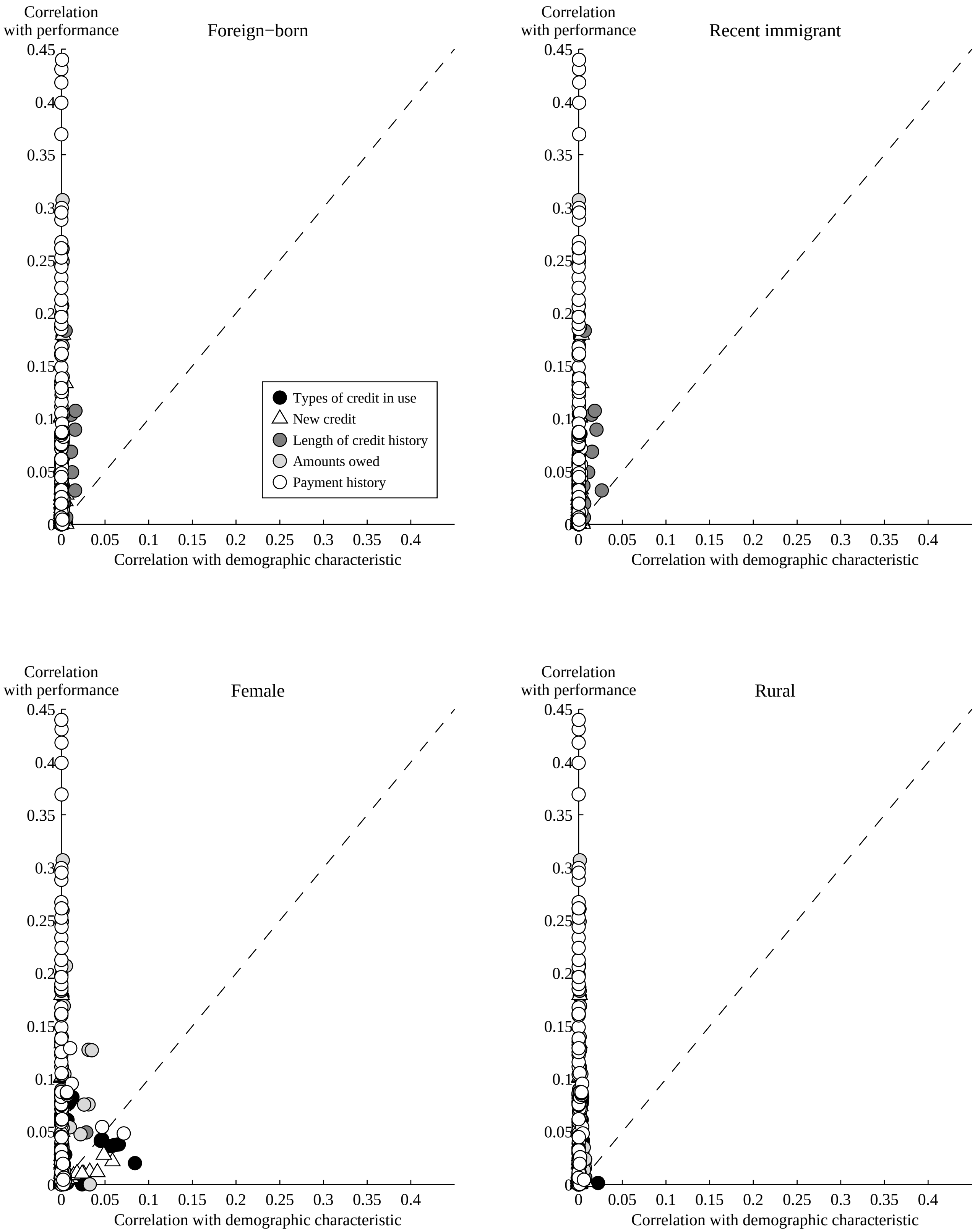


Figure 11. Correlations of the 312 Credit Characteristics in the TransUnion Database with Any−Account Performance and with Selected Demographic Characteristics − Continued

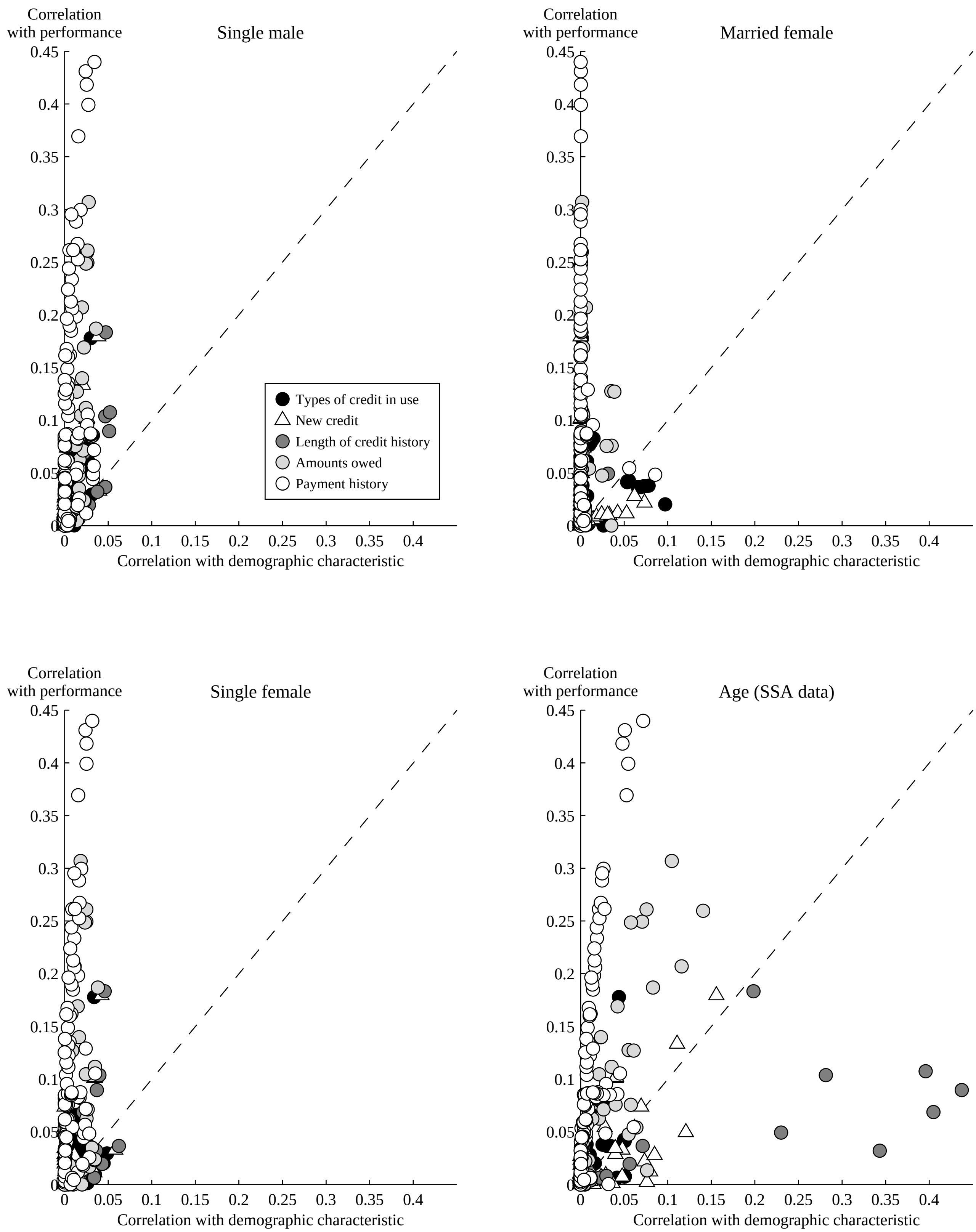
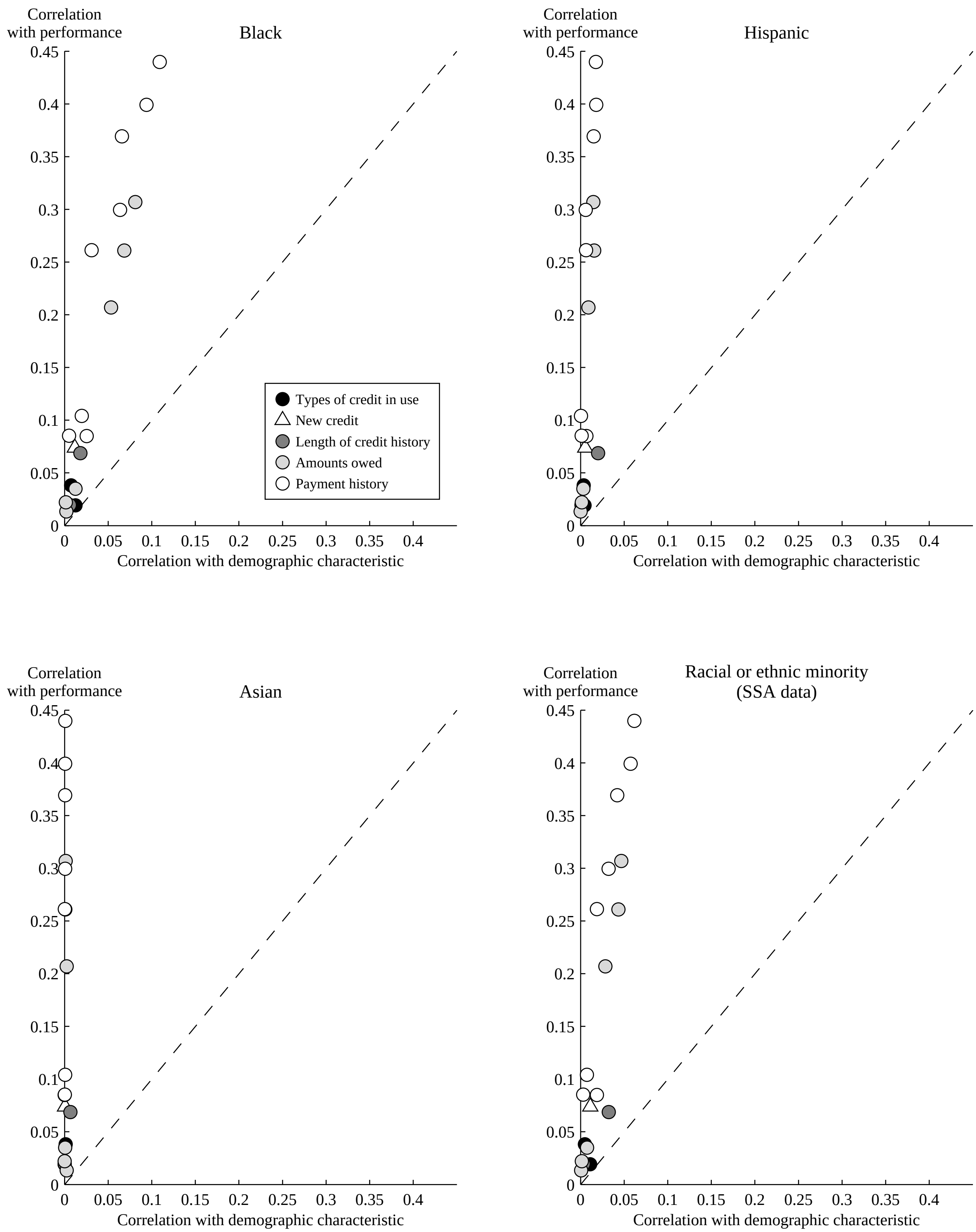


Figure 12. Correlations of the 19 Credit Characteristics in the FRB Base Model with Any−Account Performance and with Selected Demographic Characteristics



Note. The list of 19 credit characteristics is in appendix C. Refer also to the note to figure 11.

Figure 12. Correlations of the 19 Credit Characteristics in the FRB Base Model with Any−Account Performance and with Selected Demographic Characteristics − Continued

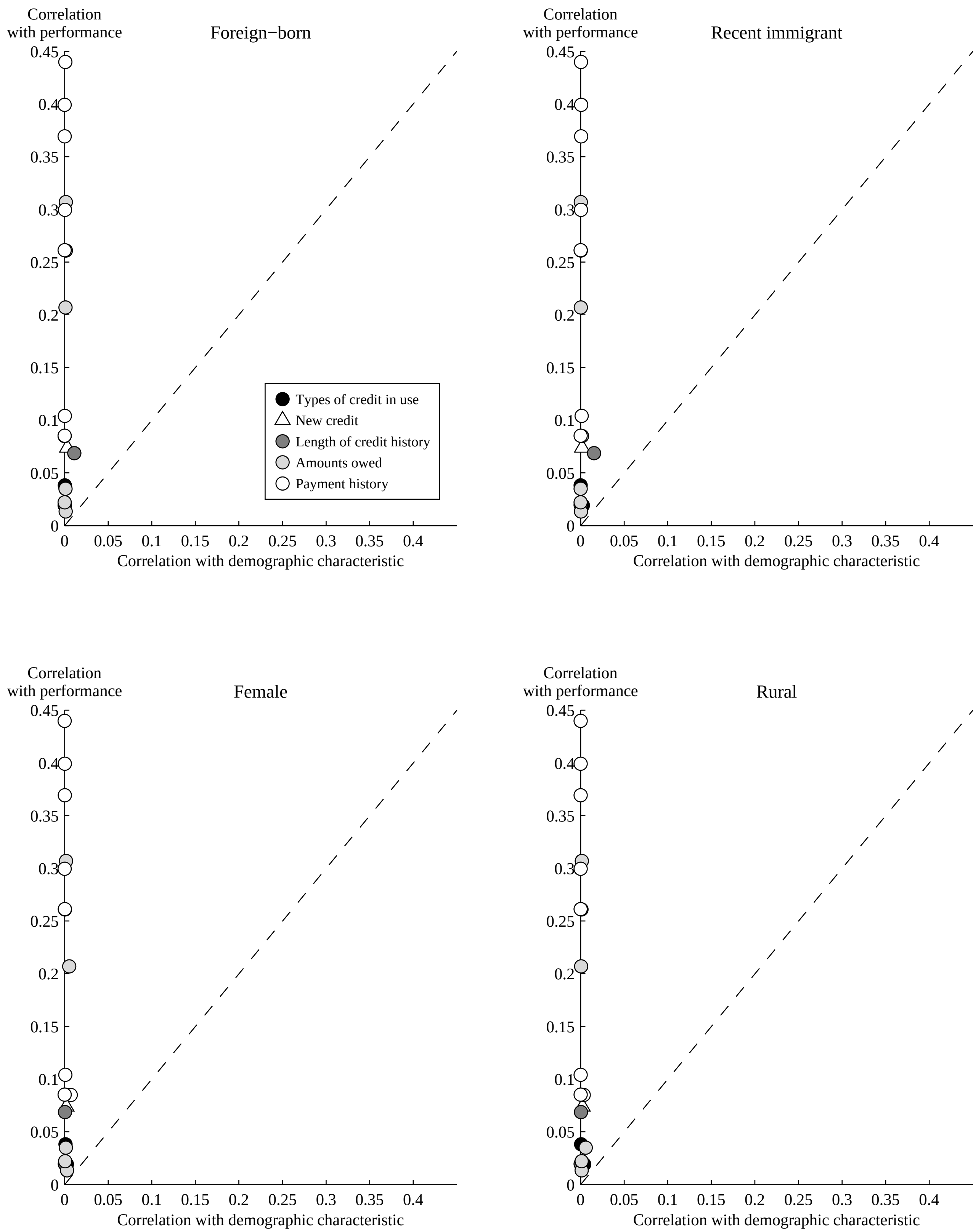


Figure 12. Correlations of the 19 Credit Characteristics in the FRB Base Model with Any−Account Performance and with Selected Demographic Characteristics − Continued