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Several articles in the popular press have asserted that a simple comparison of average mortgage default rates for white and minority applicants is necessary and sufficient to uncover discrimination in mortgage lending. The fallacy of this assertion has been examined in Peterson (1981), Tootell (1993), and Yinger (1993). These papers show that a failure to account for the financial characteristics of each application or loan makes a simple comparison of average rates meaningless. However, recent empirical work on discrimination in mortgage lending has examined both application denial and mortgage default rates conditional on the strength of each application, not average rates for whites and minorities. This paper assesses the information about discrimination contained in these conditional rates. It is found that the debate over denial versus defaults is misdirected; examining denials is a marginally better method to uncover discrimination. Much of the apparent debate was really over the potential importance of omitted variables.

Munnell, Tootell, Browne, and McEneaney (1996) (MTBM) estimates loan rejection rates conditional on the economic fundamentals of each application as well as the race of the applicant. The Boston Fed collected the additional application data in order to avoid a comparison of average denial rates. Berkovec, Canner, Gabriel, and Hannan (1994) (BCGH), and Van Order, Westin, and Zorn (1992) (VWZ), have also attempted to examine discrimination in mortgage lending by estimating default rates conditional on the economic and personal characteristics of each borrower rather than by comparing the average default rates of each group. The superiority of one or the other approach has not been analyzed in detail. It is shown here that the assumptions needed for conditional loan default data to uncover discrimination are sufficient for conditional application denial studies to do the same. In fact, the ability of default studies to reveal discrimination requires further assumptions that denial studies do not need.

The first section of the paper outlines a simple model of loan acceptance. The next section reviews how an examination of conditional denial rates avoids many difficulties with uncovering discrimination. The third section discusses the problems associated with analyzing conditional default rates. It is shown that the assumptions necessary to make conditional default rate analysis an effective approach to uncover discrimination are sufficient to make studies of conditional denial rates effective tools. The paper concludes by analyzing the relative power of default and denial studies to reveal discrimination in mortgage lending when less restrictive assumptions are made.

I. The Framework

A simple model of lender decision-making, found in Tootell (1993), helps to organize the issues. Lenders maximize expected profits,

$$\max_{M} \quad M_i\,(1-P_i^d)\,r_m - M_i\,P_i^d\,\alpha - M_i\,r_s, \tag{1}$$

by deciding whether to grant the mortgage, M_i, given the mortgage interest rate, r_m, the alternative rate, r_s, the percentage of the mortgage lost during a default, α, and the probability that the mortgage will default, P^d_i. The lender will make the loan if

$$P_i^d < P_T^d = \frac{r_m - r_s}{r_m + \alpha}, \tag{2}$$

that is, if the probability of the mortgage default is less than some threshold level, P^d_T. P^d_T depends positively on the excess returns from the loan if the mortgage does not default, $r_m - r_s$, and negatively on the size of any losses if the loan does default. Thus, the higher the excess returns on mortgage loans and the lower the costs of default, the higher the risk lenders are willing to bear.

Equation 2 highlights that an application acceptance depends on the determinants of P^d_i. Since the probability of default is not known, the lender must form an expectation about the probability of default when considering a mortgage application. This probability of default,

$$P_i^d = f(LTV_i,\ CH_i,\ Obr_i, \ldots), \tag{3}$$

depends on the application-specific variables in the information set of the lender, which include, for example, the loan-to-value ratio on the proposed property, LTV_i, as well as the applicant's credit history, CH_i, and expense-to-income ratio, Obr_i. The properly weighted arguments in the P^d function comprise the applicant's "creditworthiness".[1]

Figure 1 displays the probability of default as a function of the application's creditworthiness. The curve is downward-sloping since the more creditworthy the applicant, the lower the loan-to-value ratio on the loan or the stronger the applicant's credit history, the lower the probability that the applicant will default.

If discrimination occurs in this model and the discrimination takes the form of forcing minorities to meet higher credit standards, as is usually assumed, then the threshold probability of default for minorities, $P^d_{T,M}$, must be lower than that for whites, $P^d_{T,W}$. In other words, minorities must have a stronger application at the margin to get accepted for a loan. Just such a case, where $P^d_{T,M} < P^d_{T,W}$, is presented in Figure 1. Minority applicants with creditworthiness greater than T_M are granted the loan, while minority applicants with creditworthiness less than T_M are rejected. Similarly, all applications by whites with creditworthiness greater than T_W are accepted and those with creditworthiness less than T_W are rejected. For the range of creditworthiness between T_W and T_M, white applicants are being accepted with a probability of default greater than that for the marginal minority applicant at T_M. Discrimination is occurring. The horizontal distance between T_W and T_M represents the higher hurdle, or stronger economic characteristics, lenders require of minorities to receive a mortgage.

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1 Other factors besides the probability of default determine loan profitability. For example, the probability that an individual will prepay the loan affects the expected profitability of the mortgage. If, however, the lender assumes the probability of prepayment is identical across all individuals, then only the probability of default is important in the decision to lend across individuals.

II. Average versus Conditional Denial and Default Rates

Using this basic framework, Tootell (1993), Yinger (1993), and Peterson (1981) show that examining average default rates is ineffective in uncovering discrimination. The average loan default rate of a group depends not just on the threshold level of creditworthiness that is acceptable to make the loan, the T_i, but on the distribution of creditworthiness for the accepted applications of each group. To illustrate this point, Figure 2 again presents a case where discrimination is occurring, but these distributions differ. Although minorities at the margin face a higher hurdle, $P^d_{T,M}$ is less than $P^d_{T,W}$, the average default rate for minorities can be higher, lower, or equal to that of whites. Assume that the mean of the creditworthiness distribution of minority applications, M(CW), is less than the mean of the distribution for whites.[2] Even though the marginal minority application, T_M, must be stronger than the marginal application by a white, T_W, to get a loan, the average creditworthiness for <u>accepted</u> minority applications, CW_M, is lower than that for accepted applications of whites, CW_W. Although some minority applicants with a higher creditworthiness than their accepted white counterparts are being rejected, the average default rate is higher for minorities. The average rates of default alone reveal nothing about the presence of discrimination.

Any conclusions about the existence of discrimination in mortgage lending that arise from the analysis of average default rates would, therefore, be spurious. The possible differences in the distributions of creditworthiness across each group must be accounted for by including each

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[2] For ease of exposition it is also assumed that the variances of the two distributions are similar.

applicant's level of creditworthiness in the analysis. Controlling for each applicant's creditworthiness, examining default rates conditional on the applicant's creditworthiness, accounts for the differences in each group's distributions. With more extensive data on both mortgage applications and mortgage defaults, as seen in MTBM and BCGH, the debate has moved on to interpreting the conditional default and denial rates, not the average rates. However, a slightly more complicated dispute still exists about the information that can be gleaned from these conditional rates. This question is taken up in the next two sections.

III. The Debate about Conditional Rates

Studying defaults is often believed to be superior to studying denials because lenders' profits, and thus their behavior, depend on the outcomes of the loans. When application denials show a significant effect of race on the lending decision, so lenders are less apt to lend to minorities given the known characteristics of the borrowers, it could be because loans to minorities are less profitable than loans to whites with these same characteristics. Perhaps minorities tend to default more frequently than whites because of omitted variables correlated with race, whether seen by the lender or not. If so, then the finding that minorities are less apt to be granted a loan would have an economic basis. Is the effect of race found in the denial studies due to the omission of variables correlated with race and mortgage performance that the lender knows, or due to omitted variables correlated with race that the lender does not know but which allow the lender to use race as a signal for these variables (the "statistical" discrimination outlined in Phelps (1972), Spence (1974), and Ashenfelter and Hannan (1986)), or due to discrimination not justified by economic forces ("taste-based" discrimination)? Although the latter explanations are illegal, statistical discrimination could be rational.[3]

Uncovering either statistical or taste-based discrimination is important for enforcement. Understanding lender behavior requires distinguishing between the two. However, the ability of conditional default analysis and conditional denial analysis to identify these two types of discrimination is widely misunderstood. The remainder of this paper examines the ability of these two types of analysis to perform this function.

Studying Defaults with Omitted Variables the Lender Knows

The use of default data to uncover taste-based discrimination suffers from several problems when no omitted variables exist, either known or unknown by the lender. In such a case, Tootell (1993) shows that default analysis provides no information on whether taste-based discrimination is occurring. The basic argument is outlined in Figure 2. Although in the region between T_W and T_M white applications are being accepted with higher probabilities of default than rejected minority applications, a regression of the default probability on loan creditworthiness and race would fail to capture that discrimination. To the right of T_M minorities and whites are treated identically; they are all accepted, as their probability of default is below

[3] This paradigm assumes discrimination is economically rational. Discrimination may take other forms, like randomly rejecting minority applications regardless of their fundamentals, which would pose no problem for the interpretation of the race coefficient in the denial regression. To analyze the rationality of using race as a signal, the expected costs of getting caught must be considered.

both the white and the minority threshold levels. To the left of T_M the two groups are not treated similarly; whites with higher default probabilities are being accepted over minorities with lower probabilities. However, there are no minority observations in the default sample from this region. As a result, examining defaults does not allow the researcher to observe the differential treatment. A sample of denials, on the other hand, includes all the minority applications to the left of T_M that are being discriminated against. Even though taste-based discrimination is occurring, a default regression will produce a coefficient on minority status of zero, while a denial regression will produce a significant coefficient.

In a study of conditional default rates, BCGH makes an additional assumption that would allow default studies to reveal taste-based discrimination. BCGH assumes that the researcher measures only imperfectly the lender's assessment of the applicant's creditworthiness; variables are omitted from the researcher's analysis, but not the lender's, that are correlated with loan performance and not with race. Figure 3 shows the effect of this assumption on the model. For a given level of the researcher's estimate of the applicant's creditworthiness, for example CW', the applicant's true probability of default now takes on a range of possible values, centered on the $P^d(CW)$ curve. For each level of measured creditworthiness, there is now a distribution of the probability of default around the mean probability of default.

The assumption of omitted variables known by the lender produces some minority acceptances to the left of T_M. In Figure 3, if a minority applicant with a measured creditworthiness equal to CW' has omitted variables that are very strong, the true P^d of that applicant will be in the bottom, shaded, tail of the P^d distribution at CW', $P^d(CW')$, and it will be in the default sample. Furthermore, some minority rejections to the right of T_M, at the top tail of the P^d distribution at, for example, CW", will also occur. Note that the probability of a minority acceptance to the left of T_M declines as the measured creditworthiness moves toward the origin, and the probability of a minority rejection to the left of T_M decreases as the measured creditworthiness moves away from the origin, since the probability of such large omitted-variable realizations must move toward the tails of the P^d distributions.[4]

If taste-based discrimination is occurring in the model, as in Figure 3, every minority acceptance that does occur to the left of T_M will have an actual probability of default less than $P^d_{T,M}$, the minority threshold. White acceptances to the left of T_M will, on average, have a higher probability of default than their minority counterparts, even holding measured creditworthiness constant, since the acceptable risk on applications by whites gets as high as $P^d_{T,W}$, the higher threshold for white applications. All white applications whose default probabilities are on segment A are accepted, while all minority applications on segment A are rejected. Furthermore, the rejection of minorities and whites to the right of T_M also helps produce a lower minority default rate when taste-based discrimination is occurring.

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[4] The omitted variables uncorrelated with race are captured in the error term of the default regression. As the measured creditworthiness of the application gets weaker, moving from T_M to the origin, the error produced by the omitted variables has to be larger, and less likely to offset the application's weakness. Thus, the probability of finding a minority acceptance to the left of T_M falls as the measured creditworthiness falls.

Minority applications with true probabilities of default on segment B in Figure 3 are rejected, while white applications along this segment are not. Thus, on average, the minority default rate on loans to the right of T_M should also be lower. The conditional probability of default for accepted applications will be higher for whites, since the minority acceptances given the creditworthiness of the applicant are truncated at $P^d_{T,M}$ and the white acceptances are truncated at the higher $P^d_{T,W}$. As a result, the estimated minority probability of default will be lower even for a given level of creditworthiness. All this is due to the added assumption of omitted variables uncorrelated with race.

Whether the effect of race on the probability of default will be statistically significant is, however, not as clear. The difference in default probabilities will be statistically significant if, and only if, the numbers of accepted minority applications to the left of T_M and rejected applications to the right of T_M are large: in other words, if the measurement error between the researcher's and the lender's assessments of the applicant's creditworthiness has a large variance. The omitted variable must be important.

Figure 4 illustrates this last point. The dashed lines on each side of the $P^d(CW)$ curve represent the projection of, say, a two standard deviation range around the mean of the $P^d(CW^i)$ distributions. To the left of T_M, omitted variables can produce some minority acceptances as the lender's assessment of the applicant's creditworthiness produces a default probability below $P^d_{T,M}$. These minority acceptances will cluster in region A, where the omitted variables result in less than a standard deviation difference between the researcher's and the lender's assessments of the applicant's probability of default. The same is true about rejections to the right of T_M. Note that to get a minority acceptance as applicant creditworthiness moves left of region A requires even larger deviations between the researcher's and the lender's assessments of the borrower's creditworthiness; the error has to be further outside the two standard deviation range, as the measured creditworthiness of the applicant declines.

If the omitted variable or variables creating this error have either a low variance or little effect on the profitability of the loan, race will not be significant in a default regression even though taste-based discrimination is occurring. In Figure 4, a low variance of the error term around the researcher's estimate of the probability of default is represented by a tight band of the dashed lines, small regions A and B, and few minority acceptances to the left of T_M. The fewer the minority acceptances to the left of T_M, or the fewer acceptances to the right, the lower the power an analysis of defaults has to uncover the taste-based discrimination. Denial studies, on the other hand, include all the observations rejected to the left of T_M, and would easily discern discrimination.

These assumptions allow for a richer debate but, as will be shown, they do not alter the basic conclusion that default regressions are not superior to denial regressions in discerning taste-based discrimination.

Studying Defaults When Statistical Discrimination Can Occur

The debate over the appropriate methodology gets slightly more complicated once it is assumed that statistical discrimination can occur. Holding the data in the information set of the lender constant, minorities may have a higher probability of defaulting on their mortgages.[5] If so, then the coefficient on minority status in a default regression, holding all the other variables in the lender's information set constant, should be positive. In this case, race could be used as a signal for loan performance, and minorities rationally could be denied more frequently than whites at the margin. Given this possibility, the interpretation has sometimes been that a negative coefficient in a default regression reveals taste-based discrimination, while a positive one could justify statistical discrimination.

This conclusion, however, is invalid. Figure 5 presents the case where lenders can use race as a signal - the default probabilities of minorities are higher than those of whites for a given level of creditworthiness. The higher minority conditional default probability is represented by the vertical distance between the two $P_i^d(CW)$ curves. Figure 5 also presents the case where taste-based discrimination exists.

Again, when no minority applications are accepted between T_W and T_M, a default regression cannot detect the taste-based discrimination. In fact, the coefficient on minority status in the default regression would be positive, which gives the sign opposite to that expected when taste-based discrimination is occurring. In this case, the minority status coefficient in a regression of default probabilities on measured creditworthiness and race would capture only the vertical distance between these two curves, the statistical

[5] The discussion in this paper centers on statistical discrimination, rather than on the omission of a variable correlated with race that is in the lender's information set, because the latter omission biases both denial and default studies. The assumption is that the equations are correctly specified; otherwise, the omitted variable presents the traditional problem.

discrimination, but say nothing about whether $P^d_{T,M}$ is less than $P^d_{T,W}$, the taste-based discrimination.

The more interesting case is found when the BCGH assumption of omitted variables uncorrelated with race is added to the model. Now there are both omitted variables that are uncorrelated with race but in the information set of the lender and omitted variables correlated with race but not in the lender's information set. With the added BCGH assumption, some minority acceptances will, again, occur to the left of T_M and some minority rejections to the right. Yet the motivation for statistical discrimination makes the ability to discern taste-based discrimination in default data much more difficult, even with the added assumptions.

Over the entire sample of accepted applications, the occurrence of statistical discrimination along with taste-based discrimination would reduce the ability of default analysis to discern taste-based discrimination in two ways. First, the range to the left of T_M, where the estimated effect of minority status on the probability of default would be unequivocally negative, is much smaller when the conditional probability of default is higher for minorities. Without the difference between the two groups' $P^d(CW)$ curves, the entire range to the left of T_M would tend to produce a negative coefficient on minority status. With this difference, only minority acceptances to the left of point A in Figure 5, not to the left of T_M, will unambiguously have an expected conditional probability of default below that for accepted whites. As a result, the number of observations that would reveal the taste-based discrimination is much smaller than in the case when no statistical discrimination is possible, since the size of the error required to produce an acceptance to the left of A must be much larger than the error needed to produce an acceptance to the left of T_M.

In fact, the significance of the region where the minority default probability is definitely lower, from the origin to A, can become arbitrarily small. If the error around the measured creditworthiness is low, so that the omitted variables known to the lender but unknown to the researcher are unimportant, or the gap between the two default probability loci is larger, so the omitted variables correlated with race are important, then the region where the taste-based discrimination can be detected becomes very small. The variance of the error due to the omitted variables, the variance around the $P^d(CW)$, must be large for minority acceptances to occur beyond point A; the smaller that variance, the less likely that actual minority acceptances will occur where the conditional probability of default for minorities is less than that for whites, even though all the minority applications to the left of T_M with default probability between $P_{T,M}{}^d < P_{T,W}{}^d$ are victims of taste-based discrimination. If the omitted variables known to the lender but not the researcher are few and unimportant, then the variance will be small, and the probability of an acceptance to the left of point A is small. In the extreme, when the variance of the error term approaches zero, the model reverts to that in Figure 2, where no minority acceptances occur to the left of T_M. Furthermore, the larger the gap between the two mean probability of default loci, the further the distance between point A and T_M, and the smaller the range where the measured conditional minority default probability will be lower than the white probability.

As a result, the sign of the estimated coefficient on race to the right of point A could easily be positive, not negative, in a default regression. At a given level of measured creditworthiness, the probability of default for each group's average applicant is $P^d_i(CW)$. The observed probability, however, will be slightly smaller, because applications with omitted variables known by the lender that push their probability of default above the threshold level will not be accepted. For a given level of creditworthiness, the higher white applicant acceptance threshold would tend to make the estimated conditional default rate for whites higher than that for minorities. On the other hand, the higher probability of default for minorities given the level of measured creditworthiness would tend to make the measured conditional default rate for minorities higher. Which effect dominates is uncertain. For the entire range of mortgages, the coefficient on minority status could be positive, negative, or zero, depending on how frequently minority acceptances occur to the left of A, how frequently minority rejections between $P^d_{T,W}$ and $P^d_{T,M}$ occur to the right of A, and the distance between the two curves. As a result, default analysis will have a difficult time uncovering taste-based discrimination if statistical discrimination could occur.

Default studies have the same problems denial studies have, plus a few. The assumptions required to make default analysis potentially useful in revealing taste-based discrimination are precisely the ones that make denial regressions a preferred alternative. Analysis of conditional denial rates is sufficient to uncover taste-based discrimination if it is assumed that the conditional probability of default is uncorrelated with race. Default analysis requires the same assumption, plus the assumption that other important omitted variables exist which are uncorrelated with race and known by the lenders. This added assumption highlights the superiority of denial analysis; examining denials includes all the observations that were discriminated against - the denial sample includes <u>all</u> the rejected observations with default probabilities between $P_{T,M}{}^{d}$ and $P_{T,W}{}^{d}$. For default analysis to capture <u>some</u> of these observations requires the additional assumption of important omitted variables uncorrelated with race and known by the lender. As a result, denial studies are more powerful tools.

Table 1 summarizes the strengths and weaknesses of the two approaches. The ability of each method to uncover taste-based discrimination under various circumstances, or falsely suggest it, is outlined. The first two columns highlight the finding that when no omitted variables correlated with race are present, the study of denials is superior. It reveals the taste-based discrimination while the default studies do not. When omitted variables exist that are correlated with race, both approaches have problems. Whether these omitted variables correlated with race are in the information set of the lender or not, denial studies will tend to find a significant effect of race and default studies will find that minorities tend to default more often, regardless of whether taste-based discrimination is occurring. Omitted variables correlated with race are equally a problem for default and denial analysis.

IV. Conclusion

Many have advocated examining mortgage defaults instead of application denials when testing for discrimination. Yet, studies of application denials are sufficient to uncover taste-based discrimination if no omitted variables correlated with race exist. In the model used here, denial regressions capture all the observations that are experiencing disparate treatment, minority applications with creditworthiness between T_W and T_M in Figure 3, while default regressions must rely only on the acceptances to the left and rejections to the right of T_M for their results. The number of such observations depends on the importance of the presumed omitted variables uncorrelated with race. Under the assumption that the equation is properly specified, denial studies are a more powerful tool for uncovering taste-based discrimination.

When omitted variables correlated with race do exist, uncovering taste-based discrimination with either default or denial analysis is problematic. Denial studies will tend to find an increased probability that minorities will be rejected, and thus evidence of discrimination, while default studies will tend to find an increased probability that minorities will default, thus no evidence of discrimination. Not surprisingly, neither approach is reliable when it is assumed that the equation is misspecified. When the assumed omitted variable correlated with race is known by the lender, both approaches have their problems. When the omitted variable correlated with race is not known by the lender, analyzing denials is best for issues of enforcement since both taste-based and statistical discrimination are illegal. Separating the two effects in studies of defaults and denials remains problematic.

Examining default data can provide useful information, however. It can be a good test of whether denial equations are misspecified. If variables are found that are related to default probability but not contained in the denial analysis, then there is a potential problem of omitted variable bias in the denial regression. Further, if a default regression with the same variables as a denial regression produces a positive and significant coefficient on race, it raises questions about statistical discrimination or omitted variables. If it is a variable not contained in the lender's information set, it is a signal. The relationship between race's role as a signal and race's role in application denials can be compared. When statistical discrimination occurs, both types of studies are required to determine whether the discrimination found in a denial regression is economically driven. If it is assumed that the equation is not misspecified, an analysis of denials is sufficient. In an uncertain world, an examination of defaults can help troubleshoot for denial analysis but cannot supplant it.

Figure 1
Discrimination and Default Probabilities

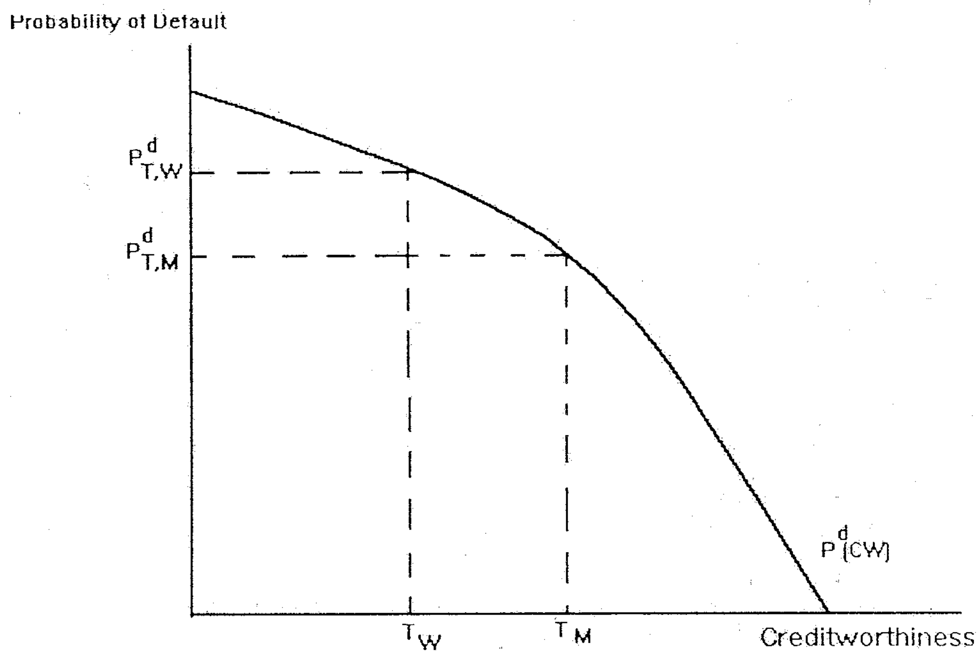

Figure 2
Marginal vrs. Average Default

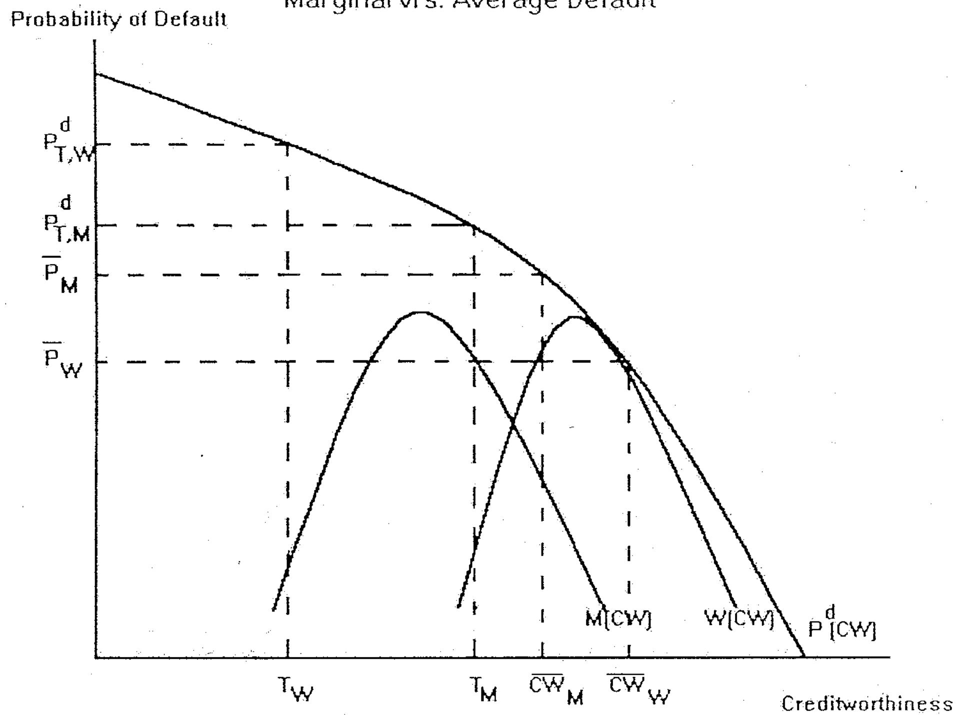

Figure 3
Default Probabilities with Omitted Variables

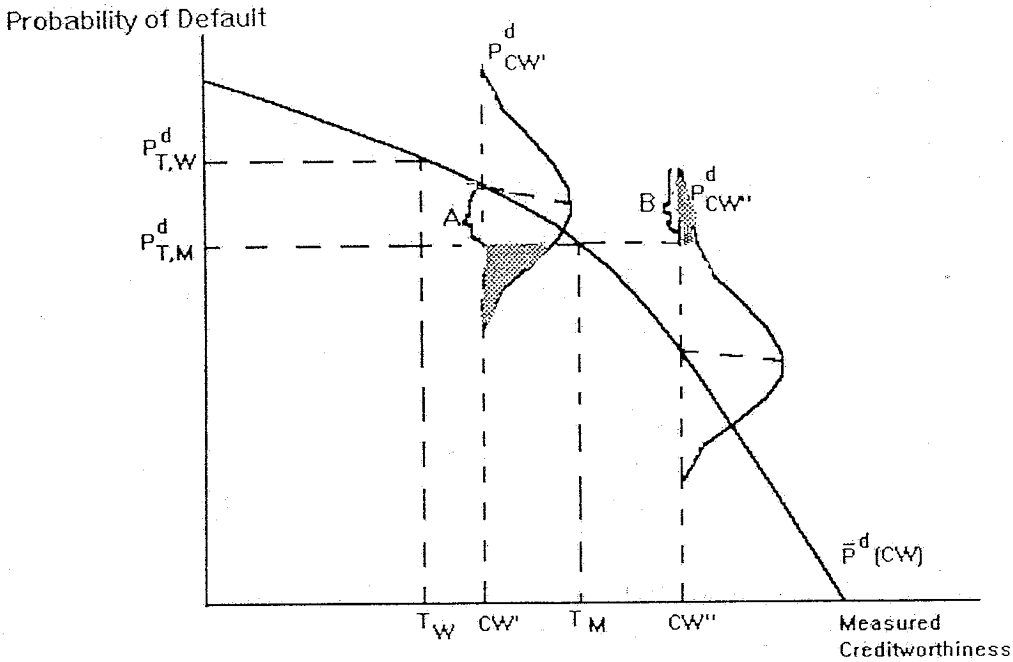

Figure 4
Importance of Omitted Variables

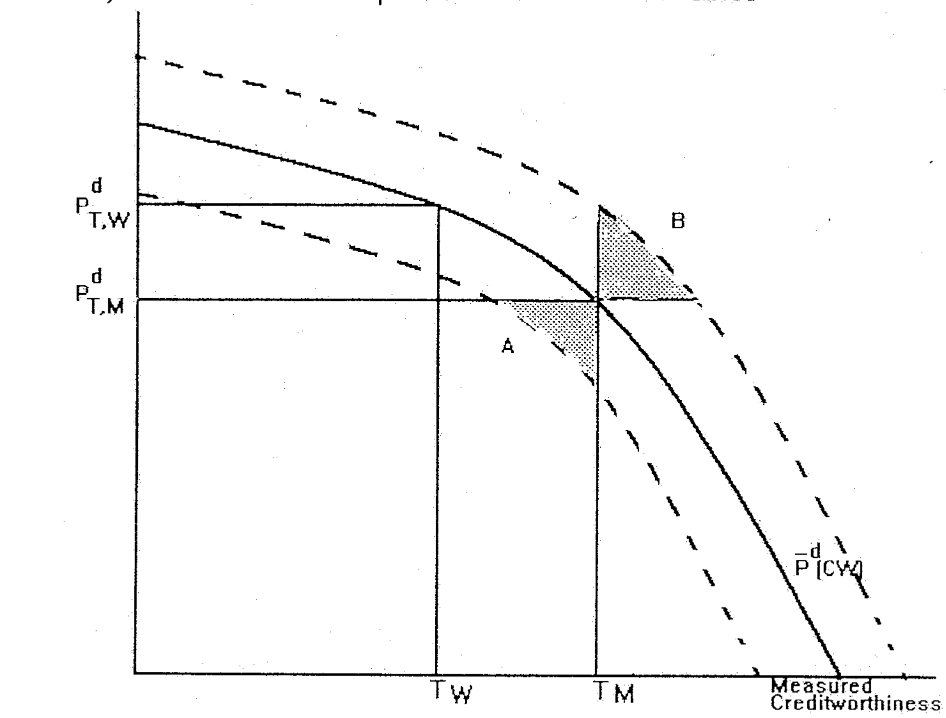

Figure 5

Statistical Discrimination and Defaults

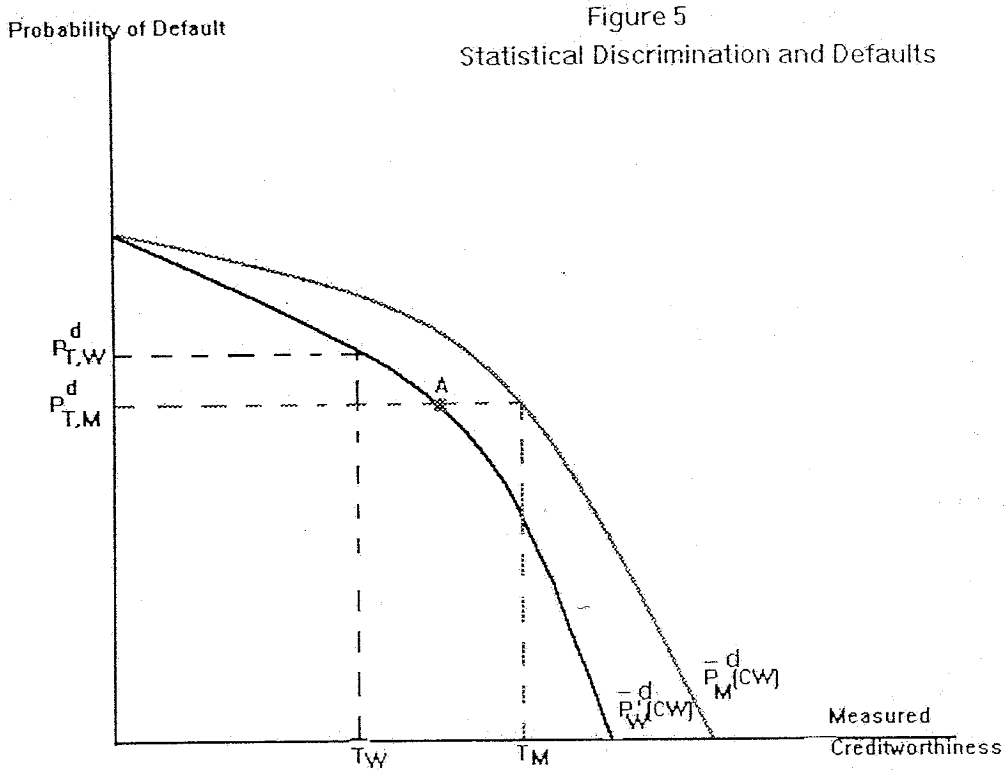

TABLE 1

Reliability of Denial and Default Analysis

	No Omitted Variables	Omitted Variables Uncorrleated with Race	Omitted Variables Correlated with Race
Denials/ Discrim-ination	Revealed	Revealed	Confounds effects Show a problem
Defaults/ Discrim-ination	Not Revealed	Might revealed	Confounds effects Tends to show no problem
Denials/ No Di-scrimination	No Discrim-ination	No Discrim-ination	Confounds effects Shows a problem
Defaults/ No Di-scrimination	No Discrim-ination	No Discrim-ination	Confounds effects Tends to show no problem

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