Federal Reserve Bank of Dallas

presents

RESEARCH PAPER

No. 9312

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

by

John V. Duca, Research Department
Federal Reserve Bank of Dallas

and

Stuart S. Rosenthal
Faculty of Commerce and Business Administration
University of British Columbia

April 1993

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

John V. Duca, Research Department
Federal Reserve Bank of Dallas

and

Stuart S. Rosenthal
Faculty of Commerce and Business Administration
University of British Columbia

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

John V. Duca
Research Department
Federal Reserve Bank of Dallas
Dallas, Texas 75222

Stuart S. Rosenthal
Faculty of Commerce and Business Administration
University of British Columbia
Vancouver, B.C. CANADA V6T 1Z2

February 1993

Proposed Running Head: Borrowing Constraints, Debt, and Race

JEL Codes: E51, J71, D12

The views expressed here are those of the authors and do not reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. We are grateful to Robert Avery and Arthur Kennickell for giving us access to their cleaned data tape of the 1983 Survey of Consumer Finances. We also thank the following people for helpful comments: Iain Cockburn, Larry Jones, Bob Helsley, Murray Frank, Bill Whitesell, Anil Kashyap, two anonymous referees, and seminar participants at Cornell University, Syracuse University, and the Winter 1990 Econometric Society session on Empirical Evidence on Credit Rationing. Any remaining errors, of course, are our own.

ABSTRACT

Two-step selection methods are applied to the 1983 Survey of Consumer Finances to examine both 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 percent 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 household income and wealth, but are relaxed for families with a good credit history. In addition, even after controlling for household income, wealth, credit history, and many other variables, minorities face tighter debt limits and are more likely to be credit constrained than white families.

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 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 contraints affect household behavior regardless of the motivation for those constraints.

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, 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 (SCF) 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 (forthcoming) 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 (forthcoming).[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 Mortgage Disclosure Act (HMDA).[4] An initial Federal Reserve report based on those data indicated that in 1990, mortgage applications from black households across the United States were denied at a rate 2.4 times higher 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 Boston Federal Reserve Bank 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 various work described above, our study addresses the two questions posed at the outset by drawing on certain special features of the 1983 SCF, including a wide range of information on household credit history and wealth. 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.

Results indicate that 30 percent of young households 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.

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.

To establish these results the plan for the paper is as follows. Section II presents our empirical methodology. Section III describes the data, section IV presents findings, and section V provides concluding comments.

II. 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 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

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

Note that credit constrained families always prefer to hold positive debt, while 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 $[e_1, u_1, u_2]$ is distributed trivariate normal with mean zero and variance matrix (V),

$$V = \begin{matrix} \sigma_1^2 & \sigma_{1,u1} & \sigma_{1,u2} \\ \sigma_{1,u1} & 1 & \sigma_{u1,u2} \\ \sigma_{1,u2} & \sigma_{u1,u2} & 1 \end{matrix} .$$

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,

$$\sum \{(1\text{-Dbt0})\cdot\log[F(-xa)] + \text{Dbt0}\cdot\text{Cr}\cdot\log[G(xa,zg,\sigma_{u1,u2})] \qquad (6)$$

$$+ \text{Dbt0}\cdot(1\text{-Cr})\cdot\log[G(xa,-zg,-\sigma_{u1,u2})]\},$$

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

Based on work by Rosenbaum (1963), Tunali (1986) shows that,

$$E[e_1 : u_1 > -xa,\ u_2 > -zg] = \sigma_{1,u1}M_{1,u1} + \sigma_{1,u2}M_{1,u2}, \qquad (7)$$

where $M_{1,u1}$ and $M_{1,u2}$ are functions of xa, zg, and $\sigma_{u1,u2}$. For the special case when $\sigma_{u1,u2}$ equals zero, $M_{1,u1}$ and $M_{1,u2}$ 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 $M_{1,u1}$ and $M_{1,u2}$, respectively. More generally, however, when $\sigma_{u1,u2}$ differs from zero the expressions for $M_{1,u1}$ and $M_{1,u2}$ become complicated and are not presented here to conserve space.[13] Expressions for $M_{1,u1}$ and $M_{1,u2}$ are provided in Appendix A and can also be found in Maddala (1983, page 282) and Tunali (1986).

Using estimates of a, g, and $\sigma_{u1,u2}$ from the bivariate probit routine, $M_{1,u1}$ and $M_{1,u2}$ were formed for each household. Consistent estimates of the debt function parameters (d) were then obtained by including $M_{1,u1}$ and $M_{1,u2}$ 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 $M_{1,u1}$ and $M_{1,u2}$ also give consistent estimates of $\sigma_{1,u1}$, and $\sigma_{1,u2}$, while further manipulation yields a consistent estimate of σ_1^2. Correct asymptotic standard errors are obtained based on formulae described by Maddala (1984) and extentions 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, $x\mathit{d}$ 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 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 $x\mathit{d}$. 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,

$$E[e_1 : u_1 > D_c/\sigma_1 - x\mathit{a},\ u_2 < -z\mathit{g}] = \sigma_{1,u1}m_{1,u1} + \sigma_{1,u2}m_{1,u2}, \tag{8}$$

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 $m_{1,u1}$ and $m_{1,u2}$ 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,

$$E[D^* | x,z;\ \mathit{d},\mathit{a},\mathit{g};\ Dbt0=1,\ Cr=0,\ D_c] = x\mathit{d} \tag{9}$$

$$+\ E[e_1 : u_1 > D_c/\sigma_1 - x\mathit{a},\ u_2 < -z\mathit{g}].$$

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

$$E[D^* - D_c |\ Dbt0=1,\ Cr=0,\ D_c] \tag{10}$$

$$= E[D^* | x,z;\ \mathit{d},\mathit{a},\mathit{g};\ Dbt0=1,\ Cr=0,\ D_c] - D_c.$$

III. 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 over sampled in the survey, and households over age 34. The remaining 1224 observations comprise a representative sample for 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 <u>thought</u> 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]

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 non-pension assets and total debt (in $100,000 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 $100,000 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 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 (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 their 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 was 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]

IV. Results

Summary statistics for the sample are in Table I. Observe that nearly 30 percent of young households in 1983 perceived themselves as credit constrained (Cr = 0). Moreover, nonwhites account for 27.4 percent of credit constrained families but only 14.0 percent 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.

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 $\sigma_{u1,u2}$ to differ from zero, equation (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 $\sigma_{u1,u2}$ 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 $\sigma_{u1,u2}$ 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]

In reviewing the variable coefficients in Table II, recall that the likelihood that a prospective borrower is credit constrained is positively related to the demand for debt but is negatively related to the debt ceiling imposed by lenders. Hence, the sign of a variable in the credit constraint model depends on the effect of that variable on D^* *relative* to the variable's effect on lender imposed debt ceilings. Bearing that thought in mind, observe that households are more likely to face binding borrowing constraints if they have a bad credit history (BADHST=1) or no 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 the demand for debt, these results confirm that lenders tighten debt limits on borrowers with limited or bad credit histories.

Another striking result in column (2) is that wealth, income, and income security (as proxied by UNEMP) do not have a statistically significant 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 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 desired level of credit. In contrast, these variables have positive effects on the demand for credit. Given the combination of estimated effects on 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 upwards 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. 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.[28]

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 IV, respectively.[29] The only exception is that neither selection terms, $M_{1,u1}$ or $M_{1,u2}$, are significant in the linear case, but $M_{1,u2}$ has a negative and significant coefficient in the log-linear model.[30] 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 $M_{1,u1}$ and $M_{1,u2}$.[31]

The Impact and Incidence of Borrowing Constraints

Two methods were used to evaluate whether borrowing constraints affect household behavior. First, columns (1) through (3) of Table IV present 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.[32] The resulting test statistic equals 79.1 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 demand for debt.

As discussed earlier, the difference between the actual and 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 models in Table III.[33] 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-liner model was sensitive to outliers when predicting D* for constrained families, causing us to view results from that model with caution.[34] 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 as providing our preferred estimates of the impact of borrowing constraints. In those cases, 50 percent of the credit constrained households would hold at least $12,000 (1982 dollars) more debt if borrowing constraints had been relaxed, *ceteris paribus*.[35]

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 each simulation we calculate the expected proportion of credit constrained households based on the sample mean of the probability of being credit constrained, $[1 - G(xa,zg,\sigma_{u1,u2}) - F(-xa)]$, 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 prefers to hold zero debt, and the remaining notation is defined as in Section II. 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, while 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 frequency of credit constrained families among Nonwhite and White households is 46.4 percent and 27.3 percent, respectively, a difference of roughly 19 percentage points. However, if the Nonwhite sample had otherwise been White, ceteris paribus, 37.5 percent 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 the remaining 9 percentage points of the observed racial difference in the probability of being credit constrained.[36]

Further examination of Table VI also provides insight into the importance of credit history relative to loan applicant race when applying for a loan. Using the white sample, for example, note that regardless of whether the simulated race is white or nonwhite, a bad simulated credit history increases the frequency of credit constrained families by roughly 40 percentage points relative to a good simulated credit history. Moreover, a similar result holds if we use the nonwhite sample. Hence, the probability of being credit constrained is roughly 4-1/2 times more sensitive to a loan applicant's credit history than to the loan applicant's race.

VI. Conclusions

Using a unique set of variables in the 1983 Survey of Consumer Finances (SCF), this study finds that 30 percent 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), and Stiglitz and Weiss (1981, 1983)].

We also find that controlling for household wealth and credit history reduces but does not eliminate evidence that minority borrowers face tighter credit constraints than comparable white households. That result is consistent with findings from a recent Boston Federal Reserve Bank study that examined race related differences in mortgage loan denial rates in Boston. 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 4-1/2 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.

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 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.

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, 1991b) 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 note 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 inthe HMDA data.

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

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 [e.g., the CARA utility function in Caballero (1987)]. 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.

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

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 $\sigma_{u1,u2}$ differs from zero, substituting λ for $M_{1,u1}$ and $M_{1,u2}$ in the second stage OLS regression yields biased estimates.

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, $\sigma_1 = \sigma_{1,u1}$, $d/\sigma_1 = a$, and $\sigma_{u1,u2} = \sigma_{1,u2}/\sigma_1$. 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 $a = d/\sigma_1$.

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).

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, Elliehausen, and Kennickell (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.

20.Owning a mobile home was not treated as homeownership given the low quality of mobile home loans. Note, also, that OWNHSTand SOMHST (defined below) are based on pre-1980 activity to control for possible simultaneity with the probability of being turned down for credit over 1980-83 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.

22.Because the Dbt0 equation is estimated 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 (forthcoming) also evaluate the probability that a family is credit constrained using the 1983 SCF, as discussed at the outset, we include a 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 (forthcoming) 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 (forthcoming) analyze the effect of credit constraints on household debt using a methodology similar to 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 linear regressions [e.g. Fishe et. al. (1981) and Maddala (1983)]. On the other hand, if our estimate that $\sigma_{u1,u2}$ 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, Hoffman and Low (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.

25.This result is in contrast to that of Jappelli (1990) who found significant evidence that higher income and more wealthy households were 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.

26.This interpretation is consistent with Boyes, Hoffman, and Low (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 signficant 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 II and III.

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 $\sigma_{u1,u2}$ 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.These findings are consistent with recent studies by Gabriel and Rosenthal (1991) and Canner, Gabriel and Woolley (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.

29.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 contrast, if the linear model is the correct specification and if expressions (1) and (2) are identical, then $\sigma_1 = \sigma_{1,u1}$, $\sigma_{u1,u2} = \sigma_{1,u2}/\sigma_1$, and $a = d/\sigma_1$. In column (1) of Tables II and III, observe that σ_1 is close to $\sigma_{1,u1}$ and both $\sigma_{u1,u2}$ and $\sigma_{1,u2}$ are small and insignificant. However, a Wald test rejects the null that $a = d/\sigma_{1,u1}$ [the test statistic equaled 97.2 and is distributed $X^2(16)$]. To form the Wald statistic, we took d and $\sigma_{1,u1}$ from column (1) of Table III, a from column (1) of Table II, and formed the variance matrix for $d/\sigma_{1,u1}$ based on the Delta method [see Billingsley (1979) for a discussion of the Delta method].

30.For the linear model we also alternately dropped $M_{1,u1}$ and $M_{1,u2}$ 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 $M_{1,u1}$ included; in both cases $M_{1,u1}$ was not significant.

31.In addition, note that column (1) of Table IV presents results from a Tobit debt demand function estimated over families that are not credit constrained. In contrast to the selection model in column (1) of Table III, the tobit model restricts the debt demand function and the process governing whether families prefer to hold zero debt [expressions (1) and (2)] to be 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 $X^2(16)$ distribution).

32.The test statistic was constructed by forming $T = -2 \cdot [(-131.90 + 46.29) - 125.16] = 79.1$, where T has a Chi-Square distribution with 16 degrees of freedom, the number of restrictions between the stratified and full sample models.

33.Formulae used to predict the impact of borrowing constraints for each of the models in Tables III and IV are provided in Appendix A.

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

35.These results are consistent with findings by Rosenthal and Duca (1991) (obtained using the same data as here) which suggest that borrowing constraints significantly lower homeownership rates.

36.That result also holds for the different simulated credit histories (good and bad) in Table VI.

TABLE I
Variable Summary Statistics

Variable	Constrained 376 obs. Mean	Std. Dev.	Unconstrained 848 obs. Mean	Std. Dev.	Unconstained Dbt0=1 710 obs. Mean	Std. Dev.	Full Sample 1224 obs. Mean	Std. Dev.
Cr	.00000	.00000	1.0000	.00000	1.0000	.00000	.69281	.46152
Dbt0	1.0000	.00000	.83726	.36934	1.0000	.00000	.88725	.31641
Debt	.08858	.17046	.19116	.29542	.22831	.30946	.15964	.26757
Wealth	.13475	.32998	.35558	.66143	.39295	.67114	.28774	.58887
WHat	.15848	.24355	.34506	.36865	.38115	.37932	.28774	.34601
INC82	.16254	.11570	.23993	.17590	.25862	.17815	.21616	.16373
PENINC	.07358	.12816	.13852	.17986	.15597	.18594	.11857	.16834
UNEMP	5.2151	5.8984	5.4973	6.1506	5.4415	5.8976	54.107	60.732
ED	.84043	.36670	.87382	.33225	.88732	.31642	.86356	.34339
MALE	.48138	.50032	.56132	.49652	.54930	.49791	.53676	.49885
RACE	.27394	.44657	.14033	.34753	.11408	.31814	.18137	.38548
MARR	.47606	.50009	.65212	.47658	.70986	.45415	.59804	.49049
HSIZE	2.7500	1.5769	2.7748	1.4333	2.8676	1.4110	2.7672	1.4783
AVERSE	.44681	.49783	.37028	.48317	.36197	.48091	.39379	.48879
CONSUMP	.19947	.40013	.15330	.36049	.15493	.36209	.16748	.37356
LUX	.30053	.45910	.28656	.45242	.30423	.46040	.29085	.45434
DUR	.93883	.23996	.91745	.27536	.93944	.23870	.92402	.26508
EMERG	.90160	.29826	.88208	.32271	.87465	.33135	.88807	.31541
CUREMP	2.4122	3.0538	3.3774	3.6232	3.5563	3.7101	3.0809	3.4856
BADHST	.31117	.46359	.15566	.36275	.18310	.38702	.20343	.40272
OWNHST	.10904	.31211	.26061	.43923	.30000	.45858	.21405	.41033
SOMHST	.84574	.36167	.87382	.33225	.84930	.35801	.86520	.34165
WELFARE	.24468	.43047	.08255	.27536	.06479	.24633	.13235	.33901
CHECK	.61436	.48739	.77241	.41953	.82535	.37993	.72386	.44727

TABLE II
The Likelihood of Not Being Credit Constrained*

	MODEL I		MODEL II	
Variable	Coeff.	T-ratio	Coeff.	T-ratio
CONST	.52831	.7303	0.26995	1.00
WHat	.13265	.2606	-	-
INC82	1.2094	.8169	3.13927	3.92
INCSQ82	-.34768	-.2214	-1.59111	-1.91
PENINC	.454948	.8245	0.58223	1.59
UNEMP	-.00674	-.7764	-0.00145	-0.20
ED	-.19724	-1.405	-0.04760	-0.37
MALE	.05982	.4491	0.02729	0.30
RACE	-.33900	-2.537	-0.47123	-4.15
MARR	.353886	1.850	0.35645	3.02
HSIZE	-.06965	-1.652	-0.07232	-1.97
AVERSE	-.05031	-.5060	-0.06141	-0.70
CONSUMP	-.13390	-1.156	-0.14791	-1.32
LUX	-.16260	-1.442	-0.14908	-1.55
DUR	-.24708	-.7786	-0.21592	-1.19
EMERG	-.11367	-.7508	-0.09443	-0.71
CUREMP	.022571	1.172	-	-
BADHST	-.28448	-2.637	-	-
OWNHST	.442444	2.035	-	-
SOMHST	.061575	.4828	-	-
WELFARE	-.37921	-2.616	-	-
CHECK	.190092	1.695	-	-
$\sigma_{u1,u2}$	-.14696	-0.126	-	-
Log-L	-974.15		-620.83	
Smp. Size	1086		1086	

*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.

TABLE III
Debt Demand Functions Based on Unconstrained Households

Variable	Linear Demand Selectivity-Adjusted* Coeff.	T-ratio	Linear Demand Unadjusted OLS Coeff.	T-ratio	Log-Linear Demand with Cr Selection Only* Coeff.	T-ratio
CONST	-.27436	-1.866	-.13330	-2.175	-4.5317	-8.602
WHat	.11789	2.039	.09533	2.197	.5290	1.287
INC82	1.02988	4.864	.91072	5.109	4.3788	3.281
INCSQ82	-.29627	-1.656	-.18927	-1.342	-2.6224	-2.255
PENINC	.13298	1.690	.09770	1.431	.21305	.389
UNEMP	-.00595	-3.488	-.56917E-03	-3.380	-.02051	-1.738
ED	.02970	.896	.02179	.699	.62643	2.873
MALE	.03349	1.244	.04989	2.458	.10865	.753
RACE	-.05228	-1.450	-.04088	-1.309	.20851	.887
MARR	.01928	.467	-.01264	-.458	.06868	.313
HSIZE	.02687	2.685	.02549	2.872	.19549	2.888
AVERSE	-.01563	-0.757	-.01934	-.952	.03037	.213
CONSUMP	-.04202	-1.541	-.04437	-1.669	-.08168	-.439
LUX	.04648	1.976	.03913	1.822	.25072	1.635
DUR	.05874	0.899	.01095	.275	.54503	1.905
EMERG	-.16996E-03	-0.006	.01103	.388	.00127	.006
$M_{1,u1}$ $(\sigma_{1,u1})$	.23188	0.980	-	-	-	-
$M_{1,u2}$ $(\sigma_{1,u2})$	.00624	0.077	-	-	-1.9204	-3.649
σ_1		.26885		.24517		1.9266
F		25.657		29.040		29.991
R^2		.38661		.38563		.40913
SSR		41.648		41.715		1437.6
Log-L		-		-		-
Obs		710		710		710

*T-ratios are adjusted for selection effects.

TABLE IV
Tobit Debt Demand Functions

	Not Constrained		Constrained		Full Sample	
Variable	Coeff.	T-ratio	Coeff.	T-ratio	Coeff.	T-ratio
CONST	-.25565	-4.351	-.07623	-1.202	-.21209	-4.637
WHat	.13554	3.102	.22686	3.906	.16721	4.732
INC82	.90477	5.162	.10650	.420	.74234	5.279
INCSQ82	-.24844	-1.778	.43702	1.196	-.16588	-1.423
PENINC	.15594	2.274	.20011	1.989	.18017	3.158
UNEMP	-.52482E-03	-3.270	-.22252E-03	-1.345	-.46010E-03	-3.693
ED	.02520	.840	.03404	1.199	.03186	1.405
MALE	.02734	1.369	.02619	1.266	.02459	1.587
RACE	-.05902	-1.990	-.02474	-1.076	-.05044	-2.429
MARR	.03631	1.356	.06384	2.437	.05031	2.478
HSIZE	.02406	2.738	-.00555	-.689	.01189	1.824
AVERSE	-.01287	-.645	.02013	1.013	-.00183	-.120
CONSUMP	-.03954	-1.517	-.01036	-.436	-.03226	-1.659
LUX	.04318	2.020	.01296	.613	.03398	2.070
DUR	.06736	1.862	.02980	.727	.06045	2.106
EMERG	-.00598	-.211	-.03724	-1.237	-.01514	-.681
σ_1	.25476	28.218	.16526	23.305	.23477	44.041
Log-L		-131.90		46.29		-125.16
Obs.		848		376		1224

TABLE V
Median and Mean Impacts of Borrowing Constraints
In 100,000 Dollar Units (1982 dollars)

	Mean	Median
Linear Selection Model	.047	.045
OLS Model	.095	.120
Tobit Model	.216	.200
Log-linear Model	-	.550

TABLE VI
The Effect of Race and Credit History
on the Proportion of Credit Constrained Households*

	Actual Credit History and Simulated Race		**Good Credit History and Simulated Race**		**Bad Credit History and Simulated Race**	
	White	Nonwhite	White	Nonwhite	White	Nonwhite
Actual Sample						
White (n=1002)	**.2725**	.3610	.1424	.2188	.5476	.6386
Nonwhite (n=222)	.3748	**.4640**	.1731	.2543	.5771	.6493

*Numbers in bold are the actual frequencies of credit constrained families.

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,

$$E[e_1 \mid u_1 > -x\alpha,\ u_2 > -zg] = \sigma_{1,u1}M_{1,u1} + \sigma_{1,u2}M_{1,u2}, \tag{A.1}$$

while the conditional expectation of D* is,

$$E[D \mid x,z;d,\alpha,g;u_1 > -x\alpha,\ u_2 > -zg] = xd + \sigma_{1,u1}M_{1,u1} + \sigma_{1,u2}M_{1,u2}. \tag{A.2}$$

Based on work by Rosenbaum (1961), Fishe et al (1981), and Maddala (1983), for $k_1 = -x\alpha$ and $k_2 = -zg$, $M_{1,u1}$ and $M_{1,u2}$ can be written as,

$$M_{1,u1} = (1-\sigma^2_{u1,u2})^{-1} \cdot [P_{u1} - \sigma_{u1,u2}P_{u2}], \tag{A.3}$$

$$M_{1,u2} = (1-\sigma^2_{u1,u2})^{-1} \cdot [P_{u2} - \sigma_{u1,u2}P_{u1}], \tag{A.4}$$

where,

$$P_{u1} = \left\{ \int_{k2}^{\infty} \int_{k1}^{\infty} u_1\, g(u_1,u_2)\, du_1 du_2 \right\} / G(-k_1,-k_2), \tag{A.5}$$

$$P_{u2} = \left\{ \int_{k1}^{\infty} \int_{k2}^{\infty} u_2\, g(u_1,u_2)\, du_2 du_1 \right\} / G(-k_1,-k_2), \tag{A.6}$$

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

$$P_{u1} = \left\{ f(k_1)[1-F(k_2^*)] + \sigma_{u1,u2} f(k_2)[1-F(k_1^*)] \right\} / G(-k_1,-k_2), \tag{A.7}$$

$$P_{u2} = \left\{ f(k_2)[1-F(k_1)] + \sigma_{u1,u2} f(k_1)[1-F(k_2^*)] \right\} / G(-k_1,-k_2), \tag{A.8}$$

where,

$$k_1^* = (k_1 - \sigma_{u1,u2}k_2)/(1-\sigma^2_{u1,u2}), \tag{A.9}$$

$$k_2^* = (k_2 - \sigma_{u1,u2}k_1)/(1-\sigma^2_{u1,u2}), \tag{A.10}$$

and f and F are the unit normal density and distribution functions, respectively. Observe that $M_{1,u1}$ and $M_{1,u2}$ depend on the parameters a, g, and $\sigma_{u1,u2}$ which can be estimated based on bivariate probit methods as described in the text.

When households are credit constrained $m_{1,u1}$ and $m_{1,u2}$ 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 $u_2 < -zg$.[1] To form $m_{1,u1}$ and $m_{1,u2}$, k_1 is redefined as $D_c/\sigma_1 - xa$, while k_2 is defined as zg; these expressions are then substituted into the formulae 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,

$$P_{u1} = \left\{f(k_1)[1-F(k_2^*)] - \sigma_{u1,u2}f(k_2)[1-F(k_1^*)]\right\}/G(-k_1,-k_2), \tag{A.11}$$

$$P_{u2} = \left\{-f(k_2)[1-F(k_1)] + \sigma_{u1,u2}f(k_1)[1-F(k_2^*)]\right\}/G(-k_1,-k_2), \tag{A.12}$$

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 $\sigma_{1,u2}$ is set equal to zero and we impose the assumption that (1) and (2) are identical. In that case, (A.2) becomes,

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

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.

---

[1]If expressions (1) and (2) differ, in principle it would be desireable to control for three forms of truncation when forming $m_{1,u1}$ and $m_{1,u2}$; $e_1 > D_c - xd$, $u_1 > -xa$, and $u_2 < -zg$. As an alternative, the procedure described above implicitly sets $-xd$ equal to negative infinity (when forming $m_{1,u1}$ and $m_{1,u2}$). 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.

APPENDIX B
Variable Definitions

Cr equals 1 if not credit constrained and 0 otherwise.

Dbt0 equals 1 if the family holds debt and 0 if the family has zero debt.

D equals total household debts (book value) in 1982 dollars (in 100,000 dollar units).

WHat equals the fitted value from the Wealth regression (in Appendix C) in 1982 dollars (in 100,000 dollar units).

INC82 equals total household income in 1982 dollars (in 100,000 dollar units).

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

ED equals 1 if the household head has a highschool 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 equal 1 if either the household head or spouse expect 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 three 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 was 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.

APPENDIX C

TABLE C-I
Net Wealth Ordinary Least Squares Regression*

Variable	Coefficient	T-ratio
CONST	-.135017	-1.348
INC82	1.14104	3.694
INCSQ82	.515413	2.077
PENINC	-.556817	-4.904
UNEMP	-.441634E-03	-1.650
ED	.035891	.819
MALE	-.014405	-.461
RACE	-.059005	-1.455
MARR	-.032300	-.799
HSIZE	.022844	1.699
AVERSE	-.058037	-1.945
CONSUMP	-.032627	-.847
LUX	-.046383	-1.420
DUR	.012548	.232
EMERG	-.027596	-.617
CUREMP	.026941	5.668
BADHST	-.069304	-1.953
OWNHST	.331459	8.892
SOMHST	.075648	1.827
WELFARE	-.019966	-.404
CHECK	.036459	.963
FULLTIME	.016831	.326
EXPINHER	.016277	.284
INHERIT	-.067418	-1.340
FULLINC	-.347664	-1.811
EXPINC	.771757	4.006

Std. Error of Regr.	.481436
SSR	277.673
R^2	.345258
Obs	1224

*Variables used in the net wealth equation that are not included in Tables I through IV are defined as follows. **FULLTIME** equals 1 if the household head 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.

TABLE C-II
Bivariate Probit of Who Would Like to Hold Positive Debt

Variable	Coefficient	T-ratio
CONST	.2645	.7876
WHat	.2944	.8094
INC821	.5569	1.230
INCSQ82	-1.2926	-1.077
PENINC	.8829	1.547
UNEMP	-.00612	-.7710
ED	.1014	.6430
MALE	-.3133	-2.624
RACE	-.1056	-.7142
MARR	.3912	2.528
HSIZE	.0429	.7868
AVERSE	.0540	.4511
CONSUMP	.0357	.2398
LUX	.1884	1.407
DUR	.5956	3.488
EMERG	-.1924	-1.029
$\sigma_{u1,u2}$	-.1470	-0.126

Log-Likelihood -974.15
Sample Size 1224

REFERENCES

Avery, R,B., and Elliehausen, G.,E. (August 1988). 1983 Survey of Consumer Finances: Technical Manual and Codebook, Federal Reserve Board.

Avery, R.,B., Elliehausen, G.,E., and Kennickell, A., B. (October 1987). Changes in consumer installment debt: evidence from the 1983 and 1986 Surveys of Consumer Finances, *Federal Reserve Bulletin*, 761-778.

Bernanke, B., and Gertler, M. (February 1990). Financial fragility and economic performance, *Quarterly Journal of Economics*, **105**, 87-114.

Bernanke, B., and Gertler, M. (March 1989). Agency costs, collateral, and business fluctuations, *American Economic Review*, **79**, 14-31.

Billingsley, P. (1979). "Probability and Measure," John Wiley and Sons, New York, NY.

Boyes, W.,J., Hoffman, D.,L., and Low, S.,A., (January 1989). An econometric analysis of the bank credit scoring problem, *Journal of Econometrics*, **40**, 3-14.

Canner, G.,B., Gabriel, S.,A., and Woolley, M., (July 1991). Race, default risk and mortgage lending: a study of the FHA and conventional loan markets, *Southern Economic Journal*, **58**, 249-261.

Canner, G.,B., and Smith, D.,S., (November 1991). Home mortgage disclosure act: expanded data on residential lending, *Federal Reserve Bulletin*, 859-881.

Cox, D., and Jappelli, T., (forthcoming). The effect of borrowing constraints on consumer liabilities, *Journal of Money Credit and Banking*.

Duca, J. and Rosenthal, S.,S., (1991). An econometric analysis of borrowing constraints and household debt, University of British Columbia working paper, 90-ULE-014.

Fishe, R., Trost, R., and Lurie, P., (Spring 1981). Labor force earnings and college choice of young women: an examination of selectivity bias and comparative advantage, *Economics of Education Review*, **1**, 169-191.

Gabriel, S.,A., and Rosenthal, S.,S., (May 1991). Credit rationing, race, and the mortgage market, *Journal of Urban Economics*, **29**, 371-379.

Hall, R.,E., and Mishkin, F., (1982). The sensitivity of consumption to transitory income: estimates from panel data on households, *Econometrica*, **50**, 461-481.

Hayashi, F., (February 1985). The effect of liquidity constraints on consumption: a cross-section analysis, *Quarterly Journal of Economics*, **50**, 183-206.

Jaffee, D.,M., and Russell, T., (November 1976). Imperfect information, uncertainty, and credit rationing, *Quarterly Journal of Economics*, **90**, 651-666.

Jappelli, T., Who is credit constrained in the U.S., (February 1990). *Quarterly Journal of Economics*, **105**, 219-234.

Maddala, G.S., "Limited-Dependent and Qualitative Variables in Econometrics," (1983). Cambridge University Press, New York N.Y.

Munnell, A.,H., Browne, L.,E., McEneaney, J., and Tootell, G., Mortgage lending in Boston: interpreting the HMDA data, (October 1992). Federal Reserve Bank of Boston Working Paper Series No. 92-7.

Orgler, Y.,E., "Analytical Methods in Loan Evaluation," (1975). D.C. Health and Company: Lexington, Massachusetts.

Rehm, B.,A., (October 15, 1991). ABA rebuts bias charge in Fed study on lending, *American Banker*, pages 1 and 19.

Rehm, B.,A., (October 22, 1991). Data on bias in lending sparks demands for action, *American Banker*, pages 1 and 9.

Rosenbaum, S. (1961). Moments of a truncated bivariate normal distribution, *Journal of the Royal Statistical Society* (Ser. D) **23**, 405-408.

Rosenthal, S.,S., and Duca, J., (1991). An econometric analysis of credit constraints and access to owner-occupied housing, University of British Columbia working paper, 90-ULE-013.

Stiglitz, J.,E., and Weiss, A., (June 1981). Credit rationing in markets with imperfect information, *American Economic Review*, **71**, 393-410.

Stiglitz, J.,E. and Weiss, A., (December 1983). Incentive effects and terminations, *American Economic Review*, **73**, 912-927.

Tunali, I., (1986). A general structure for models of double-selection and an application to a joint migration/earnings process with remigration, *Research in Labor Economics*, **8(B)**, 235-282.

Williamson, S., (December 1986). Costly monitoring, financial intermediation, and equilibrium credit rationing, *Journal of Monetary Economics*, **18**, 159-189.

Zeldes, S.,P., (April 1989). Consumption and liquidity constraints: an empirical investigation, *Journal of Political Economy*, **97**, 305-346.

RESEARCH PAPERS OF THE RESEARCH DEPARTMENT
FEDERAL RESERVE BANK OF DALLAS

Available, at no charge, from the Research Department
Federal Reserve Bank of Dallas, Station K
Dallas, Texas 75222

9201 Are Deep Recessions Followed by Strong Recoveries? (Mark A. Wynne and Nathan S. Balke)

9202 The Case of the "Missing M2" (John V. Duca)

9203 Immigrant Links to the Home Country: Implications for Trade, Welfare and Factor Rewards (David M. Gould)

9204 Does Aggregate Output Have a Unit Root? (Mark A. Wynne)

9205 Inflation and Its Variability: A Note (Kenneth M. Emery)

9206 Budget Constrained Frontier Measures of Fiscal Equality and Efficiency in Schooling (Shawna Grosskopf, Kathy Hayes, Lori Taylor, William Weber)

9207 The Effects of Credit Availability, Nonbank Competition, and Tax Reform on Bank Consumer Lending (John V. Duca and Bonnie Garrett)

9208 On the Future Erosion of the North American Free Trade Agreement (William C. Gruben)

9209 Threshold Cointegration (Nathan S. Balke and Thomas B. Fomby)

9210 Cointegration and Tests of a Classical Model of Inflation in Argentina, Bolivia, Brazil, Mexico, and Peru (Raúl Anibal Feliz and John H. Welch)

9211 Nominal Feedback Rules for Monetary Policy: Some Comments (Evan F. Koenig)

9212 The Analysis of Fiscal Policy in Neoclassical Models[1] (Mark Wynne)

9213 Measuring the Value of School Quality (Lori Taylor)

9214 Forecasting Turning Points: Is a Two-State Characterization of the Business Cycle Appropriate? (Kenneth M. Emery & Evan F. Koenig)

9215 Energy Security: A Comparison of Protectionist Policies (Mine K. Yücel and Carol Dahl)

9216 An Analysis of the Impact of Two Fiscal Policies on the Behavior of a Dynamic Asset Market (Gregory W. Huffman)

9301 Human Capital Externalities, Trade, and Economic Growth (David Gould and Roy J. Ruffin)

9302 The New Face of Latin America: Financial Flows, Markets, and Institutions in the 1990s (John Welch)

9303 A General Two Sector Model of Endogenous Growth with Human and Physical Capital (Eric Bond, Ping Wang, and Chong K. Yip)

9304 The Political Economy of School Reform (S. Grosskopf, K. Hayes, L. Taylor, and W. Weber)

9305 Money, Output, and Income Velocity (Theodore Palivos and Ping Wang)

9306 Constructing an Alternative Measure of Changes in Reserve Requirement Ratios (Joseph H. Haslag and Scott E. Hein)

9307 Money Demand and Relative Prices During Episodes of Hyperinflation (Ellis W. Tallman and Ping Wang)

9308 On Quantity Theory Restrictions and the Signalling Value of the Money Multiplier (Joseph Haslag)

9309 The Algebra of Price Stability (Nathan S. Balke and Kenneth M. Emery)

9310 Does It Matter How Monetary Policy is Implemented? (Joseph H. Haslag and Scott E. Hein)

9311 Real Effects of Money and Welfare Costs of Inflation in an Endogenously Growing Economy with Transactions Costs (Ping Wang and Chong K. Yip)

9312 Borrowing Constraints, Household Debt, and Racial Discrimination in Loan Markets