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Borrowing Constraints, Household Debt, and Racial Discrimination in Loan Markets*

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Two-step selection methods are applied to the 1983 Survey of Consumer Finances to examine the extent to which borrowing constraints restrict household access to debt and the manner in which lenders vary debt limits across borrowers. Results indicate that 30% of young families are credit constrained, and that roughly half of these families would hold at least $12,000 (1982 dollars) more debt if borrowing constraints were relaxed. Debt limits increase with income and wealth, and are relaxed for families with a good credit history. In addition, minorities face tighter debt limits and are more likely to be credit constrained than white families. *Journal of Economic Literature* Classification Numbers: E51, J71, D12.

I. INTRODUCTION

This study addresses two distinct but related questions: to what extent do borrowing constraints affect the level of debt held by households, and

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how do lenders vary debt ceilings across prospective borrowers, especially with regard to race?[1] While the former question has been studied primarily in the academic literature by analysts interested in testing the perfect capital markets assumptions of the Life-Cycle/Permanent Income Hypothesis (LCPIH), the latter question has sparked a heated debate in the public press and among various branches of government. Under these conditions, the implications of borrowing constraints for the LCPIH and the possibility of racial discrimination in loan markets have been analyzed in isolation from one another. In fact, however, the two questions are linked since binding borrowing constraints affect household behavior regardless of the motivation for those constraints.

Applying two-step selection methods to the 1983 Survey of Consumer Finances (SCF), our study finds that 30% of young households in the United States are credit constrained, and that half of these families would hold at least $12,000 more debt (in 1982 dollars) if borrowing constraints were relaxed, ceteris paribus. This suggests that many young households may have a limited ability to smooth their consumption, in contrast to assumptions underlying the LCPIH. That finding is consistent with various studies that have found evidence of excess volatility in household consumption relative to behavior implied by a strict interpretation of the LCPIH (e.g., Hall and Mishkin, 1982; Hayashi, 1985; Zeldes, 1989).

Further analysis indicates that households with strong intrinsic preferences for holding debt are more likely to be credit constrained, lenders set higher debt limits for families with higher levels of income and wealth, and debt limits are relaxed for families with a good credit history. Moreover, minority households are significantly more likely to be credit constrained than comparable white families, but there is no discernible difference in the demand for debt among white and nonwhite households. This pattern of results suggests that racial discrimination limits minority access to debt, consistent with recent findings in the Boston mortgage market (Munnell *et al.*, 1992).

To establish these results the plan for the paper is as follows. Section II discusses how our study builds off of previous work. Section III presents our empirical methodology. Section IV describes the data, Section V presents results, and Section VI provides concluding comments.

II. PREVIOUS STUDIES

Given that this paper has implications both for studies on the validity of the LCPIH as well as studies on racial discrimination in credit markets,

[1] Explanations for borrowing constraints generally fall into one of two groups. The first, typified by Williamson (1986), suggests that debt constraints arise because of agency costs of default that lenders face but borrowers escape. The other strand of literature, including

guidance for our work can be taken from both literatures. On the one hand, important research testing the robustness of the LCPIH includes a number of cross section and panel data analyses, such as those by Hall and Mishkin (1982), Hayashi (1985), and Zeldes (1989). These papers provide evidence that the time path of consumption expenditures for households that are not credit constrained differs from that of families for whom borrowing constraints *may* be binding. Based on those findings the authors typically conclude that borrowing constraints have an important impact on a subset of the population. A limitation of these studies, however, is that the data used do not directly identify credit-constrained and unconstrained families.[2] This has raised questions about whether the analyses above suffer from coding errors when splitting the sample on the basis of who is not credit constrained.

On the other hand, the Federal Reserve's Survey of Consumer Finances allows the researcher to directly identify families that have recently been turned down for credit, received smaller than desired loans, or have been dissuaded from applying for credit. Using the SCF, Jappelli (1990) investigated the characteristics of credit-constrained families, and Cox and Jappelli (1993) estimated the extent to which borrowing constraints reduced the levels of debt held by such families. These two studies, however, did not control for a number of variables used by lenders in evaluating loan applications, including credit history in the case of Jappelli (1990) and both credit history and wealth in the case of Cox and Jappelli (1993).[3]

The importance of controlling for wealth and credit history when analyzing household access to credit has been underscored by recent debate about whether racial discrimination restricts the ability of minority households to obtain credit. Although that controversy dates back at least to the 1970s when a wave of Fair Lending legislation was enacted, the debate has become especially sharp in the last few years with the release of 1990 mortgage application data that were collected as part of the Home Mort-

Jaffee and Russell (1976) and Stiglitz and Weiss (1981), emphasizes the role of asymmetric information, adverse selection, and moral hazard.

[2] Instead, the studies above typically assume that families with either high wealth-to-income ratios or high savings rates are not credit constrained. Given that most household debt is used to finance consumer durables such as housing, the demand for which increases with income and wealth, many high-income and high-wealth families could still encounter binding borrowing constraints because of an elevated demand for debt. This raises the possibility that earlier studies may suffer from substantial measurement error. Jappelli (1990) provides evidence on this point.

[3] The effect of borrower credit history and wealth on loan contracts has been emphasized in various theoretical models of lending. Jaffee and Russell (1976) and Stiglitz and Weiss (1983, p. 918), for example, suggest that lenders impose less stringent constraints on households with a favorable credit history, while studies by Bernanke and Gertler (1989, 1990) emphasize that access to credit increases with the level of collateral available to borrowers.

gage Disclosure Act (HMDA).[4] An initial report based on aggregates obtained from those data indicated that in 1990, mortgage applications from black households across the United States were denied at a substantially higher rate than applications from white households with similar income (Canner and Smith, 1991). As noted by Rehm (1991b), that finding prompted House Banking Committee Chairman Henry Gonzalez to ask ". . . top regulators for an 'immediate' report on what their agencies plan to do to correct the lending problems revealed [by the HMDA data]." However, the HMDA data do not include household credit history or wealth, in addition to other important variables that appear on loan application forms. As a result, many other individuals in government, the banking industry, and academia have questioned whether the HMDA data imply that lenders discriminate against minority loan applicants.[5]

Partly in response to that debate, the Federal Reserve Bank of Boston has conducted a study of mortgage application denial rates in Boston [Munnell *et al.*, 1992) using a much wider range of loan applicant characteristics than previously analyzed. An important finding of the study is that allowing for differences in loan applicant wealth and credit history reduces but does not eliminate race-related differences in mortgage denial rates. Although these results provide a new perspective on the Boston mortgage market, the study still has limitations. In particular, the decision to apply for a loan is treated as exogenous. If instead minority applicants are disproportionately discouraged from applying for a mortgage, then the Boston study may understate discrimination effects.[6] On the other hand, if households are able to substitute different forms of debt to offset constraints on access to a given type of loan, then the Boston study could overstate the effect of discrimination on the ability of minority households to obtain credit.[7]

Building off of the studies above, this paper addresses the two questions posed at the outset by drawing on certain special features of the 1983

[4] Beginning in 1990, lenders were required by HMDA to report the location of residential loans made along with the income, race, and gender of loan applicants and whether the loan application was withdrawn (by the applicant), approved, or denied. See Rehm (1991a,b) and Munnell *et al.* (1992) for further discussion of the HMDA data.

[5] For example, Rehm (1991b) also notes that although Governor LaWare of the Federal Reserve described the HMDA data as "very worrisome," he indicated that more information was needed. Similarly, Rehm (1991b) reports that ". . . leading industry groups, such as the American Bankers Association, have maintained that the Fed data do not take into account information crucial to credit decisions, such as a loan applicant's credit history, other debts, or employment."

[6] As noted by Jappelli (1990), for example, data from the 1983 SCF suggest that lenders discourage many households from applying for a loan. However, only families that file a loan application are included in the HMDA data.

[7] A further limitation of the Federal Reserve Bank of Boston study is that it focuses on a single SMSA. In contrast, our work is based on a sample that is representative of the United States.

SCF, including information on household credit history and wealth, and whether the family has recently been turned down or dissuaded from applying for credit. We restrict our analysis to a group of households that are representative of families in the United States with heads under age 35, the age group most likely to be affected by borrowing constraints.[8] Using these data a bivariate probit model is first estimated based on who is not credit constrained and who would like to hold positive debt. In a second stage, a reduced-form household debt demand function is estimated using only unconstrained households that hold positive debt, controlling for selection effects related to both the decision to apply for credit and the absence of binding borrowing constraints.[9] By examining the total amount of debt held by households, we allow for the possibility that families may be able to substitute different forms of debt to offset idiosyncratic constraints on access to a given type of credit. As a result, estimates from the debt function enable us to predict the total level of debt that credit-constrained families would prefer to hold in the absence of binding borrowing constraints. In addition, in a manner to be clarified later, comparing coefficients of the credit model to those of the debt function allows us to characterize the qualitative manner in which lenders vary debt ceilings across households.

III. ECONOMETRIC MODEL AND ESTIMATION METHOD

Our model is specified by three principal equations. The first equation is the household's *preferred* level of debt (D^*) at current market interest rates. Because we use cross section data, all households in the sample face the same set of market interest rates which are captured primarily through the constant.[10] Hence, D^* is given by

$$D^* = xd + e_1, \tag{1}$$

where x are household characteristics and d are the parameters. The second equation is an unobservable index that determines whether a

[8] Indeed, young households are the only age group in the SCF with a relatively large number of credit-constrained families.

[9] A reduced form debt function is estimated because closed-form solutions for consumption and saving (and by implication for household debt) are impossible to obtain without strong restrictions on the underlying utility function. In addition, testing for Euler equation violations to evaluate the potential effect of borrowing constraints [as in Zeldes (1989)] was not feasible because the 1983 SCF lacked the necessary time series data.

[10] We argue shortly that any variation in interest rates offered to constrained and unconstrained families affects the error term in (1) and is controlled for through the selection model.

household prefers to hold positive or zero debt at market interest rates,[11]

$$I_1 = xa + u_1. \tag{2}$$

This equation controls for the fact that debt holdings are truncated below by zero. The third equation is an unobservable index that determines whether the household is unaffected by borrowing constraints (i.e., the debt ceiling set by lenders exceeds D^*) under current market conditions,

$$I_2 = zg + u_2. \tag{3}$$

If a household is credit constrained or if it prefers to hold zero debt, then D^* is not observed. Note, also, that if the demand function determines whether households hold zero debt, (1) and (2) are identical, which is testable as will become apparent below. In addition, given that a household is credit constrained only when it would like to borrow more debt than lenders will allow, z should include all of the determinants of the demand for debt (x) as well as any additional regressors that affect lender-imposed debt limits but which do not affect the demand for debt itself.

The observable discrete analogues to (2) and (3) are given by

$$\text{Dbt0} = \begin{cases} 1, & I_1 > 0 \Rightarrow \text{positive debt} \\ 0, & I_1 < 0 \Rightarrow \text{zero debt} \end{cases} \tag{4}$$

and

$$\text{Cr} = \begin{cases} 1, & I_2 > 0 \Rightarrow \text{not constrained} \\ 0, & I_2 < 0 \Rightarrow \text{constrained.} \end{cases} \tag{5}$$

These expressions indicate that Dbt0 equals 1 or 0 depending on whether families prefer to hold positive debt or zero debt, respectively, while Cr equals 1 or 0 depending on whether families are not credit constrained or are credit constrained, respectively. Since families are credit constrained only if they prefer to hold more debt than lenders will allow, credit-constrained families must prefer to hold positive debt; similarly, families that prefer to hold zero debt cannot be credit constrained. Hence, Cr is defined only over households for whom Dbt0 = 1, and there are only three distinct cells in the model, Cr = Dbt0 = 1, Cr = 0 and Dbt0 = 1, and Dbt0 = 0. Estimation of this model is simplified by assuming that $[e_1, u_1,$

[11] Roughly 29% of constrained families and 16% of unconstrained families in the sample hold zero debt.

$u_2]$ is distributed trivariate normal with mean zero and variance matrix (V).

$$V = \begin{bmatrix} \sigma^2 & \sigma_{1,u_1} & \sigma_{1,u_2} \\ \sigma_{1,u_1} & 1 & \sigma_{u1,u_2} \\ \sigma_{1,u_2} & \sigma_{u1,u_2} & 1 \end{bmatrix}.$$

Observe, also, that the same model as above can be used to estimate a log-linear debt demand function simply by reinterpreting D^* in (1) as the log of debt. To simplify exposition, however, we focus on the linear case here (selected results from the log-normal model are presented later in the paper).

To estimate the model above two-step methods were used as described by Tunali (1986).[12] Initially, a bivariate probit model is estimated by maximum likelihood to evaluate the probability that families are unconstrained and would like to hold positive debt (Cr = Dbt0 = 1). Following Tunali (1986), the log-likelihood function for this model is given by

$$\begin{aligned} \sum \{(1 - \text{Dbt0}) \cdot \log[F(-xa)] \\ + \text{Dbt0} \cdot \text{Cr} \cdot \log[G(xa, zg, \sigma_{u_1,u_2})] \\ + \text{Dbt0} \cdot (1 - \text{Cr}) \cdot \log[G(xa, -zg, -\sigma_{u_1,u_2})]\}, \quad (6) \end{aligned}$$

where F and G are the unit and bivariate standard normal distribution functions, respectively.

Based on work by Rosenbaum (1961), Tunali (1986) shows that

$$E[e_1 : u_1 > -xa, u_2 > -zg] = \sigma_{1,u_1} M_{1,u_1} + \sigma_{1,u_2} M_{1,u_2}, \quad (7)$$

where M_{1,u_1} and M_{1,u_2} are functions of xa, zg, and σ_{u_1,u_2}. For the special case when σ_{u_1,u_2} equals zero, M_{1,u_1} and M_{1,u_2} both collapse to the traditional Mills ratio $\lambda(s) = f(s)/F(s)$, where f and F are the unit normal density and distribution functions, and λ is evaluated at xa and zg for M_{1,u_1} and M_{1,u_2}, respectively. More generally, however, when σ_{u_1,u_2} differs from zero the expressions for M_{1,u_1} and M_{1,u_2} become complicated and are not presented here to conserve space.[13] Expressions for M_{1,u_1} and M_{1,u_2} are provided in Appendix A and can also be found in Maddala (1983, page 282) and Tunali (1986).

[12] Tunali (1986) clarifies many of the technical issues underlying estimation of bivariate probit selection models with incomplete classification.

[13] Nevertheless, Fishe *et al.* (1981) show that if σ_{u_1,u_2} differs from zero, substituting λ for M_{1,u_1} and M_{1,u_2} in the second-stage OLS regression yields biased estimates.

Using estimates of a, g, and σ_{u_1,u_2} from the bivariate probit routine, M_{1,u_1} and M_{1,u_2} were formed for each household. Consistent estimates of the debt function parameters (d) were then obtained by including M_{1,u_1} and M_{1,u_2} in a second-stage ordinary least-squares (OLS) regression of the debt function (1) using only unconstrained households that hold positive debt. The coefficients on M_{1,u_1} and M_{1,u_2} also give consistent estimates of σ_{1,u_1}, and σ_{1,u_2}, while further manipulation yields a consistent estimate of σ_1^2. Correct asymptotic standard errors are obtained based on formulas described by Maddala (1983) and extensions developed by Tunali (1986).[14]

To clarify how these estimates enable us to evaluate the impact of borrowing constraints on household debt, we should emphasize that D^* [expression (1)] is the preferred level of debt at prevailing interest rates regardless of whether the household is unconstrained or constrained. In addition, under the assumption that unconstrained households with positive debt intend to pay back their loans, the estimated parameters of (1) are indicative of household behavior when families abide by their budget constraints. Hence, xd is the expected demand for debt for an arbitrary household with characteristics x at prevailing market interest rates. Idiosyncratic differences in household preferences for debt, as well as differences in loan interest rates across borrowers that affect debt holdings, are reflected in e_1.

If e_1 is independent of u_1 and u_2, the expected value of D^* for constrained families is xd. But if there are unobservable components that affect both D^* and either u_1 or u_2 (like differences in interest rates), the expected value of D^* for constrained families would be sensitive to correlation between the error terms. To control for such effects, the conditional mean of e_1 is formed as

$$E[e_1 : u_1 > D_c/\sigma_1 - xa,\ u_2 < -zg] = \sigma_{1,u_1} m_{1,u_1} + \sigma_{1,u_2} m_{1,u_2}, \qquad (8)$$

where D_c is the observed level of debt held by the constrained household.[15] Observe that (8) is based on the assumption that the preferred level of debt for constrained households is greater than or equal to D_c. As above, expressions for m_{1,u_1} and m_{1,u_2} are provided in Appendix A.

From (1) and (8), the expected preferred level of debt for a constrained household with characteristics x and z is given by

[14] Estimates of σ_1 and the correct asymptotic covariance matrix were obtained based on the three-cell asymptotic covariance formula developed by Tunali (1986, page 278). Note, also, that if expressions (1) and (2) are identical, $\sigma_1 = \sigma_{1,u_1}$, $d/\sigma_1 = a$, and $\sigma_{u_1,u_2} = \sigma_{1,u_2}/\sigma_1$. These restrictions are tested later in the paper using estimates from the bivariate probit and OLS models.

[15] Expression (8) is based implicitly on the assumption that expressions (1) and (2) are identical, in which case u_1 equals e_1/σ_1 and $a = d/\sigma_1$.

$$E[D^* \mid x, z; d, a, g; \text{Dbt0} = 1, \text{Cr} = 0, D_c] = xd + E[e_1 \mid u_1 > D_c/\sigma_1 - xa, u_2 < -zg]. \quad (9)$$

Subtracting D_c from (9) gives the difference between the expected preferred and the actual levels of debt held by constrained families at prevailing market interest rates,

$$E[D^* - D_c \mid \text{Dbt0} = 1, \text{Cr} = 0, D_c] = E[D^* \mid x, z; d, a, g; \text{Dbt0} = 1, \text{Cr} = 0, D_c] - D_c. \quad (10)$$

IV. DATA AND VARIABLES

Data for the study were taken from the 1983 SCF which contains 4303 households. From these households we excluded individuals with wealth over 1 million dollars (in 1982 dollars), observations with relevant missing values, households belonging to a special high-income group that was oversampled in the survey, and households over age 34. The remaining 1224 observations comprise a representative sample of the United States in 1982 of households under age 35 with under 1 million dollars in net wealth. Summary statistics for these data are presented in Table I, while detailed definitions of variables used in the study are provided in Appendix B.

A special feature of the SCF is that households were asked if they "had a request for credit turned down by a particular lender or creditor in the past few years, or had been unable to get as much credit as he/she had applied for." Families that had been turned down or received less credit than desired were further asked whether they had successfully reapplied for the desired level of credit at another lender. Households were also asked if "there had been any time in the past few years that he/she (or their spouse) had *thought* about applying for credit at a particular place, but changed their mind because [the household] thought it might be turned down." Based on these three questions, a household was defined to be credit constrained in the 1980–1983 period (Cr) if (i) the household had not applied for credit because it thought that it would be turned down or (ii) a lender had turned down or not fully granted a household's loan request and the household did not successfully reapply for the desired level of credit.[16]

[16] We also estimated the entire model excluding type (i) households on the possibility that some of these families may have misunderstood the survey questions. The qualitative and (in most cases) the quantitative nature of our results were not sensitive to whether type (i) families were included. Selected results from that analysis are provided in Duca and Rosenthal (1991).

A further strength of the 1983 SCF is the extreme detail given to real and financial household assets and debts which enabled us to form the debt variables (*D* and Dbt0). We also formed net wealth as the difference between total nonpension assets and total debt (in $1,000 units).[17] Presumably net wealth could affect the demand for debt, although the direction of effect is unclear. On the one hand, more wealthy families have less need to borrow against future income to smooth current consumption, but wealthy individuals may also choose to lever up further in the housing market which could increase their demand for debt. In deciphering these effects it is also important to recognize that debt holdings could influence the observed level of wealth held by a family.[18] Accordingly, to control for possible simultaneity effects net wealth is regressed on all of the exogenous variables in the model as well as some additional variables taken from the SCF. The fitted value from the wealth equation (WHat) was then included in the demand function and the discrete choice models. Results from the wealth regression are provided in Appendix C.

Total household income in $1,000 units (INC82) and INC82 squared (INCSQ82) were also included in the debt equations, as was the unemployment rate in 1982 for the household head's profession (UNEMP). Higher income families likely have an increased demand for debt given their elevated demand for consumer durables like housing. Also, to the extent that a household's future income is secure, presumably the family would be more willing to borrow against future income to smooth current consumption which would increase the demand for debt.

Theory also suggests that households that expect to receive pension benefits will hold more debt today. To control for such effects, income is interacted with a dummy variable that equals 1 if either the household head or the spouse expect to receive pension income, and zero otherwise. The resulting variable (PENINC) proxies expected future pension income and is expected to have a positive sign.

Preferences for holding debt are further proxied based on whether households felt it was "all right for someone like [the respondent] to borrow money to . . . finance medical expenses or to finance living expenses when income is cut (EMERG); to finance auto or furniture purchases (DUR); to finance luxury items (LUX);[19] to finance a vacation

[17] The asset data taken from the SCF include the principal financial assets that households might hold other than pension wealth, plus the current market value of residential property and autos. Note, also, that information on debts is based on book as opposed to market value. See Avery *et al.* (1987) for further details on these data.

[18] Borrowing to finance nondurable consumption immediately lowers net wealth which implies a simultaneous relationship between wealth and debt. Also, the observed level of wealth in 1983 is potentially sensitive to whether the family was credit constrained over the 1980 to 1983 period.

[19] These included financing for jewelry, fur coats, boats, snowmobiles, and other hobby equipment.

(CONSUMP)," and whether a household would not be ". . . willing to take any financial risks . . . when [saving or making] investments (AVERSE)." Presumably, people who feel it is all right to borrow will hold more debt. On the other hand, families that are relatively risk averse may be less inclined to lever up in the housing market and would, therefore, hold less debt. Finally, preferences for holding debt were also proxied by traditional demographic variables, including the household head's marital status (MARR), sex (SEX), education (ED), and race (RACE), as well as household size (HSIZE).

All of the variables above are included in the probit model of who is not credit constrained since the demand for debt affects the extent to which families bump into lender-imposed debt ceilings. Also included in the credit constraint model are additional variables frequently requested on loan application forms. These variables include the number of years the household head has worked at the current employer (CUREMP), whether the household has a checking account (CHECK), whether the household has received public assistance (WELFARE), and whether the household has had problems making loan payments in the past three years (BADHST). In addition, a household was defined as having a history of homeownership if it purchased or inherited its current home (as of the survey date) prior to 1980 (OWNHIST).[20] Similarly, a household was defined as having a credit history other than homeownership if it had a nonmortgage loan still outstanding that originated prior to 1980 (SOMHST). These variables in conjunction with the household's demographic and financial characteristics control for essentially all of the information requested on most loan application forms.[21]

V. RESULTS

Summary statistics for the sample are in Table I. Observe that nearly 30% of young households in 1983 perceived themselves as credit constrained (Cr = 0). Moreover, nonwhites account for 27.4% of credit-constrained families but only 14.0% of unconstrained families. These data suggest that many young households are credit constrained, and that nonwhite households account for a disproportionate share of such families.

[20] Owning a mobile home was not treated as homeownership given the low quality of mobile home loans. Note, also, that OWNHST and SOMHST (defined below) are based on pre-1980 activity to control for possible simultaneity with the probability of being turned down for credit over the 1980–1983 period.

[21] The only exception is the location and characteristics of the household's neighborhood which could potentially affect access to mortgage credit given that neighborhood quality and stability affect housing prices. However, the 1983 SCF does not include information on the family's neighborhood which precludes analysis of that question.

TABLE I
VARIABLE SUMMARY STATISTICS[a]

Variable	Constrained (376 observations) Mean	Constrained (376 observations) SD	Unconstrained (848 observations) Mean	Unconstrained (848 observations) SD	Unconstrained Dbt0 = 1 (710 observations) Mean	Unconstrained Dbt0 = 1 (710 observations) SD	Full sample (1224 observations) Mean	Full sample (1224 observations) SD
Cr	0.00000	0.00000	1.0000	0.00000	1.0000	0.00000	0.69281	0.46152
Dbt0	1.0000	0.00000	0.83726	0.36934	1.0000	0.00000	0.88725	0.31641
Debt	8.8582	17.046	19.116	29.542	22.831	30.946	15.964	26.757
WHat	15.848	24.355	34.506	36.865	38.115	37.932	28.774	34.601
INC82	16.254	11.570	23.993	17.590	25.862	17.815	21.616	16.373
PENINC	7.3580	12.816	13.852	17.986	15.597	18.594	11.857	16.834
UNEMP	5.2151	5.8984	5.4973	6.1506	5.4415	5.8976	54.107	60.732
ED	0.84043	0.36670	0.87382	0.33225	0.88732	0.31642	0.86356	0.34339
MALE	0.48138	0.50032	0.56132	0.49652	0.54930	0.49791	0.53676	0.49885
RACE	0.27394	0.44657	0.14033	0.34753	0.11408	0.31814	0.18137	0.38548
MARR	0.47606	0.50009	0.65212	0.47658	0.70986	0.45415	0.59804	0.49049
HSIZE	2.7500	1.5769	2.7748	1.4333	2.8676	1.4110	2.7672	1.4783
AVERSE	0.44681	0.49783	0.37028	0.48317	0.36197	0.48091	0.39379	0.48879
CONSUMP	0.19947	0.40013	0.15330	0.36049	0.15493	0.36209	0.16748	0.37356
LUX	0.30053	0.45910	0.28656	0.45242	0.30423	0.46040	0.29085	0.45434
DUR	0.93883	0.23996	0.91745	0.27536	0.93944	0.23870	0.92402	0.26508
EMERG	0.90160	0.29826	0.88208	0.32271	0.87465	0.33135	0.88807	0.31541
CUREMP	2.4122	3.0538	3.3774	3.6232	3.5563	3.7101	3.0809	3.4856
BADHST	0.31117	0.46359	0.15566	0.36275	0.18310	0.38702	0.20343	0.40272
OWNHST	0.10904	0.31211	0.26061	0.43923	0.30000	0.45858	0.21405	0.41033
SOMHST	0.84574	0.36167	0.87382	0.33225	0.84930	0.35801	0.86520	0.34165
WELFARE	0.24468	0.43047	0.08255	0.27536	0.06479	0.24633	0.13235	0.33901
CHECK	0.61436	0.48739	0.77241	0.41953	0.82535	0.37993	0.72386	0.44727

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Dummy variables equal 1 for a positive response and 0 otherwise. All variables are defined in Appendix B.

Model I in Table II presents estimates from the bivariate probit model of who is not credit constrained (Cr = 1) based on the likelihood function in expression (6).[22] As discussed earlier, by allowing σ_{u_1,u_2} to differ from zero, Eq. (6) controls for possible selection effects stemming from the fact that Cr is defined only for individuals that want to hold positive debt (Dbt0 = 1). In practice, however, observe that our estimate of σ_{u_1,u_2} is small and insignificant which suggests that selection effects in the discrete choice model are not an issue for our sample. In addition, an estimate of σ_{u_1,u_2} close to zero indicates that households with an unexpectedly high propensity to desire positive debt (relative to xa) are no more likely to be credit constrained than families with average preferences for holding positive debt. As shown later, however, that result does not necessarily imply that the demand for debt has no impact on the propensity to be credit constrained.[23]

[22] Because the Dbt0 equation is estimated only to control for selection effects when evaluating the demand for debt, results from the Dbt0 equation are presented in Appendix C.

[23] Although Jappelli (1990) and Cox and Jappelli (1993) also evaluate the probability that a family is credit constrained using the 1983 SCF, as discussed at the outset, we include a

Before reviewing the variable coefficients in Tables II and III, we should emphasize that in our model a borrower is credit constrained if his or her preferred demand for debt exceeds the amount of debt lenders are willing to provide. Although debt ceilings likely vary across borrowers because of perceived differences in credit risk, it is difficult to measure such variation because debt ceilings typically are not directly observable. On the other hand, recall that the SCF data to enable us to estimate both the likelihood that a borrower is credit constrained and the borrower's preferred demand for debt, D^*, as in Tables II and III, respectively. In addition, consider that the sign of a variable's coefficient in the credit-constraint model depends on the effect of that variable on D^* *relative* to the variable's effect on the unobserved debt ceiling imposed by lenders. Accordingly, by comparing the signs of the estimated coefficients in Tables II and III it is possible to make qualitative statements about the direction of effect different variables have on the amount of debt lenders are willing to provide.

Bearing that thought in mind, in column (1) of Table II observe that households are more likely to face binding borrowing constraints if they had a bad credit history (BADHST = 1) or no mortgage credit history (OWNHIST = 0), if they do not have a checking account (CHECK = 0), or if the family has recently been on welfare (WELFARE = 1).[24] The variables SOMHST and CUREMP also have the anticipated signs, but are insignificant. Assuming that credit history does not directly affect a borrower's preferred demand for debt, these results confirm that lenders tighten debt limits on borrowers with limited or bad credit histories.

Another striking result in column (1) is that wealth, income, and income security (as proxied by UNEMP) do not have a statistically significant

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number of important variables that have not previously been analyzed. These variables include UNEMP, PENINC, AVERSE, CONSUMP, LUX, DUR, EMERG, CUREMP, BADHST, OWNHIST, SOMHST, CHECK, and WELFARE. Also, whereas Cox and Jappelli (1993) include a measure of permanent income, we stress the role of household wealth for reasons described earlier. On a more methodological note, Jappelli (1990) includes the actual levels of household net wealth and the log of debt in his model without addressing the simultaneity between net wealth, debt, and the propensity to be credit constrained, and without accounting for households that hold zero debt. Similarly, although Cox and Jappelli (1993) analyze the effect of credit constraints on household debt using a methodology similar to the one used here, they set the covariance of the error terms from the two selection equations equal to zero. As described earlier, such restrictions can bias estimates from censored discrete choice models and second-stage liner regressions [e.g., Fishe *et al.* (1981) and Maddala (1983)]. On the other hand, if our estimate that σ_{u_1,u_2} is small and insignificant carries over to other samples, then correlation between the zero debt and credit constraint selection equations may be less of a concern.

[24] These results are consistent with empirical findings by Boyes *et al.* (1989) and Orgler (1970) which indicate that the acceptance/rejection of loan applications and consumer loan defaults are significantly correlated with creditworthiness variables similar to those above.

TABLE II
THE LIKELIHOOD OF NOT BEING CREDIT CONSTRAINED[a]

	MODEL I[b]		MODEL II[b]	
Variable	Coefficient	T ratio	Coefficient	T ratio
CONST	0.52831	0.7303	0.26995	1.00
WHat	0.13265	0.2606	—	—
INC82	0.01209	0.8169	0.03139	3.92
INCSQ82	−0.34768E-04	−0.2214	−1.59111E-04	−1.91
PENINC	0.45495E-02	0.8245	0.58223E-02	1.59
UNEMP	−0.00674	−0.7764	−0.00145	−0.20
ED	−0.19724	−1.405	−0.04760	−0.37
MALE	0.05982	0.4491	0.02729	0.30
RACE	−0.33900	−2.537	−0.47123	−4.15
MARR	0.35389	1.850	0.35645	3.02
HSIZE	−0.06965	−1.652	−0.07232	−1.97
AVERSE	−0.05031	−0.5060	−0.06141	−0.70
CONSUMP	−0.13390	−1.156	−0.14791	−1.32
LUX	−0.16260	−1.442	−0.14908	−1.55
DUR	−0.24708	−0.7786	−0.21592	−1.19
EMERG	−0.11367	−0.7508	−0.09443	−0.71
CUREMP	0.02257	1.172	—	—
BADHST	−0.28448	−2.637	—	—
OWNHST	0.44244	2.035	—	—
SOMHST	0.06158	0.4828	—	—
WELFARE	−0.37921	−2.616	—	—
CHECK	0.19009	1.695	—	—
σ_{u_1,u_2}	−0.14696	−0.126	—	—
Log likelihood	−974.15		−620.83	
Sample size	1086		1086	

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Dummy variables equal 1 for a positive response and 0 otherwise. All variables are defined in Appendix B.

[b] Model I is estimated based on the bivariate probit likelihood function in expression (6). For the more parsimonious specification in Model II a simple univariate probit model was used because the bivariate probit model would not converge. Both models are estimated only over households that prefer to hold positive debt (Dbt0 = 1), the group over which the credit constraint variable is defined.

effect on the probability of being credit constrained.[25] But this result is at least partially explained by examining results from the debt demand functions in Table III. Observe that for various specifications of the demand function, wealth and income generally have a positive and significant

[25] This result is in contrast to that of Jappelli (1990) who found that higher income and more wealthy households were significantly less likely to be credit constrained. However, the differences between our results and those of Jappelli (1990) may reflect differences in specification as noted earlier.

TABLE III
DEBT DEMAND FUNCTIONS BASED ON UNCONSTRAINED HOUSEHOLDS[a]
(T RATIOS ARE ADJUSTED FOR SELECTION EFFECTS)

	Linear demand selectivity-adjusted		Linear demand unadjusted OLS		Log-linear demand Cr selection only	
Variable	Coefficient	T ratio	Coefficient	T ratio	Coefficient	T ratio
CONST	−27.436	−1.866	−13.330	−2.175	−4.5317	−8.602
WHat	0.11789	2.039	0.09533	2.197	0.5290	1.287
INC82	1.0299	4.864	0.91072	5.109	4.3788	3.281
INCSQ82	−0.29627E-02	−1.656	−0.18927E-02	−1.342	−2.6224E-02	−2.255
PENINC	0.13298	1.690	0.09770	1.431	0.21305	0.389
UNEMP	−0.59521	−3.488	−0.05692	−3.380	−2.0515	−1.738
ED	2.9706	0.896	2.1797	0.699	62.643	2.873
MALE	3.3493	1.244	4.9894	2.458	10.865	0.753
RACE	−5.2287	−1.450	−4.0888	−1.309	20.851	0.887
MARR	1.9282	0.467	−1.2642	−0.458	6.8682	0.313
HSIZE	2.6871	2.685	2.5497	2.872	1.9549	2.888
AVERSE	−1.5631	−0.757	−1.9342	−0.952	3.0377	0.213
CONSUMP	−4.2024	−1.541	−4.4379	−1.669	−8.1685	−0.439
LUX	4.6485	1.976	3.9131	1.822	25.072	1.635
DUR	5.8744	0.899	1.0952	0.275	54.503	1.905
EMERG	−0.01700	−0.006	1.1038	0.388	0.12731	0.006
M_{1,u_1} (σ_{1,u_1})	23.188	0.980	—	—	—	—
M_{1,u_2} (σ_{1,u_2})	6.2423	0.077	—	—	−192.04	−3.649
σ_1	26.885		.24517		1.9266	
F	25.657		29.040		29.991	
R^2	.38661		.38563		.40913	
SSR	416481		417152		14376267	
Obs.	710		710		710	

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Dummy variables equal 1 for a positive response and 0 otherwise. All variables are defined in Appendix B.

effect on the demand for debt, while the coefficient on UNEMP is negative and significant. Accordingly, it appears that the amount of debt that lenders are willing to extend increases with borrower income and wealth, as well as with job and income security.

Marital status (1 if married) has a positive and significant coefficient in the credit constraint model (in Table II) and a small and insignificant effect on the demand for debt. Hence, it appears that borrowing limits are less stringent for married families, ceteris paribus.[26] Household size (HSIZE) and a willingness to borrow for luxury (LUX) items have negative and marginally significant effects on the propensity to obtain the

[26] This interpretation is consistent with Boyes *et al.* (1989) who find that marriage has a negative and significant effect on the probability that a borrower defaults on a consumer loan. Note, also, that MALE has a small and insignificant coefficient in the credit constraint model, but a positive and significant coefficient in the unadjusted OLS demand function. That result suggests that male loan applicants may face less restrictive debt ceilings than female borrowers. However, such findings should be viewed with caution given that the significance of the coefficient on MALE is not robust to the alternative specifications of the debt function presented in Tables III and IV.

desired level of credit. In contrast, these variables have positive effects on the demand for credit. Given the combination of estimated effects of HSIZE, it is not possible to determine the direction of effect (if any) of HSIZE on lender-imposed borrowing constraints. On the other hand, recall that LUX pertains to whether households felt it was "all right" for someone like themselves to borrow to finance the purchase of luxury items. Given the subjective nature of LUX, presumably such preference-related information does not influence lender decisions. Accordingly, the negative coefficient on LUX in the credit constraint model further suggests that families with a higher intrinsic demand for debt are more likely to be credit constrained.

To evaluate the effect of RACE (1 if nonwhite) on access to credit, first compare results in Model I of Table II to the more parsimonious specification in Model II that omits WHat and the credit history variables.[27] Observe that failing to control for wealth and credit history biases upward the significance and estimated coefficient on RACE. This finding supports arguments that 1990 HMDA data overstate the effect of race on mortgage rejection rates because those data do not control for wealth and credit history (e.g., Rehm, 1991a). Nevertheless, RACE still has a negative and significant coefficient in Model I.[28] In addition, RACE has a generally negative (but marginally significant) effect on the demand for debt in Table III. Hence, it appears that lenders set tighter credit limits for nonwhite families, even after controlling for credit history, wealth, income, and the other regressors.[29]

We should emphasize that the results above are robust to alternative specifications of the debt demand function. For example, observe that the sign and significance of the demand function coefficients are similar for the linear and log-linear selection models in columns (1) and (3) of Table III, respectively.[30] The only exception is that neither of the selection terms, M_{1,u_1} or M_{1,u_2}, are significant in the linear case, but M_{1,u_2} has a

[27] The bivariate probit model failed to converge when WHat and the credit variables were omitted from the credit constraint equation. For that reason Model II in Table II reports results from a univariate probit model using only families that prefer to hold positive debt (Dbt0 = 1), the group over which the credit constraint variable (Cr) is defined. To the extent that σ_{u_1,u_2} is close to zero, as suggested by results in Model I, then specification errors resulting from the use of a simple probit model in Model II are likely to be slight.

[28] Munnell *et al.* (1992) also find a significant race effect even after controlling for loan applicant wealth and credit history in their study of mortgage application denial rates in Boston.

[29] These results are consistent with recent studies by Gabriel and Rosenthal (1991) and Canner *et al.* (1991). Those studies evaluate borrower choice of FHA versus conventional mortgages, recognizing that FHA loans are more expensive than conventional loans but have less restrictive downpayment requirements. Findings indicate that nonwhite homeowners are more likely to receive FHA mortgages than comparable white households.

[30] Note that if the log-normal model is the "correct" specification for the demand function, then expressions (1) and (2) must differ since the log of zero debt is not defined. In

negative and significant coefficient in the log-linear model.[31] Note, also, that coefficients from the linear selection model are not statistically different from estimates based on the OLS model in column (2) even though the OLS model omits M_{1,u_1} and M_{1,u_2}.[32]

The Impact and Incidence of Borrowing Constraints

Two methods were used to evaluate whether borrowing constraints affect household behavior. First, Table IV presents results from Tobit models of the debt demand function based on families that are not credit constrained, families that are credit constrained, and the full sample of both constrained and unconstrained families, respectively. If borrowing constraints do not affect household debt, coefficients from the three models should be similar. To test that hypothesis a likelihood ratio test was constructed based on the log-likelihood from the full sample model and the sum of the log-likelihoods from the stratified models.[33] The resulting test statistic equals 79 which overwhelmingly rejects the hypothesis of a unified sample in favor of the stratified models. Hence, it appears that borrowing constraints have a significant effect on the behavior of some households, at least with respect to the observed demand for debt.

As discussed earlier, the difference between the actual and the preferred levels of debt held by constrained families can be predicted using expression (10). Such estimates are presented in Table V for each of the

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contrast, if the linear model is the correct specification and if expressions (1) and (2) are identical, then $\sigma_1 = \sigma_{1,u_1}$, $\sigma_{u_1,u_2} = \sigma_{1,u_2}/\sigma_1$, and $a = d/\sigma_1$. In column (1) of Tables II and III, observe that σ_1 is close to σ_{1,u_1} and both σ_{u_1,u_2} and σ_{1,u_2} are small and insignificant. However, a Wald test rejects the null that $a = d/\sigma_{1,u_1}$ [the test statistic equalled 97.2 and is distributed $\chi^2(16)$]. To form the Wald statistic, we took d and σ_{1,u_1} from column (1) of Table III and a from column (1) of Table II, and formed the variance matrix for $d/\sigma_{1,u_1}$ based on the Delta method [see Billingsley (1979) for a discussion of the Delta method].

[31] For the linear model we also alternately dropped M_{1,u_1} and M_{1,u_2} to determine whether collinearity between the two terms might account for their low t ratios. In both cases the included selection term was not significant. Similarly, the log-linear model was also estimated including both selection terms, and again with only M_{1,u_1} included; in both cases M_{1,u_1} was not significant.

[32] A further robustness check is obtained by comparing estimates from the linear selection model in Table III to column (1) of Table IV which presents results from a Tobit debt function estimated only over families that are not credit constrained. Relative to the selection model, the tobit model imposes the restriction that the debt function and the process governing whether families prefer to hold zero debt [expressions (1) and (2)] are alike. Nevertheless, a Wald test fails to reject the null that coefficient estimates from the two models are equal (the test statistic equals 4.4 and has a $\chi^2(16)$ distribution).

[33] The test statistic was constructed by forming $T = -2 \cdot [-4688.9 - (-3401.6 - 1247.8)] = 79$, where T has a χ^2 distribution with 16 degrees of freedom, the number of restrictions between the stratified and full sample models.

TABLE IV
TOBIT DEBT DEMAND FUNCTIONS[a]

	Not constrained		Constrained		Full sample	
Variable	Coefficient	*T* ratio	Coefficient	*T* ratio	Coefficient	*T* ratio
CONST	−25.565	−4.351	−7.6232	−1.202	−21.209	−4.637
WHat	0.13554	3.102	0.22686	3.906	0.16721	4.732
INC82	0.90477	5.162	0.10650	0.420	0.74234	5.279
INCSQ82	−0.24844E-02	−1.778	0.43702E-02	1.196	−0.16588E-02	−1.423
PENINC	0.15594	2.274	0.20011	1.989	0.18017	3.158
UNEMP	−0.05248	−3.270	−0.02225	−1.345	−0.04601	−3.693
ED	2.5208	0.840	3.4042	1.199	3.1868	1.405
MALE	2.7343	1.369	2.6193	1.266	2.4595	1.587
RACE	−5.9024	−1.990	−2.4742	−1.076	−5.0445	−2.429
MARR	3.6313	1.356	6.3846	2.437	5.0317	2.478
HSIZE	2.4067	2.738	−0.55537	−0.689	1.1891	1.824
AVERSE	−1.2871	−0.645	2.0132	1.013	−0.18343	−0.120
CONSUMP	−3.9540	−1.517	−1.0369	−0.436	−3.2264	−1.659
LUX	4.3182	2.020	1.2967	0.613	3.3988	2.070
DUR	6.7362	1.862	2.9805	0.727	6.0452	2.106
EMERG	−0.59871	−0.211	−3.7243	−1.237	−1.5145	−0.681
σ_1	25.476	28.218	16.526	37.313	23.477	44.041
Log likelihood	−3401.6		−1247.8		−4688.9	
Obs.	848		376		1224	

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Dummy variables equal 1 for a positive response and 0 otherwise. All variables are defined in Appendix B.

models in Table III as well as for the unconstrained Tobit model (column (1) of Table IV).[34] Observe that the estimated median impact based on the selectivity-adjusted linear demand function is small relative to the other models, but this result should probably be discounted given the insignificant selectivity terms upon which the estimate is based. In addition, the log-linear model was sensitive to outliers when predicting D^* for constrained families, causing us to view results from that model with caution.[35] In contrast, the OLS model and the Tobit models did not appear to be sensitive to outliers. Given the lack of selectivity effects in the linear case, we are inclined to focus on the OLS or Tobit models for providing our preferred estimates of the impact of borrowing constraints. In those cases, 50% of the credit-constrained households would hold at least $12,000 (1982 dollars) more debt if borrowing constraints had been relaxed, *ceteris paribus*.[36]

[34] Formulas used to predict the impact of borrowing constraints for each of the models in Table V are provided in Appendix A.

[35] The estimated impact of borrowing constraints based on the log-linear model exceeds $300,000 for roughly 10% of constrained households in the sample.

[36] These results are consistent with findings by Duca and Rosenthal (forthcoming) (obtained using the same data as here) which suggest that borrowing constraints significantly lower homeownership rates.

TABLE V
MEDIAN AND MEAN IMPACTS OF BORROWING CONSTRAINTS[a] IN $1000 UNITS (1982 DOLLARS)

	Mean	Median
Liner selection model	4.7	4.5
OLS model	9.5	12.0
Log-linear model	—	55.0
Tobit model	21.6	20.0

[a] The sample consists of credit-constrained households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Formulas to calculate the predicted impacts are provided in Appendix A. The linear selection, OLS, and log-linear models refer to the models in Table III. The Tobit model refers to the unconstrained sample Tobit model in column 1 of Table IV.

Table VI presents several simulations that enable us to evaluate the effect of race and credit history on the frequency of credit-constrained households. For the first three simulations we calculate the expected proportion of credit-constrained households based on the sample mean of the probability of being credit constrained, $[1 - G(xa, zg, \sigma_{u_1,u_2}) - F(-xa)]$, where $G(\cdot)$ is the probability that a family prefers to hold positive debt and is not credit constrained, $F(\cdot)$ is the probability that a family

TABLE VI
THE EFFECT OF RACE AND CREDIT HISTORY ON THE PROPORTION OF CREDIT-CONSTRAINED HOUSEHOLDS[a]

	Simulated credit history and simulated race						Ignoring wealth/credit history	
	Actual credit history		Good credit history		Bad credit history			
Actual Sample	White	Nonwhite	White	Nonwhite	White	Nonwhite	White	Nonwhite
White (n = 1002)	**0.2725**	0.3610	0.1424	0.2188	0.5476	0.6386	**0.2725**	0.4178
Nonwhite (n = 222)	0.3748	**0.4640**	0.1731	0.2543	0.5771	0.6493	0.3233	**0.4640**

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Numbers in bold are the actual frequencies of credit-constrained families. Simulations for the first three groups were based on coefficients taken from Model I of Table II as described in the text. Simulations for the fourth group were based on Model II of Table II with the predicted probability of being credit constrained set equal to zero for families that prefer to hold zero debt (Dbt0 = 0).

prefers to hold zero debt, and the remaining notation is defined as in Section III. To simulate a good credit history, BADHST and WELFARE were set equal to 0 and OWNHIST, SOMHST, and CHECK were set equal to 1 when forming zg, where opposite values were used to simulate a bad credit history. By setting RACE equal to either 0 or 1 when forming xa and zg, a given set of households was effectively turned into all white or all nonwhite families, respectively. In all cases the remaining variables in x and z were set equal to the actual values for each household. Also, each simulation was conducted separately for the white and nonwhite families in our sample.

Observe that the actual frequencies of credit-constrained families among nonwhite and white households are 46.4 and 27.3%, respectively, a difference of roughly 19 percentage points. However, if the nonwhite sample had otherwise been white, ceteris paribus, 37.5% of the sample would have been credit constrained, a difference of roughly 10 percentage points from the white sample. That 10-point gap can be attributed to racial differences in demographic, financial, and credit history characteristics. On the other hand, loan applicant race accounts for 9 percentage points of the observed racial difference in the probability of being credit constrained, ceteris paribus.[37] Interestingly, these findings are consistent with those of Munnell *et al.* (1992), who estimate that mortgage application denial rates among black and Hispanic borrowers in Boston would fall roughly 8 percentage points if those families were otherwise white, ceteris paribus.[38]

Table VI also provides insight into the importance of credit risk relative to loan applicant race when applying for credit. For a given actual sample (white or nonwhite) and for a given simulated race (white or nonwhite), observe that a bad simulated credit history increases the frequency of credit-constrained families by roughly 40 percentage points relative to a good simulated credit history. Hence, the probability of being credit constrained is roughly 4.5 times more sensitive to a loan applicant's credit history than to the loan applicant's race.[39] Moreover, if credit history and wealth are ignored—as in the fourth group in Table VI—observe that the

[37] This estimate is robust to whether we use the white or nonwhite sample and to the different simulated credit histories in Table VI.

[38] The similarity between our results and those of Munnell *et al.* (1992) should be viewed with caution given that Munnell *et al.* (1992) focus on mortgage application denial rates in Boston, while results in Table VI are based on a broader definition of who is credit constrained and a sample that is representative of young households across the United States. Nevertheless, the similarity between our results and those of Munnell *et al.* (1992) further supports claims of racial discrimination in credit markets.

[39] This result is robust to the four different possible combinations of actual sample and simulated race.

impact of race on the probability of being credit constrained jumps from 9 to 14 percentage points, causing us to overstate the effect of race. These results are consistent with the findings in Table II and confirm the importance of controlling for wealth and credit history when evaluating questions concerning access to credit.[40]

VI. CONCLUSIONS

Using a unique set of variables in the 1983 Survey of Consumer Finances, this study finds that 30% of households under age 35 in the early 1980s would like to hold more debt than lenders will allow, and that roughly half of these families would hold at least $12,000 (1982 dollars) more debt if borrowing constraints were relaxed, ceteris paribus. These findings provide one explanation for why empirical studies frequently find evidence that consumer spending and behavior do not display characteristics that are consistent with a strict interpretation of the Life-Cycle Hypothesis.

Results also indicate that households with intrinsically strong preferences for holding debt are more likely to be constrained by a given set of debt limits. In addition, families with low income, little wealth, a limited credit history, or a bad credit history face tighter debt limits, consistent with various theoretical models of credit availability [e.g., Bernanke and Gertler, 1989, 1990; Jaffee and Russell, 1976; Stiglitz and Weiss, 1981, 1983).

We also find that controlling for household wealth and credit history explains much of the observed difference in access to credit between minority and white borrowers. Nevertheless, even after accounting for wealth and credit history a significant race effect remains, consistent with findings from a recent study by the Federal Reserve Bank of Boston that examined race-related differences in mortgage loan denial rates in Boston (Munnell *et al.*, 1992). To put our race results in perspective, however, we should emphasize that additional simulations suggest that the probability that a given borrower is credit constrained is roughly 4.5 times more sensitive to the loan applicant's credit history than to the loan applicant's race. Hence, although race has a significant effect on access to credit, the impact of race on access to debt appears to be small relative to borrower credit history characteristics.

[40] Although Munnell *et al.* (1992) control for wealth and credit history when evaluating racial differences in mortgage application denial rates, they do not provide sufficient information to allow for an appropriate comparison to the fourth simulation in Table VI.

APPENDIX A

Selection Variables and Predicting the Impact of Borrowing Constraints on Household Debt

As noted in the text, given the assumption that $[e_1, u_1, u_2]$ are distributed trivariate normal with zero means and variance matrix V, the conditional expectation of e_1 given that a household is not credit constrained (Cr = 1) and holds positive debt (Dbt0 = 1) can be written as

$$E[e_1 \mid u_1 > -xa,\ u_2 > -zg] = \sigma_{1,u_1} M_{1,u_1} + \sigma_{1,u_2} M_{1,u_2}, \qquad \text{(A.1)}$$

while the conditional expectation of D^* is

$$E[D \mid x, z; d, a, g; u_1 > -xa,\ u_2 > -zg] = xd + \sigma_{1,u_1} M_{1,u_1} + \sigma_{1,u_2} M_{1,u_2}. \qquad \text{(A.2)}$$

Based on work by Rosenbaum (1961), Fishe *et al.* (1981), and Maddala (1983), for $k_1 = -xa$ and $k_2 = -zg$, M_{1,u_1} and M_{1,u_2} can be written as

$$M_{1,u_1} = (1 - \sigma^2_{u_1,u_2})^{-1} \cdot [P_{u_1} - \sigma_{u_1,u_2} P_{u_2}], \qquad \text{(A.3)}$$

$$M_{1,u_2} = (1 - \sigma^2_{u_1,u_2})^{-1} \cdot [P_{u_2} - \sigma_{u_1,u_2} P_{u_1}], \qquad \text{(A.4)}$$

where

$$P_{u_1} = \left\{\int_{k_2}^{\infty} \int_{k_1}^{\infty} u_1\, g(u_1, u_2)\, du_1\, du_2\right\} \Big/ G(-k_1, -k_2), \qquad \text{(A.5)}$$

$$P_{u_2} = \left\{\int_{k_1}^{\infty} \int_{k_2}^{\infty} u_2\, g(u_1, u_2)\, du_2\, du_1\right\} \Big/ G(-k_1, -k_2), \qquad \text{(A.6)}$$

and g and G are the standard bivariate normal density and distribution functions, respectively. Expressions (A.5) and (A.6) can be simplified as

$$P_{u_1} = \{f(k_1)[1 - F(k_2^*)] + \sigma_{u_1,u_2} f(k_2)[1 - F(k_1^*)]\}/G(-k_1, -k_2), \qquad \text{(A.7)}$$

$$P_{u_2} = \{f(k_2)[1 - F(k_1)] + \sigma_{u_1,u_2} f(k_1)[1 - F(k_2^*)]\}/G(-k_1, -k_2), \qquad \text{(A.8)}$$

where

$$k_1^* = (k_1 - \sigma_{u_1,u_2} k_2)/(1 - \sigma^2_{u_1,u_2}), \qquad \text{(A.9)}$$

$$k_2^* = (k_2 - \sigma_{u_1,u_2} k_1)/(1 - \sigma^2_{u_1,u_2}), \qquad \text{(A.10)}$$

and f and F are the unit normal density and distribution functions, respectively. Observe that M_{1,u_1} and M_{1,u_2} depend on the parameters a, g, and σ_{u_1,u_2} which can be estimated based on bivariate probit methods as described in the text.

When households are credit constrained m_{1,u_1} and m_{1,u_2} can be obtained based on a methodology similar to that above. If we impose the restriction that expressions (1) and (2) in the text are alike, $u_1 > D_c/\sigma_1 - xa$, where D_c is the level of debt actually held by the household (as described in the text), and $u_2 < -zg$.[41] To form m_{1,u_1} and m_{1,u_2}, k_1 is redefined as $D_c/\sigma_1 - xa$, while k_2 is defined as zg; these expressions are then substituted into the formulas above. In addition, because the direction of integration for u_2 has been reversed (u_2 is less than $-zg$ instead of greater than $-zg$), (A.7) and (A.8) are written as

$$P_{u_1} = \{f(k_1)[1 - F(k_2^*)] - \sigma_{u_1,u_2} f(k_2)[1 - F(k_1^*)]\}/G(-k_1, -k_2), \quad \text{(A.11)}$$

$$P_{u_2} = \{-f(k_2)[1 - F(k_1)] + \sigma_{u_1,u_2} f(k_1)[1 - F(k_2^*)]\}/G(-k_1, -k_2), \quad \text{(A.12)}$$

where a negative sign now appears before $f(k_2)$.

When calculating impacts based on the Tobit model in Table IV, expression (A.2) simplifies considerably since σ_{1,u_2} is set equal to zero and we impose the assumption that (1) and (2) are identical. In that case, (A.2) becomes

$$E[D \mid x; d; e_1/\sigma_1 > k_1/\sigma_1] = xd + \sigma_1 f(k_1)/[1 - F(k_1)], \quad \text{(A.13)}$$

where $k_1 = D_c/\sigma_1 - xd/\sigma_1$. Expression (A.13) was also used to calculate impacts associated with the OLS model in Table III.

APPENDIX B

Variable Definitions

Cr equals 1 if not credit constrained and 0 otherwise.

Dbt0 equals 1 if the family prefers to hold debt and 0 if the family prefers to hold zero debt.

Debt equals level of debt in 1982 dollars (in \$1000 units).

[41] If expressions (1) and (2) differ, in principle it would be desirable to control for three forms of truncation when forming m_{1,u_1} and m_{1,u_2}; $e_1 > D_c - xd$, $u_1 > -xa$, and $u_2 < -zg$. As an alternative, the procedure described above implicitly sets $-xd$ equal to negative infinity (when forming m_{1,u_1} and m_{1,u_2}). This eliminates one form of truncation by imposing the assumption that $u_1 > D_c/\sigma_1 - xa$ instead of $u_1 > -xa$. To the extent that expressions (1) and (2) in the text are similar, errors associated with this approach are unlikely to affect the qualitative nature of our findings.

D equals total household debt (book value) in 1982 dollars (in \$1000 units).

WHat equals the fitted value from the wealth regression (in Appendix C) in 1982 dollars (in \$1000 units).

INC82 equals total household income in 1982 dollars (in \$1000 units).

INCSQ82 equals INC82 squared.

UNEMP equals the 1982 unemployment rate of the household head's profession.

ED equals 1 if the household head has a high school degree or more.

MALE equals 1 if the household head is male.

RACE equals 1 if the household head is nonwhite.

MARR equals 1 if married.

HSIZE equals the number of people in the household.

PENINC equals INC82 multiplied by a dummy variable (PEN), where PEN equals 1 if either the household head or spouse expects to receive pension income upon retirement.

AVERSE equals 1 if the household was not willing to take on any risk in investing family savings.

CONSUMP equals 1 if the household head felt it was "all right for someone like [the respondent] to borrow money to finance a vacation."

LUX equals 1 if the household head felt it was "all right for someone like [the respondent] to borrow money to finance the purchase of a fur coat, boat, or other luxury items."

DUR equals 1 if the household head felt it was "all right for someone like [the respondent] to borrow money to finance the purchase of furniture or a car."

EMERG equals 1 if the household head felt it was "all right for someone like [the respondent] to borrow money to finance medical expenses or to finance living expenses when income is cut."

CUREMP equals the number of years working at current employer.

BADHST equals 1 if the household had problems making loan payments in the last 3 years.

OWNHST equals 1 if the household bought a home prior to 1980.

SOMHST equals 1 if the household has a nonmortgage loan outstanding that originated prior to 1980.

WELFARE equals 1 if the household received public assistance in 1982.

CHECK equals 1 if the household has a checking account.

CONST is a constant.

FULLTIME equals 1 if the head of household is currently working fulltime.

EXPINHER equals 1 if the household anticipates receiving a "large" inheritance.

INHERIT equals 1 if the household has received a "large" inheritance.
FULLINC equals FULLTIME multiplied by INC82.
EXPINC equals EXPINHER multiplied by INC82.

APPENDIX C

TABLE C-I
NET WEALTH ORDINARY LEAST-SQUARES REGRESSION[a]

Variable	Coefficient	T ratio
CONST	−13.5017	−1.348
INC82	1.14104	3.694
INCSQ82	0.515413E-02	2.077
PENINC	−0.556817	−4.904
UNEMP	−0.441634	−1.650
ED	3.58908	0.819
MALE	−1.44051	−0.461
RACE	−5.90050	−1.455
MARR	−3.23001	−0.799
HSIZE	2.28435	1.699
AVERSE	−5.80367	−1.945
CONSUMP	−3.26270	−0.847
LUX	−4.63826	−1.420
DUR	1.25476	0.232
EMERG	−2.75956	−0.617
CUREMP	2.69413	5.668
BADHST	−6.93045	−1.953
OWNHST	33.1459	8.892
SOMHST	7.56476	1.827
WELFARE	−1.99662	−0.404
CHECK	3.64597	0.963
FULLTIME	1.68308	0.326
EXPINHER	1.62771	0.284
INHERIT	−6.74185	−1.340
FULLINC	−34.7664	−1.811
EXPINC	0.771757	4.006
σ	48.1436	
SSR	2776729	
R^2	.3452	
Obs.	1224	

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Dummy variables equal 1 for a positive response and 0 otherwise. All variables are defined in Appendix B.

TABLE C-II
BIVARIATE PROBIT OF WHO WOULD LIKE TO HOLD POSITIVE DEBT[a]

Variable	Coefficient	T ratio
CONST	0.2645	0.7876
WHat	0.2944E-02	0.8094
INC82	1.5569E-02	1.230
INCSQ82	−1.2926E-04	−1.077
PENINC	0.8829E-02	1.547
UNEMP	−0.00612	−0.7710
ED	0.1014	0.6430
MALE	−0.3133	−2.624
RACE	−0.1056	−0.7142
MARR	0.3912	2.528
HSIZE	0.0429	0.7868
AVERSE	0.0540	0.4511
CONSUMP	0.0357	0.2398
LUX	0.1884	1.407
DUR	0.5956	3.488
EMERG	−0.1924	−1.029
σ_{u_1,u_2}	−0.1470	−0.126
Log likelihood	−974.15	
Sample size	1224	

[a] The sample consists of households with family heads under age 35 taken from the 1983 Survey of Consumer Finances. Dummy variables equal 1 for a positive response and 0 otherwise. All variables are defined in Appendix B.

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