On the Economics of Discrimination in Credit Markets*

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Abstract

This paper develops a general equilibrium model of both taste-based and statistical discrimination in credit markets. We find that both types of discrimination have similar predictions for intergroup differences in loan terms. The commonly held view has been that if there exists taste-based discrimination, loans approved to minority borrowers would have higher expected profitability than to majorities with comparable credit background. We show that the validity of this profitability view depends crucially on how expected loan profitability is measured. We also show that there must exist taste-based discrimination if loans to minority borrowers have higher expected rate of return or lower expected rate of default loss than to majorities with the same exogenous characteristics observed at the time of loan origination. Using a reduced-form regression approach, we find that empirical evidence on expected rate of default loss cannot reject the null hypothesis of non-existence of taste-based discrimination.

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1 Introduction

Recent years have seen widespread concerns with discrimination in credit markets. Many studies documented significant higher rejection rate among minority loan applicants than majorities with the same observable characteristics (e.g. Black, Schweitzer and Mandell, 1978; Duca and Rosenthal, 1993; Munnell, Tootell, Browne and McEneaney, 1996; Blanchflower, Levine and Zimmerman, 1998). However, there are many controversies on whether the observed racial disparity is indeed caused by discrimination. Besides concerns with data quality and empirical methods, the debates raise an important theoretical issue. In public discourse, discrimination is often referred to as prejudice or taste-based discrimination (Becker, 1971). But the observed disparity may also be caused by statistical discrimination. That is, with a lack of full information on borrower's credit worthiness, a lender may apply group stereotypes to individual borrowers in evaluating expected loan profitability (Arrow, 1972; Phelps, 1972).[1] Because of their different implications to public policy, it is important to distinguish taste-based discrimination from statistical discrimination. But since both types of discrimination imply higher rejection rates among minority applicants, rejection rate is not a reasonable measure of taste-based discrimination in lending.

To determine what constitutes evidence of prejudice in lending, we have to know theoretically how each type of discrimination would affect credit market outcomes, such as screening, loan terms and performance, for different groups of borrowers, and how the effects of taste-based discrimination would be different from those of statistical discrimination. Thus a general equilibrium model that can incorporate both types of discrimination is crucial to obtaining these theoretical results and providing guides for the empirical analysis. Surprisingly, despite of many debates in this area, such a model is largely non-existing (Ladd, 1998; Longhofer and Peters, 1998).[2]

[1] Besides taste-based and statistical discrimination, other factors, such as culture affinity and self-selection, have also been suggested as possible causes of the observed disparity in rejection rate (e.g. Cornell and Welch, 1996; Hunter and Walker, 1996; Ferguson and Peters, 1997; Longhofer and Peters, 1998). These factors are not considered in this paper.

[2] Peterson (1981) explicitly modeled a lender's taste for discrimination, but didn't develop a complete model to analyze how prejudice would affect loan terms and expected performance. Becker (1993a,b,1995) discussed possible impacts of taste-based discrimination, but didn't present a theoretical model. Berkovec, Canner, Gabriel and Hannan (1994) didn't model bank's taste directly. Instead, they assumed that taste-based discrimination implied higher underwriting standards for minority borrowers but had no impacts on loan terms. Previous models on statistical discrimination also had partial equilibrium settings (e.g. Ferguson and Peters, 1995; Shaffer, 1996; Tootell, 1993).

The present paper attempts to fill up this gap. We develop a model of credit market discrimination, both taste-based and statistical. In a general equilibrium framework, we analyze how loan terms and expected performance would be different among minority and majority borrowers under each type of discrimination. The results are then used to determine under what conditions we can empirically detect taste-based discrimination and what would be the appropriate empirical methods and data to do so.

Our general equilibrium framework implies that both taste-based and statistical discrimination would affect not only a lender's underwriting criterion but also the terms of the loans to the accepted minority applicants. This contrasts to the partial equilibrium models in previous studies, where loan terms are assumed exogenous and discrimination only affects a lender's underwriting criterion (e.g. Berkovec et al., 1994; Ferguson and Peters, 1995; Shaffer, 1996). But we believe that endogenizing loan terms is crucial to understanding the full impacts of discrimination in lending. First, although loan terms on the loan application files appear predetermined, they are not exogenous. They depend on not only borrower's own financial situations but also lender's mortgage menu, "advices" and negotiations. A lender's menu, with a combination of downpayment, interest rate, maturity and other terms, may vary across different borrowers. Second, it has been suggested in the literature that the effective interest rates–those taking into account both contract rates and such items as fees, points, and closing costs–may vary significantly among different borrowers (Schafer and Ladd, 1981; Ellis, 1985; Courchane and Nickerson, 1997; Huck and Segal, 1997). Finally, recent development of risk-based pricing in mortgage markets also implies that lenders can affect loan terms such as interest rates through varying credit scores for different groups of borrowers.

While our model improves on the existing studies in endogenizing loan terms, our model of taste-based discrimination also extends the Becker's (1971) theory of discrimination to credit markets. The extension is much needed because the results based on existing models of discrimination in other markets are not directly applicable to credit markets. For example, applying the principle developed in Becker (1971), previous authors correctly pointed out that one should use the profitability of loans to determine if there exists discrimination in lending (Peterson, 1981; Becker, 1993*b*). The idea is that a lender with taste for discrimination would require higher expected profits to compensate for the higher psychic costs in lending to minorities. Unfortunately, the data needed for estimating the direct measure of profitability–the rate of return of loans–are often not available. As a result, various other measures of loan performance, such as interest rate and default rate, have been suggested.[3] But does taste-based discrimination imply a higher interest rate or lower default rate on loans to minority borrowers? Are those effects unique to taste-based discrimination? Intuitively, the answer is "not necessarily." For example, while a higher interest rate increases expected profits if a loan is paid, it could, given other things equal, increase default probability and in turn, decreases expected profits. This suggests two things: First, the default rate is not necessarily lower on loans to minority borrowers even if there exists taste-based discrimination; Second, interest rate alone may not provide a satisfactory measure of a lender's prejudice because, if a biased lender wants to obtain higher expected profits, he has to adjust not only the interest rate but also other variables such as loan size. This contrasts to studies on labor market discrimination, where employer's prejudice can be measured by differences in price, i.e., wage rate, between minority and majority workers (e.g. Becker, 1971).

Our model is motivated by the limitations discussed above of existing models and credit markets data. The model will allow us to analyze to what extent alternative measures and determinants of profitability can be used to detect discrimination in lending. We find that the validity of the conventional profitability view depends crucially on how expected loan performance is measured. For example, we find that if there exists taste-based discrimination, default rates of loans to minority borrowers should be higher, but not lower, than loans to majorities with the same credit worthiness. We also find that both taste-based and statistical discrimination imply that loans made to minority borrowers would have higher interest rates, smaller sizes and higher default rates than to majorities with the same exogenous characteristics at the time of loan originations. So these variables cannot be used to distinguish taste-based discrimination from statistical discrimination. We do find that there must exist taste-based discrimination if loans to minority borrowers have higher expected rates of return or lower expected rates of default loss than to majorities with the same exogenous characteristics observed at the time of loan originations.

We apply the above results to test the existence of taste-based discrimination using a

[3]Becker (1993*b*) suggested that "a valid study of discrimination in lending would calculate default rates, late payments, interest rates, and other determinants of the profitability of loans" (Page 18). A non-exhaustive list of the variables studied in the literature include default probability (Berkovec et al., 1994; Van Order and Zorn, 1995; Martin and Hill, 2000), expected rate of default loss (Berkovec et al. 1996,1998), delinquency rates (Canner, Gabriel and Woolley, 1991), and expected rate of default loss conditional on default and expected rate of gain conditional on non-default (Peterson, 1981).

dataset of FHA mortgage loans. The data only allow us to estimate expected rate of default loss. A main methodological implication of our model is that the empirical implementation of the above tests should use reduced form regressions. That is, only exogenous variables observed at the time of loan originations are used as independent variables in the regressions.[4] Our empirical analysis finds higher expected rate of default loss among loans to minority borrowers than to majorities given the exogenous variables observed at the time of originations. So we cannot reject the null hypothesis of non-existence of taste-based discrimination.

The remainder of the paper is organized as follows. Section 2 presents the model setup. Sections 3 and 4 study how taste-based and statistical discrimination, respectively, would affect the terms and expected performance of the loans to minority borrowers, comparing those to majority borrowers with the same credit worthiness. In each case, we first try to obtain the results analytically, then use empirical approaches to resolve some of the ambiguities in the analytical predictions. Section 5 examines under what conditions we can empirically distinguish taste-based discrimination from statistical discrimination. We also present the results of an empirical test of the existence of taste-based discrimination. Section 6 summarizes our main findings and points out their implications for future research.

2 The Model Setup

We consider a two-period model with $t = 0, 1$. A household applies for a loan at $t = 0$. If approved, loan terms such as loan size and interest rate are determined. At $t = 1$, the household, if indebted, optimally chooses the amount of payment based on realized income and default penalty. Default occurs when the payment is less than the contractual obligation. Below, we specify the household's income risk, default decision, and the lender's preferences.

2.1 Household's Income Risk and Default Decision

Denote household's income at $t = 1$ by the random variable y, with $y \in [\underline{y}, \overline{y}]$. We assume that the distribution of y only depends on θ, which is a function of a set of the house-

[4] Existing studies often estimated structural form regressions of loan performance in the sense that loan terms such as loan-to-value ratios are included as covariates. The appropriateness of the structural form regressions is discussed in depth in Section 5. The reduced-form regression approach has been used widely in studies on labor market discrimination, such as Neal and Johnson (1996) and Neumark (1998).

hold's characteristics Z, or $\theta = \theta(Z)$. We call θ the household's *credit worthiness.*[5] Let the cumulative distribution function and probability density function of y be $F(y|\theta)$ and $f(y|\theta)$, respectively. Let g indicate the borrower's group identity. We make the following assumptions.

Assumption 1 Z does not contain g and $\theta(Z, g) = \theta(Z)$.

Assumption 2 $\theta(Z)$ is increasing in Z and is bounded on $[\underline{\theta}, \overline{\theta}]$.

Assumption 3 $F(y|\theta)$ satisfies the First Order Stochastic Dominance (FOSD) property: If $\theta_1 \leq \theta_2$, then $F(y|\theta_2) \leq F(y|\theta_1), \forall y \in [\underline{y}, \overline{y}]$.

Assumption 1 implies that group identity g does not improve the prediction of the household's future income if we can observe the set of household characteristics other than g. This excludes such possibilities as labor market discrimination where group identity is a predictor of future income distribution given other characteristics. This assumption is merely for simplicity and can be easily relaxed, as discussed in Section 4.3. Assumption 2 is without loss of generality, assuming that credit worthiness is monotonic in Z. Assumption 3 states that the income risk we consider has the FOSD property: The higher the credit worthiness, the smaller the probability of future income falling below any given income level.

A debt contract is a pair $\langle B_0, B_1 \rangle$ with $B_1 = (1 + r)B_0$, where B_0 is the size of loan, r is the interest rate, and B_1 is the contractual payment.[6] At $t = 1$, a debtor chooses an optimal payment by comparing the benefit and cost of default. For default penalties, it is assumed that for every dollar unpaid, the household suffers a utility loss $c > 0$.[7] Let household's

[5]We can think credit worthiness θ as a sufficient statistic of the household's future income distribution. By our definition, credit worthiness is an exogenous variable. We use "credit worthiness" to distinguish from "credit score" and "credit risk." Credit score, calculated by lenders, is usually a function of not only variables determining credit worthiness but also variables related to the loan asked, such as loan-to-value ratio. Credit risk, or the risk of loan default, is also determined by both household characteristics and loan terms. So unlike credit worthiness, both credit score and credit risk are endogenous.

[6]The loan considered here is unsecured. The model can be readily extent to secured loans, such as mortgage. Basically, one can interpret B_0 as the property's purchasing price minus downpayment and y as income plus the property's market value at $t = 1$. The debt payment decision discussed below can be modified accordingly by taking into account the fact that the loan is secured. Most of the results reported here hold also for secured loans. But the analysis is more tedious because of the additional uncertainty in the property's market value (see Han 1998).

[7]Costs of default include the social stigma attached to breaching contract and losing the privilege of borrowing in the future. Fay, Hurst and White (1998) and White (1998) showed that the social stigma attached to default might be substantial. Telser (1980) showed that when a debtor is a partner to a self-enforcement agreement, he will try to repay the loan to keep a good "credit rating" because defaulted debtors

utility function be $u(\cdot)$ with $u' > 0$ and $u'' < 0$. After realizing the second period income y, a debtor solves the following maximization problem by choosing an optimal payment p:

$$\max_{p} \; u(y-p) - c \cdot (B_1 - p) \quad \text{subject to:} \quad 0 \le p \le B_1, \tag{1}$$

where $y - p$ is after-payment income and $B_1 - p$ is the amount of unpaid principle and interest.

Let v be the level of consumption at which the marginal utility of consumption equals c, or $u'(v) = c$. The solution to the above optimization problem, denoted by p^*, has the following property.

Lemma 1 The optimal payment for given y and B_1 is :

$$p^* = \begin{cases} B_1 & \text{if } y \ge B_1 + v, \\ \max(y - v, 0) & \text{if otherwise.} \end{cases}$$

All proofs are in the Appendix. The lemma shows that a debtor defaults if income falls below $B_1 + v$. Given a contract $\langle B_0, B_1 \rangle$ and the default technology described above, the expected utility to a loan applicant with credit worthiness θ is

$$U(\langle B_0, B_1 \rangle) = u(B_0) + \beta \int [u(y - p^*) - c \cdot (B_1 - p^*)] f(y|\theta)\, dy \tag{2}$$

Note that $p^* = p^*(y, B_1)$ is a function of both realized future income y and contractual payment B_1. The household's preferences have the following properties.

Lemma 2 Define household's indifference curves in a (B_0, B_1) plane by $U(\langle B_0, B_1 \rangle) = U$. Then

$$\left.\frac{dB_1}{dB_0}\right|_U > 0, \quad \left.\frac{d^2 B_1}{{dB_0}^2}\right|_U < 0, \quad \left.\frac{\partial}{\partial \theta}\frac{dB_1}{dB_0}\right|_U > 0.$$

Thus, drawn in the (B_0, B_1) plane, the household's indifference curves are upward-sloping and concave, and at any point, have steeper slopes for larger θ (see Figure 1). The latter implies that the marginal increase in contractual payment B_1 that a household is willing to accept, in exchange for a marginal increase in loan size B_0, is increasing in credit worthiness.

are "blacklisted" and lose their future borrowing privileges. Loss of borrowing privileges can be very costly for some people in terms of attainable lifetime utility.

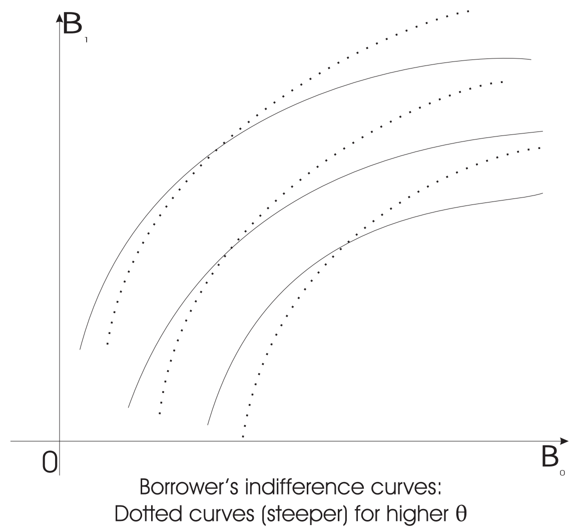

Figure 1: Properties of a borrower's indifference curves

2.2 Lender's Preferences

A lender has a taste for discrimination if the lender incurs some psychic cost or disutility when in direct contact or association with a certain group of borrowers (Becker, 1971). This psychic cost, together with the money cost of the funds that the lender uses to finance the loan, would be the total effective costs of lending. The size of the psychic cost can be measured by money: It is equal to the maximum expected profits that the lender is willing to forfeit for not making the loan to a borrower, or, equivalently, the minimum expected profits required for the lender to be willing to make the loan.

Let the lender's marginal money cost of funds be r_0 and the marginal psychic cost (monetized) of lending be δ. For given $\langle B_0, B_1 \rangle$, the lender's utility from lending to a borrower with θ is

$$\pi(\langle B_0, B_1 \rangle) = \int p^* f(y|\theta)\, dy - B_0(1 + r_0 + \delta), \tag{3}$$

where p^* is determined as in Lemma 1.

The above specification implies that the size of psychic cost of lending is measured by $B_0\delta$, which is increasing proportionally in loan size B_0. The assumption captures the ideas that the psychic cost incurred by the discriminatory lender is increasing in the amount of interaction with the borrower and that it is reasonable to assume that the amount of the interaction is increasing in the loan size. One might argue that in credit transactions, it is not unreasonable to assume that the amount of interaction between lender and borrower, and in turn, the psychic cost, might be independent of loan size. We will discuss the implications of this fixed psychic cost specification in Section 3.1.3.

The lender's preference has the following properties.

Lemma 3 Define the lender's indifference curves in the (B_0, B_1) plane by $\pi(\langle B_0, B_1\rangle) = \Pi$. Then

$$\left.\frac{dB_1}{dB_0}\right|_{\Pi} > 0, \quad \left.\frac{d^2B_1}{dB_0{}^2}\right|_{\Pi} > 0, \quad \left.\frac{\partial}{\partial\theta}\frac{dB_1}{dB_0}\right|_{\Pi} < 0, \quad \left.\frac{\partial}{\partial\delta}\frac{dB_1}{dB_0}\right|_{\Pi} > 0.$$

So the lender's indifference curves are upward sloping and convex. Also, at any point, they have flatter slopes for larger θ or smaller δ (Figure 2). This implies that the marginal increase in contractual payment B_1 that a lender is willing to accept, in order to extend a marginally larger loan, is decreasing in borrower's credit worthiness and increasing in the lender's psychic cost of lending.

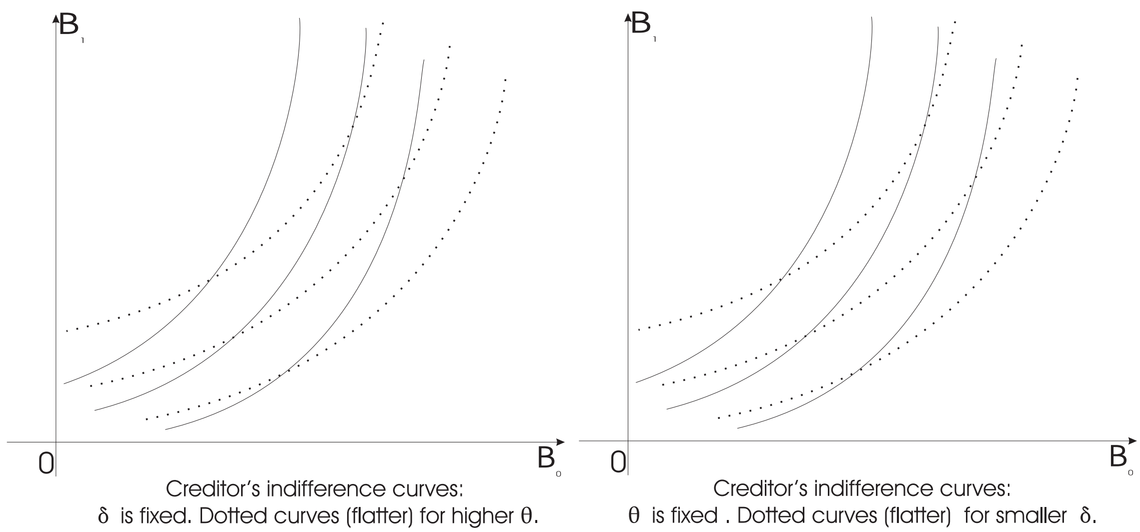

Figure 2: Properties of a lender's indifference curves

Suppose that there are two groups of borrowers, $g = I, J$, representing minority and majority (i.e., mInority vs maJority), respectively.[8] Without loss of generality, assume that the lender has a taste for discrimination against borrowers from group I, that is, $\delta(I) > \delta(J)$.

[8]The terms "minority" and "majority" here do not necessarily refer to the relative number of borrowers of the two groups.

2.3 Market Structure and Information

We assume that credit markets are perfect competitive in the sense that banks have unconstrained access to the capital market and can finance their loans by borrowing from the rest of the world at the constant interest rate r_0. We will study the cases of both symmetric and asymmetric information. With symmetric information, lenders can observe all variables Z that determine borrowers' credit worthiness. In this case, only taste-based discrimination is possible. With asymmetric information, borrowers have private information on some of the variables that determine their credit worthiness. In particular, asymmetric information causes statistical discrimination, because the lender will use group identity to predict borrower's credit worthiness. In the next two sections, we study the effects of both taste-based and statistical discrimination on equilibrium loan terms and expected loan profitability.

3 Taste-Based Discrimination

In this section, we assume that lenders can observe all variables Z and hence obtain accurate estimates of borrowers' credit worthiness $\theta = \theta(Z)$. Given θ, the differences in the market outcomes, such as loan terms and expected loan performance, between borrowers I and J are solely determined by lenders' tastes. We first present the results with variable psychic cost, then the results with fixed psychic cost.

3.1 Results with Variable Psychic Cost

The question we are interested in is: Under taste-based discrimination, how would the loans to minority borrowers be different from those to majority borrowers with the same credit worthiness θ. We start with the analytical results of the impact of taste-based discrimination on the equilibrium loan terms, B_0, B_1 and r, and then on expected loan performance. Then we show how the ambiguities in the analytical results can be resolved.

3.1.1 Loan Terms

With perfect competition among banks, the equilibrium loan terms for households who can obtain loans[9] are determined such that households can maximize their utility while keeping

[9]Define the feasible set of contracts, Δ, by all loans that can make both the lender and the household better off than autarky. It can be shown that there exists a critical value $\hat{\theta}$ such that Δ is non-empty if $\theta > \hat{\theta}$, empty otherwise. So households with $\theta > \hat{\theta}$ will become debtors and those with $\theta < \hat{\theta}$ will either stay

banks no worse-off than investing the funds on other assets. So by normalizing bank's opportunity cost of making the loan to zero,[10] optimal loan terms are the solution to the following program.

$$\max_{\langle B_0, B_1\rangle \in \Re^2_+} \quad u(B_0) + \beta \int [u(y-p^*) - c\cdot(B_1 - p^*)] f(y|\theta) dy$$
$$\text{subject to:} \quad \int p^* f(y|\theta) dy - B_0(1 + r_0 + \delta) \geq 0 \tag{4}$$

The interpretation of the above program is the following. Because of the pressure of competition, all loan terms that can make a lender at least better off than autarky, i.e., terms satisfying (4), will be offered by some lenders. Borrowers shop around among different lenders so that in the equilibrium borrowers can maximize their utility while keeping a lender marginally indifferent between lending and autarky. So constraint (4) holds in equality in equilibrium (Milde and Riley, 1988; Calomiris, Kahn and Longhofer, 1994).

The two-period model is not as restrictive as it seems. For multi-period loans, contract terms are usually decided at the time of originations. So it is the expected present values of loan size and payment that matter in determining both borrower's and lender's expected utility. In other words, to map the two-period model into a more realistic multi-period loan, we can interpret B_0 as the purchase price minus downpayment and B_1 as the present value at $t = 1$ of all contractual payments, including monthly payments and other obligations such as closing costs, fees and points.[11]

Finally, because each lender is assumed to be able to obtain loanable funds at the same interest rate r_0, only the least discriminating lender can survive in the competitive market. So we can interpret the lender in the above program as the least discriminating one in the credit markets. Alternatively, we can assume that all lenders are homogeneous in δ. This latter interpretation is useful because the main concern in the public policy debates is whether there exists *widespread* discrimination in credit markets. The model with homogeneous lenders tells us what we could observe if there does so.

For the interior solutions to the above program, the first order condition (FOC) of the

autarky or save.

[10]The normalization can be done as follows. If the opportunity cost of making the loan is $B_0\tau$, then we can redefine the total money cost of funds as $\tilde{r}_0 = r_0 + \tau$.

[11]See also Peterson (1981) for similar arguments.

maximization problem is

$$\frac{1-F(y^*|\theta)}{1+r_0+\delta} = \frac{\beta \int \min(c, u'(y-B_1)) f(y|\theta) dy}{u'(B_0)}. \tag{5}$$

One can interpret the ratio on the left hand side as the *marginal rate of technical substitution* since it is equal to $-\frac{\partial \pi}{\partial B_1}/\frac{\partial \pi}{\partial B_0}$, and the ratio on the right hand side as the *marginal rate of substitution* since it is equal to $-\frac{\partial U}{\partial B_1}/\frac{\partial U}{\partial B_0}$. So in the equilibrium, we have the usual optimization condition for resource allocations: marginal rate of substitution must be equal to marginal rate of technical substitution. This also implies that the equilibrium loan terms are the tangent point between household's and lender's indifference curves. In Figure 3, the tangent points, E^I and E^J, are the equilibrium loans to minority and majority borrowers, respectively.

To see how taste-based discrimination affects the equilibrium contract terms, we conduct a comparative static analysis with respect to δ, to the system consisting of (5) and (4) at equality. The following proposition summarizes the result.

Proposition 1 For borrowers who obtain loans, we have

1. $\dfrac{\partial B_0}{\partial \delta} \le 0$; 2. $\dfrac{\partial B_1}{\partial \delta} \begin{cases} \ge 0, & \text{if } \epsilon_u \ge 1; \\ < 0, & \text{if otherwise;} \end{cases}$ 3. $\dfrac{\partial r}{\partial \delta} \begin{cases} \ge 0, & \text{if } \epsilon_u \ge 1-(1+r)\xi(\theta); \\ < 0, & \text{if otherwise;} \end{cases}$

where $\epsilon_u = -\frac{B_0 U''(B_0)}{U'(B_0)}$ and $\xi(\theta) > 0$.[12]

So if there exists taste-based discrimination against borrower I, i.e., $\delta(I) > \delta(J)$, then the size of the loan to borrower I is smaller than that to borrower J given the same credit worthiness (i.e., $B_0(\theta, \delta(I)) < B_0(\theta, \delta(J))$). But in general, the effects of discrimination on the interest rate r and contractual payment B_1 are ambiguous.

The intuition is the following. When there exists taste-based discrimination, the marginal cost of obtaining a loan for borrower I is higher by δ than borrower J with the same θ. Since a loan is used mainly to smooth consumption over time, we can interpret the higher marginal cost as if the relative "price" of today's consumption is higher for borrower I. The higher price has the usual *substitution effect* and *wealth effect.* By the substitution effect, borrower I would consume less today and relatively more tomorrow, compared to borrower J with the same θ. With other things equal, this implies that borrower I would borrow less today and

[12] To be precise, $\xi(\theta) = \frac{1-F(y^*|\theta)}{1+r_0+\delta} + B_0 \left[\frac{f(y^*|\theta)}{1-F(y^*|\theta)} - \frac{\int_{y^*}^{\overline{y}} U''(y-B_1) f(y|\theta) dy}{\int \min(c, U'(y-B_1)) f(y|\theta) dy} \right] > 0$.

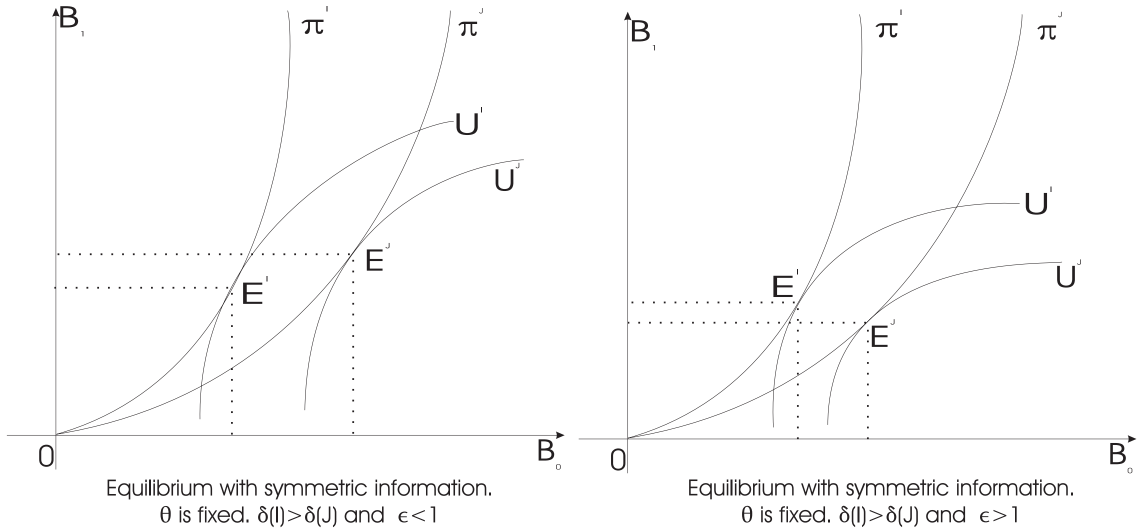

Figure 3: Two examples of equilibrium with symmetric information

have a smaller debt payment tomorrow. By the wealth effect, borrower I would consume less both today and tomorrow, compared to borrower J with the same θ. With other things equal, this implies that borrower I would borrow less today and have a larger debt payment tomorrow. So both the substitution and wealth effects imply that borrower I borrows less today (i.e., smaller B_0) than borrower J given θ. But the effect of discrimination on B_1 is ambiguous: Whether borrower I has larger B_1 depends on whether the wealth effect dominates the substitution effect. The strength of the substitution effect mainly depends on the elasticity of intertemporal substitution between today's and tomorrow's consumption, which is measured by (the inverse of) ϵ_u. By the same reasoning, the effect of discrimination on interest rate is also ambiguous and depends on ϵ_u and other model parameters. The graphs in Figure 3 show two examples of how the equilibrium loans to minority and majority borrowers are compared for $\epsilon < 1$ and $\epsilon > 1$, respectively.

The proposition implies that theoretically, we can only make one clear-cut prediction for the effects of taste-based discrimination: Loans made to borrower I have smaller sizes than loans to borrower J with the same credit worthiness. Without more precise knowledge of the model's parameters, the effects of taste-based discrimination on other equilibrium terms are ambiguous. Because expected loan performance depends on contract terms, this implies that, as shown below, the effects on some measures of expected loan profitability may be also ambiguous.

3.1.2 Expected Loan Profitability

As stated earlier, it has been suggested that one can detect taste-based discrimination by comparing expected loan profitability between different groups of borrowers with similar credit worthiness (Becker, 1993*a*; Peterson, 1981). The profitability measure that a lender ultimately cares about is expected rate of return–expected profits per dollar of loan net of the rate of monetary cost of funds. Because the data needed to estimate expected rates of return are difficult to obtain, previous authors have suggested that the profitability view also hold for alternative measures of expected loan profitability (Footnote 3). So we also examine two of the measures below: expected rate of default loss and default probability.

By our notations, expected rate of return is defined as

$$E(R|\theta,\delta) = \frac{\int p^* f(y|\theta)\,dy}{B_0} - (1 + r_0),$$

with p^* defined as in Lemma 1. So $E(R|\theta,\delta)$ depends on both θ and δ. Since constraint (4) holds as an equality in equilibrium, we have

$$E(R|\theta,\delta) = \delta. \tag{6}$$

That is, because of competition between lenders, the expected rate of return on each loan is just high enough to compensate the psychic cost of lending. Therefore, if there exists taste-based discrimination against borrower I (i.e., $\delta(I) > \delta(J)$), the expected rate of return on loans made to borrower I must be higher than to borrower J with the same θ.

Expected rate of default loss, denoted by $E(\text{loss}|\theta,\delta)$, is defined as the ratio of expected unpaid obligations to loan size, i.e.,

$$E(\text{loss}|\theta,\delta) = \frac{B_1 - \int p^* f(y|\theta)}{B_0} = r(\theta,\delta) - r_0 - \delta. \tag{7}$$

Because

$$\frac{\partial E(\text{loss}|\theta,\delta)}{\partial\delta} = \frac{\partial r(\theta,\delta)}{\partial\delta} - 1, \tag{8}$$

whether expected rate of default loss on loans made to borrower I is lower than to borrower J with the same θ depends on whether the difference in interest rates is smaller than the difference in δ, i.e., whether $\frac{\partial r}{\partial\delta} < 1$. Analytically, because it is ambiguous whether $\frac{\partial r}{\partial\delta}$ is greater than 1, the sign of (8) is also undetermined.

By Lemma 1, default probability, denoted by $\mathrm{P}(\text{default}|\theta,\delta)$, is the probability that the second period income falls below $y^* = B_1(\theta,\delta) + v$. That is,

$$\mathrm{P}(\text{default}|\theta,\delta) = F(y^*|\theta), \tag{9}$$

Because

$$\frac{\partial \mathrm{P}(\text{default}|\theta,\delta)}{\partial \delta} = f(y^*|\theta)\frac{\partial B_1}{\partial \delta}, \tag{10}$$

whether the default probability of the loans approved to borrower I is lower than loans to borrower J depends on whether loans to borrower I have lower contractual payment B_1. Analytically, because the sign of $\frac{\partial B_1}{\partial \delta}$ is undetermined, the sign of (10) is also ambiguous.

3.1.3 Resolving the Ambiguities

The above analysis shows that our theoretical model has two clear-cut predictions: If there exists widespread taste-based discrimination, loans to minority borrowers will have smaller loan sizes and higher expected rate of return than loans to majorities with the same credit worthiness. The model's predictions for other loan terms and other measures of expected loan performance are in general ambiguous. Because the data on rates of return are usually not available, it is desirable to resolve the above ambiguities to yield testable implications for empirical study.

One thing we observe is that the effects of taste-based discrimination seem to depend crucially on the magnitude of the borrower's elasticity of intertemporal substitution (EIS), which depends on the concavity of the utility function, i.e., ϵ_u. In fact, if the utility function has the form of constant relative risk aversion (CRRA), the EIS is the inverse of ϵ_u. Many studies have estimated that EIS is less than 1 (e.g. Ogaki and Reinhart, 1998), which implies that $\epsilon_u > 1$ for a CRRA utility function. If this is the case, Proposition 1 implies that loans to minority borrowers have higher contractual payments and interest rates, and hence, higher default probability than loans to majority borrowers with the same θ (by (10)). Still we don't know for sure whether the expected rate of default loss is higher or lower for minority borrowers, because it is still ambiguous whether $\frac{\partial r}{\partial \delta}$ is greater than 1.

Our model also suggests an alternative approach to resolving the ambiguities. Recall that we use the discrimination coefficient δ to model the lender's marginal disutility caused by taste. Note also that δ enters lender's utility the same way the marginal money cost of lending r_0 does. So the effects of δ on equilibrium loan terms and expected profitability should be the same as the effects of r_0 on these variables. That is,

$$\frac{\partial x}{\partial r_0} = \frac{\partial x}{\partial \delta}, \tag{11}$$

where x is an endogenous variable such as a loan term or a measure of expected loan profitability. Hence, if we can obtain the empirical relationship between x and r_0, we can deduce the empirical relationship between x and δ. Below we show our estimates of $\frac{\partial r}{\partial r_0}$ and $\frac{\partial \mathrm{P(default)}}{\partial r_0}$. By (8) and (10), the estimates allow us to make inferences on $\frac{\partial \mathrm{E(loss)}}{\partial r_0}$ and $\frac{\partial B_1}{\partial r_0}$. We first discuss the data and the specifications we use, then present the results and discuss the robustness of the estimations. We then use (11) to deduce the effects of δ on these variables.

Data

The ideal data to estimate the empirical relationship between $r, \mathrm{P(default)}$ and r_0, are cross-sectional micro data on not only interest rate and default incidence but also the banks' cost of funds for each individual loan. In the absence of such data, we use annual data on the average terms and default rates of conventional mortgage loans originated in 1971-1997. Specifically, the nominal loan rate is measured by the average effective interest rate constructed by Federal Home Loan Banks (FHLB) on the mortgages closed. It equals the contract rate plus amortized fees, commissions, discounts, and "points," assuming prepayment at the end of 10 years. We use the foreclosure rate of conventional mortgage loans as a measure of the default rate. The data are from the National Delinquency Survey. The foreclosure rate used here is the average number of foreclosures started among 100 mortgages in a calendar year. We use three alternative measures of the cost of funds: 6-month CD rate, 3-year and 10-year Treasury bill rates. The terms of the cost of funds are shorter than the maturities of the average mortgage loans because banks usually borrow short and lend long. Real rates are used in our regressions. To compute real cost of funds and real interest rates of the mortgage loans, we subtract expected inflation rates from the nominal rates. The expected inflation rates are from the Livingston Survey by the Federal Reserve Bank of Philadelphia.

Estimating $\frac{\partial r}{\partial r_0}$ and Inferring $\frac{\partial E(loss)}{\partial r_0}$

We regress r on r_0 as well as other two variables: personal disposable income per capita and average purchase price of the housing units. Both variables are in log and in 1996 dollar. For each measure of the cost of funds, we report the result from an OLS regression as well as the result from a regression with the assumption that the regression error follows an AR(1) process. The results are shown in Table 1.

Table 1: Regressions of effective mortgage rate on three alternative measures of the cost of funds r_0

	r_0 =6-mon CD		r_0 =3-yr T-bill		r_0 =10-yr T-bill	
	OLS	AR(1)	OLS	AR(1)	OLS	AR(1)
r_0	0.59 (0.13)	0.40 (0.15)	0.88 (0.08)	0.86 (0.09)	0.96 (0.07)	0.97 (0.07)
income	0.07 (0.03)	0.05 (0.06)	0.02 (0.02)	0.03 (0.02)	-0.01 (0.02)	-0.00 (0.02)
house price	-0.05 (0.04)	-0.03 (0.05)	-0.01 (0.02)	-0.02 (0.03)	0.01 (0.02)	0.00 (0.02)
ρ		0.61 (0.16)		0.18 (0.19)		0.01 (0.20)
R^2	0.47	0.17	0.83	0.80	0.91	0.90

Figures in parentheses are standard errors. Intercepts are not shown.
Data are from Federal Reserve Bulletin, 1971-1997. All variables are in real terms.

All regressions show that the effect of the cost of funds on mortgage rates is positive but less than one-to-one: A one percentage point increase in the cost of funds leads to less than a one percentage point increase in mortgage rates. The estimates are all statistically significant. This finding is similar to that by Berger and Udell (1992), where they found that the interest rates of commercial loans increase with the cost of funds, but by less than one-to-one. The autocorrelation of the regression error is only significant when the cost of funds is measured by 6-month CD rate. By (7), the above result also implies that the effect of the cost of funds on expected rate of default loss is negative, because

$$\frac{\partial E(\text{loss})}{\partial r_0} = \frac{\partial r}{\partial r_0} - 1 < 0.$$

Estimating $\frac{\partial P(default)}{\partial r_0}$ *and Inferring* $\frac{\partial B_1}{\partial r_0}$

Since most mortgages don't default right away, it makes sense to link foreclosure rates in year t to the market condition in year $t - l$. We conduct experiments by varying the lag l from zero to five years because most of defaults occur in the first several years (e.g. Quigley and Van Order, 1995). Since the results from those experiments are similar, we only report those with $l = 3$. As above, for each measure of the cost of funds, we report the results from both an OLS regression and a regression with an AR(1) error process. They are shown in Table 2.

Table 2: Regressions of foreclosure rate on three alternative measures of the cost of funds r_0

	r_0 =6-mon CD		r_0 =3-yr T-bill		r_0 =10-yr T-bill	
	OLS	AR(1)	OLS	AR(1)	OLS	AR(1)
r_0	0.36 (0.19)	-0.01 (0.22)	0.49 (0.20)	0.23 (0.25)	0.56 (0.20)	0.38 (0.25)
income	0.30 (0.04)	0.26 (0.07)	0.28 (0.04)	0.26 (0.06)	0.26 (0.04)	0.25 (0.06)
house price	0.18 (0.05)	0.20 (0.07)	0.19 (0.05)	0.20 (0.06)	0.21 (0.05)	0.21 (0.21)
ρ		0.57 (0.16)		0.44 (0.17)		0.39 (0.18)
R^2	0.94	0.74	0.94	0.83	0.95	0.87

Figures in parentheses are standard errors. Intercepts are not shown.

Data are from Federal Reserve Bulletin, 1971-1997. All variables are in real terms.

The table shows that the effects of the cost of funds on foreclosure rates are positive and significant in all OLS regressions. When estimated with serially correlated error terms, the effects are still positive except when the cost of funds is measured by 6-month CD rate, but all estimates become statistically insignificant.[13] By (10), the positive correlation between foreclosure rate and the cost of funds suggests that $\frac{\partial B_1}{\partial r_0} > 0$, i.e., the effect of the cost of funds on contractual payments is positive.

Robustness

To check the robustness of the above empirical results, we conduct a number of other experiments. First, we use ex post inflation and adaptive expected inflation in computing real interest rates and real cost of funds. Second, we study foreclosure rates in the FHA mortgage loans and the overall mortgage market for the same sample period. We also study the relationship between the foreclosure rate and the cost of funds in the period of 1933-1968 using the data compiled by Glen (1975). All exercises produce similar results as reported above.

To make sure the above inference on $\frac{\partial B_1}{\partial r_0}$ is consistent with data, we study empirically how B_1 is affected by r_0. We find that B_1 (measured by debt services burden) is significantly positively correlated with r_0. We also find that B_0 (measured by loan-to-value ratio) is weakly negatively correlated with r_0.

[13] All regressions also reveal that foreclosure rates are positively correlated with real disposable income! This seems contradict to the conventional view that financial distress is counter-cyclical. Using foreclosure rates for the period of 1933-1968 compiled by Glen (1975), we found that foreclosure rates are positively correlated with the cost of funds (measured by real one-year commercial paper rate), but negatively correlated with log real per capita disposable income.

Implications for the Effects of Taste-Based Discrimination

Our empirical analysis shows that $\frac{\partial r}{\partial r_0}$, $\frac{\partial B_1}{\partial r_0}$, and $\frac{\partial \mathrm{P(default)}}{\partial r_0}$ are all positive, and that because $\frac{\partial r}{\partial r_0} < 1$, $\frac{\partial E(\mathrm{loss})}{\partial r_0} < 0$. By (11), the effects of the variable psychic cost δ have the same properties: $\frac{\partial r}{\partial \delta}$, $\frac{\partial B_1}{\partial \delta}$, and $\frac{\partial \mathrm{P(default)}}{\partial \delta}$ are all positive, and that $\frac{\partial E(\mathrm{loss})}{\partial \delta} < 0$. In other words, they imply that if there exits taste-based discrimination and the psychic cost is variable, loans to minority borrowers should have higher interest rates, larger contractual payments and default rates, but smaller expected rate of loss than loans to majority borrowers with the same credit worthiness. These results are also consistent with those when assuming $\epsilon_u > 1$.

3.2 Results with Fixed Psychic Cost

The above empirical approach to resolving the analytical ambiguities depends on the assumption that the psychic cost is proportional to the size of transaction. As mentioned earlier, because of the nature of credit application process, it may not be unreasonable to argue that the amount of interactions between loan officer and borrower, and in turn, the psychic cost of taste, is independent of loan size. How will the model's predictions change if we assume fixed psychic cost? Let the fixed psychic cost be D. Then the lender's utility function is

$$\pi(\langle B_0, B_1\rangle) = \int p^* f(y|\theta)\, dy - B_0(1 + r_0 + \delta) - D, \tag{12}$$

where p^* is determined as in Lemma 1. The equilibrium loan terms can be found by replacing (4) with the above utility function. Comparative static analysis leads to the following results.

Proposition 2 Given θ,

1. $\frac{\partial B_0}{\partial D} \leq 0$, $\frac{\partial B_1}{\partial D} \geq 0$, $\frac{\partial r}{\partial D} \geq 0$;

2. $\frac{\partial E(R)}{\partial D} \geq 0$, $\frac{\partial E(\mathrm{loss})}{\partial D} \geq 0$, $\frac{\partial P(\mathrm{default})}{\partial D} \geq 0$.

So the effects of fixed psychic cost on loan terms and expected loan performance are qualitatively the same as those of proportional psychic cost, except that loans to minority borrowers now have a *higher* expected rate of default loss than loans to majority borrowers with the same credit worthiness.

3.3 Summary

We now summarize both our results as "Result T" (with "T" for taste-based discrimination):

Result T Given the same credit worthiness θ,

1. the strongest predictions of taste-based discrimination are that loans to minority borrowers have smaller size and higher expected rate of return than loans to majority borrowers;

2. empirical evidence also suggests that loans to minority borrowers have higher interest rates, larger contractual payments and higher default probability;

3. if the psychic cost of lending is proportional to the size of transaction, loans to minority borrowers should have smaller expected rate of default loss; but if the psychic cost is independent of the size of transaction, loans to minority borrowers should have higher expected rate of default loss.

Our results show that the commonly held profitability hypothesis - that taste-based discrimination implies that loans to minorities should have higher expected profitability - may only hold when the appropriate measure, namely expected rate of return, is used. It is very likely that, for example, default probability for loans to borrower I is higher than loans to borrower J given θ.

4 Statistical Discrimination

In the previous section, we assumed that a borrower's credit worthiness is determined by a set of variables Z and that both the lender and the borrower can observe Z. Recall that we also assume that Z does not contain group identity g (Assumption 1). So given Z, the intergroup differences in equilibrium loan terms are solely determined by lenders' tastes. In this section, we consider the case when borrowers possess some private information about Z. Here lenders have pecuniary incentives to use the least-costly method to obtain additional information to form finer estimates of borrowers' credit worthiness. Therefore, when group identity is correlated with the information private to borrowers, lenders would use it as a predictor of a borrower's credit worthiness. This practice is called "statistical discrimination." When statistical discrimination occurs, equilibrium terms of loans to different groups of borrowers with the same observables would be different, even if there is no taste-based discrimination.

To fix ideas, let $Z = [X, H]$ where X contains variables that are observable to both lenders and borrowers, and H contains the borrower's private information (H for "Hidden" information). For simplicity, we consider a case in which group identity is a perfect proxy of the unobservables, i.e.,

$$\theta(X, H) = \theta(X, g). \tag{13}$$

Statistical discrimination against minorities occurs when

$$\theta(X, I) < \theta(X, J). \tag{14}$$

We first present the analytical results on the effects of statistical discrimination on equilibrium loan terms and expected performances. It turns out that without more precise information on the model's parameters, some of the effects are ambiguous. We then propose a method to empirically resolve some of the ambiguities. Finally, we discuss the implications of labor market discrimination, a case where Assumption 1 is violated. To contrast with the effects of taste-based discrimination, we assume that there is no taste-based discrimination in this section.

4.1 Analytical Results

4.1.1 Loan Terms

As above, the equilibrium loan terms still satisfy the FOC (5) and are the tangent points between household's and lender's indifference curves (Figure 4). The question we are interested in is: Given X, how do the terms of loans to borrower I differ from those to borrower J? Because of (14), we can answer this question by analyzing the effects of lower θ on equilibrium contract terms. This is done by conducting a comparative static analysis with respect to θ, applied to the system consisting of FOC (5) and constraint (4) at equality.

The comparative static analysis is shown in Appendix. There we show that the model has only one clear-cut analytical prediction:

Proposition 3 $\frac{\partial B_0}{\partial \theta} \geq 0$.

That is, equilibrium loan size is increasing in θ. In general, the effects of higher θ on B_1 and r, i.e., the signs of $\frac{\partial r(\theta,\delta)}{\partial\theta}$ and $\frac{\partial B_1(\theta,\delta)}{\partial\theta}$, are ambiguous.

Intuitively, since borrowers with higher θ have higher average future income, they gain more from substituting today's consumption for future consumption. So they would borrow more today. Higher θ means lower risk for given loan size, but larger loan size for higher credit worthiness borrowers could increase the default risk. So it is unclear whether default probability is increasing or decreasing in θ, which in turn implies the effects of higher θ on interest rate r and contractual payment B_1 are also ambiguous. Figure 4 shows an example of how loans to minority and majority borrowers (E^I and E^J, respectively) are related in the equilibrium . There both B_0 and B_1 are larger, but r is lower for majority borrowers.

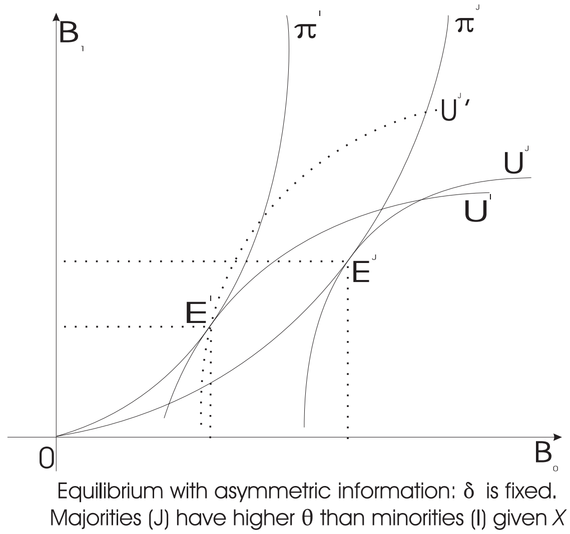

Figure 4: An example of equilibrium with asymmetric information

The comparative static analysis shows that if there exists only statistical discrimination, loans approved to borrower I have smaller sizes than loans to borrower J given X. But without further knowledge of the model parameter, the effects of statistical discrimination on other terms would be unclear. This also suggests that, as shown below, the effects of statistical discrimination on some measures of expected loan profitability be ambiguous.

4.1.2 Expected Loan Profitability

As above, we study three alternative measures of expected loan performance. By (6), expected rate of return on loans to any borrower should be just enough to offset the marginal disutility caused by taste, measured by the discrimination coefficient δ. So if $\delta(I) = \delta(J)$, i.e., in the absence of taste-based discrimination, expected rates of return must be same for the loans made to both borrowers I and J whether there exists statistical discrimination.

For expected rate of default loss, (7) implies that

$$\frac{\partial E(\text{loss}|\theta,\delta)}{\partial\theta} = \frac{\partial r(\theta,\delta)}{\partial\theta}. \tag{15}$$

Since the effect of lower credit worthiness on r (i.e., the sign of $\frac{\partial r(\theta,\delta)}{\partial\theta}$) is in general ambiguous, the effect of statistical discrimination on expected rate of default loss is also ambiguous.

The effect of lower θ on default probability is also ambiguous. To see this, use (9) to obtain

$$\frac{\partial \mathrm{P}(\text{default}|\theta,\delta)}{\partial\theta} = f(y^*|\theta)\frac{\partial B_1}{\partial\theta} + F_\theta(y^*|\theta), \tag{16}$$

with $y^* = B_1 + v$ (see Lemma 1). That is, θ affects default probability through both B_1 and cumulative distribution function F. First, although default probability is increasing B_1 given θ, whether B_1 is increasing in θ is in general ambiguous. So the sign of the first term on the right hand side cannot be determined. Second, given B_1, default probability is decreasing in θ (Assumption 3). So the sign of the second term on the right hand side is negative. In general the net effects of the two parts are not clear.

In summary, the theoretical model predicts that statistical discrimination implies that loans to minority borrowers have smaller sizes than, but the same expected rate of return as, loans to majority borrowers with the same observable characteristics at the time of loan originations. In general, however, the analytical prediction for the effects of statistical discrimination on other loan terms and other measures of expected loan performance depends on the model's parameters. In the following section, we propose an empirical approach to resolve some of the ambiguities.

4.2 Deducing the Effects of Statistical Discrimination

4.2.1 The Approach

Our approach to resolving the ambiguities in the analytical predictions of statistical discrimination is the following. Suppose that we are interested in a variable, say T, where T can be the interest rate, a measure of expected loan performance or other endogenous variables. Because the existence of statistical discrimination implies that minority borrower's credit worthiness is lower than majority borrower's credit worthiness given other measured characteristics (see (14)), the effects of statistical discrimination on T should be *qualitatively* the same as the effects of lower credit worthiness. So we can use empirical relationship between T and some determinants of credit worthiness to make inference on how statistical discrimination affects T. For example, if we know that credit worthiness is increasing in borrower's income, and that T is increasing in borrower's income, then we claim that if there exists only statistical discrimination, minority borrowers should have lower T.

To state our approach precisely, write $X = (x_i, x_{-i})$, where x_i indicates, say, borrower's income, and x_{-i} variables other than x_i. Suppose that we know $\theta(X, g)$ is increasing in x_i and decreasing in g in the range of the data. Then the sign of $\frac{\partial T}{\partial x_i}(= \frac{\partial T(\theta(X,g))}{\partial \theta}\frac{\partial \theta}{\partial x_i})$ will be the opposite of the sign of $\frac{\partial T}{\partial g}(= \frac{\partial T(\theta(X,g))}{\partial \theta}\frac{\partial \theta}{\partial g})$. So we first estimate how T is related to x_i, and then make inference on how T would be related to g. To isolate the effect of statistical discrimination, however, we also have to strip away the variations in T caused by possible taste-based discrimination. The way to do so is to estimate the correlation between T and determinants of credit worthiness for a *single* group.

4.2.2 Data

The dataset consists of a random sample from records of FHA-insured single-family mortgage loans originated over the 1987-88 period. Information about loan status and other characteristics of the loans is drawn from two files maintained by the U.S. Department of Housing and Urban Development (HUD): the F42 EDS Case History File and the F42 BIA Composite File. The data contain information on a number of loan, debtor, and property-related characteristics at the time of loan originations and are augmented with 1980 and 1990 census tract characteristics so as to proxy neighborhood attributes where the properties are located. The data we obtain do not have detailed information on mortgage rates and contractual payments. But they do indicate loan defaults occurred through the first quarter of 1993, where defaults are defined as terminations caused either by lender foreclosure or because the borrower conveys title of the property to the lender in lien of foreclosure. For defaulted loans that have been settled, information is available on the size of the loss incurred by FHA after disposition of the property and settlement of outstanding claims.[14] So the

[14]Although FHA loan are guaranteed, they are not risk-free to banks. The losses incurred by banks in case of default may be proportional to the losses incurred by FHA so that the variations in the bank's losses may be similar to those in FHA's losses. The reasons are, first, FHA only reimburses 2/3 of attorney

variables T we can estimate are default probability and expected rate of default loss. Note that because settlements of defaulted loans are time-consuming, information on the size of default loss is only available for a fraction of defaulted loans. Among the total of 100013 loans, 5203 (or 5.2%) of these loans have been defaulted and 785 defaulted loans have been settled.

The independent variables X in our estimation include the variables characterizing the attributes of the borrower, the property and the neighborhood. So X does not contain any endogenous variables such as loan-to-value and debt-to-income ratios. To be more specific (see Table 4), X includes variables on borrower's characteristics and household balance sheet: borrower's race, age, gender, marital status, the number of dependents, total liquid assets and income at the time of loan originations, percentage of income from non-salary sources, percentage of income from co-borrower. X also includes characteristics of the property: appraisal value at origination and its squared value, the state where the property is located; and of the neighborhood: census tract (CT) median income, changes in median value of home in CT, median age of property in CT, vacancy rate of 1-4 units houses in CT, percentage black in CT, unemployment rate in CT, percentage houses for rent in CT, and regional dummies. A dummy variable indicating whether a observation is from the 1987 or 1988 cohort is also included. Finally, observations with missing values on any of the above variables are deleted. Definitions and sample statistics of those variables are shown in Tables 4 and 5, respectively.

4.2.3 Estimation Method

We consider separately two groups of borrowers: minority (including Black and Hispanics) and Whites. Sample statistics of default rate and rate of default loss for each group are shown in Tables 6 and 7, respectively. What we want to estimate is, for a single group of borrowers, the relation between default probability and expected rate of default loss and the observable characteristics that determine credit worthiness at the time of loan originations.

fees to the banks in the foreclosure process; Second, most of FHA loans are sold on the secondary market. When a loan is defaulted, banks have to keep making payments to investors until the title of the property is transferred to FHA. But FHA doesn't reimburse interest payments in the first month of default, and FHA reimburses other months' interest payments according to a debenture rate. Since the debenture rate is a weighted average rate of all government securities, it has always been lower than mortgage loan rate. Finally, it is also reasonable to think that other administrative costs incurred by banks are proportional to the size of default. So although FHA loans are not the ideal data to exam credit market discrimination, they are useful for our purpose.

Denote default by $d = 1$ and non-default by $d = 0$. Let

$$I = X\beta + \nu \tag{17}$$

so that $d = 1$ if $I > 0$ and $d = 0$ otherwise. Recall that we use "loss" to denote ex post rate of default loss. Let

$$\text{loss} = E(\text{loss}|X) + \epsilon = X\alpha + \epsilon. \tag{18}$$

That is, ϵ is the projection error of expected rate of default loss. So ϵ is uncorrelated with X. Assume that ϵ and ν are binomially distributed with correlation ρ. Normalize the standard deviation of ν to 1 and denote the standard deviation of ϵ by σ_ϵ. We use a maximum likelihood (ML) method to jointly estimate (17) and (18).

In writing the ML function, we also take into account the fact that we cannot observe the realized rate of default loss for all defaulted loans, because some of those cases are not settled. Let k be the probability of observing default loss conditional on default. We assume that whether a defaulted loan is settled is independent of ν and ϵ. The ML function is

$$\begin{aligned} \log L = & \sum_{\text{non-default}} \log \Phi(-X\beta) + \\ & \sum_{\text{defaulted but loss unobservable}} \log[(1-k)\cdot\Phi(X\beta)] + \\ & \sum_{\text{defaulted and loss observable}} \log[k \cdot \text{Prob}(I > 0) f(\text{loss}|I > 0)] \end{aligned} \tag{19}$$

Note that the relations we are interested in are reduced-form in the sense that they are mappings from the exogenous characteristics at the time of loan originations to default probability and expected rate of default loss. So in our regressions, no endogenous variables, such as loan-to-value ratios, are included in X (more on this in Section 5). The covariates in both estimations include all exogenous variables observed at the time of loan originations.

4.2.4 Results

The results of the regressions are shown in Tables 8. For the purpose of deduction, we first have to know how each variable is related to credit worthiness, or in our model, the distribution of future income (including future house value). Although we don't have clear-cut priors on the relationships between all variables and credit worthiness, we have high confidence in variables such as income, liquidity assets and neighborhood house value. Since income is usually positively correlated over time, higher initial income is an indicator of better future income distribution (in FOSD sense), and in turn, higher credit worthiness given other variables constant. The same can also be said to liquid assets and neighborhood house value. The tables show that both default probability and expected rate of default loss are negatively correlated with initial income, liquid assets and changes in the neighborhood house value, although the correlations are not always statistically significant for income. From this, we can conclude that both default probability and expected rate of default loss are negatively correlated with credit worthiness. Therefore, if there exists statistical discrimination, loans approved to minority borrowers should have higher default probability and expected rate of default loss, and by (15), higher interest rates, than loans to majority borrowers with the same observable characteristics.

We now summarize our analytical results and empirical findings as "Result S" (with "S" referring to statistical discrimination):

Result S Suppose there is no taste-based discrimination. Given the same characteristics observed at the time of loan originations,

1. if there exists statistical discrimination, then loans made to minority borrowers have smaller sizes than, but the same expected rate of return as, to majority borrowers;

2. for the FHA mortgage loans we studied, statistical discrimination against minorities implies that loans to minority borrowers should have higher interest rates, default probabilities and expected rates of default loss than to majority borrowers.

4.3 A Remark on Labor Market Discrimination

So far, we assume that the determinant Z of credit worthiness does not contain group identity, or $\theta(Z) = \theta(Z, g)$. In the case of symmetric information, lenders observe Z. In the case of asymmetric information, lenders only observe part of Z, and the unobservables are assumed to be correlated with group identity. A closely related but conceptually different situation is when information is symmetric but group identity is a predictor of future income distribution even after controlling all other variables. That is, lenders observe Z, but $\theta(Z) \neq \theta(Z, g)$. For instance, if there exists labor market discrimination against borrower I, the income distribution of borrower I may be riskier (for instance, in the FOSD sense) than that of borrower J with the same Z. The observed differences in screening, contract terms and expected loan performance between different groups of borrowers are exactly the same as what we observe in the model of statistical discrimination with X, H replaced by Z, g, respectively.

5 Detecting Taste-Based Discrimination: Theory and Some Evidence

Based on both analytical and empirical results in the previous sections, we now try to figure out if we can develop some measures to distinguish taste-based discrimination from statistical discrimination. As mentioned above, we keep the assumption throughout the paper that researchers know all information that banks know.

The task of detecting taste-based discrimination is easy when information on Z is symmetric. Because statistical discrimination is impossible under symmetric information, taste-based discrimination is the only possible cause of any observed variations in rejection rates, loan terms, and expected loan performance among different groups of borrowers with the same Z. In other words, any observed intergroup difference in those variables is the evidence of taste-based discrimination. In particular, given Z, any of the following suggests there exists taste-based discrimination against minorities: That (i) expected rates of return on loans approved to minority borrowers are higher than loans to majorities; (ii) loans approved to minority borrowers have smaller sizes, larger contractual payments, higher interest rates, or higher default probabilities than loans to majorities (see Result T).

Under asymmetric information, the observed intergroup differences in the above variables may be caused by either taste-based or statistical discrimination or both. Logically, in order to determine whether the cause is at least partly taste-based discrimination, we have to find out whether those differences can only be caused by taste-based discrimination. Below we show that conditional expected rate of return can be used to detect taste-based discrimination. But without more precise knowledge of the model's parameters, we cannot use loan terms or other measures of expected loan profitability to detect taste-based discrimination. So we have to rely on the empirical results established in the previous sections to develop reasonable measures. We also discuss the key methodological implications of our analysis. Finally, we present some empirical analysis of detecting taste-based discrimination.

5.1 Expected Rate of Return as A Measure of Prejudice

We tabulate our results from the previous sections in Table 3. The upper panel shows the analytical results, and the lower panel the results from empirical deductions. Analytically, both taste-based and statistical discrimination imply that loans to minority borrowers would have smaller sizes than loans to majority borrowers with the same observables. But if there exists only statistical discrimination, expected rate of return should be the same for loans to both minority and majority borrowers. If there exists taste-based discrimination, the loans approved to minority borrowers should have higher expected rates of return, by the magnitude of $\delta + \frac{D}{B_0}$, than the loans to majority borrowers. Therefore, the following is true.

Proposition 4 If expected rate of return on the loans approved to minority borrowers is strictly higher than the loans to majorities with the same exogenous characteristics observed at the time of loan origination, then there exists taste-based discrimination against minorities. Moreover, the difference in expected rate of return is a measure of the magnitude of taste-based discrimination.

This result confirms the claims made in Peterson (1981) and Becker (1993a,b) that we can compare expected loan performance of the loans approved to different groups of borrowers to detect taste-based discrimination, *provided that we measure expected loan performance by conditional expected rate of return.* The result also stresses that expected rate of return is a valid measure of not only the existence but also the magnitude of taste-based discrimination. Moreover, the result is robust in the sense that that loans to minority borrowers have higher expected rate of return is a sufficient and necessary condition for the existence of taste-based discrimination against minorities.

It is important to note that the appropriate econometric method to implement Proposition 4 should be reduced-form regressions. That is, we want to estimate how expected rate of return is related to the exogenous variables observed at the time of loan origination that determines borrower's credit worthiness. The previous studies often estimate a structural form relationship between a measure of profitability and group identity, in the sense that some endogenous variables such as loan-to-value ratios are also included as independent variables (e.g., Berkovec et al. (1994,1998)). However, under our assumption that researchers know all variables that banks use in underwriting, structural form regressions are not ap-

Table 3: Comparing the effects of taste-based discrimination with the effects of statistical discrimination

	Taste-based discrimination	Statistical discrimination
	Analytical results	
Loan sizes	$B_0^I < B_0^J$	$B_0^I < B_0^J$
E(rate of return)	$\mathbf{E(R)^I > E(R)^J}$	$\mathbf{E(R)^I = E(R)^J}$
	Results deduced from empirical analysis	
Contractual payments	$B_1^I > B_1^J$	ambiguous
Interest rate	$r^I > r^J$	$r^I > r^J$
Default probability	$\mathrm{P}^I > \mathrm{P}^J$	$\mathrm{P}^I > \mathrm{P}^J$
E(rate of default loss)	$\mathbf{E(loss)^I < E(loss)^J}$ (proportional psychic cost) $\mathrm{E(loss)}^I > \mathrm{E(loss)}^J$ (fixed psychic cost)	$\mathbf{E(loss)^I > E(loss)^J}$
	I: minority; J: majority	

propriate methods to test Proposition 4.[15] The reason is that, given the same loan terms and the characteristics other than group identity, the intergroup variations in expected rate of return are determined solely by the statistical correlation between group identity and credit worthiness. So by controlling loan terms and other exogenous variables, structural form regressions cannot uncover the effects of taste. Intuitively, if a lender has a taste for discrimination, the only way he/she can compensate the higher psychic cost in lending to the *approved* borrowers is to adjust the loan terms to achieve higher profits. Thus, in order to detect the taste, we have to allow loan terms to vary across groups of borrowers.

For the mortgage market, the ideal data to apply Proposition 4 should be disaggregated micro data with three sets of information: characteristics of borrower, property and neighborhood at the time of loan origination; loan terms such as contract rate, closing cost, "points," and downpayments etc.; and history of loan performance. Since most defaults on mortgage loans occurs in the first several years, a partial history could also be sufficient. The first

[15]Because of this, Berkovec et al. (1994,1996) relied on the assumptions that researchers cannot observe some of the information that banks used in underwriting, which Ross and Yinger (1999) called "unobserved underwriting variables." Under their assumption, their model "essentially replicates the comparison of average default rates, except that the influence of observed underwriting variables has been removed before the calculation of intergroup differences in default" (Ross and Yinger (1999) pp. 109-110). Previous authors have pointed out the limitations of using average default rate to detect taste-based discrimination. For example, the validity of average default rate as a measure of taste-based discrimination depends on the assumption that the distribution of the unobservables is the same for both minority and white borrowers (Browne, 1993; Tootell, 1993). Because loan terms are endogenous, there are also difficult econometric problems in structural form regressions (Yezer, Phillips and Trost, 1994).

set of information allows the researcher to make controlled comparisons between different groups of borrowers. The last two sets of information should be enough for the researcher to compute realized rate of return for both defaulted and non-defaulted loans.

5.2 A Measure Derived from Empirical Deductions

Despite of the robustness of Proposition 4, the data required to carry out the test are extremely hard to obtain. So alternative measures of loan performance, such as default rates and expected rates of default loss, or loan terms, have been suggested to replace rate of return (Peterson, 1981; Schafer and Ladd, 1981; Becker, 1993*a*; Becker, 1993*b*; Berkovec, Canner, Gabriel and Hannan, 1996). But without more precise knowledge of the model's parameters, those measures are generally not useful. This is because analytically, the effects of both taste-based and statistical discrimination on interest rates, contractual payments, default rates, and expected rates of default loss are in general ambiguous. However, in the previous sections, we were able to resolve some of these ambiguities by using empirical evidence to deduce the effects of discrimination. We now sort out the unique effects of taste-based discrimination implied by these deductions.

In the lower panel of Table 3, we compare the effects of taste-based discrimination (Result T) with the effects of statistical discrimination(Result S). The Table shows that contractual payments as well as interest rates and default probability are not reasonable measures of taste-based discrimination, since both taste-based and statistical discrimination can have similar predictions for the relations between these variables and group identity (given X). Specifically, both types of discrimination imply that loans to minority borrowers have higher interest rates and default probabilities than loans to majorities with the same exogenous variables at the time of originations.

The Table does suggest that if there does not exist taste-based discrimination, expected rate of default loss on loans made to minority borrowers should be no smaller than those on loans to majority borrowers with the same observables. On the other hand, if there exists taste-based discrimination, expected rate of default loss can be smaller for loans made to minority borrowers. Hence, to detect taste-based discrimination, we can compare expected rate of default loss on loans to different groups of borrowers, as stated in the following proposition.

Proposition 5 Under Results T and S, if the loans made to minorities have lower expected rate of default loss than the loans to majorities with the same exogenous characteristics observed at the time of loan originations, then there exists taste-based discrimination against minorities.

Note that Proposition 5 provides only a sufficient condition for detecting taste-based discrimination. To see this, consider a regression of rate of default loss on variables X and a dummy variable g indicating group identity. In particular, $g = 1$ for minority borrowers, $g = 0$ for majority borrowers. Let the coefficient of g be β. Under asymmetric information, the intergroup difference in the rate of default loss reflects the net effect of possible taste-based discrimination, denoted by β_t and statistical discrimination, denoted by β_s. That is, $\beta = \beta_t + \beta_s$.

By Result T, $\beta_t \leq 0$ if the psychic cost of taste is proportional to the loan size, and $\beta_t \geq 0$ if the psychic cost is fixed, with equality if there is no taste-based discrimination. By Result S, $\beta_s \geq 0$, with equality if there is no statistical discrimination. So if the regression shows that $\beta < 0$, we must have $\beta_t < 0$, indicating the existence of taste-based discrimination (and that the psychic cost of taste is at least partly proportional to the loan size). However, if $\beta \geq 0$, it does not necessarily imply that $\beta_t = 0$. It might be that either $\beta_t < 0$ but its absolute value is smaller than β_s, or the psychic cost is fixed. So although lower expected rate of default loss for minority borrowers is sufficient for us to claim that there exists taste-based discrimination, the converse is not necessarily true.

As above, the empirical method to apply Proposition 5 should be reduced-form regressions. But the data requirement is less demanding. In order to compute the realized rate of default loss, we only need to know loan size and the amount of contractual obligations written off in default. Of course, we also need to know borrower and neighborhood characteristics at the time of loan origination to make the controlled comparisons between different groups of borrowers. Because the realized rate of default loss is a limited dependent variable, appropriate econometric methods, such as the one developed in Section 4.2, should be used to estimate expected rate of default loss.

5.3 Some Empirical Evidence

This section presents an empirical test of the existence of taste-based discrimination. The testing hypothesis is based on Proposition 5. We use the data on FHA loans used in Section 4.2. Our goal is to estimate how expected rate of default loss varies with group identity conditional on other determinants of credit worthiness. As in Section 4.2, the estimation is carried out by using a maximum likelihood (ML) method to jointly estimate (17) and (18). The ML function is the same as (19). The only differences from Section 4.2 are that we use the sample with both minority and majority borrowers and that a group dummy variable, explained below, is included in the regressors. We want to test if the coefficients of minority dummy variables are strictly negative.

Although Berkovec, Canner, Gabriel and Hannan (1998) studied the rate of default loss using the same data set, our test is different from theirs in two ways. First, as argued in Section 5, our theory suggests that we estimate a reduced-form relationship between rate of default loss and group identity. That is, in our regression, independent variables contain only exogenous variables observed at the time of loan originations. In theirs study, endogenous variables such as loan-to-value ratio are also included as independent variables. Second, we use a maximum likelihood method in our estimations to take into account the fact that the realized rate of default loss is a limited dependent variable, while they use ordinary least squared regressions.

Table 7 displays average rate of default loss for those defaulted loans whose cases are settled. On average, the realized rate of default loss is highest on loans to black borrowers (43%) and lowest on loans to white borrowers (35%). The differences in the average rate of default loss among different groups of borrowers, however, cannot serve as the ultimate criterion to determine whether there exists taste-based discrimination against minorities, because they may be due to differences in factors other than race, such as income, house values, etc. Hence we have to rely on a regression approach to control the impacts of other factors.

Table 9 reports two maximum likelihood estimations: the first is with black and Hispanics dummies; the second with minority dummies. The results show that the coefficients of group dummies are positive and statistically significant (except for Hispanic). That is, given other exogenous variables observed at the time of loan applications, loans to minority borrowers have higher default probability and higher expected rate of default loss than loans to majorities. In particular, the expected rates of default loss on loans to black and Hispanics borrowers are, respectively, 4% and 1% higher than loans to whites with the same other determinants of credit worthiness. By Proposition 5, we cannot reject the null hypothesis of non-existence of taste-based discrimination.

Note that despite non-rejection of the null hypothesis, conclusive claims on the existence of taste-based discrimination cannot be made. As pointed out in Section 5, theoretically, that expected rate of default loss is lower for loans made to minority debtors than loans to majorities is only a sufficient but not necessary condition for one to observe the actual occurrence of taste-based discrimination. When statistical and taste-based discrimination coexist, we can observe actual taste-based discrimination through expected rate of default loss only if the (proportional) psychic costs are strong enough relative to the effects of statistical discrimination. So failure to reject the null hypothesis does not necessarily imply there is no taste-based discrimination.

6 Summary and Conclusions

In this paper we develop a model of both taste-based and statistical discrimination in credit markets. Lack of such a theoretical framework has been one of the main reasons for the considerable controversies in the literature. This paper provides a link between theory and empirical studies in this area.

Our model is a general equilibrium one, where loan terms, such as interest rate and loan size, are endogenously determined. We study the impacts of both types of discrimination on equilibrium loan terms and expected loan performance. Based on these results, we examine what would be the legitimate empirical methods and data to statistically distinguish taste-based discrimination from statistical discrimination. In the following, we summarize our main findings, show how they fit into the previous literature, and point out their implications for future research.

6.1 Taste-Based and Statistical Discrimination Have Similar Predictions for Loan Terms

We first try to obtain analytical results on the effects of discrimination on equilibrium loan terms. When the analytical predictions are ambiguous, we propose empirical approaches to resolve some of the ambiguities. In particular, we use the effects of the increases in lender's money cost of lending to infer the effects of taste-based discrimination, and use the effects of lower borrower's income or liquid assets to infer the effects of statistical discrimination.

We find that analytically both taste-based and statistical discrimination imply that loans to minority borrowers have smaller sizes than to majorities with the same exogenous characteristics at the time of loan originations. Our empirical deductions also suggest that for both types of discrimination, loans to minority borrowers would have higher interest rates. That is, both types of discrimination have similar predictions for loan terms. Thus, contrary to the suggestions by Becker (1993*b*), intergroup differences in loan terms cannot be used to distinguish taste-based discrimination from statistical discrimination.

6.2 The Validity of the Conventional Profitability View Depends on the Measures of Expected Loan Performance

We also study how each type of discrimination would affect expected loan performance. The widely held view of the unique prediction of taste-based discrimination is that loans approved to minorities would be expected more profitable than to majorities with the same observable characteristics. Our results show that the validity of this profitability view depends crucially on how expected loan profitability is measured. We obtain three results: First, both taste-based and statistical discrimination imply that loans to minority borrowers would have higher default rates than to majorities with the same observable characteristics at the time of originations; Second, if there exists only taste-based discrimination, loans to minority borrowers should have higher expected rate of returns, while for statistical discrimination, the expected rate of returns on the loans to both minority and majority borrowers should be the same; Third, while expected rate of default loss is always higher on the loans made to minority borrowers when there exists only statistical discrimination, it can be lower when there exists taste-based discrimination.

The implications of the above results are: First, conditional default rate is not a valid measure of taste-based discrimination; Second, we can use expected rate of return and expected rate of default loss to detect taste-based discrimination. That is, there must exist taste-based discrimination if loans to minority borrowers have higher expected rate of return or lower expected rate of default loss than to majorities given the exogenous characteristics observed at the time of originations.

The existing data cannot be used to estimate expected rate of return. But empirical evidence from the data set of FHA mortgage loans shows that expected rate of default loss is higher among minority borrowers than majorities given the exogenous characteristics observed at the time of loan originations. Hence, we cannot reject the null hypothesis of non-existence of taste-based discrimination.

6.3 The Valid Empirical Method Should Be Reduced Form Regressions

A main methodological implication of our theoretical model is that empirical implementation of the above tests should use reduced form regressions. That is, only the exogenous variables observed at the time of loan originations can be used as covariates in the statistical regressions. In Section 5, we have argued that structural form regressions–regressions by including loan terms–are not appropriate methods to uncover the effect of taste. That is because by "controlling" loan terms and other exogenous variables determining the borrower's credit worthiness, the intergroup variations in expected loan profitability are solely determined by the statistical correlation between group identity and credit worthiness.

6.4 Future Research

There are several directions worth pursuing in the future research. To detect taste-based discrimination, the test based on expected rate of return (Proposition 4) is more robust than that on expected rate of default loss (Proposition 5). As we have argued, there are several reasons of why it is so: First, higher expected rate of return on minority loans is not only a necessary but also a sufficient condition of the existence of taste-based discrimination, while lower expected rate of default loss is only a sufficient condition; Second, intergroup difference in expected rate of return is a measure of not only existence but also magnitude of taste-based discrimination, while expected rate of default loss is only a measure of existence; Third, the result on expected rate of return is analytical and doesn't depend on model's parameters, while the result on expected rate of default loss is derived from empirical deduction. Unfortunately, the existing data don't allow us to estimate expected rate of return. So in the future research, it is highly desirable to obtain better data on loan performance preferably on conventional mortgage loans.

In the present paper, our attention is mainly on the conditions under which we can identify and measure the effects of taste-based discrimination. The counterpart of the issue is how to measure the effects of statistical discrimination. That is, to what extent do lenders use group identity such as race as a predictor of loan profitability? Although this issue is out of the scope of the present paper, our study does suggest a direction to answer the question. The fundamental cause of statistical discrimination is because a lender may not have full information on the determinants of a borrower's credit worthiness. As private information revealed over time, the information content of group identity would become less and less important to the lender. So we can measure the significance of statistical discrimination by how the importance of group identity changes with the length of credit history over a borrower's lifetime or how it varies across borrowers with different lengths of credit histories. This strategy will be adopted in our future research.

Finally, to study the nature of credit market discrimination, an alternative to directly analyzing credit transactions is to study how well minority households smooth their consumption, compared to majority households (Townsend, 1997). The idea is that if there exists credit market discrimination, minority households would be unable to borrow enough money to smooth their consumption over time. This approach would be especially useful when there are no satisfactory micro data on loan performance.

Appendix

A Proofs

Proof of Lemma 1 The Lagrangian function of the optimal payment problem is $L = u(y-p) - c(B_1 - p) + \lambda_1 p + \lambda_2(B_1 - p)$ with λ_1 and λ_2 as Kuhn-Tucker multipliers. The First Order Condition (FOC) is $-u'(y-p)+c+\lambda_1-\lambda_2 = 0$ plus slackness conditions. Let $u'(v) = c$. There are three possibilities. (i) $\lambda_1 > 0$. Then $p^* = 0$ and, hence, $\lambda_2 = 0$. That implies $-u'(y) + c < 0$. So $y < v$; (ii) $\lambda_1 = 0$ and $\lambda > 0$. Then $p^* = B_1$ and $-u'(y - B_1) + c > 0$. So $y > B_1 + v$; (iii) $\lambda_1 = \lambda_2 = 0$. Then $-u'(y - p^*) + c = 0$. So $p^* = y - v$ and $y \in [v, B_1 + v]$.

Proof of Lemma 2 First, we calculate

$$\frac{\partial U}{\partial B_1} = -\beta \int \min(c, u'(y - B_1)) f(y|\theta) dy < 0,$$
$$\frac{\partial^2 U}{\partial B_1^2} = \beta \int_{y^*}^{\overline{y}} u''(y - B_1) f(y|\theta) dy < 0.$$

Because $\frac{dB_1}{dB_0}\Big|_U = -\frac{\partial U}{\partial B_0} / \frac{\partial U}{\partial B_1}$, we have

$$\frac{dB_1}{dB_0}\Big|_U = \frac{u'(B_0)}{\beta \int \min(c, u'(y - B_1)) f(y|\theta) dy} > 0,$$
$$\frac{d^2 B_1}{dB_0{}^2}\Big|_U = -\frac{u''(B_0)\frac{\partial U}{\partial B_1} - u'(B_0)\frac{\partial^2 U}{\partial B_1^2}\frac{dB_1}{dB_0}\big|_U}{\left[\frac{\partial U}{\partial B_1}\right]^2} < 0.$$

That $\frac{\partial}{\partial \theta}\frac{dB_1}{dB_0}\Big|_U > 0$ is a direct result of Lemma 4 stated below.

Lemma 4 Let y be a random variable with CDF $F(y|\theta)$. Assume that the CDF has First Order Stochastic Dominance property, i.e., for $\theta_1 \geq \theta_2$, $F(y|\theta_1) \leq F(y|\theta_2)$. If the function $\gamma(y)$ is bounded, continuous, increasing (decreasing), and piecewisely differentiable with finite kinks, then $E(\gamma(y)|\theta)$ is increasing (decreasing) in θ.

The proof of Lemma 4 is straightforward by using the standard technique of change of variables.

Proof of Lemma 3 The creditor's iso-profit curves are upward-sloping and convex because

$$\frac{dB_1}{dB_0}\Big|_\Pi = \frac{1 + r_0}{1 - F(y^*|\theta)} > 0; \quad \frac{d^2 B_1}{dB_0{}^2}\Big|_\Pi = \frac{(1 + r_0 + \delta) f(y^*|\theta)}{(1 - F(y^*|\theta))^2} \cdot \frac{dB_1}{dB_0}\Big|_\Pi > 0.$$

Because $F(y^*|\theta)$ is decreasing in θ, $\frac{\partial}{\partial \theta}\frac{dB_1}{dB_0}\big|_\Pi < 0$. It is obvious that $\frac{\partial}{\partial \delta}\frac{dB_1}{dB_0}\Big|_\pi > 0$.

Proof of Proposition 1 We restate the FOC of the optimization problem here

$$D \equiv \frac{1+r_0+\delta}{1-F(y^*|\theta)} - \frac{u'(B_0)}{\beta \int \min(c, u'(y-B_1))f(y|\theta)dy} = 0, \tag{5}$$

So the system of equations for comparative statics with respect to δ is

$$\begin{cases} \frac{\partial \pi}{\partial B_0}\frac{\partial B_0}{\partial \delta} + \frac{\partial \pi}{\partial B_1}\frac{\partial B_1}{\partial \delta} = -\frac{\partial \pi}{\partial \delta} \\ \frac{\partial D}{\partial B_0}\frac{\partial B_0}{\partial \delta} + \frac{\partial D}{\partial B_1}\frac{\partial B_1}{\partial \delta} = -\frac{\partial D}{\partial \delta}. \end{cases}$$

Note that

$$\frac{\partial \pi}{\partial B_0} = -(1+r_0+\delta) < 0, \quad \frac{\partial \pi}{\partial B_1} = 1-F(y^*|\theta) > 0, \quad \frac{\partial \pi}{\partial \delta} = -B_0 < 0,$$

and

$$\frac{\partial D}{\partial B_0} = -\frac{u''(B_0)}{\beta \int \min(c, u'(y-B_1))f(y|\theta)dy} > 0$$

$$\frac{\partial D}{\partial B_1} = \frac{(1+r_0+\delta)f(y^*|\theta)}{(1-F(y^*|\theta))^2} - \frac{u'(B_0)\left[\beta \int_{y^*}^{\overline{y}} u''(y-B_1)f(y|\theta)dy\right]}{\left[\beta \int \min(c, u'(y-B_1))f(y|\theta)dy\right]^2} > 0$$

$$\frac{\partial D}{\partial \delta} = (1-F(y^*|\theta))^{-1} > 0.$$

Because

$$\Delta = \frac{\partial D}{\partial B_1}\frac{\partial \pi}{\partial B_0} - \frac{\partial D}{\partial B_0}\frac{\partial \pi}{\partial B_1} < 0,$$

so

$$\frac{\partial B_0}{\partial \delta} = \frac{1}{\Delta}\left[-\frac{\partial D}{\partial B_1}\frac{\partial \pi}{\partial \delta} + \frac{\partial D}{\partial \delta}\frac{\partial \pi}{\partial B_1}\right] < 0.$$

Using the FOC, we have

$$\begin{aligned} \frac{\partial B_1}{\partial \delta} &= \frac{1}{\Delta}\left[-\frac{\partial D}{\partial \delta}\frac{\partial \pi}{\partial B_0} + \frac{\partial D}{\partial B_0}\frac{\partial \pi}{\partial \delta}\right] \\ &= \frac{1}{\Delta}\left[\frac{1+r_0+\delta}{1-F(y^*|\theta)} + \frac{B_0 u''(B_0)}{\beta \int \min(c, u'(y-B_1))f(y|\theta)dy}\right] \\ &= \frac{1+r_0+\delta}{\Delta(1-F(y^*|\theta))}(1-\epsilon_u) \end{aligned}$$

with $\epsilon_u = -\frac{B_0 U''(B_0)}{U'(B_0)}$. So $\frac{\partial B_1}{\partial \delta} \leq (\geq) 0$ is $\epsilon_u \leq (\geq) 1$.

For interest rates, it is tedious but straightforward to show that

$$\frac{\partial r}{\partial \delta} = \frac{1+r_0+\delta}{\Delta(1-F(y^*|\theta))B_0} \cdot [1-\epsilon_u - (1+r)\xi(\theta)]$$

with

$$\xi(\theta) = \frac{1-F(y^*|\theta)}{1+r_0+\delta} + B_0\left[\frac{f(y^*|\theta)}{1-F(y^*|\theta)} - \frac{\int_{y^*}^{\overline{y}} U''(y-B_1)f(y|\theta)dy}{\int \min(c, U'(y-B_1))f(y|\theta)dy}\right] > 0.$$

So $\frac{\partial r}{\partial \delta} \leq (\geq) 0$ if $\epsilon_u \leq (\geq) 1 - (1+r)\xi(\theta)$.

Proof of Proposition 2 The proof is similar to the case with proportional psychic cost. Available upon request.

Proof of Proposition 3 and comparative statics discussed in Section 4.1.1 Take the FOC (5). The system of equations for comparative statics with respect to θ is

$$\begin{cases} \frac{\partial \pi}{\partial B_0}\frac{\partial B_0}{\partial \theta} + \frac{\partial \pi}{\partial B_1}\frac{\partial B_1}{\partial \theta} = -\frac{\partial \pi}{\partial \theta} \\ \frac{\partial D}{\partial B_0}\frac{\partial B_0}{\partial \theta} + \frac{\partial D}{\partial B_1}\frac{\partial B_1}{\partial \theta} = -\frac{\partial D}{\partial \theta}. \end{cases}$$

Note that the terms $\frac{\partial \pi}{\partial B_0}, \frac{\partial \pi}{\partial B_1}, \frac{\partial D}{\partial B_0}, \frac{\partial D}{\partial B_0}$ and Δ are the same as above. Moreover,

$$\frac{\partial \pi}{\partial \theta} > 0, \quad \frac{\partial D}{\partial \theta} = \frac{\partial}{\partial \theta}\frac{dB_1}{dB_0}\Big|_{\pi} - \frac{\partial}{\partial \theta}\frac{dB_1}{dB_0}\Big|_{U} < 0.$$

So

$$\frac{\partial B_0}{\partial \theta} = \Delta^{-1}\left[\frac{\partial \pi}{\partial B_1}\cdot\frac{\partial D}{\partial \theta} - \frac{\partial D}{\partial B_1}\cdot\frac{\partial \pi}{\partial \theta}\right] > 0.$$

Using the FOC, it is tedious but straightforward to show that, with $\epsilon_u = -\frac{B_0 u''(B_0)}{u'(B_0)}$,

$$\begin{aligned} \frac{\partial B_1}{\partial \theta} &= \Delta^{-1}\left[\frac{\partial \pi}{\partial \theta}\cdot\frac{\partial D}{\partial B_0} - \frac{\partial D}{\partial \theta}\cdot\frac{\partial \pi}{\partial B_0}\right] \\ &= \frac{(1+r_0+\delta)(\epsilon_u - \eta(\theta))}{B_0(1-F(y^*|\theta))\Delta \int p^* f_\theta(y|\theta)dy} \end{aligned}$$

with

$$\eta(\theta) = -\frac{(1+r_0+\delta)B_0}{\int p^* f_\theta(y|\theta)dy}\left[\frac{F_\theta(y^*|\theta)}{1-F(y^*|\theta)} + \frac{\int \min(c, u'(y-B_1))f_\theta(y|\theta)dy}{\int \min(c, u'(y-B_1))f(y|\theta)dy}\right] > 0.$$

So $\frac{\partial B_1^*}{\partial \theta} \geq (\leq) 0$ if $\epsilon_u \leq (\geq) \eta(\theta)$.

For interest rates,

$$\frac{\partial r}{\partial \theta} = \frac{F(y^*|\theta) - A(\theta)}{(1+r)\Delta}\cdot\frac{\partial D}{\partial \theta}$$

with

$$A(\theta) = -(1+r)^{-1}\left[(r_0+\delta-r) + \frac{\partial \pi}{\partial \theta}\left[\frac{\partial D}{\partial B_0} + \frac{\partial D}{\partial B_1}\right]\left[\frac{\partial D}{\partial \theta}\right]^{-1}\right] > 0.$$

So in general the sign of $\frac{\partial r}{\partial \theta}$ is ambiguous.

B Tables

Table 4: Definition of variables. FHA mortgage loans originated over 1987-88

year	1 if the observation if from 1987 cohort, 0 otherwise
black	1 if race is black, 0 otherwise
Hispanic	1 if race is Hispanic, 0 otherwise
age	age of the debtor
dependents	number of dependent
single	1 if the debtor is single
liquid asset	total liquid asset at origination in $1000
income	total annual effective family income at origination in $1000
other income	percent of income from non-wage sources
cosigner's inc	percent of income from co-borrower
house value	appraised value of home at origination in $1000
med. income(CT)	median income of neighborhood in $1000
chg med. h-val	change between 1980 and 1990 in the median value of owner-occupied homes in the census tract
med. h-age(CT)	median age of property in census tract
med. h-val(CT)	median home value in census tract in $1000
vacancy rate	percentage of 1-4 family units vacant in census tract
% of black(CT)	percent of black families in census tract
% of Hispn(CT)	percent of Hispanic families in census tract
unemploymt rate	unemployment rate of the census tract
rent rate	proportion of housing units in census tract for rental

Table 5: Sample statistics of FHA mortgage loans originated in 1987-88

variable	mean	std. err.	variable	mean	std. err.
year	.2642	.4409	house value	62.7388	21.1850
black	.1913	.3933	med. income(CT)	102.4651	23.4877
Hispanic	.0691	.2537	med. h-age(CT)	.5909	.4261
age	1.1930	.8636	med. h-val(CT)	19.4152	12.7805
dependents	.9051	1.2120	chg med. h-val	53.5999	20.0310
single	.1856	.3888	vacancy rate	.0616	.0513
liquid asset	8.8587	11.6939	% of black(CT)	.0801	.1746
income	36.4455	14.8515	% of Hispn(CT)	.0645	.1186
other income	.0561	.1183	unemploymt rate	.0609	.0358
cosigner's inc	22.8735	23.8045	rent rate	.2683	.1559
number of obs: 100013					

Table 6: Sample statistics of average default rate: FHA loans, originated in 1987-88

Average default rate			
race	nobs	mean	s.e.
black	19185	0.078	0.26
Hispanics	6944	0.070	0.25
white	73884	0.044	0.20
All	100013	0.052	0.22

Table 7: Sample statistics of average rate of default loss conditional on that default loss was observed

Average rate of default loss			
race	nobs	mean	s.e.
black	205	0.43	0.21
Hispanics	75	0.41	0.18
whites	505	0.35	0.19
All	785	0.38	0.20

Table 8: Determining the implications of statistical discrimination for default rate and expected ate of default loss. Maximum likelihood estimations of default probability and expected rate of default loss using single group samples.

	White sample				Minority sample			
indepnt variable	$E(def\|X)$		$E(loss\|X)$		$E(def\|X)$		$E(loss\|X)$	
year	0.16	(8.67)	0.08	(5.57)	0.17	(6.78)	0.03	(1.67)
age<25	0.00	(0.26)	0.01	(0.18)	0.01	(0.41)	0.03	(0.95)
age 25-35	-0.11	(-3.53)	-0.04	(-1.74)	0.02	(0.54)	0.05	(1.31)
age 35-45	-0.01	(-0.30)	-0.02	(-0.71)	0.04	(0.93)	0.03	(0.80)
dependents	0.07	(10.08)	0.03	(4.79)	0.04	(5.85)	0.01	(2.13)
single	-0.01	(-0.52)	0.01	(0.86)	0.06	(1.72)	0.04	(1.46)
log(liquid asset)	-0.23	(-24.95)	-0.07	(-7.32)	-0.21	(-17.55)	-0.06	(-5.05)
log(income)	-0.13	(-4.03)	-0.00	(-0.03)	-0.09	(-2.40)	-0.02	(-0.56)
other income	0.35	(4.93)	0.09	(1.70)	0.15	(1.71)	0.19	(2.66)
cosigner's inc	-0.06	(-1.37)	-0.01	(-0.44)	-0.14	(-2.54)	-0.03	(-0.66)
log(house value)	0.20	(5.38)	0.00	(0.14)	0.10	(1.99)	-0.08	(-1.68)
% of black(CT)	0.46	(6.03)	0.37	(6.50)	0.45	(8.84)	0.23	(4.89)
% of Hispn(CT)	0.63	(6.43)	0.12	(1.35)	0.19	(2.72)	0.09	(1.63)
med. income(CT)	-0.00	(-4.83)	-0.00	(-1.99)	-0.00	(-3.06)	0.00	(1.13)
chg. med. h-val	-0.17	(-6.61)	-0.18	(-6.55)	-0.16	(-4.91)	-0.11	(-3.73)
med. h-age(CT)	-0.01	(-10.44)	-0.00	(-1.52)	-0.01	(-7.75)	0.00	(0.24)
med. h-val(CT)	-0.01	(-15.40)	-0.00	(-8.28)	-0.01	(-10.99)	-0.00	(-5.41)
vacancy rate	1.06	(6.47)	0.47	(3.23)	0.57	(2.38)	0.07	(0.31)
unemploymt rate	-2.78	(-9.02)	-1.60	(-6.27)	-3.38	(-8.84)	-0.96	(-2.49)
rent rate	-0.13	(-1.95)	0.02	(0.35)	0.02	(0.23)	-0.11	(-1.25)
ρ	0.97 (11.23)				0.95 (5.29)			
σ_ϵ	0.36 (1.54)				0.33 (11.11)			
	$\ln L = -0.16$				$\ln L = -0.24$			
Num. obs.	73884				26129			

Note that a constant and dummies representing the regions in which properties are located are also used in the estimations. Their coefficients are not shown here. Figures in parentheses are t-statistics.

Table 9: A test based on Proposition 5 to determine if there exists taste-based discrimination. Maximum likelihood estimations of expected rate of default loss and default rate using whole sample. Number of observations is 100013.

	$E(def\|X)$		$E(loss\|X)$		$E(def\|X)$		$E(loss\|X)$	
indepnt variable	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
year	0.16	(10.98)	0.06	(5.50)	0.16	(10.99)	0.06	(5.54)
age<25	0.02	(0.81)	0.01	(0.76)	0.02	(0.77)	0.01	(0.73)
age 25-35	-0.06	(-2.45)	-0.00	(-0.43)	-0.06	(-2.48)	-0.00	(-0.46)
age 35-45	0.01	(0.51)	0.00	(0.06)	0.01	(0.48)	0.00	(0.04)
dependents	0.06	(11.40)	0.02	(5.06)	0.06	(11.32)	0.02	(5.01)
single	0.00	(0.17)	0.02	(1.41)	0.00	(0.15)	0.02	(1.41)
log(liquid asset)	-0.22	(-30.38)	-0.07	(-8.90)	-0.22	(-30.43)	-0.07	(-8.92)
log(income)	-0.11	(-4.47)	-0.00	(-0.36)	-0.11	(-4.40)	-0.00	(-0.33)
other income	0.27	(4.95)	0.14	(3.04)	0.28	(4.98)	0.14	(3.06)
cosigner's inc	-0.09	(-2.83)	-0.01	(-0.56)	-0.10	(-2.91)	-0.01	(-0.59)
log(house value)	0.16	(5.50)	-0.02	(-0.90)	0.16	(5.52)	-0.02	(-0.88)
% of black(CT)	0.46	(11.56)	0.29	(8.50)	0.47	(11.88)	0.29	(8.62)
% of Hispn(CT)	0.35	(5.82)	0.15	(2.92)	0.32	(5.65)	0.13	(2.85)
med. income(CT)	-0.00	(-6.02)	-0.00	(-1.00)	-0.00	(-5.99)	-0.00	(-1.00)
chg. med. h-val	-0.17	(-8.45)	-0.16	(-7.88)	-0.17	(-8.51)	-0.16	(-7.95)
med. h-age(CT)	-0.01	(-13.41)	-0.00	(-1.18)	-0.01	(-13.41)	-0.00	(-1.19)
med. h-val(CT)	-0.01	(-18.94)	-0.00	(10.37)	-0.01	(-19.00)	-0.00	(-10.39)
vacancy rate	0.93	(6.91)	0.38	(3.03)	0.93	(6.88)	0.37	(3.03)
unemploymt rate	-2.98	(-12.46)	-1.46	(-6.81)	-2.98	(-12.45)	-1.45	(-6.79)
rent rate	-0.08	(-1.58)	-0.03	(-0.70)	-0.08	(-1.58)	-0.03	(-0.70)
minority					0.09	(5.30)	0.03	(2.57)
black	0.10	(5.53)	0.04	(2.61)				
Hispan	0.05	(1.69)	0.01	(0.76)				
ρ	0.97 (9.60)				0.96 (10.80)			
σ_ϵ	0.36 (18.21)				0.35 (18.21)			
	$\ln L = -0.18$				$\ln L = -0.18$			

Note that a constant and dummies representing the regions in which properties are located are also used in the estimations. Their coefficients are not shown here. Figures in parentheses are t-statistics.

References

Altonji, Joseph G. and Charles R. Pierret (2001), 'Employer learning and statistical discrimination', *Quarterly Journal of Economics* **116**(1), 313–50.

Arrow, Kenneth J. (1972), Models of job discrimination, *in* A. H.Pascal, ed., 'Racial Discrimination in Economic Life', Lexington Books, Lexington, MA.

Avery, Robert B., Patricia E. Beeson and Paul S. Calem (1997), 'Using HMDA data as a regulatory screen for fair lending compliance', *Journal of Financial Services Research* **11**(1-2), 9–42.

Becker, Gary (1971), *The Economics of Discrimination*, 2nd edn, University of Chicago Press.

Becker, Gary S. (1993*a*), 'The evidence against banks doesn't prove bias', Business Week.

Becker, Gary S. (1993*b*), 'Nobel lecture: The economic way of looking at behavior', *Journal of Political Economy* **101**(3), 395.

Becker, Gary S. (1995), 'How bad studies get turned into bad policies', Business Week.

Berger, Allen N. and Gregory F. Udell (1992), 'Some evidence on the empirical significance of credit rationing', *Journal of Political Economy* **100**(5), 1047–77.

Berkovec, James A., Glenn B. Canner, Stuart A. Gabriel and Timonthy H. Hannan (1996), 'Mortgage discrimination and FHA loan performance', *Cityscape: A Journal of Policy Development and Research* **2**(1), 9–24.

Berkovec, James A., Glenn B. Canner, Stuart A. Gabriel and Timothy H. Hannan (1994), 'Race, redlining, and residential mortgage loan performance', *Journal of Real Estate Finance and Economics* **9**(3), 263–94.

Berkovec, James A., Glenn B. Canner, Stuart A. Gabriel and Timothy H. Hannan (1998), 'Discrimination, competition, and loan performance in FHA mortgage lending', *Review of Economics and Statistics* **80**(2), 241–50.

Bester, Helmut (1985), 'Screening vs rationing in credit market with imperfect information', *American Economic Review* **75**(4), 850–55.

Black, Harold, Robert L. Schweitzer and Lewis Mandell (1978), 'Discrimination in mortgage lending', *American Economic Review* **68**(2), 186–91.

Blanchflower, David G., Phillip B. Levine and David J. Zimmerman (1998), 'Discrimination in the small business credit market', NBER Working Paper No. W6840.

Boyd, Laura A. (1997), 'Discrimination in mortgage lending: The impact on minority defaults in the stafford loan program', *Quarterly Review of Economics and Finance* **37**(1), 23–37.

Browne, Lynn E. (1993), 'Default rates aren't the way to determine bias in Boston', Business Week.

Calem, Paul and Michael Stutzer (1995), 'The simple analytics of observed discrimination in credit markets', *Journal of Financial Intermediation* **4**(3), 189–212.

Calomiris, Charles W., Charles M. Kahn and Stanley D. Longhofer (1994), 'Housing-finance intervention and private incentives: helping minorities and the poor', *Journal of Credit, Money, and Banking* **26**(3), 634–74.

Canner, Glenn B., Stuart A. Gabriel and J. Michael Woolley (1991), 'Race, default risk mortgage lending: A study of the FHA and conventional loan markets', *Southern Economic Journal* **58**(1), 249–62.

Cornell, Bradford and Ivo Welch (1996), 'Culture, information, and screening discrimination', *Journal of Political Economy* **104**(3), 542–571.

Courchane, Marsha and David Nickerson (1997), 'Discrimination resulting from overage practices', *Journal of Financial Services Research* **11**, 133–152.

Duca, John V. and S.S. Rosenthal (1993), 'Borrowing constrains, household debt, and racial discrimination in loan markets', *Journal of Financial Intermediation* **3**, 77–103.

Dymski, Gary Arthur (1995), 'The theory of bank redlining and discrimination: An exploration', *Review of Black Political Economy* **23**(3), 37–74.

Dymski, Gary and Lisa Mohanty (1999), 'Credit and banking structure: Asian and African-American experience in Los Angeles', *American Economic Review* **89**(2), 362–66.

Ellis, Pierre A. (1985), The Role of Borrower Attributes in Mortgage Loan Pricing, PhD thesis, Department of Economics, The Unversity of Chicago.

Evanoff, Douglas D. and Lewis M. Segal (1996), 'CRA and fair lending regulations: resulting trends in mortgage lending', *Federal Reserve Bank of Chicago: Economic Perspectives* **20**(6), 19.

Fay, Scott, Erik Hurst and Michelle J. White (1998), 'The bankruptcy decision: The roles of stigma and financial benefit', Working paper 98-01, University of Michigan, Department of Economics.

Ferguson, Michael F. and Stephen R. Peters (1995), 'What constitutes evidence of discrimination in lending?', *Journal of Finance* **L**(2), 739–748.

Ferguson, Michael F. and Stephen R. Peters (1997), 'Cultural affinity and lending discrimination: The impact of underwriting errors and credit risk distribution on applicant denial rates', *Journal of Financial Services Research* **11**(1-2), 153–67.

Fix, Michael and Raymond J. Struyk (1992), *Clear and Convincing Evidence: Measurement of Discrimination in America*, The Urban Institute Press, Washinton, D.C.

Flowers, Gwendolyn (1999), 'What can we expect from community-based lending for the District of Columbia', *American Economic Review* **89**(2), 367–71.

Gabriel, Stuart A. and Stuart S. Rosenthal (1991), 'Credit rationing, race, and the mortgage market', *Journal of Urban Economics* **29**(3), 371–79.

Henderson, Christopher C. (1999), 'The economic performance of African-American-owned banks: The role of loan loss provisions', *American Economic Review* **89**(2), 372–76.

Huck, Paul and Lewis M. Segal (1997), 'New data on mortgage lending', Chicago Fed Letter.

Hunter, William C. and Mary Beth Walker (1996), 'The cultural affinity hypothesis and mortgage lending decisions', *Journal of Real Estate Finance and Economics* **13**(1), 57–70.

Ladd, Helen F. (1982), 'Equal credit opportunity: Women and mortgage credit', *American Economic Review* **72**(2), 166–70.

Ladd, Helen F. (1998), 'Evidence on discrimination in mortgage lending', *Journal of Economic Perspectives* **12**(2), 41–62.

Lindsey, Debby A. (1998), 'Attitudes on race, culture and discrimination in mortgage lending', *Studies in Economics and Finance* **19**(1), 48–76.

Longhofer, Stanley D. (1996), 'Cultural affinity and mortgage discrimination', *Federal Reserve Bank of Cleveland Economic Review* **32**(3), 12–24.

Longhofer, Stanley D. and Stephen R. Peters (1998), 'Self-selection and discrimination in credit markets', Federal Reserve Bank of Cleveland Working Paper.

Martin, R. E. and R. C. Hill (2000), 'Loan performance and race', *Economic Inquiry* **38**(1), 136–150.

Milde, Hellmuth and John G. Riley (1988), 'Signaling in credit markets', *Quarterly Journal of Economics* **103**(1), 101–29.

Munnell, Alicia H., Georffrey M.B. Tootell, Lynn E. Browne and James McEneaney (1996), 'Mortgage lending in boston: interpreting HMDA data', *American Economic Review* **86**(1), 25–53.

Neal, Derek A. and William R. Johnson (1996), 'The role of premarket factors in black-white wage differences', *Journal of Political Economy* **104**(4), 869–95.

Neumark, David (1998), 'Labor market information and wage differentials by race and sex', NBER Working Paper. No. W6573.

Ogaki, Masao and Carmen M. Reinhart (1998), 'Measuring intertemporal substitution: The role of durable goods', *Journal of Political Economy* **106**(5), 1078–98.

Olney, Marthad L. (1998), 'When your word is not enough: Race, collateral, and household credit', *Journal of Economic History* **58**(2), 408–31.

Peterson, Richard L. (1981), 'An investigation of sex discrimination in commercial banks' direct consumer lending', *The Bell Journal of Economics* **12**, 547–561.

Phelps, Edmund S. (1972), 'The statistical theory of racism and sexism', *American Economic Review* **62**(4), 659–661.

Quercia, Roberto G. and Michael A. Stegman (1992), 'Residential mortgage default: A review of the literature', *Journal of Housing Research* **3**(2), 341–379.

Quigley, John M. and Robert Van Order (1995), 'Explicit tests of contingent claims models of mortgage default', *Journal of Real Estate Finance and Economics* **11**(2), 99–117.

Ross, Stephen A. (2000), 'Morgage lending, sample selection, and default', *Real Estate Economics* **28**(4), 581–621.

Ross, Stephen L. and John Yinger (1999), The default approach to studying mortgage discrimination: A rebuttal, *in* M. A.Turner and F.Skidmore, eds, 'Mortgage Lending, Discrimination: A Review of Existing Evidence', The Urban Institute, Washington, D.C., pp. 107–136.

Schafer, Robert and Hellen F. Ladd (1981), *Discrimination in Mortgage Lending*, M.I.T. Press, Cambridge, Mass.

Shaffer, Sherrill (1996), 'Evidence of discrimination in lending: An extension', *Journal of Finance* **LI**(4), 1551–4.

Telser, Lester G. (1980), 'A theory of self-enforcement agreements', *Journal of Business* **53**, 27–44.

Tootell, Geoffrey M. B. (1993), 'Defaults, denials, and discrimination in mortgage lending', *New England Economic Review* **0**(0), 45–51.

Townsend, Robert (1997), 'Discrimination in financial services: How should we proceed?', *Journal of Financial Services Research* **11**(1-2), 215–17.

Turner, Margery Austin and Felicity Skidmore, eds (1999), *Mortgage Lending, Discrimination: A Review of Existing Evidence*, The Urban Institute, Washington, D.C.

Van Order, Robert, Ann-Margaret Westin and Peter Zorn (1993), 'Effects of the racial composition of neighborhood on default and implications for racial discrimination in mortgage markets', Paper presented at the ASSA meetings in Anaheim, California.

Van Order, Robert and Peter Zorn (1995), Testing for discrimination: Combining default and rejection data, *in* A. M.Yezer, ed., 'Fair Lending Analysis: A Compendium of Essays on the Use of Statistics', American Bankers Association, Washinton, pp. 105–112.

Wachter, Susan (1997), 'Discrimination in financial services: What do we know?', *Journal of Financial Services Research* **11**(1-2), 205–8.

White, Michelle J. (1998), 'Why don't more households file for bankruptcy?', *Journal of Law, Economics, and Organization* **14**(2), 205–231.

Yezer, Anthony M.J., Robert E. Phillips and Robert P. Trost (1994), 'Bias in estimates of discrimination and default in mortgage lending: the effects of simultaneity and self-selection', *Journal of Real Estate Finance and Economics* **9**, 197–215.

Yinger, John (1998), 'Evidence on discrimination in consumer markets', *Journal of Economic Perspectives* **12**(2), 23–40.