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Racial Dispersion in Consumer Credit Interest Rates

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Abstract

Most of the literature exploring racial disparities in consumer credit markets focuses on the issue of access to loans. But the disparate terms on which loans are issued are equally revealing. In this paper, I examine disparities in a variety of consumer loan interest rates using a reduced-form framework. I find that interest rates on loans issued before the 1995 show a statistically significant degree of unexplained racial heterogeneity even after controlling for the financial costs of issuing debt. However, racial dispersion in rates falls off for loans originated after 1995.

The unexplainable racial disparity in consumer loan rates issued before 1995 implies that in this earlier period minorities faced unaccountably higher interest-rate premiums on the order of—in two examples—20 basis points for first mortgages and 80 basis points for automobile loans. Overall, evidence of unexplainable racial dispersion in interest rates is more robust among homeowners than renters.

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Introduction

Most of the literature exploring racial disparities in consumer credit markets focuses on the issue of access to loans. But the disparate terms on which loans are issued are just as revealing. A well-functioning consumer credit market, however, should not have racial disparities in either form, after controlling for the financial costs that lenders incur. This paper will examine racial dispersion in interest rates. A reduced-form framework is used, similar to that used in previous empirical investigations of discrimination in the accept/reject margin, which will estimate the unexplained racial heterogeneity in interest rates that remains after accounting for default risk and the other financial costs of issuing debt.

This investigation examines a broad spectrum of consumer loans issued from 1955 to 2004: first and second mortgages, automobile loans, other consumer loans, credit card loans, and education loans. According to the model developed in this paper, interest rates on first and second mortgages, automobile loans and other consumer loans issued before the mid-1990s exhibit a statistically significant degree of unexplained racial heterogeneity. However, for loans originated after 1995 racial dispersion in rates is less robust and appears to generally fall off.

The unexplainable racial disparity in consumer loan rates issued before 1995 implies that, in this earlier period, minority households with apparently similar financial characteristics to white households faced higher interest rates on the order of 20 basis points for first mortgages and 80 basis points for automobile loans, to choose two examples. The decline over the 1990s in unexplainable racial dispersion in interest rates may reflect the technological improvements in credit markets that decade witnessed.

Racially-based differences in interest rates are lower for collateralized loans than for other consumer loans, where differences are statistically significant across the specifications employed in this analysis. For example, for first mortgages originated prior to 1995, as mentioned above, minorities faced an interest rate premium of about 20 basis points, while for other consumer loans the premium may have been more than 150 basis points.

Homeownership clearly plays a complicated role in interest rate determination. If the analysis is limited to households who do not own homes, the only consumer loans that exhibit statistically significant evidence of unexplained heterogeneity are automobile loans originated prior to 1995. However, mortgages and other consumer loans to households who are homeowners exhibit more evidence of statistically significant unexplained heterogeneity. For example, second mortgages and automobile loans issued to homeowners exhibit unexplained racial dispersion in interest rates, even for loans issued after 1995. These results suggest that lenders may view homeowners as fundamentally different from households who do not own homes, and specifications that do not correctly control for this difference might produce a spurious result. Due to data limitations, I do not account for a number of potentially important sources of unexplained heterogeneity in interest rates such as measures of income volatility that lenders may observe and market imperfections that allow for the exploitation of disparities in financial experience.

Literature review

The extensive empirical literature on racial discrimination in credit markets by and large explores disparities in access to credit markets. One strain of the literature attributes to discrimination any remaining variation in acceptance and rejection of loan applications after accounting for the reasons for variation related to profit. The Boston Federal Reserve Study (Tootell, 1996) is one particularly well-known (and controversial) example: it finds unexplained differences in access to mortgage markets across racial and ethnic groups. Cavalluzo et al. (2002) find higher rates of rejection among (otherwise equivalent) minority-owned businesses looking to borrow. In a similar vein, Duca and Rosenthal (1993) find that minorities face tighter debt limits and are more likely to be credit constrained.

Becker (1971) argues against modeling the access to debt margin. First, he argues that this method is biased toward finding evidence of discrimination if one assumes that minorities have less advantageous distributions of any omitted variables. Second, preferences may play a role in explaining why minorities make less use of debt markets.

Becker defines two types of discrimination in the marketplace: statistical and prejudicial. Lenders engage in *statistical discrimination* if they impose stricter underwriting criteria for minorities on the basis of a relationship between minority status and financial risk characteristics that are unobservable at the individual level. Lenders engage in *prejudicial discrimination* if they impose any further severity in underwriting criteria for minorities. Prejudicial discrimination will imply that lenders reject some loan applications by minorities that would have resulted in loans with positive expected profits. In such a situation, loans to minorities will be more profitable, on average, than in the absence of prejudicial discrimination. Thus, Becker argues that a cleaner test for prejudicial discrimination is to examine whether loans to minorities are more profitable than loans to other borrowers.

As profitability is difficult to measure, much of the literature instead focuses on default rates among approved borrowers assuming that minorities should have lower default rates in the presence of prejudicial discrimination. This approach generally finds no discrimination in credit markets: e.g. Berkovec et al. (1996) and Martin and Hill (2000) find no evidence of lower default rates among minorities relative to white borrowers.

However, this approach is problematic. Ross and Yinger (2002) argue that minorities may have higher average default rates, on average. They cite evidence that "minority applicants tend to lave larger debt burdens, higher loan-to-value ratios, and poorer credit histories than white applicants, on average." Even after accounting for observed variables such as these, unobserved variables may still lead to higher default rates among minorities. For example, Ross and Yinger speculate that unexpected economic downturns may have harsher effects on minorities owing to discrimination in labor markets. As a result, "minority borrowers may be more likely to default than are white borrowers with identical applications."

If lenders practice statistical discrimination and make underwriting decisions based on these variables unobserved for individuals, then—in the absence of prejudicial discrimination—race should have no predictive power for default rates. However, if lenders do practice prejudicial discrimination against minorities on the basis of some financial characteristic that is uncorrelated with race and that is unobserved by the econometrician, then minority status should predict lower default rates. However, statistical discrimination using race as a proxy for unobserved financial characteristics may not be fully implemented (simply because it is illegal) so that race may predict marginally higher default risk, to the extent that minorities have a less advantageous distribution of unobserved variables. Furthermore, one is hard pressed to think of some characteristic that lenders might use to practice prejudicial discrimination that is, itself, uncorrelated with race. In the end, this method is biased against finding discrimination—a point that several studies, including Berkovec et al. (1996), make.

In a later paper, Berkovec et al. (1998) contend with this bias by examining whether unexplained racial dispersion in access to credit varies by market concentration. Even if the analysis of any one market is biased against finding evidence of unexplained dispersion, such dispersion should be *more* pronounced in less competitive environments. In fact, these authors find no statistically significant variation by market concentration in access to credit by race, after accounting for other explanatory factors.

A relatively small empirical literature examines discrimination in loan terms. This approach is less subject to the complications introduced by preferences then are the accept/reject margin studies. While a household's preferences may certainly affect the incidence of debt, all households with debt would prefer less stringent terms. (Preferences do play a complicating role, as we will later discuss.) However, any finding of discrimination is subject to the critique of omitted variable bias, and these studies are most convincing when they find no evidence of discrimination. For example, both Crawford and Rosenblatt (1999) and Courchane and Nickerson (1997) have bank level data on mortgage loans, and both find some evidence of small but statistically significant unexplained dispersion in interest rates. However, Crawford and Rosenblatt, who use data from 1988 to 1989, find potentially offsetting features in other loan terms, such as the rate-lock period. Schafer and Ladd (1981) find evidence of significant differences in loan pricing by race on the order of 1 to 5 basis points using 1977 and 1978 California data.

On the other hand, Goldberg (1996) finds no evidence of racial discrimination in motor vehicle loan discounts using Consumer Expenditure Survey data from the 1980s. She notes that her results can be reconciled with matched-pair studies that find widespread evidence of systematic differences in the terms of sale (e.g. Ayres and Siegelman, 1995) by considering the role of selection bias: "Suppose that households that are discriminated against drop out of the market…Then an estimation that is based on actual purchases would underestimate the importance of race or gender discrimination since the sample would not include corresponding observations."

Despite the potentially important role of selection bias, very few empirical studies explicitly control for it. One of these is Cavalluzo et al. (2002), which examines small business loans in 1993 using the National Survey of Small Business Finances. This survey reports that among discouraged borrowers who did not apply for loans, about 20 percent of African-American males cited prejudice as a reason that they expected to be rejected, further suggesting a role for selection bias. Cavalluzo, Cavalluzo, and Wolken find little evidence of significant variation in interest rates by race, while acknowledging that interest rates do not vary much by other characteristics, either. On the other hand, the authors do find evidence consistent with racial discrimination in denial rates.

General Set-up

This paper uses a reduced-form framework, similar to that in the empirical investigations of discrimination in the accept/reject margin and loan terms: any unexplained racial heterogeneity in interest rates that remains after accounting for the financial reasons for heterogeneity is potential evidence of discrimination. The model is defined in detail below, but, in brief, the baseline model allows interest rates to be explained by the financial costs of issuing debt, loan terms, and default risk. Default risk is estimated as a function of race, allowing for two potential effects. First, race may be correlated with variables not included in our data set but observed by the lender. Second, lenders may use race as a proxy for unobserved financial characteristics, practicing statistical discrimination.

Any unexplained heterogeneity in interest rates found here will be potential evidence of prejudicial discrimination. Other possible sources of the unexplained heterogeneity include market imperfections, such as the exploitation of disparities in financial experience. As an example of the potential effects of such disparities, Ross and Yinger (2002) cite a 2000 study conducted by the U.S. Department of Housing and Urban Development and the U.S. Treasury showing that "upper-income blacks are almost twice as likely as low-income whites (25 percent compared to 13 percent) to apply for a sub-prime loan." More generally, Ross and Yinger also cite several studies from 2000 that examine what percentage of households borrowing outside of the prime market could have qualified in the prime markets; estimates range from 15 to 50 percent. In addition, Pennington-Cross et al. (2000) find that minorities more often use less conventional means of accessing credit markets. For example, they state that in 1997 44% of loans to minorities were made through independent mortgage companies, compared to 35% of loans to whites, after controlling for credit history.

The methodology in this paper is similar to that used in Cavalluzo et al. (2002), which explores the link between prejudicial discrimination in business loan pricing and market concentration. These authors find little evidence of interest rate variation by demographic (or financial) characteristics of the small-business borrower in 1993. The method used in this paper has some advantages and some disadvantages relative to that used in Cavalluzo et al. (2002). While I do not look at the role of market concentration due to data limitations, I do use cleaner data on ex-post delinquencies and on ex-post bankruptcy risk measure that improves our evaluations of default risk.

Because of important changes in consumer loan markets in the 1990s, I will examine the significance of unexplained heterogeneity before and after 1995. In particular, risk-based pricing did not take hold in consumer lending markets until after 1995, as shown in Edelberg (2006) and as suggested, perhaps, by the lack of interest rate variation by financial characteristics found in Cavalluzo et al. (2002). The introduction of variation in interest rates by risk may have facilitated prejudicial discrimination in loan terms, as loan terms were no longer simply "posted" for potential borrowers. In contrast, the widely-held belief that credit underwriting has become more automated and transparent in recent years suggests we should see less evidence of any unexplained racial heterogeneity in interest rates since the 1990s. Thus, it is an important question whether the amount of unexplained heterogeneity in interest rates changed in the mid-1990s.

Data

This analysis uses the Surveys of Consumer Finances (SCFs) from 1989 to 2004, which are released triennially. First and second mortgages, automobile loans, general consumer loans, credit card loans and education loans are considered.[1] Households are

[1] General consumer loans include loans for household appliances, medical bills, loans from individuals and others. When these loans are collateralized, the collateral is less secure than an automobile or a house. Generally, the borrower keeps possession inside the house (making seizure difficult) and the value of the asset is quite variable.

actively making payments on loans during the survey month, including credit card loans.[2] In other words, convenience use of credit cards is not considered. In addition, multiple loans in a category are summed and the highest interest rate is used. In analyzing the role of race, two categories are considered: white borrowers and other borrowers. For the category “other”, respondents defined themselves as black, Hispanic, Asian, Native American, or Pacific Islander. The alternative categorization of black borrowers and non-black borrowers is also considered, and, while results are generally robust to these classifications, the implications are noted throughout the paper.

Table 1 shows the average interest rates paid by white and non-white households for all loan types considered here, for loans originated in 1998.[3] In all cases, the average rate paid by non-white borrowers exceeds the rate paid by white borrowers, and in four cases statistically significantly so. In addition, the table shows the number of observations for loans issued in 1998 and the total observations across the six years of data for the various loan categories, anticipating some of the differences in the results' robustness.

Table 1. Interest rate data for origination year 1998**

	Average Rates		Observations		Observations for all years	
	White Borrowers	Non-white Borrowers	White Borrowers	Non-white Borrowers	White Borrowers	Non-white Borrowers
First Mortgage*	7.4	8.1	550	74	8854	1543
Second Mortgage	10.0	10.5	63	5	779	125
Automobile Loan*	9.3	11.8	397	94	5245	1317
Credit Card Loan*	14.4	14.8	1161	271	4549	1292
Other Consumer Loan*	11.9	14.3	83	24	1460	493
Education Loan	6.6	7.5	72	24	1523	466

* Difference in average rates for white and non-white borrowers is significant at a 10% confidence level.
** Results are quite similar for differences in average rates for black and non-black borrowers, except that in this case, the difference in average rates for education loans is significant at a 10% confidence level.

2 Credit card balances are only defined as loans when the household is carrying the balance long enough to pay interest on it. One drawback that Gross and Souleles (2002) point out in the SCF is that respondents underreport credit card debt. This poses a problem to the credit card results if underreporting is significantly correlated with risk, and this correlation changes over time.

3 Sampling weights are used for first and second moments. Following Deaton (1997), the data are not weighted in the empirical models as coefficients are assumed not to vary across the population.

The Michigan Panel Study of Income Dynamics (PSID) is also employed as it contains panel data on household demographic and financial characteristics, including some data on bankruptcy filings.[4]

Empirical Approach

The primary goal of this empirical analysis is to estimate the role of race in interest rate determination after accounting for the financial costs of issuing debt. If race is significant such that there is remaining unexplained hetereogeneity in interest rates by race, prejudicial discrimination may be the cause. In order to account for these financial costs, the following approach is used: $I_i(L,d_i,F,r)$, the interest rate offered by the lender, is a function of loan characteristics, L, default risk, d, other measures of financial costs to the lender, F, and, potentially race, r.

Loan characteristics, L, are captured by including the value of the original loan balance and, when statistically significant and helpful for model stability, the current loan balance and the loan-to-value ratio.[5] Measures of d are described in detail below. In addition, the financial costs of issuing debt, F, are captured in a number of ways. The cost of funds is assumed constant over a year and is captured by year dummies.[6] Inasmuch as fixed costs are recovered through the interest rate (and not fees), their effect should be captured by including the loan amount. Recovery rates in default should be roughly constant for each type of non-collateralized loan and hence captured by a varying constant term for each loan type. For collateralized loans, recovery rates should rise with

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[4] The PSID slightly underestimates the frequency of bankruptcy in the US population (Fay et al, 1998).

[5] Dollar values are deflated using the CPI. For general consumer loans, current loan balances are better predictors than original loan amounts. This may be due to the more informal nature of these loans. For example, these loans may be renegotiated more easily so that current balance is also highly relevant for the terms.

For first mortgages, points and fees are not included due to data limitations. To the extent that, for example, the choice to substitute higher points for lower interest rates is related to race, the omission of these data may influence the results. In addition, refinancing risk is not included in the analysis. However, in this case the resulting bias should go against finding unexplainably higher interest rates charged to minorities. Black households are less likely to refinance or pre-pay mortgages than white households, so on this front minorities will be more profitable, not less profitable (Van Order and Zorn, 2004).

[6] This should in part reflect the required rate of return to those supplying loanable funds. Ausubel (1991) finds that credit card issuers earned possibly five times the ordinary banking rate of return from 1983 to 1988. Here, no specific rate of return is imposed, but it is assumed that markets are competitive.

collateral, and hence the equity in the collateral is included.[7] Examples of other measures of financial costs to the lender include the lender's cost of funds and the expected recovery rate in case of default, which may vary by borrower. Finally, the race of the head of the household, *r,* is captured by an indicator variable.

In order to account for all the variables that should affect the financial cost of issuing debt, a good deal of attention is paid to default risk. Default risk is comprised of the risks of bankruptcy and delinquency. A detailed explanation of my approach to estimating default risk is shown in Edelberg (2006). In brief, the SCF contains no bankruptcy data before 1998, and the bankruptcy data it does contain is backward looking. The PSID is used to estimate a model of future bankruptcy, and bankruptcy risk is imputed for SCF households.[8] A household is defined as "bankrupt" in year t if it declares bankruptcy over the course of years t to $t+2$. Note that the PSID reports a number of bankruptcies for households that held no debt two years earlier. As a result, bankruptcy probabilities can be computed separately for households with debt and for all households. This will prove useful later when accounting for potential selection bias in the interest rate models.

In light of the extensive research on bankruptcy, the following variables are used in a probit to predict bankruptcy risk: year, age, a checking account indicator, income, a self employment indicator, home ownership status, unsecured debt, an indicator of whether the ratio of unsecured debt to income exceeds two, net worth (with negative net worth set to zero), unemployment indicator, single parent indicator, and education. Race is included to proxy for variables observed by the lender but not in the data set and variables unobserved by the lender but possibly accounted for through statistical discrimination.[9] Time variation in coefficients is also included for the few cases it is

[7] The possible complication that recovery rates may be in part a function of d – for example, *ex ante* high-risk people in default may be more difficult to collect from than low-risk people in default – is not considered here.

[8] The imputation of bankruptcy risk is based on a similar methodology in Jappelli et al. (1998).

[9] An example of another paper that allows race to predict default risk is Canner, Gabriel, and Wooley (1991), which examines whether race matters in the decision to get an FHA loan. Other potentially important predictors of default risk are not included due to data limitations. These include a lack of health insurance and recent divorce.

significant. Overall, the coefficients are consistent with the bankruptcy literature.[10] A detailed discussion of these results can be found in Edelberg (2006).

Counterparts in the SCF that are close to the bankruptcy determinants in the PSID are used in order to impute bankruptcy risk for SCF households. Unfortunately, the PSID only contains bankruptcy data through 1996, and yet the SCF data extends through 2004. The limited evidence of significant time variation in coefficients suggests that the bankruptcy model coefficients on household characteristics are generally stable. However, time dummies reveal the well documented result that bankruptcy has become more common over time in a way that these sorts of reduced form models cannot explain. For example, the coefficients for the time dummies suggest that bankruptcy is 0.2 percent more likely in 1994 than in 1989 for the average household with debt, all else equal. In order to capture this effect, at least in part, imputed bankruptcy risk in the SCF sample uses constructed time dummy coefficients for 1998 through 2004 that assume bankruptcy increased at the same pace as over the early 1990s.[11]

Table 2. Probability distribution of default risk in percentage points

	Borrowers			*All Households*	
	Bankruptcy Risk		*Delinquency Risk*	*Bankruptcy Risk*	
Percentiles:	*PSID**	*SCF**	*SCF*	*PSID**	*SCF**
1%	0	0	0.1	0	0
10%	0	0	1	0	0
25%	0.2	0.2	2.4	0.2	0.1
50%	0.7	0.7	4.6	0.6	0.5
75%	1.4	1.6	9.5	1.2	1.1
90%	2.2	2.8	18.4	1.8	1.8
99%	5.1	6.4	40	3.4	3.3
Memo:					
Mean	1	1.2	7.6	0.8	0.7
Standard deviation	1.2	1.6	8.6	0.8	0.8

* Bankruptcy risk in the PSID is estimated with data through 1996. Bankruptcy risk in the SCF is imputed for surveys through 2004.

[10] Research used to identify explanatory variables includes Sullivan et al. (1989), Johnson (1992), Domowitz and Sartain (1999), Gross and Souleles (1999), Sullivan et al. (2000), and Fay et al. (2002).

[11] As discussed later in the paper, a broad range of robustness checks, including estimating models using actual bankruptcies as reported in the most recent SCFs and excluding the bankruptcy risk measure altogether, show that the main results to not depend on these constructed time dummy coefficients.

Table 2 shows the distribution of bankruptcy risk in the PSID and imputed risk in the SCF, which are roughly similar. The bankruptcy risk is quite small: The average bankruptcy risk within the 90th percentile of the bankruptcy risk distribution of borrowers in the SCF is only 2.8 percent, implying that even these relatively risky households with debt have only a 2.8 percent probability of declaring bankruptcy within the next two years. Note that the imputed bankruptcy risk in the SCF is slightly higher than the bankruptcy risk in the PSID for households holding debt. This follows from the different time periods over which these risk measures are computed. Bankruptcy risk in the PSID is estimated with data through 1996. Recall that bankruptcy risk in the SCF is imputed for surveys through 2004, and bankruptcy risk is projected to have risen over time.

Delinquency risk is the second measure of default risk. The SCF reports whether respondents have been more than sixty days late on a loan payment in the previous year.[12] Nearly 9% of the households report a delinquency, showing it is much more common than bankruptcy. A probit is used to determine delinquency risk using the same determinants that are in the bankruptcy model of households with debt.[13] Again, significant time variation in coefficients is also included. Delinquency risk—conditional on holding debt—is reported in the last column of Table 2. Note that the correlation between bankruptcy and delinquency risk is only 0.46, suggesting these are distinct measures of default risk.

In the empirical analysis, the role of default risk in explaining interest rate variation is not constant over time. Risk-based pricing did not take hold in lending markets until after the mid-1990s (Edelberg, 2006). In the earlier period of interest rate homogeneity, lenders generally posted one interest rate for a consumer loan and then either accepted or rejected applicants. To account for this change in lending markets, the estimated role of default risk is allowed to vary over the two pricing regimes.

[12] As will be clear in the empirical analysis, a good bit of the information in late payments is indeed used by lenders in pricing interest rates at loan origination. For every loan considered, average rates paid are higher for those who made late payments versus those who had no late payments, with the differences ranging from a low of 0.2 percentage point for education loans to a high of nearly 2.5 percentage points for automobile loans.

[13] A model accounting for selection bias is estimated, as delinquency data only exists for households with debt. As described in Edelberg (2006), attitudinal variables with regards to holding debt ensure identification.

Using predicted default risk instead of actual default risk has a number of benefits. First, default risk can be measured for households with and without debt, which will prove important in trying to correct for selection bias. Second, this measure contains far more information that actual default risk. As a continuous measure it can differentiate between two households, for example, that both are in default and yet are quite different ex-ante in the eyes of lenders. Third, using predicted default risk alleviates the potential problem of endogeneity highlighted in Han (2002). Essentially, default risk is instrumented, and any variation due to interest rates is excluded from the estimation. However, the baseline model is also estimated using observed delinquencies and bankruptcies, using data from the SCF survey years where observed bankruptcies are available.

Of course, a more ideal data set for assessing default risk would include credit scores. Fortunately, the SCF appears to contain most of the important predictors of credit scores, while not actually containing any credit score data. Bostic et al. (2003) develop an empirical model of credit scores using a proprietary data set of credit score records. These authors find that the most significant predictors of credit scores include delinquency measures in particular, as well as credit card utilization rates, total debt balances and age.

For the models estimated in this paper, all active loans in the household's portfolio are considered regardless of how old the loans are. This approach assumes that a lender's goal is to predict a borrower's default risk throughout the life of the loan, which of course would include predicting default risk of as the survey date. The data in the Survey of Consumer Finances poses one complication in this regard as it reports the borrower's characteristics as of the survey date and not as of the loan's origination date. The empirical approach underlying the baseline specifications assumes that the borrower's characteristics as of the survey date are a good proxy for the characteristics as of the loan origination date. In alternative specifications where this assumption is perhaps more valid, only loans within a few years of the survey date are considered. Important differences in results are noted.

Two sources of potential bias in the results are apparent: selection bias and the simultaneous-equation bias given that other loan terms aside from interest rates are likely not exogenous. The results from the baseline model, described in the next section, do not account for selection bias. However, the section titled “Selection bias” presents an approach to control for this bias in the race coefficients given that the SCF does contain data on households with and without debt.

The possible endogeneity of other loan terms is harder to account for. Most of the (few) empirical studies that examine discrimination in interest rates simply include the other loan terms, *L*, on the right hand side of the interest rate equation, without worrying too much about any endogeneity of these other terms (for example, Cavalluzzo et al, 2002). Among the papers warning of endogeneity problems in loan terms, several papers point out that loan terms may be endogenous to a borrower’s riskiness. For example, Ross and Yinger (2002) argue lenders may learn something about borrowers’ riskiness by the terms borrowers request. In addition, Han (2002) shows that statistical discrimination leads to higher interest rates for black households and may lead to higher default rates as a direct result.

In the end, few sure-fire solutions are available. Schafer and Ladd (1981) identify a simultaneous-equation model of interest rates, loan maturity and loan-to-value ratio by assuming some exclusion restrictions, which are reasonable but without much empirical evidence. Rachlis and Yezer (1993) argue that the biases are such that one can only truly identify the absence of discrimination in the absence of multiple-equation models. LaCour-Little (1999) concludes that the problem of simultaneity of loan terms and the accept/reject margin in the context of examining discrimination in credit markets is alleviated if lenders can use interest rates to clear the market. As lenders use interest rates to clear loan markets post-1995, simultaneity may pose less of a problem in this more recent data.

Results

Baseline model with actual loan default indicators

The baseline models are estimated by pooling all households across all years, and time variation in interest rates is captured by time dummies for loan origination years. First, default risk is measured using observed bankruptcies and delinquencies. Using the constructed measures of predicted default risk instead of observed defaults might ignore valuable information if lenders have more accurate measures of default risk. On the other hand, as noted above, an indicator variable for actual default does not distinguish between two households that both are in default and yet are quite different ex-ante in the eyes of lenders. In addition, the bankruptcy indicator from the SCF measures past bankruptcies, which have quite different implications for lenders than future bankruptcies, and is only available beginning in 1998. To address the lack of bankruptcy data in the earlier SCF survey years, the models are estimated over all survey years using only delinquency as a default measure and over survey years from 1998 and on using both default measures. These later surveys contain loans made as early as 1955.

Table 3. Race Coefficients – Actual Bankruptcy and Delinquency Measures

Loan Type	Bankruptcy and Delinquency**	Delinquency
First Mortgage	0.1*	0.2*
Second Mortgage	1.7*	1.1*
Automobile Loan	0.8*	0.8*
Credit Card Loan	0.8*	0.7*
Other Consumer Loan	1.8	2.0*
Education Loan	0.7*	0.7*

* Significant at a 5% confidence level.
** Due to data limitations, models including actual bankruptcy data do not use SCFs before 1998. However, loan origination years for the more recent SCFs extend back to 1968.

Baseline results are shown in Table 3. According to this specification, a significant degree of unexplained racial heterogeneity in interest rates remains even after attempting to control for the financial costs of issuing debt. The table reports the coefficients on the race indicator variable, r, where r is one if the head of the household is not white. This coefficient is meant to capture the explanatory power of race in determining interest rates, after accounting for the financial costs of issuing debt. Using actual bankruptcies and delinquencies to measure default risk, the race coefficient is positive for every loan type, and statistically significant in all cases except other consumer loans. Using only delinquencies to measure default risk (and using data from all the survey years), the race coefficient is positive and statistically significant in all cases, suggesting that there is some unexplained racial disparity in interest rates. However, the significance of the interest rate coefficient for credit card loans is suspicious, given the relatively anonymous nature of credit card loans, and, in fact, might suggest evidence of an improperly specified model. For the remaining loan markets, Table 3 shows that white households face interest rates that are between 20 and 200 basis points lower than interest rates for non-white households, after accounting for important loan characteristics and a household's failure to make loan payments. The robustness of the baseline results—including their strength before and after 1995—is explored later in the paper.[14]

Baseline model using default risk measures

Results from the baseline models with the constructed continuous default risk measures also reveal that a significant degree of unexplained racial heterogeneity in interest rates remains even after attempting to control for the financial costs of issuing debt. Coefficients on the race indicator are shown in Table 4 for this preferred specification. In most cases, the implied heterogeneity appears to be similar to those in the previous specification using actual default measures. However, for the case of credit card loans, the race coefficient is now only about one-third as large and not statistically significant. For the remaining loan markets, Table 4 shows that white households face interest rates that are between 20 and 180 basis points lower than interest rates for non-white households, after accounting for important loan characteristics and default risk. However, less constrained specifications that also use predicted default risk suggest that this dispersion is somewhat less robust in the more recent data, and that unexplained racial dispersion in interest rates is more of an issue for homeowners than non-homeowners.

Table 4. Race Coefficients – Baseline Model with constructed default risk measures

Loan Type	Interest rate regressions
First Mortgage	0.2*
Second Mortgage	1.1*
Automobile Loan	0.8*
Credit Card Loan	0.3
Other Consumer Loan	1.8*
Education Loan	0.5*

* Significant at a 5% confidence level.

According to this specification, dividing households on whether the head is white or not white produces results that are logically consistent across specifications—generally speaking—and robust to most tweaks in specification, such as only looking at loans

[14] For first mortgages, the unexplained racial heterogeneity in first mortgage interest rates is insignificant if the sample is split by households with FHA or VA loans. These results are discussed at the end of the paper.

issued within a few years of the survey date. If however, the race indicator is redefined to examine interest rate disparities between black and non-black households, the coefficient of race for "other consumer loans" falls to 0.3 percent is and no longer statistically significant. (With this alternatively defined race indicator, other results are unchanged from those reported in Table 3.) The strength of the results before and after 1995 is examined next.

Allowing for time-variation

Significant changes took place in credit markets over this time period, and the extent of unexplained heterogeneity may not be constant. On the one hand, opportunities to express prejudicial discrimination may have become more prevalent in recent years as the lending process allowed more flexible pricing. As argued in the popular press and implied by a 2002 lawsuit against Fannie Mae, the use of credit scores to price interest rates—and thus produce widespread variation in interest rates—may have led the way for variation in pricing not related to risk or costs, and, according to a 2002 article in *The Washington Post,* may have opened the door for prejudicial discrimination in loan terms (Harney).

The use of credit scores can facilitate either statistical or prejudicial discrimination in the setting of interest rates if the credit scores themselves are discriminatory. While both statistical and prejudicial discrimination are illegal, the framework used here tests for the possible role of prejudicial discrimination; predicted default risk, this paper's proxy for a credit score, is allowed to vary by race for the reasons mentioned earlier. Whether prejudicial discrimination in credit scores reported by credit bureaus leads to interest rate variation by race that cannot be explained by the financial cost of issuing debt is an empirical question that is beyond the scope of this paper.

On the other hand, the overall increase in competition in credit markets as well as the increase in the sophistication of credit markets may have led to a reduction in any unexplained racial heterogeneity in interest rates. In particular, the use of credit scores to determine interest rates may have rationalized and automated the setting of interest rates, rendering race unimportant.

Table 5. Time-varying Race Coefficients
Baseline Model estimated over Different Periods

Loan Type	Pre-1995	Post-1995
First Mortgage	0.2*	0.1
Second Mortgage	0.9*	1.6*
Automobile Loan	0.6*	0.9*
Credit Card Loan	Na	0.3
Other Consumer Loan	1.8*	1.9
Education Loan	0.5*	0.7*

* Significant at a 5% confidence level.

In order to test for significant time variation in the coefficient on race, models were estimated separately for loans issued before and after 1995. As shown in Table 5, first mortgages and other consumer loans exhibit significant unexplained racial heterogeneity in interest rates before 1995, but not after 1995. For second mortgages and educations loans, the coefficient on race is significant in both periods. The model of credit card loan rates can only be estimated post-1995 due to data limitations and shows no evidence of unexplained dispersion in interest rates over this period.[15] Overall, these results present some evidence that the changes in consumer credit markets in the 1990s led to a rationalization of interest rates in some consumer loan markets.[16]

Accounting for the role of home ownership

The automobile and non-collateralized loan models were re-estimated separately by respondents' homeownership status. In the baseline model, homeownership enters into the default risk models in two ways: net worth enters linearly and whether a household owns a home enters as an indicator variable. However, the underwriting process may be entirely different for households who do and do not own homes. For example, lenders may assess different measures of default risk and different costs of recovery in default to both kinds of households. As a result, the baseline models are re-

[15] These results are generally robust to simply allowing the race coefficient to vary over time in the baseline model. The only exception in this case is that we can reject a zero coefficient on race for other consumer loans issued post-1995.

[16] These results are not entirely robust to defining the race dummy for black versus non-black households relative to the baseline definition of white versus non-white households. With the alternative definition, the race coefficient for first mortgages remains significant post-1995, and the race coefficients for second mortgages and automobile loans dips below significance pre-1995. The question of changes over time in interest rate dispersion will be addressed further later in the paper.

estimated separately for these two kinds of households. Race coefficients on a dummy variable for non-white versus white households are shown in Table 6.

Table 6. Race Coefficients by Homeownership

	Non-Homeowners	Homeowners
Loan Type	Interest rate regressions	Interest rate regressions
Automobile Loan	0.9*	0.7*
Credit Card Loan	-0.3	0.6*
Other Consumer Loan	2.7*	1.6*
Education Loan	0.6	0.7*

* Significant at a 5% confidence level.

Excluding homeowners does not dramatically alter the point estimates of the coefficients on the indicator variable for white versus non-white households. However, the race coefficient for the education loan model is no longer statistically significant, and the coefficient in the credit card loan model, while still insignificant, is now negative.[17] In addition, if the sample is limited to loans originated within two years of the survey date, the race coefficient for other consumer loans is no longer significant (though the point estimate is roughly unchanged). As noted above, using recent loans may be preferable as the empirical approach uses borrowers' financial characteristics as of the survey date.

Limiting the sample to homeowners suggests that homeownership may play a complicated role in the determination of interest rates. In this case, as shown in the second column of results in Table 6, the coefficient on race is significant and positive for automobile, other consumer loans, and education loans, and, surprisingly—given their anonymous nature—for credit card loans. (Using recent loans, the race coefficient for education loans is much smaller and insignificant.)

These findings suggest that the model may not be well specified for households who own their homes and thus have far more flexibility in their borrowing decisions. Lenders may view households who are homeowners as fundamentally different from

[17] Of course, limiting the analysis to households who do not own their homes reduces the number of observations and perhaps the precision of the estimation. For example, across all the survey years, 6,562 households hold automobile loans, but only 1,803 households who do not own their homes hold automobile loans. Other methods of accounting for the direct effect of homeownership on interest rates that pool households in the empirical models—such as using a dummy variable for homeownership in the baseline model—show results more similar to those from the baseline model, in terms of point estimates and statistical significance.

those who do not own their homes, and specifications that do not control for this difference produce a spurious result of statistically significant heterogeneity.[18] Furthermore, these households may have different models of reservation interest rates. For example, households who are not homeowners cannot substitute between lower-interest home-equity-backed debt and higher-interest non-collateralized debt. The next section attempts to address this possible variation in reservation loan interest rates and the selection bias this variation would imply.

Selection bias

Accounting for selection bias is particularly important in trying to isolate any incremental explanatory power of race (Rachlis and Yezer, 1993). If race plays any role in explaining household reservation interest rates, the coefficient on race in an interest rate equation is inconsistent. For example, if African-American households have fewer outside borrowing options, their reservation interest rates may be higher. The interest rates offered to households by lenders can be modeled as an interest rate function that also comprises a random idiosyncratic component. Borrowers with higher reservation interest rates will more readily accept loans with interest rates that are boosted by a positive random shock. Without accounting for selection bias, any result showing that African-American households pay higher interest rates, all else equal, may be due to these households accepting higher interest rates owing to weaker outside options and not due to race playing any role in the interest rate function.

Returning to the model set-up, assume that a household has a reservation interest rate $R_i(L,P_i,r)$, which is a function of loan characteristics, L, household characteristics, P, and potentially race, r. We can infer that R is greater than or equal to the interest rate offered by the lender, I, for those consumers who have positive loan balances. The interest rate function is unchanged from its definition above: $I_i(L,d_i,F,r)$, with I allowed to vary with L, default risk, d, other measures of financial costs to the lender, F, and, potentially r. To formalize:

[18] Estimating a model that allows race coefficients to vary by homeownership produces interest rate regression results similar to what is shown in Table 5. The only difference from this pooled model is that in this case the race coefficient in the credit card rate model is not significant for homeowners—eliminating one of the surprising results from a model exclusively estimated for homeowners.

$$R_i(L,P_i,r)-I_i(L,d_i,F,r)=H_i\beta+u_i$$
$$\Pr ob(R_i-I_i>0)=\Phi(H_i\beta)$$

H_i is a vector of characteristics that helps predict whether the loan is observed for household i. I_i and R_i, are subscripted i to allow for an idiosyncratic individual specific shock, ε_i.

$$I_i(L,d_i,F,r)=\mathrm{X}_i\gamma+\varepsilon_i,\ observed\ when\ R_i-I_i>0$$

Note that the linearity in the equation for I assumes lenders are risk neutral or are diversified enough to appear risk neutral. X_i is a vector of characteristics that help predict I.[19] X includes direct measures or proxies, where necessary, for the four variables, *L*, *d*, *F*, and *r*. These four variables are captured just as in the previous analysis that did not correct for selection bias.

H includes both supply and demand variables that influence whether a household holds a loan. On the supply side, *H* includes variables that help predict denial such as second-order polynomials of default risk. The future measure of bankruptcy in the PSID allows for two forms of bankruptcy risk: conditional and unconditional on a household holding debt. Conditional bankruptcy risk is relevant for lenders assessing interest rates for loans. Because the unconditional bankruptcy risk measure does not include any debt measures, it is included in *H*, the vector of characteristics predicting whether a household holds a certain loan. Note a full 14% of these "bankrupt" households have no debt in year *t*. For the unconditional estimation, asset levels are used in place of debt and home ownership status.

To account for demand, other financial and demographic characteristics, P_i, are included: an age polynomial, marriage status, the number of children, whether the family has a checking account, education, log of income, net worth, level of assets, race and variables that reflect borrowing attitudes.[20] Including race in *H* explicitly allows for race

[19] Note that this model essentially does not allow for a rejection by the lender. However, we can consider a loan rejected any time $R_i-I_i\le 0$.For example, if a lender at least knows the upper bound for a household's reservation interest rate, it may choose to simply reject a loan rather than offer an interest rate above this upper bound.

[20] Net worth is defined a number of ways. Measures of net worth are constructed including and excluding the loan in question. In addition, an instrumented net worth variable is constructed as in Duca and Rosenthal (1993) which excludes the explanatory power of the endogenous debt variables.

to play a role in preferences for certain debt instruments as well as for discrimination on the accept/reject margin. The attitudinal variables show whether households consider borrowing to be good, bad, or okay and whether they believe borrowing is acceptable in certain circumstances—such as for a loss in income or to buy a house or take a vacation. These variables ensure identification, as they are excluded from X. Correlation estimates confirm that these responses are not simple functions of borrowers' debt portfolios.[21]

Table 7. Race Coefficients – Baseline Model accounting for Selection Bias

Loan Type	Interest rate regressions	Loan probit
First Mortgage	0.1*	-0.3*
Second Mortgage	1.3*	-0.0
Automobile Loan	0.8*	0.0
Credit Card Loan	0.3	0.3*
Other Consumer Loan	1.8*	0.1*
Education Loan	0.5*	0.1*

* Significant at a 5% confidence level.

Table 7 shows results from the baseline model, which uses predicted default risk, across the various loan types. The first column shows the coefficients on the race indicator variable, *r* from the estimation of equation *I*. The race coefficient is statistically significant and positive for all loan types except credit card loans. These results are quite similar to those in Table 4, which do not account for selection bias, suggesting that white households face interest rates that are between 10 and 180 basis points lower than interest rates for non-white households, after accounting for important loan characteristics and default risk.

The last column of Table 7 shows results from the loan probit. The probit results show that white households are more likely to borrow in first mortgage loan markets, and non-white households are more likely to borrow in non-collateralized loan markets. The results for both the interest rate regressions and the loan probits are generally robust to defining the race variable as black versus non-black households instead of white versus non-white households.

[21] Numerous variables are included in *H* but not in X, such that the demands on the attitudinal variables as appropriate instruments are less than they might be. However, robustness checks were still done. All the significant attitudinal variables from the probits were included in their respective regressions: For example, if an attitudinal variable significantly predicted mortgage use, it was included in the mortgage interest rate equation. In all cases, most or nearly all of these coefficients in the interest rate regressions were insignificant.

Interactions between home ownership, time, and race

The previous results on the respective roles of time variation and homeownership suggest that unexplained racial dispersion in interest rates may be more significant prior to 1995 and for households who are homeowners. These results, however, did not control for potential selection bias, which may be particularly relevant in accounting for the role of home equity. Homeownership may be closely tied to reservation loan interest rates, as households without home equity cannot substitute between lower-interest home-equity-backed debt and higher-interest non-collateralized debt. Table 8 presents the race coefficients from models estimated separately for homeowners and households who do not own their homes, after accounting for the selection bias that may result from variation in reservation loan rates.

Table 8. Race Coefficients by Homeownership after accounting for Selection Bias

Loan Type	Non-Homeowners	Homeowners
Automobile Loan	0.9*	0.7*
Credit Card Loan	-0.3	0.7*
Other Consumer Loan	2.7	1.3*
Education Loan	0.0	0.7*

* Significant at a 5% confidence level.

These point estimates are quite similar to those reported in Table 5, which derive from models that do not account for selection bias. In both cases, race coefficients are significant in all loan markets for both homeowners and those who do not own their homes. However, for households who do not own their homes, the race coefficient for other consumer loans is insignificant, whereas in the previous analysis this coefficient was significant. Furthermore, if these fully-specified selection models are estimated with the alternative black versus non-black household race dummy, the race coefficient for the automobile loan market is also insignificant for households who do not own their homes.

These results suggest that homeowners and non-homeowners face different pricing policies in lending markets. The finding of widespread statistically significant racial dispersion in interest rates for homeowners suggests two possible conclusions. One, minority homeowners are not fully compensated in the form of lower interest rates for a reduction in default risk. Or, two, that this model, even with these attempts to account for variations in reservation interest rates, may not be well specified for households who own their homes.

Table 9. Race Coefficients by Homeownership and over Time

	Non-Homeowners		Homeowners	
Loan Type	Pre-1995	Post-1995	Pre-1995	Post-1995
Automobile Loan	0.9*	0.5	0.5*	1.1*
Credit Card Loan	na	-0.2	na	0.6*
Other Consumer Loan	0.6	2.7	2.4*	0.9
Education Loan	-0.3	0.1	-0.8	0.0

* Significant at a 5% confidence level.

Table 9 presents evidence on the interactions between homeownership, time, and race. The first two columns of results show the race coefficients for households do not own their homes pre- and post-1995, and the last two columns of results show the race coefficients for homeowners pre- and post-1995.[22]

Again, there is little evidence of statistically significant unexplained racial dispersion in interest rates for households who do not own their homes. Automobile loans originated before 1995 are the only exception. For loans originated after 1995, the race coefficient is insignificant for all four loan categories. These results are robust to the alternative specification that considers black and non-black households instead of white and non-white households. In addition, the race coefficient is statistically significant for automobile and other consumer loans issued to homeowners prior to 1995, where the race dummy distinguishes between white and non-white households. For loans issued to homeowners after 1995, the race coefficient is significant for automobile and credit card loans. However, the race coefficient for credit card loans is insignificant if the race dummy distinguishes between black and non-black borrowers.

Overall, these results confirm that racial dispersion in interest rates appears to be more of an issue for homeowners than non-homeowners. In addition, racial dispersion is clearly less robust in the more recent data, bolstering the view that the overall increase in competition in credit markets as well as the increase in the sophistication of credit markets led to a reduction in any unexplained racial heterogeneity in interest rates.

[22] These results are generally robust to alternative specifications. For example, estimating the model separately pre-1995 and post-1995 produces very similar results.

Robustness checks for first mortgages

The first-mortgage models shown above only account for rudimentary loan terms aside from the interest rate, such as the original loan amount and the loan-to-value ratio. Table 10 shows results from estimations accounting for other mortgage loan terms in detail. The first set of results is limited to FHA and VA mortgages, and the second set is limited to non-FHA and non-VA loans. Gabriel and Rosenthal (1991) find that black borrowers are more likely to hold an FHA loan, suggesting the possibility that discrimination may be more prevalent in standard loan markets or that preferences drive mortgage loan selection. As a result, estimating a model with all types of mortgages may obscure an analysis of unexplained racial dispersion in interest rates.

Table 10. Race Coefficients – Modeling First Mortgages, accounting for selection bias

Loan terms	Interest rate regressions	Loan probit
1. Baseline model	0.1*	-0.3*
FHA/VA loans		
2. Selection: all households†	0.2**	0.1*
3. Selection: mortgages†	0.0	0.5*
No FHA/VA loans		
4. Selection: all households	0.1	-0.4*
5. Selection: mortgages	-0.1	-0.4*
No Balloon mortgages		
6. Selection: all households	0.1*	-0.3*
7. Selection: mortgages	0.2*	0.3*
Loan-to-value<0.8		
8. Selection: all households	0.2**	-0.2*
9. Selection: mortgages	0.2**	-0.2*
Fixed mortgages		
10. Selection: all households	0.1	-0.2*
11. Selection: mortgages	0.1*	0.0
12. Terms added linearly	0.2*	-0.3*

* Significant at a 5% confidence level. ** Significant at a 10% confidence level.
† Selection models are estimated by either selecting on those with the particular mortgage in question relative to the population of all households (referred to as Selection: all households) or those with the particular mortgages relative to those with any type of mortgage (Selection: mortgages).

In limiting the focus to first mortgages with certain attributes, the role of selection bias is complicated by the presence of two latent variables. For example, households still must choose whether to hold debt as in the baseline model, but households holding FHA or VA have also revealed a preference for these loans over standard mortgages (though this preference may be the result of persuasion on the part of the lender). Other attributes pose a similar two-stage problem. To account for this complication, each selection decision is modeled separately, and the results are compared. For example, line 2 of Table 10 selects on households holding FHA or VA mortgages relative to the entire survey population, and line 3 selects on households holding FHA or VA mortgages relative to all households holding a mortgage.

Roughly speaking, the results support the hypothesis that the selection of mortgage type is important in understanding interest rate variation. Line 1 of Table 10 reproduces the results from the baseline model for first mortgages after accounting for selection bias, as reported in Table 7. Pooling all first mortgages together, these loans display statistically significant unexplained racial variation in interest rates. Lines 2 through 5 split the sample by use of FHA and VA loans, allowing the interest rate function to be altogether different for these government-backed loans. No robust statistical evidence of unexplained heterogeneity in first mortgage rates remains, under this more flexible framework.

Table 11. Average first mortgage rates among households holding FHA or VA loans

	Average Mortgage Rate
All households	
Actual rate paid	8.0
Predicted rate with no FHA/VA loans	7.7
Minority households	
Actual rate paid	8.0
Predicted rate with no FHA/VA loans	7.8
Non-minority households	
Actual rate paid	8.0
Predicted rate with no FHA/VA loans	7.7

Both a model of FHA and VA loans and a model that excludes these loans show that minorities are statistically significantly more likely to FHA and VA loans than other households, confirming the results in Gabriel and Rosenthal (1991). In addition, the models underlying the results in lines 2 through 5 suggest that households get slightly lower first mortgage rates by avoiding FHA and VA loans. Table 11 shows the average mortgage rate under the counterfactual scenario that households with FHA and VA loans did not hold these government-backed loans. This crude analysis suggests that all FHA and VA borrowers, regardless of race, would face lower interest rates by avoiding these loans. Of course, FHA and VA loans may have other attractive attributes to borrowers that compensate for higher interest rates.

Returning to Table 10, the remaining results are generally consistent with those for first mortgages from the baseline model. Limiting the investigation to those without balloon mortgages (the reverse leaves too few observations), those with loan-to-value ratios less than 0.8, or those with fixed mortgages does not change the basic result that an economically significant degree of unexplained racial heterogeneity in interest rates remains even after attempting to control for the financial costs of issuing debt. (However, the results are somewhat less statistically robust than in the baseline model.) For first mortgages, this heterogeneity appears to be on the order of 10 to 20 basis points. This result is also true if the various mortgage characteristics are added linearly, as shown in line 12. Furthermore, non-white households generally have a lower probability of holding a first mortgage than white households, though this methodology cannot separately identify the role of supply-side and demand-side factors. Again, this variation in the probability of holding a mortgage may reflect unexplained supply-side factors on the part of the lender or households' may have less of a preference for this kind of debt (possibly due to real or perceived discrimination on the part of lenders).

Conclusion

According to the model developed here, interest rates on first and second mortgages, automobile loans and other consumer loans issued before the mid-1990s exhibit a statistically significant degree of unexplained racial dispersion even after attempting to control for default risk and the other financial costs of issuing debt. However, for loans originated after 1995, racial dispersion in rates is less robust and generally appears to fall off.

The unexplainable racial disparity in consumer loan rates issued before 1995 implies that, in this earlier period, minority households with apparently similar financial characteristics to white households faced higher interest rates on the order of 20 basis points for first mortgages and 80 basis points for automobile loans. Racially-based differences in interest rates are lower for collateralized loans than for other consumer loans, where differences are statistically significant across the model specifications. For example, for pre-1995 first mortgages, as mentioned above, minorities faced an interest rate premium of about 20 basis points, while for other consumer loans the premium may be more than 150 basis points. The decline in unexplainable racial disparity in rates post-1995 may reflect the overall increase in competition in credit markets as well as the technological improvements in underwriting.

Homeownership plays a complicated role in consumer loan interest rate determination. If the analysis is limited to renters, only pre-1995 automobile loans exhibit statistically significant evidence of unexplained heterogeneity. However, mortgages and other consumer loans issued to homeowners display stronger evidence of statistically significant of unexplained heterogeneity. For example, even post-1995 second mortgages and automobile loans issued to homeowners exhibit unexplained racial dispersion in rates. These results suggest that homeownership may influence default risk through a more complicated channel than is allowed for in this paper's simple reduced-form framework. Or, perhaps some lenders view the relationship between homeownership and default risk as being somehow correlated with race. These possibilities suggest an interesting avenue for future research that further examines the role homeownership plays in setting loan terms.

Of course, as with all empirical investigations of this kind, the unexplained racial disparities in loan terms pre-1995 may simply reflect omitted financial costs of issuing debt. Due to data limitations, I cannot account for a number of potentially important sources of unexplained heterogeneity in interest rates such as measures of income volatility that lenders may observe and market imperfections that allow for the exploitation of disparities in financial experience.

The methodology used here is better suited to exposing prejudicial discrimination than statistical discrimination. In order to account more fully for the potential effects of omitted financial characteristics, the models use race as a proxy for these unobserved variables. This methodology cannot distinguish between the effects of omitted financial characteristics that are correlated with race but not included in the Survey of Consumer Finances and the effects of lenders practicing statistical discrimination. To the extent that this methodology captures the financial costs of issuing debt, any remaining statistically significant racial dispersion in interest rates may be evidence of prejudicial discrimination. Of course, there are always other possible sources of unexplained heterogeneity such as market imperfections that allow for the exploitation of disparities in financial experience.

As Becker (1971) points out, prejudicial discrimination in the decision to accept or reject a loan is not financially profitable: Prejudicial discrimination adds to the total perceived costs of lending to minorities. As a result, if lenders practiced prejudicial discrimination, they would reject financially profitable borrowers. In contrast, prejudicial discrimination in *loan terms* that leads lenders to charge minorities a premium to borrow likely raises the expected financial profitability of these loans. In a well-functioning consumer loan market, loans issued by those that do not practice prejudicial discrimination should, in principle, eliminate this disparate treatment of minorities on both the accept/reject margin and the loan terms margin.

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