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DISCRIMINATION IN CONSUMER CREDIT MARKETS

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INTRODUCTION

This paper analyzes consumer credit-seeking experiences with lending institutions. We examine the determinants of (1) the probability that a consumer is rejected for the credit he requests, (2) the probability that the consumer will then continue his search after an initial denial, and (3) the probability that this extended search is unsuccessful. In addition, the data allow us to identify those who are discouraged from seeking credit and we explore the determinants of that discouragement as well.

Our principal interest in this empirical work is with whether the credit allocation process is neutral with respect to the race, sex, and marital status of those who seek to borrow in financial markets. The Equal Credit Opportunity Act (1974 and amended 1976) explicitly prohibits the use of race, sex, and marital status as criteria on which to base lending decisions. We use a national probability sample of households surveyed in 1983 and thus the results here apply to an environment in which this federal legislation is in force. Despite this legislation, we find evidence of racial differences in credit experiences that are adverse to nonwhites and that cannot be explained by differences in the distribution of credit-worthiness by race. These results we interpret as evidence of racial discrimination in consumer credit markets.

Most previous empirical studies of discrimination in lending, e.g. Black and Schweitzer [1980], Black, Schweitzer, and Mandell [1978], Warner [1982], and Wiginton [1980], have generally utilized data on credit applications from banks and other lending institutions to test whether, after controlling statistically for other factors such as income, employment record, and credit history, minorities and women have lower probabilities of success in obtaining credit. The results have been mixed. Black, Schweitzer, and Mandell [1978], for example, provide empirical evidence that "blacks are less likely to be granted loans than nonblacks, *ceteris paribus*." Lindley, Selby, and Jackson [1984], using survey data, conclude that "there is no significant support for the hypothesis that [racial] discrimination exists in the extension of credit." Similarly Peterson [1981], finds "no systematic pattern of prejudicial sex discrimination," after finding no significant difference in credit default rates by sex at banks.

With the exception of the contributions by Brandt and Shay [1979] and Lindley et al. [1984], however, the above studies suffer from a potential sample selectivity problem since they ignore the process by which the particular data set is generated. As Bloom et al. [1983] point out, the problem arises because bank data draw their observations from the population of credit applicants and not the entire population of potential applicants. Potential applicants who may be discouraged from applying never appear as actual credit applicants. For example, a lending institution can discourage a potential applicant from applying by a history of discriminatory credit decisions, by suggesting to a potential applicant that the probability of credit denial is high, or by simply being less than attentive to his credit needs and problems.[1] A sample selectivity problem is introduced into the estimation process if such discouragement is more frequent among one sex or one race, other things being equal. The result is that

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biased estimates of the effects of race and/or sex are produced and the direction of the bias is unknown if only applicant data are analyzed.

By contrast, we use data from the 1983 Survey of Consumer Finances (SCF). The SCF consists of a large random sample of U.S. households. Since it consists of data on households rather than credit applicants, our use of the SCF data allows us to avoid the sample selectivity problem altogether. As a national sample, it is larger than both Brandt and Shay [1979] who restricted their analysis to nonrural residents who had recently made a durable good purchase and Lindley et al. [1984] whose data base is less than two hundred observations from a single city, Atlanta, Georgia. In addition then to being a large database of potential credit applicants, the SCF also provides excellent household data on income, employment history, and other indicators of credit worthiness.

In Section 2 below we discuss the lending decision in the context of credit-scoring systems used by many institutions. Section 3 discusses our model, data, and empirical results. That section produces two major results. We find, using survey data from a sample of over three thousand households that, after controlling for other factors, nonwhites are more likely to be rejected for credit relative to whites *and* that nonwhites are more likely to be discouraged from applying for credit as well. The fourth and final section contains a summary and conclusions.

THE LENDING DECISION

Before turning to the models themselves, it is helpful to understand how institutional lending decisions are made. First, of course, a potential applicant must apply to a lending institution. The lending institution then assesses whether the applicant is a good or bad risk. Credit decisions are typically made on the basis of credit-scoring systems which attempt to distinguish between good and bad risks on the basis of applicant characteristics. These characteristics may include length of residence in an area, length of employment, income, net worth, whether or not the applicant is a home-owner, past credit experience, and other objective characteristics of the applicant.[2] A credit applicant's supplied information and perhaps credit reports are then scored and credit is awarded or denied depending upon whether or not the applicant's score exceeds a target score. The criteria by which points are awarded and the number of points themselves may vary from lending institution to lending institution depending on management's criteria. Capon [1978] notes, for example, that management may specify that under no circumstances may a renter score higher than a homeowner or a purchaser of a home.

One potential problem is that even without the explicit inclusion of race, sex, or other prohibited variables in the credit-scoring system, the use of proxies for these variables may produce a disparate impact on certain protected groups.[3] Such policies may discourage members of protected groups from applying at all.[4]

Finally, it is important to realize that credit decisions by lending institutions can be contested. Many credit-scoring systems allow for management discretion in overriding the point-scoring sysem if a rejected applicant complains. This practice may discriminate against applicants who meekly accept denial of credit. The impact of such managerial discretion may discriminate against protected groups if, perhaps as a result of past discrimination, they are more likely to think it is fruitless to contest a credit-scoring decision. Although creditors *must* provide applicants with a statement which explains the basis of the adverse action taken, applicants have been rejected due to low point scores without a statement of reason.[5]

MODEL, DATA AND RESULTS

The Determinants of Credit Denial

In this section we model the determinants of response from three survey questions from the 1983 SCF.

[1] In the past few years, has a particular lender or creditor turned down any request you (or your husband/wife) made for credit, or have you been unable to get as much credit as you applied for? [CRDDENY].

[2] After you were turned down, or unable to get as much credit as you applied for, did you (or your husband/wife) reapply for credit at the same or another lender or creditor? [REAPPLY]

[3] Were you finally able to get all the credit you (or your husband/wife) first applied for? [DENYFNL].

We initially modelled three discrete outcomes: (a) whether or not an applicant's requested amount of credit was rejected (CRDDENY), (b) whether or not the rejected applicant reapplied (REAPPLY), and (c) whether or not the reapplicant ultimately obtained the desired credit (DENYFNL). Each of these three discrete outcomes is modelled as a function of sixteen variables. Definitions of variables in these equations are listed in Table 1.

Six regressors are measures of ability to pay—monthly income, existing loan repayment obligations (EXPENSE), financial net worth, existing credit card balances, number of vehicles owned (AUTOS), and a dummy variable for homeownership.[6] The first two of the above are flow variables that describe the household's current financial position while the remaining four seek to capture the ability to pay with measures of stocks. The hypotheses are that the probability of credit denial is positively related to existing loan and credit card obligations and negatively related to the remaining four measures.

Four additional variables are also entered to measure stability of lifestyle and probability of repayment. These variables reflect (a) whether or not the household has paid all debts as scheduled, (b) years of residence in the community, (c) length of tenure in the respondent's current job, and (d) whether or not the respondent has a checking account. Here our expectations are that credit seeking is

TABLE 1
Variable Definitions

CRDDENY	= 1 if the respondent applied for and was denied the amount of credit requested; 0 otherwise
REAPPLY	= 1 if an initially rejected applicant for credit reapplied with the same or a different lender; 0 otherwise
DENYFNL	= 1 if the re-applicant was ultimately unsuccessful; 0 otherwise
CRDSHORT	= 1 for respondents who were initially denied credit (CRDDENY = 1) and who did not reapply, or who reapplied but were ultimately unsuccessful; 0 otherwise
DISCOURAGED	= 1 for any respondent who thought of applying for credit, but changed his/her mind because of likelihood of being turned down; 0 otherwise
MONTHLY INCOME	= total monthly income (in thousands of dollars)
NET WORTH	= financial net worth (in thousands of dollars). (Financial net worth includes total paper assets minus total debt. It does not include the current value of the respondent's home and other properties plus the value of any vehicles owned by the household.)
OWNRENT	= 1 if the household owns or has a mortgage on their home; 0 otherwise
NOPAYDEBT	= 1 if respondent sometimes got behind or missed payments on loans; 0 otherwise
YRS LOCAL	= number of years that respondent has resided in the county
JOB TENURE	= number of years spent working for current employer
NOCHECK	= 1 if the respondent does not have a checking account; 0 otherwise
AGE HEAD	= age of the head of the household
RACE HEAD	= 1 if head is white; 0 otherwise
FEMALE HEAD	= 1 if the household has a female head (children present, no spouse; 0 otherwise
MALE HEAD	= 1 if the household has a male head (children present, no spouse); 0 otherwise
SINGLE MALE	= 1 if the respondent is a single male (no children, no spouse); 0 otherwise
SINGLE FEMALE	= 1 if the respondent is a single female (no children, no spouse); 0 otherwise
AUTOS	= number or vehicles owned by household
EXPENSE	= monthly loan repayment expenses for housing, additions, and repairs, autos, and other installment loans (in thousands of dollars)
CREDCARD	= credit card balances owed (in thousands of dollars)
NW*CRDSHORT	= 1 for respondent who is both nonwhite and for whom CREDSHORT = 1; 0 otherwise

more difficult and credit denial more probable for those who have had loan repayment problems in the past, those without checking accounts and for those with little job or residential tenure.

The remaining six variables are demographic: the age and race of the head of the household and type of household (with married couples as the reference group). These variables are used to identify protected groups. They have no place in credit scoring systems.[7] Consequently, the null and also the nondiscriminatory hypothesis is that the estimated coefficients of the protected group variables are not significantly different from zero.

The data are analyzed with repeated use of dichotomous probit analysis. Note that the decisions are sequential: (a) whether or not the household has been turned down for credit, (b) among those initially turned down, whether or not they reapplied, and (c) among reapplicants, whether or not the quest for credit was ultimately successful. Maddala [1983, pp. 49–50] demonstrates that the likelihood functions for the above models can be maximized by maximizing the likelihood functions of the dichotomous models repeatedly.[8]

Of 3824 households surveyed, 3665 or 95.8% provided consistent and usable responses to variables in the specification. The unusable observations were observations with almost all dollar value items missing. Avery and Elliehausen in the SCF codebook speculate that both very high and very low income households are more likely to be non-respondents than others with less extreme financial situations. Means and standard deviations of the variables in the specification are listed in the first two columns of Table 2. The sample of 3665 consists of 2982 whites (81.4%) and 683 nonwhites (18.6%). The second pair of columns of Table 2 show the mean values for whites and nonwhites respectively. Note that the credit denial rate experienced by nonwhites was substantially higher than that of whites, 23.0% vs. 12.8%, with the sample average being 14.7%. Nonwhites however have lower monthly incomes, lower rates of homeownership, poorer credit histories (NOPAYDEBT), tend to be somewhat younger with less job tenure, and more commonly have household heads who are female. Of the 14.7% (or 538) of the sample denied the credit amounts they sought, 39.4% or 212 chose to reapply. Among the 212 who reapplied, 38.7% or 82 were ultimately denied credit. The last two columns of Table 2 report the overall means for these samples.

TABLE 2

Descriptive statistics

	FULL SAMPLE				REAPPLY	DENYFNL
	Overall Mean n = 3665	Overall Std. Dev. n = 3665	White Mean n = 2982	Nonwhite Mean n = 683	Overall Mean n = 538	Overall Mean n = 212
CRDDENY	0.147	0.354	0.128	0.230		
MONTHLY INCOME (000)	2.124	2.432	2.274	1.466	1.696	1.971
NET WORTH (000)	9.820	116.5	12.820	−3.280	−6.523	−9.591
OWN/RENT	0.639	0.480	0.682	0.451	0.403	0.462
NOPAYDEBT	0.110	0.312	0.093	0.182	0.264	0.217
YRS LOCAL	25.594	20.52	25.454	26.204	18.266	16.887
JOB TENURE	6.661	9.02	6.901	5.614	4.415	4.849
NOCHECK	0.217	0.413	0.150	0.515	0.303	0.226
AGE HEAD	46.565	17.30	47.037	44.504	35.591	35.000
RACE HEAD	0.814	0.389	1.0	0.0	0.708	0.774
FEMALE HEAD	0.082	0.275	0.056	0.195	0.156	0.108
MALE HEAD	0.010	0.100	0.007	0.023	0.011	0.004
SINGLE MALE	0.117	0.321	0.115	0.123	0.165	0.198
SINGLE FEMALE	0.180	0.384	0.179	0.180	0.113	0.113
CREDCARD (000)	0.305	0.731	0.299	0.332	0.344	0.380
EXPENSE (000)	0.317	0.553	0.324	0.285	0.363	0.425
AUTOS	1.526	1.061	1.623	1.100	0.826	1.458
CREDSHORT	0.110	0.314	0.093	0.189		
DISCOUR	0.099	0.299	0.072	0.215		
NW*CREDSHORT	0.035	0.184	0.000	0.189		
REAPPLY					0.394	
DENYFNL						0.387

Before examining the results of model estimation, a discussion of the meaning of the dependent variables may be useful. The survey questions are broad inquiries as to recent credit-seeking experience with lending institutions. The SCF survey questionnaire does not indicate the type of credit requested by the respondent. Nor is there any information on the interest rate charged or downpayments required. Thus we use the general phrase, consumer credit, throughout the paper. If such data had been available, credit denial rates are likely to be greater for certain types of loans, e.g. mortgage loans.

Begin by noting from Table 2 that the rates of credit denial differ substantially by race (23.0% v. 12.8%). Table 3 shows credit denial rates disaggregated by income class, net worth, credit repayment history problems, homeownership status, and job tenure class. In disaggregated form the differential does not disappear. The differential rates by race are not concentrated in one class of borrower and consequently are not likely to be explained by a situation in a particular credit market or particular set of markets.

The results of the estimation are listed in the first three columns of Table 4. With respect to the CRDDENY equation, net worth, homeownership, payment of debt on time, job tenure, and age each have a negative effect on CRDDENY that is significantly different from zero. Consistent with Peterson [1981], differences in CRDDENY by sex of head are not significantly different from zero. However, white heads of households are significantly less likely to be denied credit amounts requested than are nonwhite heads. The partial derivative with respect to RACEHEAD of −.046 indicates though that the

TABLE 3

White and Nonwhite Rates of Credit Denial by Selected Characteristics

Household Characteristics	Nonwhite	White	Difference
Overall	23.0%	12.8%	10.2%
Annual Income:			
less than $25,000	23.9%	15.6%	8.3%
$25,000–$50,000	21.7%	9.5%	12.2%
more than $50,000	10.7%	6.0%	4.7%
Homeownership Status;			
Renters	26.1%	23.5%	2.6%
Owners	19.2%	7.8%	11.4%
Financial Net Worth:			
less than $25,000	26.6%	22.0%	4.6%
$25,000–$100,000	15.7%	9.2%	6.5%
more than $100,000	12.5%	4.1%	8.4%
Previous Debt Repayment Problems?			
Yes	39.5%	33.5%	6.0%
No	19.3%	10.7%	8.6%
Job Tenure of Household Head			
0–1 yr.	24.8%	12.2%	12.6%
2–5 yrs.	31.7%	20.8%	10.9%
6–10 yrs.	20.3%	14.7%	5.6%
11 or more yrs.	12.7%	6.2%	6.5%

observed gross racial differential in CRDDENY of over 10% (see Table 2) is reduced by just over one-half when other demographic and credit-worthiness characteristics are taken into account.[9]

Columns 2 and 3 report the results with respect to whether denied applicants reapplied or not and whether or not those who reapplied were ultimately unsuccessful. Employing a one-tail test at the 1% level, none of the coefficients in the REAPPLY equation are significantly different from zero, though the point estimate for RACE HEAD is positive and not small. The DENYFNL estimates similarly show little relationship between an individual regressor and the probability of having a re-application denied.

Although in both REAPPLY and DENYFNL we can reject the hypothesis that all coefficients are zero, the individual coefficients yield little information. For this reason, we summarize the results of the CRDDENY, REAPPLY, and DENYFNL equations in the CRDSHORT (credit short) equation. This variable takes the value one for respondents who (a) were initially denied credit *and* did not reapply or (b) did reapply *and* were ultimately denied the credit they sought. Thus, respondents for whom CRDSHORT takes a value of unity are those whose search for credit, however long, met ultimately with failure. 9.3% of white households in the survey and 18.9% of nonwhites recently had such experiences. The results of estimating this equation were not markedly different from the CRDDENY results, with the exception that here monthly income has a significantly negative effect on CRDSHORT. Nonwhites remain disadvantaged with a 3.60 percentage point greater probability of being CRDSHORT relative to whites. This compares to a gross observed racial differential for CRDSHORT of 9.60 percentage points from Table 2.

Discouraged Credit Seekers

The analysis thus far has centered on a comparison of unsuccessful credit applicants (U) relative to all potential applicants (P). Athough we have shown that nonwhites are denied credit in greater

TABLE 4

Probit Estimates of The Determinants of Credit Denial and Discouragement

	CRDDENY	REAPPLY	DENYFNL	CRDSHORT	DISCOURAGED
MONTHLY INCOME	−0.028 (1.41) [−0.005]	0.052 (1.12) [0.02]	−0.012 (0.14) [−0.005]	−0.076 (2.59) [−0.011]	−0.045 (1.35) [−0.005]
NET WORTH	−0.001 (2.05) [−0.000]	0.001 (0.37) [0.000]	−0.011 (1.98) [−0.004]	−0.002 (1.97) [−0.000]	−0.002 (2.86) [−0.000]
OWN/RENT	−0.353 (5.18) [−0.065]	0.235 (1.67) [0.091]	−0.288 (1.19) [−0.107]	−0.379 (5.09) [−0.053]	−0.346 (4.26) [−0.037]
CREDCARD	0.040 (1.04) [0.007]	−0.030 (0.36) [−0.011]	0.365 (2.06) [−0.136]	0.002 (0.04) [0.000]	0.060 (1.28) [0.006]
EXPENSE	−0.001 (0.01) [−0.000]	0.607 (2.23) [0.235]	−1.264 (0.43) [−0.471]	−0.041 (0.47) [−0.006]	−0.033 (0.31) [−0.003]
AUTOS	0.026 (.74) [0.005]	−0.078 (1.09) [−0.030]	−0.050 (0.43) [0.019]	0.027 (0.70) [0.004]	−0.056 (1.25) [−0.006]

TABLE 4 (CONTINUED)

	CRDDENY	REAPPLY	DENYFNL	CRDSHORT	DISCOURAGED
NOPAYDEBT	0.554 (7.47) [0.103]	−0.202 (1.53) [−0.078]	0.155 (0.65) [0.08]	0.560 (7.18) [0.079]	0.347 (4.06) [0.037]
YRS LOCAL	0.000 (0.07) [0.000]	−0.001 (0.12) [−0.000]	−0.002 (0.29) [−0.001]	0.001 (0.47) [0.000]	0.001 (.38) [0.000]
JOB TENURE	−0.012 (2.87) [−0.002]	0.008 (0.78) [0.003]	−0.030 (1.65) [−0.11]	−0.012 (2.56) [−0.002]	−0.019 (3.06) [−0.002]
NOCHECK	−0.051 (0.70) [−0.009]	−0.179 (1.27) [−0.069]	−0.090 (0.37) [−0.033]	−0.039 (0.51) [−0.006]	0.153 (1.92) [0.016]
AGE HEAD	−0.020 (8.91) [−0.004]	−0.006 (1.15) [−0.002]	−0.001 (.09) [−0.000]	−0.019 (7.49) [−0.003]	−0.016 (5.82) [−0.002]
RACE HEAD	−0.247 (3.49) [−0.046]	0.160 (1.17) [0.062]	0.074 (0.32) [0.028]	−0.256 (3.42) [−0.036]	−0.303 (3.39) [−0.032]
FEMALE HEAD	0.143 (1.49) [0.026]	−0.180 (0.98) [−0.070]	0.235 (0.73) [0.088]	0.159 (1.57) [0.022]	0.449 (4.31) [0.048]
MALE HEAD	−0.061 (0.24) [−0.011]	−0.609 (0.94) [−0.236]	−5.896 (0.00) [−2.198]	−0.019 (0.07) [−0.003]	0.287 (1.03) [0.030]
SINGLE MALE	0.100 (1.15) [0.019]	0.260 (1.53) [0.101]	0.102 (.38) [0.038]	0.018 (.19) [0.003]	0.145 (1.41) [0.015]
SINGLE FEMALE	−0.140 (1.51) [−0.026]	0.061 (.31) [0.024]	0.449 (1.32) [0.167]	−0.140 (1.40) [−0.020]	0.220 (2.14) [0.023]
CRDSHORT					0.654 (6.73) [0.069]
NW*CRDSHORT					0.209 (1.26) [0.022]
CONSTANT	0.195 (1.53)	−0.381 (1.48)	0.506 (1.16)	0.035 (0.25)	−0.383 (2.43)
Likelihood Ratio Test	452.3	39.4	35.6	389.9	566.1
n	3665	538	212	3665	3665
% correctly classified	85.0%	64.9%	68.9%	89.0%	90.7%

Note: Absolute values of asymptotic t-statistics and partial derivatives are reported in parentheses and square brackets, respectively, below each coefficient.

proportions than whites:

$$(U/P)_{NW} > (U/P)_W$$

ceteris paribus, some readers may regard our inference of discrimination as unwarranted if nonwhites are disproportionately more likely to apply for credit relative to whites. Direct evidence on applications is not provided by the SCF. However, responses to another question provide indirect evidence on willingness to apply for credit:

[4] Was there any time in the past few years that you (or your husband/wife) thought of applying for credit at a particular place, but changed your mind because you thought you might be turned down? [DISCOURAGED]

In particular, we examine whether nonwhites are more or less likely to be discouraged from applying relative to whites. Let A be the population of actual applicants. Given the identity, $(U/P) = (U/A)*(A/P)$ then if $(A/P)_{NW} < (A/P)_W$, it follows that $(U/A)_{NW} > (U/A)_W$. That is, if we can show that nonwhites are less likely to apply for credit relative to whites (or alternatively, that they are more likely to be discouraged), given our results from CRDSHORT, the conclusion that nonwhite *applicants* are less likely to obtain credit relative to white *applicants* follows.

Two additional regressors were included in the analysis of discouragement in the search for credit [DISCOURAGED], CRDSHORT and NW*CRDSHORT, where NW takes the value 1 for nonwhite respondents and 0 otherwise. These variables test whether a previous rejection from a lending institution produces discouragement and, if so, whether or not the discouragement is differentially greater for nonwhites relative to whites.[10]

The last column of Table 4 reports our probit estimates of the discouragement equation. Those most likely to be discouraged include families (a) with low net worth, (b) who rent rather than own their home, (c) who do not pay their debts as scheduled, (d) whose head has little job tenure, (e) younger heads of households, (f) female heads of households and single women, and (g) nonwhite households. Finally an examination of partial derivatives of CRDSHORT and NW*CRDSHORT show that (a) an unsuccessful search for credit is the most important determinant of discouragement, but that (b) nonwhites are not differentially more likely to be discouraged by an unsuccessful credit search. Nontheless, the partial derivatives of RACE HEAD and FEMALE HEAD are large (3.2% and 4.8%) and are associated with highly significant coefficients, indicating that female heads of households and nonwhite heads are significantly more likely to be discouraged from applying relative to their reference groups. Therefore, the conclusion that nonwhites *applicants* are more likely to be denied credit relative to white *applicants* appears to be warranted.

SUMMARY AND CONCLUSIONS

Discrimination against nonwhites in credit markets can be said to exist whenever nonwhite applicants with the same characteristics relevant to credit-worthiness as white applicants are rejected for credit more frequently than whites. Credit scoring and the enforcement regulations of the ECOA require that blacks and whites be evaluated by the same criteria. More specifically, characteristics related to credit-worthiness must be given the same weight whether the applicant is black or white. Membership in a protected group must be given no weight. For this reason, we have employed a standard linear probit specification with race dummies to test whether or not nonwhites are differentially more likely to be rejected for credit. We find that they are.

The empirical evidence presented here is consistent with models based on either (a) tastes for discrimination on the part of lenders of their agents along lines developed by Becker [1971] or (b) statistical discrimination based on differential reliability of measures of credit-worthiness (e.g. NOPAYDEBT) across races. Statistical discrimination occurs if, for example, lenders base their credit decisions on differences in debt repayment practices by race and not just the debt repayment history of the applicant. Aigner and Cain [1977] demonstrate that if lenders are risk averse, both models yield predictions that are qualitatively consistent with the empirical evidence reported here.

Nevertheless, several related sets of results need to be emphasized. First, the proportion of households that experience unsuccessful credit searches is significantly greater, *ceteris paribus,* for nonwhites than for whites. Credit application data was not needed to reach this conclusion. While it is unfortunate that the 1983 Survey of Consumer Finances does not provide application data, we stress again that application data may provide a misleading picture of the willingness of lending institutions to meet minority credit requests. Furthermore, consider what is required for the higher rate of minority credit denials to be considered as outcomes of a nondiscriminatory process. First, let us assume that loan officers screen potential credit applicants turning some away prior to any formal application *but do so without regard to race.* Then the sample selectivity problem disappears. However the absence of application data presents no real problems either since the relative rates of credit denial by race out of a pool of actual applicants can be expected to be proportional to the relative rates by race out of a larger pool of all potential applicants.

Since we observe a higher rate of credit denial for nonwhites, what is necessary to reach the nondiscriminatory conclusion is that minorities apply to lending institutions in greater rates than whites, *ceteris paribus.* However, if elicited survey responses have any meaning, then in contrast to the nondiscriminatory hypothesis, the finding here is that minorities and female heads are more likely to be discouraged from applying for credit than are white and/or male heads of households. Hence our results stand in contrast to the Lindley et al. Atlanta study [1984]. In addition, single parent families are more likely to be discouraged as well. No evidence was found for either the willingness to search for credit or the frequency of credit denials that would suggest that older households are disadvantaged. Indeed older households are less likely to be discouraged and less likely to experience unsuccessful credit searches.

Finally, it must be noted that the samples responses here apply to 1983 and the years just previous to it. These years were ones of rapid change and stress among many lending institutions and a time when both nominal and real interest rates were at or near record highs. The increased stability and competitiveness of lending institutions since this period might possibly be expected to produce an erosion of the racial differentials in credit provision shown here.

NOTES

1. For example, in a different context, housing, repeated studies of housing search using matched pairs show that minorities receive less attention and fewer referrals from real estate agents, *cet. par.* See Yinger [1987] for a survey.
2. See Spence [1974] for a general discussion and Capon [1978] for specific examples. Analyses with applicant data can be found in Grablowsky and Talley [1981] and Wiginton [1980].
3. For example, industry or occupation may be a proxy for sex [e.g., see Shuman v. Standard Oil, 453 F. Supp. 1150 (1978)].
4. See Hsia [1978], particularly pages 440–441.
5. For example, see O'Quinn v. Diners Club, slip op. (no. 77 c 3491), U.S. District Court for the Northern District of Illinois, Eastern Division, September 1, 1978. Eisenbeis [1980] provides a rationale for this requirement. He also notes the complexities involved when a multitude of factors interact to yield a low point score.
6. Financial net worth does not include the current value of the respondent's home and other properties or the value of any vehicles owned by the household. A more comprehensive measure of net worth which included these variables was initially employed in the specification. However, the coefficients of this net worth variable were in general not significantly different from zero. Two plausible reasons are that these assets are (a) inherently difficult to value, resulting in measurement error and/or (b) not collateralized when applying for conventional consumer debt. Thus, in its place, we used financial net worth (which can be negative due to the omission of property), number of vehicles owned, and a dummy variable for homeownership. The coefficients and significance levels of RACEHEAD and other variables were insensitive to this choice of specification.
7. Strictly speaking, age protection applies only to the elderly. In accordance with Federal Reserve Board regulations, age may be used in credit scoring systems as long as those age 62 and over are not disadvantaged relative to younger applicants.

8. Lindley et al. [1984] argue that in general the specification should include as well race interacted with the numerous right-hand variables and that only if the race dummy itself is significant in the presence of the set of race-interaction terms is this evidence of discrimination. They present no structural model prescribing this but argue that racial differences in preferences for credit justify the approach. We use a linear approach because credit scoring systems and enforcement regulations of the ECOA require blacks and whites to be evaluated by the same criteria.
9. We recognize, as have referees, that if the type of credit or other relevant omitted financial characteristics vary systematically with RACEHEAD, then the observed racial differential will be affected. As previously discussed, the SCF does not provide such information.
10. We perceive DISCOURAGED and CRDSHORT as a recursive system of equations.

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