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AN ECONOMETRIC ANALYSIS OF BORROWING CONSTRAINTS AND HOUSEHOLD DEBT

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ABSTRACT

A unique feature of the 1983 Survey of Consumer Finances (SCF) is that it enables the researcher to determine *a priori* which households would like to hold more debt than lenders will allow [e.g., Jappelli (1990)]. Based on these data, 30 percent of households under age 35 in 1983 faced binding borrowing constraints. To evaluate the effect of borrowing constraints, this study first estimates a bivariate probit model of who is not credit constrained and would like to hold positive debt. Controlling for selection effects, a debt demand function is then estimated using only unconstrained households that hold positive debt.

Results indicate that households with strong intrinsic preferences for holding debt are more likely to be credit constrained, while lenders vary borrowing constraints across borrowers on the basis of observable characteristics that proxy credit risk, consistent with "screening" models of credit rationing. As might be expected, unconstrained and constrained families exhibit significantly different behavior (at least with respect to their demand for debt). Moreover, of the constrained households in the sample, roughly half would hold substantially more debt if borrowing constraints were relaxed, ceteris paribus. These results provide one explanation for why empirical studies of household consumption and consumer spending frequently find evidence that is not consistent with a strict interpretation of the Life Cycle and Permanent Income Hypotheses.

I. Introduction

The seminal study of Hall (1978) has spawned an empirical literature on testing the implications of the Life-Cycle and Permanent Income Hypotheses (henceforth, the LCH). A major motivation for much of the literature in this area is that a failure of the LCH to hold in its strongest form would imply that current income, in addition to anticipated or permanent income, could affect real consumption expenditures, thereby opening a potential channel for macro-stabilization policy. In addition, a failure of the LCH would also imply a possible role for current income in determining purchases of housing and other important consumer durables.[1]

Of the empirical studies in this area, one tradition has been to test whether the time series properties of nondurable consumption expenditures are consistent with the implications of the LCH [e.g., Campbell and Mankiw (1987), Flavin (1981), Hall (1978), and Wilcox (1989)]. However, time series studies that reject the LCH typically cannot identify why the LCH does not hold in their analysis, although speculation has focused on borrowing constraints.[2,3] Other studies have used cross-section or panel data to test whether the pattern of nondurable expenditures differs between families that do not face binding borrowing constraints versus families for whom borrowing constraints *may* be binding [e.g., Hall and Mishkin (1982), Hayashi (1985), and Zeldes (1989)]. A

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[1]In contrast, most empirical studies of housing demand assume that current income has no role once permanent income is included in the model.

[2]Explanations for the existence of 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 which lenders face but borrowers generally excape. The other strand of literature, including Jaffee and Russell (1976) and Stiglitz and Weiss (1981) among others, emphasizes the role of asymmetric infomration, adverse selection, and moral hazard.

[3]As is well known, the LCH may not hold because of borrowing constraints, transactions costs in the asset or credit markets, or myopic behavior.

problem with these studies, however, is that the data sets used do not directly identify which households face binding borrowing constraints. Instead, researchers typically assume that households with high wealth-to-income ratios or families with high savings rates are not credit constrained which raises the possibility of coding errors when splitting out the "unconstrained" households in the sample [see Jappelli (1990) for a discussion of this point].

In contrast to the studies above, a recently available data set does identify which households would like to hold more debt than lenders will allow at existing loan rates. Using the 1983 Survey of Consumer Finances (SCF), Jappelli (1990) investigated the characteristics of families that reported being denied credit or were dissuaded from applying for credit over the period 1980-1983. An important finding by Jappelli (1990) is that roughly 20 percent of households in the 1983 SCF perceived themselves as having been constrained by lenders. The extent to which the behavior of these families was affected by borrowing constraints, however, has not yet been evaluated.

Although the 1983 SCF does not include sufficient data to construct estimates of consumption expenditures, it can be used to assess the degree to which the total level of debt held by constrained households is depressed by binding borrowing constraints.[4] To evaluate such effects, as in Jappelli (1990) we define a household from the 1983 SCF as being credit constrained if a lender had turned down or not fully granted a household's loan request (and the household did not successfully reapply at an alternate lender), or if the household had not applied for credit because it thought that it would be turned down. For both types of "constrained" families, it is plausible that the level

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[4]We focus on the total level of debt held by households under the assumption that different forms of debt are close substitutes.

of debt held by the household is less than or equal to the amount that would be held if borrowing constraints were relaxed, ceteris paribus, bringing into question the strong perfect capital markets assumption of the LCH.

Before elaborating on our empirical method note that, consistent with screening models of credit rationing [e.g. Stiglitz and Weiss, part IV, (1981)], we assume that lenders stratify loan applicants into different groups based on perceived differences in default risk using observable, albeit imperfect, indicators of creditworthiness (such as credit history). In the absence of government intervention and prohibitive information costs, such models would imply that lenders vary loan rates across borrowers belonging to different risk categories [see Stiglitz and Weiss (1981), for example]. However, fair lending laws and the threat of legal suits create strong incentives for lenders to reduce the degree to which they vary loan rates across borrowers (at least for consumer loans).[5] In addition, the small size of most household loans (relative to business loans) and the fixed costs of evaluating loan applicant creditworthiness further discourage lenders from varying interest rates (and other terms of the loan contract) across borrowers.

Under these conditions, we assume that competitive lenders offer relatively similar loan rates to all borrowers but vary debt ceilings across households using various "rules of thumb" based on readily observable indicators of credit risk.[6] The use of debt ceilings to control for credit risk is consistent with

[5]Fair Lending laws also require that lenders to treat similar households in an equal fashion, which precludes one form of credit rationing discussed by Stiglitz and Weiss (1981), in which some observationally equivalent borrowers are issued credit while others are not.

[6]We should emphasize that our empirical model does allow for the possibility that loan rates may vary somewhat across borrowers (in a manner which will be clarified later in the paper), though our analysis focuses primarily on the degree to which debt ceilings are sensitive to household characteristics.

the Stiglitz-Weiss (1981, Part IV) screening model if one assumes that default risk increases with loan size and lenders have limited ability to vary interest rates across loan applicants.[7] Moreover, such a model is consistent with established practices of lenders who regularly use downpayment and payment-to-income ratios to set debt ceilings when evaluating household loan applications (particularly for mortgages and auto loans).

Having determined who is credit constrained in our sample, the principal strategy is to first estimate a probit model of who is not credit constrained for families under age 35.[8] A reduced form debt demand function is then estimated using only unconstrained households, controlling for selection effects, and results are compared to a model that ignores credit effects.[9] Given the estimated parameters from the selectivity-adjusted debt function, in principle it is also possible to predict the level of debt that a constrained family would

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[7]Although Stiglitz and Weiss (1981) assume a constant loan size across loan applicants, it can be readily shown that if default risk increases with loan size and lenders are unable to vary interest rates across households, the Stiglitz-Weiss screening model implies that lenders will vary debt ceilings across borrowers in the manner described above.

[8]We focus on families under age 35 for two reasons. First, life cycle models suggest that the debt demand function -- and by extension, the probit model of who is not credit constrained -- should be stratified by age group (young, middle age, and older). However, at least for our sample, only for younger households was there a relatively large concentration of credit constrained families (376). In addition, much of the academic and policy debate about access to credit has centered on younger 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.

hold if it had not otherwise been constrained, ceteris paribus.[10] Comparing the actual to the predicted preferred debt holdings of constrained households provides a consistent estimate of the distribution of impacts of borrowing constraints on household debt (in a partial equilibrium setting). Our results indicate that 30 percent of young households in 1983 wanted to hold more debt than lenders would allow, and that roughly half of these families would have held substantially more debt had borrowing constraints not been binding, ceteris paribus.

To establish these and other results, this study is organized as follows. Section II presents our empirical methodology. Section III describes the data, section IV presents the results, and section V provides concluding comments.

II. Econometric Model and Estimation Method

Estimation of the model is complicated by a nonnegativity constraint on household debt which is binding for 20 percent of the sample.[11] To control for both the nonnegativity constraint and the lender imposed borrowing constraint bivariate probit methods are used. Accordingly, 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 estimate our model using a cross-section, all households face the same set of market interest rates which are captured primarily through the constant.[12] Hence, D* is given by,

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[10]Goldberger (1983) has shown that estimates from selectivity-adjusted equations are sensitive to the distributional assumption underlying the selection equation.

[11]Roughly 29 percent of constrained households and 16 percent of unconstrained families hold zero debt.

[12]We argue shortly that although lenders likely do not vary interest rates much across borrowers, any variation which does occur affects the error term in (1) and is controlled for through the selection model as described below.

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

where x are household characteristics and *d* are the corresponding parmeters. The second equation is an unobservable index that determines whether a household prefers to hold positive or zero debt at current market interest rates,

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

while 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,

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

It follows that if a household is credit constrained or it prefers to hold zero debt then we do not observe D*.[13] 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.[14] In addition, given that a household

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[13]Observations on D* are truncated from below or above depending on whether the nonnegativity constraint [expression (2)] or the borrowing constraint [expression (3)] are binding. Note also, that the observed level of debt among constrained families does not necessarily equal the underlying debt ceiling imposed by lenders. This is because many loan applicants seeking to finance a durable (such as housing) may choose to hold zero debt if their loan is rejected. In addition, households which fail to meet loan repayment schedules may face debt ceilings on new loan applications which are actually below the amount debt currently held by those families. The level of debt held by constrained households, therefore, could be less than, equal to, or exceed the current debt ceiling imposed by lenders. Because we do not directly observe the debt ceiling for constrained households, estimates of the parameters of the debt ceiling function are difficult, if not impossible, to obtain. In early versions of this study, we attempted to estimate the parameters of the debt ceiling function based on a censored regression model with stochastic and unobserved thresholds [as described by Maddala (1984), pp. 174-178]. However, these efforts were unsuccessful because the necessary identification requirements could not be met.

[14]Henderson and Ioannides (1981) argue that families choose to own a home (and take on mortgage debt) if their investment demand for housing exceeds their consumption demand for housing. Consumption demand for housing is based on the household's demand for the flow of housing services, but the size of home acquired (and the corresponding mortgage) is determined by equating risk adjusted rates of return between housing and nonhousing investments. Accordingly, in principle the process that determines *whether* families hold mortgage debt and the

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 dichotomous representations of (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

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

Given that Cr [and expression (3)] is defined only over families that prefer to hold positive debt (Dbt0 = 1), 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 further 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).

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regime that determines the *level* of mortgage debt could differ. It follows that a similar argument holds for total household debt.

Given the distributional assumptions above, the parameters of the model can be estimated using two step methods [e.g. Tunali (1986)].[15] 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,

$$\sum\{(1\text{-Dbt0})\cdot\log[F(\text{-x}a)] + \text{Dbt0}\cdot\text{Cr}\cdot\log[G(\text{x}a,\text{z}g,\sigma_{u1,u2})] + \text{Dbt0}\cdot(1\text{-Cr})\cdot\log[G(\text{x}a,\text{-z}g,\text{-}\sigma_{u1,u2})]\}, \tag{6}$$

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

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

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

where $M_{1,u1}$ and $M_{1,u2}$ are complicated functions of xa, zg, and $\sigma_{u1,u2}$. Explicit expressions for $M_{1,u1}$ and $M_{1,u2}$ are provided in Appendix A to facilitate discussion here. Given those expressions, parameter estimates from the bivariate probit routine (for a, g, and $\sigma_{u1,u2}$) are used to form estimates of $M_{1,u1}$ and $M_{1,u2}$ for each household. These variables are then included in a second stage ordinary least squares (OLS) regression of the debt function (1) using only unconstrained households that hold positive debt. Given the distributional assumptions above, the OLS regression yields consistent estimates of d, $\sigma_{1,u1}$, and $\sigma_{1,u2}$, while further manipulation yields a consistent estimate of σ_1^2. Correct asymptotic standard errors can then be obtained based on formulae described by Maddala

[15]We are indebted to seminar participants at the Industrial Labor Relations workshop at Cornell University for directing us to Tunali's work. Tunali (1986) clarifies many of the technical issues underlying estimation of bivariate probit selection models with incomplete classification.

(1984) and extentions developed by Tunali (1986).[16] Observe also, that if expressions (1) and (2) are identical, $\sigma_1 = \sigma_{1,u1}$, $d/\sigma_1 = a$, and $\sigma_{u1,u2} = \sigma_{1,u2}/\sigma_1$, which in principle is testable given estimates from the bivariate probit and OLS models.

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.[17] 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 interest rates across borrowers which affect debt holdings, are reflected in e_1.

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[16]The bivariate probit model was estimated using Gauss. Estimates of σ_1 and the correct asymptotic covariance matrix were then obtained using Limdep. Although the Limdep selection routine is based on a four-cell (complete classification) bivariate probit model, that routine was modified to the three-cell problem by setting the index zg equal to an arbitrarily large negative value for unconstrained families that hold zero debt. For all other families zg was not modified. Among unconstrained families that hold zero debt, this adjustment causes $M_{1,u1}$ to be replaced with the traditional single selection Mill's ratio term (based on the nonnegativity constraint) while $M_{1,u2}$ equals zero, consistent with the three-cell asymptotic covariance formula developed by Tunali (1986) [see, for example, Tunali (1986), page 278].

[17]As an alternative, in principle one could evaluate the effect of borrowing constraints on the level of debt held by constrained households simply by asking those families how much debt they would like to hold. There is no guarantee, however, that families would respond to such a survey question in an informed manner which accounts for their budget constraint. The method used here avoids such problems.

If e_1 is uncorrelated with both u_1 and u_2, the expected preferred level of debt for constrained families is simply xd. More generally, however, if there are unobservable components which affect both the demand for debt and either u_1 or u_2, the expected value of D* for constrained families may be sensitive to correlation between the different error terms.[18] To account for possible selection effects the conditional mean of e_1 is formed as,

$$E[e_1 : u_1 > D_c/\sigma_1 - xa,\ u_2 < -zg] = \sigma_{1,u1}m_{1,u1} + \sigma_{1,u2}m_{1,u2}, \tag{8}$$

where D_c is the observed level of debt held by the constrained household.[19] 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,

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

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,

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

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[18]For example, if constrained families face higher interest rates than unconstrained families, the effect of the higher interest rates on the expected demand for debt for constrained households would be accounted for by (8).

[19]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 $a = d/\sigma_1$. The implications of this assumption for expression (8) are reviewed in Appendix A. In addition, as will become apparent, the qualitative nature of our estimates of the impact of borrowing constraints do not appear to be sensitive to reasonable alternative specifications of the nonnegativity constraint.

III. Data and Variables

The main data source for the study is the 1983 Survey of Consumer Finances (SCF) which contains 4303 households. From these households a subsample was used which excluded individuals with wealth over 1 million dollars (in 1982 dollars), any observations with relevant missing values, households which belong to a special high income group that was over sampled in the survey, and any 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. For each of these households, the dependent variables in the model as well as a large number of variables that belong in the credit constraint and debt equations are available. Each of these sets of variables are discussed below (summary statistics and a list of variable definitions are provided in Appendix B).

Credit Constraint and Debt Variables (Cr, D, Dbt0):

As noted earlier, a special feature of the SCF is a series of questions that enable the researcher to determine *a priori* whether a family would like to hold more debt than lenders will allow [see, for example, Jappelli (1990)]. In particular, households were asked whether 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 an alternative lender. In addition, households were asked whether "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."[20] Based on these three questions, a household was defined to be credit constrained in the 1980-1983 period if (i) the household had not applied for credit because it thought that it would be turned down (the "dissuaded" households), 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 (the "rejected" households).[21]

A further strength of the 1983 SCF for our purposes is the extreme detail given to calculating household debt, assets, and net wealth. For each household, extensive information was available on different real and financial assets and debts, which were summed to compute total household assets and debt (in $100,000

[20]Jappelli (1990) carefully compares the characteristics of (a) households that received all of the credit they want, (b) families that received less credit than requested from lenders, and (c) families that considered applying for credit but were dissuaded from doing so. Jappelli observes that families in groups (b) and (c) have very similar socioeconomic characteristics, on average, while families in group (a) are quite different from groups (b) and (c). Based on these findings Jappelli concludes that families in the "dissuaded" group (c) can be viewed as credit constrained, along with families that received less credit than requested. We adopt the same interpretation here. In addition, it is noteworthy that most households that considered applying for credit but did not because they thought they would be turned down, cited either a poor credit history, low income, or lack of job as the principle reason. Also, most of these households were dissuaded from applying for credit by an established lender.

[21]We also estimated the entire model excluding the dissuaded households on the possibility that some of these families may have misunderstood the survey questions; selected results from that analysis are provided in Appendix D. The qualitative and (in most cases) the quantitative nature of our results were not sensitive to whether the dissuaded families were included in the estimation. In addition, it should be noted that in principle we cannot distinguish between "genuinely" constrained households versus dishonest loan applicants that have no intention of repaying the loan. On the other hand, given that it is potentially costly for households to apply for credit (particularly for mortgage credit), and given that our results are not sensitive to the inclusion of dissuaded households, our findings are unlikely to be affected by dishonest loan applicants.

units).[22] Net wealth was also formed as the difference between non-pension assets and debt.

Covariates for the Debt and Credit Constraint Functions:

Focusing first on the debt function, 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 consumption, but more 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.[23] 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. (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 under the assumption that the demand for debt increases with income. Similarly, the unemployment rate in 1982 for the household head's profession (UNEMP) was included to proxy future job and

[22]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.

[23]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. Hence, the fitted value of wealth should also be included in the probit model of who is not credit constrained.

income security. To the extent that a household's future income is secure, presumably the family will 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 which 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.

Demographic variables were also included in the demand function to proxy preferences for holding debt. These variables include marital status [MARR (1 if married)], sex of the household head [SEX (1 if male)], household size (HSIZE), education of the household head [Ed (1 if highschool or more)], and race of the household head [RACE (1 if nonwhite)]. Presumably the demand for debt increases with household size but the sign on the other sociodemographic variables is unclear *a priori*.

Heterogeneity of preferences is further controlled for 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),[24] or to finance a vacation (CONSUMP)." For each of these variables an affirmative response was coded as 1 and 0 otherwise. A final dummy variable (AVERSE) equals 1 if households would not be "... willing to take any financial risks ... when [saving or making] investments." Presumably, people who feel it

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

is all right to borrow will hold more debt. On the other hand, families that are relatively risk averse (at least with respect to financial investments) may be less inclined to lever up in the housing market and would, therefore, hold less debt.

As noted earlier, all of the variables that affect the demand for debt should be included in the probit model of whether families perceive themselves as being credit constrained since the amount of debt demanded affects the probability of bumping into a debt ceiling. In addition, the observable socioeconomic variables discussed above could also influence debt limits imposed by lenders. In particular, one would expect that lenders would be willing to issue more debt to wealthy households, higher income households, and families with secure jobs (low UNEMP). On the other hand, the impact of education, sex, race, marital status, and household size on debt limits less clear, while lenders typically do not consider pension wealth when making loan decisions and are unlikely to consider or even be aware of subjective variables like AVERSE, CONSUMP, LUX, DUR, and EMERG. The expected sign of all of these variables in the probit model of who is not credit constrained depends on the effect of these variables on the demand for debt *relative* to their effect on the debt limits imposed by lenders.[25]

In addition to variables that could also appear in the debt demand function, when lenders evaluate loan applications they typically base decisions on information that is indicative of the likelihood of default. Accordingly, variables were included in the credit constraint equation that indicate the

[25]For example, the sign on income in the probit model is ambiguous since income likely has a positive effect on both the demand for debt and the debt ceiling. On the other hand, one would anticipate a positive coefficient on LUX to the extent that LUX increases the demand for debt but has little effect on lender imposed debt ceilings.

number of years the household head has worked at the current employer (CUREMP), whether the household has a checking account [CHECK (1 if yes)], whether the household has received public assistance [WELFARE (1 if yes)], and whether the household has had problems making loan payments in the past three years [BADHST (1 if yes)].[26] 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 (1 if yes)].[27] 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 (1 if yes)].[28] In general, variables above that imply a greater risk of default would be expected to have a negative sign in the probit model of who is not credit constrained, while variables that imply greater creditworthiness would have a positive coefficient.

IV. Results

Table I presents results from the bivariate probit model of who would like to hold positive debt (Dbt0=1) and who is not credit constrained (Cr=1) based on the log-likelihood function in expression (6).[29] Note, first, that $\sigma_{u1,u2}$ is not

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[26]Whether the family had received unemployment insurance payments (UI) was also tested. However this variable was insignificant in all of the models tested and was dropped from the estimation to simplify the presentation.

[27]Ownership of a mobile home was treated as nonhome ownership given the very low quality of mobile home loans.

[28]The variables OWNHIST and SOMHST are defined based on pre-1980 activity to control for possible simultaneity with the probability of being turned down for credit over 1980-83 period (the period over which the dichotomous Cr variable is defined).

[29]Although Jappelli (1990) estimates a logit model of who is credit constrained using all of the age groups in the 1983 SCF, there are important differences in our work. First, Jappelli (1990) includes the observed levels of household net

significant, which suggests that households with an unexpectedly high propensity to desire positive debt (relative to x*a*) are no more likely to be credit constrained than families with average preferences for holding positive debt. As will be shown shortly, however, this result does not necessarily imply that the demand for debt (conditional on wanting to hold positive debt) has no impact on the propensity to be credit constrained.

Turning to the Dbt0 equation, observe that wealth (What) does not have a statistically significant effect on whether households would like to hold positive debt. One possible explanation for this result is that the desire to borrow against future income to smooth consumption may decline with wealth, while the incentive to borrow to lever up in the housing market (the principal consumer durable) could increase with wealth as new investment opportunities become available. At least with respect to the zero-one decision to hold positive debt, potentially these effects could be offsetting.

Although none of the three income variables (INC82, INCSQ82, and PENINC) are individualy significant, the three are jointly significant and have a positive effect on the propensity to hold positive debt when evaluated at the mean level of income. Similarly, male headed households (SEX = 0) and married households (MARR = 1) are significantly more likely to hold positive debt.

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wealth and debt in his logit model without addressing the simultaneity between net wealth, debt, and the propensity to be constrained. Second, Jappeli includes the log of debt in his logit model without explicitly controlling for families that hold zero debt. Given the large number of families in the SCF (both constrained and unconstrained) that hold zero debt the resulting specification error could be severe. In contrast, our procedure explicitly controls for any selection effects related to the decision to hold positive debt. In addition, our estimation includes several variables related to household creditworthiness and preferences that are not used by Jappelli (1990); these variables include UNEMP, PENINC, AVERSE, CONSUMP, LUX, DUR, EMERG, CUREMP, BADHST, OWNHIST, SOMHST, CHECK, and WELFARE. Many of these variables are significant in the credit constraint and debt equations and provide further insight into the determinants of who is credit constrained.

Observe also, that families that feel it is all right to borrow to finance a durable (DUR) or a luxury (LUX) item are more likely to hold positive debt. As will be seen shortly, all of these variables have similar qualitative effects on the level of debt families would like to hold.

Focusing on the credit constraint function, several variables that appear on loan applications and which are more closely associated with creditworthiness than the demand for debt are significant predictors of who is credit constrained. 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).[30] The variables SOMHST and CUREMP also have the anticipated signs but are not significant.

Given that the remaining variables in the credit constraint probit model appear in the demand function as well, it is useful to review those variables in conjunction with the selectivity-adjusted demand function, the OLS demand function, and the Tobit demand function in Table II. As will be discussed shortly, the selectivity variables are not significant, which suggests that the OLS model or possibly the Tobit routine provides a more accurate representation of the relative importance of the different covariates in the model.

In Table I it is striking that household wealth, income, and income security (as proxied by UNEMP) do not have a statistically significant effect on

[30]These results are consistent with empirical findings by Boyes, Hoffman and Low (1989) and Orgler (1970) which indicate that the acceptance/rejection of credit card applications and consumer loan defaults are significantly correlated with creditworthiness variables similar to those above.

the propensity of families to be credit constrained.[31] But this result is at least partially explained by the positive and generally significant impact of wealth and income on the demand for debt in Table II, and the negative and significant effect of UNEMP.[32] Accordingly, it appears that the amount of debt lenders are willing to extend increases with borrower income and wealth, as well as with increased job and income security.

RACE (1 if nonwhite) has a negative and significant effect on the propensity to obtain the desired level of credit, and a negative (but marginally significant) effect on the demand for debt. This result suggests that credit limits are tighter for nonwhite families, at least after controlling for the other regressors in the model, consistent with findings by Gabriel and Rosenthal (forthcoming).[33] The opposite result holds for marital status (1 if married) which has a positive and significant effect on the propensity to obtain the desired level of credit, and a generally positive (and insignificant) effect on

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[31]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.

[32]If households borrow only to purchase nondurables, with relatively minor additional restrictions the demand for debt would decline with income and wealth. In contrast, if households borrow to purchases durables (such as housing), the demand for debt could increase with income and wealth as above. Although it would be interesting to distinguish between borrowing for nondurables versus borrowing to finance the purchase of durables, to simplify the analysis throughout this paper it is implicitly assumed that different forms of debt are close substitutes. Then, under the null that borrowing constraints do not matter, one can test whether the total level of household debt is sensitive to binding borrowing constraints; evidence for such an effect is sufficient to indicate that household behavior is sensitive to binding borrowing constraints.

[33]These results, of course, do not necessarily imply the presence of "bigotry" on the part of lenders, but could indicate that race is correlated with other (unobservable) variables that proxy default risk. For example, discrimination in labor markets (where nonwhites historically have been last hired and first fired) affects job and income security which in turn influences lender decisions.

the demand for debt. Hence, it appears that borrowing limits are less stringent for married families, ceteris paribus.[34]

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. In addition, when viewed as a whole, our model results [and findings from Jappelli (1990)] suggest that lenders vary credit limits across borrowers on the basis of observable characteristics that proxy credit risk, consistent with "screening" models of credit rationing (e.g., Stiglitz and Weiss (1981), part IV).[35]

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[34]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.

[35]Given the degree to which debt limits vary with observable household characteristics, these findings suggest that most households probably have (or can easily acquire) considerable information to determine whether they would qualify for a desired loan. To the extent that households are well informed about their access to credit, this lends support to our contention [and that of Jappelli (1990)] that carefully constructed data sets such as the 1983 SCF enable the researcher to determine *a priori* which households face binding borrowing constraints.

Turning to the selectivity variables in the demand function, it is apparent that neither $\sigma_{1,u1}$ or $\sigma_{1,u2}$ are significant. One possible explanation for this result is that $M_{1,u1}$ could be collinear with $M_{1,u2}$. In that case, however, one might expect that controlling for selectivity related to Cr while ignoring the nonnegativity constraint, or vice versa, would yield significant estimates of selectivity effects. Results based on the single selection models are presented in columns (1) and (2) of Table III. In both cases the selection terms still are not significant and the estimated parameters of the debt function (*d*) are not statistically different from the selection model in Table II (based on a series of Wald tests).[36]

Alternatively, functional form could account for the apparent lack of selectivity-related effects. In column (3) of Table III, when a log-linear debt demand function was estimated controlling only for credit-related selectivity, $\sigma_{1,u2}$ was negative and significant. (In contrast, similar tests of the nonnegativity constraint still indicated that $\sigma_{1,u1}$ was not significant).[37] This result suggests that households with an unexpectedly high demand for debt may in fact be more likely to encounter binding borrowing constraints, but that our ability to discern such effects is sensitive to the functional form imposed.

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[36]We should note, of course, that our ability to identify $\sigma_{1,u1}$ relies primarily on the nonlinearity of the selectivity variable given that (1) and (2) are based on the same covariates. This is especially apparent in column (2) of Table III where only the nonnegativity constraint is modelled. In contrast, recall that the probit model of who is not constrained contains a number of variables not included in the demand function.

[37]The log-linear model was also estimated based on the dual selection specification and controlling only for the nonnegativity constraint; in both cases $\sigma_{1,u1}$ was small and not significant. In addition, the estimated parameters from those demand functions were nearly identical to estimates presented in column (3) of Table III and are not presented for that reason.

Note that if the log-normal model is the "correct" specification, then the regime that determines whether households hold positive or zero debt [expression (2)] must differ from the debt demand function [expression (1)]. In contrast, for the linear model recall that if equations (1) and (2) are identical, $\sigma_1 = \sigma_{1,u1}$, $a = d/\sigma_1$, and $\sigma_{u1,u2} = \sigma_{1,u2}/\sigma_1$. Test results of these restrictions were mixed. Our estimate of σ_1 is close to that of $\sigma_{1,u1}$ (in any of the relevant models), both $\sigma_{u1,u2}$ and $\sigma_{1,u2}$ are not significant (in the linear case), but a Wald test rejects the null that $a = d/\sigma_{1,u1}$.[38]

Given mixed evidence about the "correct" specification of the nonnegativity constraint, it is desireable to evaluate how sensitive our results are to changes in the model specification. In that regard, for the class of linear debt functions, since neither selectivity term ($M_{1,u1}$ or $M_{1,u2}$) in Table II is significant, the debt demand function could be estimated by OLS using only unconstrained households that hold positive debt (column (2) of Table II). If instead, we simply impose the restriction that expressions (1) and (2) are alike, the debt model can be estimated by maximum likelihood Tobit (column (3) of Table II). As above, parameter estimates from these models were not statistically different from estimates based on the selectivity model in Table II or the linear models in Table III.[39] These results suggest that, at least for the linear case, estimates of the debt function parameters are not sensitive to reasonable alternative specifications of the nonnegativity constraint.

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[38]A Wald statistic was formed based on $d/\sigma_{1,u1}$ [from column (3)] and a from the bivariate probit model where the variance matrix for $d/\sigma_{1,u1}$ was calculated based on the Delta method [see Billingsley (1979) for a discussion of the Delta method]. The test statistic equalled 97.2 and is distributed $X^2(16)$.

[39]A Wald test statistic based on the selectivity-adjusted and Tobit demand functions in Table II, for example, equals 4.4 and is distributed $X^2(16)$ which fails to reject the null that the coefficients from the two models are alike.

The Impact of Borrowing Constraints on Constrained Households:

Two methods were used to evaluate the impact of borrowing constraints on constrained households. Initially, a Tobit model of household debt was estimated for constrained families as well as for the full sample (columns (1) and (2) of Table IV, respectively). Note that under the null that borrowing constraints do not matter, one natural specification for the debt function would be a Tobit model. A likelihood ratio test based on the Tobit models in Table II and Table IV, however, strongly rejects the null hypothesis of a unified sample (the test statistic equals 80). Accordingly, it appears that binding borrowing constraints have a significant effect on the behavior of households, at least with respect to their demand for debt.

As discussed earlier, an alternative method of evaluating the impact of borrowing constraints is to use expression (10) to predict the difference between actual and preferred levels of debt held by constrained families. Histograms of the predicted impacts (and the corresponding mean impact) are presented in Figures I through III for the models in columns (1) through (3) of Table II, and in Figure IV for column (3) of Table III.

The estimated impacts based on the dual selectivity-adjusted linear demand function (Figure I) are small relative to the other models, but this result should probably be discounted given the insignificant selectivity terms upon which the histogram is based. In addition, the log-liner model (Figure IV) was sensitive to outliers when predicting D* for constrained families, causing us to view results from Figure IV with some caution.[40] Instead, given that the OLS model and the Tobit models did not appear to be sensitive to outliers, and given

[40]The estimated impact of borrowing constraints based on the log-linear model exceeds $300,000 for roughly 10 percent of constrained households. In addition, a number of families had predicted impacts over $500,000.

the lack of selectivity effects in the linear case, we are inclined to focus on Figures II and III as our preferred estimates of the impact of borrowing constraints. In those figures, note that of the constrained households in the sample, roughly half would hold at least $12,000 (1982 dollars) more debt if borrowing constraints had been relaxed, ceteris paribus.[41]

V. Conclusions

If the Life Cycle and Permanent Income Hypotheses (LCH) do not hold in their strongest form, current income could affect current consumption which suggests a potential role for macro-stabilization policy.[42] In addition, the demand for consumer durables (such as housing) could be sensitive to current as well as to permanent income. 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 substantially more debt if borrowing constraints were relaxed, ceteris paribus. In addition, binding borrowing constraints appear to have a significant effect on the behavior of households, at least with respect to the amount of debt families hold.

It should be emphasized that these results do not imply that the underpinnings of the LCH are without merit. Indeed, 70 percent of our sample report that they hold as much debt as they would like, suggesting that the

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[41]These results are consistent with findings by Rosenthal and Duca (1990) (obtained using the same data as here) which suggest that binding borrowing constraints significantly reduce the likelihood that a constrained household would reside in owner-occupied housing.

[42]In their strongest form, the Life-Cycle and Permanent Income Hypotheses (LCH) suggest that households maximize intertemporal utility subject to a single lifetime budget constraint. A well known implication of this model is that households base consumption decisions on permanent as opposed to current income.

behavior of these families may be relatively more consistent with the LCH. On the other hand, the presence of binding borrowing constraints for an important subset of the population provides 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 LCH.

Our study also provides new insights into the determinants of who is credit constrained. In particular, households with intrinsically strong preferences for holding debt are more likely to be constrained, while families that are more likely to default or have trouble making loan payments face tighter debt limits. In addition, it appears that lenders vary credit limits across borrowers on the basis of a wide range of observable characteristics that proxy credit risk, consistent with "screening" models of credit rationing.

TABLE I
Bivariate Probit Model of Who is Not Credit Constrained and Who Would Like to Hold Positive Debt

	Holding Positive Debt (Dbt0 = 1)		Not Being Credit Constrained (Cr = 1)	
Variable	Coefficient	T-ratio	Coefficient	T-ratio
CONST	.264527	.7876	.528315	.7303
WHAT	.294378	.8094	.132651	.2606
INC82	1.55687	1.230	1.20941	.8169
INCSQ82	-1.29261	-1.077	-.347683	-.2214
PENINC	.882930	1.547	.454948	.8245
UNEMP	-.611600E-02	-.7710	-.673700E-02	-.7764
ED	.101374	.6430	-.197239	-1.405
SEX	-.312862	-2.624	.598200E-01	.4491
RACE	-.105567	-.7142	-.338997	-2.537
MARR	.391180	2.528	.353886	1.850
HSIZE	.428940E-01	.7868	-.696530E-01	-1.652
AVERSE	.539810E-01	.4511	-.503120E-01	-.5060
CONSUMP	.357080E-01	.2398	-.133900	-1.156
LUX	.188375	1.407	-.162595	-1.442
DUR	.595603	3.488	-.247080	-.7786
EMERG	-.192403	-1.029	-.113668	-.7508
CUREMP	-	-	.225710E-01	1.172
BADHST	-	-	-.284481	-2.637
OWNHIST	-	-	.442444	2.035
SQMHST	-	-	.615750E-01	.4828
WELFARE	-	-	-.379207	-2.616
CHECK	-	-	.190092	1.695
$\sigma_{u1,u2}$	-.146965	-0.126		

Log-Likelihood..... -974.15
Observations 1224

TABLE II
Linear Debt Demand Functions for Unconstrained Households

Variable	Selectivity-Adjusted* Coefficient	Selectivity-Adjusted* T-ratio	Unadjusted OLS Coefficient	Unadjusted OLS T-ratio	Tobit Model Coefficient	Tobit Model T-ratio
CONST	-.274362	-1.866	-.133302	-2.175	-.255654	-4.351
WHAT	.117897	2.039	.953357E-01	2.197	.135538	3.102
INC82	1.02988	4.864	.910720	5.109	.904771	5.162
INCSQ82	-.296274	-1.656	-.189272	-1.342	-.248435	-1.778
PENINC	.132980	1.690	.977025E-01	1.431	.155941	2.274
UNEMP	-.594836E-02	-3.488	-.569174E-03	-3.380	-.524815E-03	-3.270
ED	.297026E-01	.896	.217758E-01	.699	.252023E-01	.840
SEX	.334884E-01	1.244	.498674E-01	2.458	.273429E-01	1.369
RACE	-.522844E-01	-1.450	-.408808E-01	-1.309	-.590191E-01	-1.990
MARR	.192826E-01	.467	-.126395E-01	-.458	.363123E-01	1.356
HSIZE	.268745E-01	2.685	.254904E-01	2.872	.240607E-01	2.738
AVERSE	-.156284E-01	-0.757	-.193413E-01	-.952	-.128697E-01	-.645
CONSUMP	-.420212E-01	-1.541	-.443660E-01	-1.669	-.395452E-01	-1.517
LUX	.464768E-01	1.976	.391252E-01	1.822	.431772E-01	2.020
DUR	.587353E-01	0.899	.109511E-01	.275	.673588E-01	1.862
EMERG	-.169958E-03	-0.006	.110281E-01	.388	-.598401E-02	-.211
$M_{1,u1}$	.231881	0.980	-	-	-	-
$M_{1,u2}$	.623833E-02	0.077	-	-	-	-
σ_1	.268847		.245168		.254765	
R^2	.386612		.385625		-	
F	25.6565		29.0402		-	
SSR	41.6476		41.714651		-	
Log-L	-		-		-131.90	
Mean of D	.228309		.228309		.191155	
Std. Dev. of D	.309460		.309460		.295420	
Obs	710		710		848	

*T-ratios are adjusted for selection effects.

TABLE III
Debt Demand Functions With Different Selection Terms*

Variable	Linear Demand Functions: Cr Selection Only Coefficient	Cr Selection Only T-ratio	DbtO Selection Only Coefficient	DbtO Selection Only T-ratio	Log-Linear Demand Function with Cr Selection Only Coefficient	T-ratio
CONST	-.148173	-1.957	-.259811	-1.693	-4.53167	-8.602
WHAT	.107463	1.896	.109983	2.239	.529036	1.287
INC82	.928421	5.030	1.00840	4.637	4.37875	3.281
INCSQ82	-.213749	-1.350	-.272661	-1.554	-2.62236	-2.255
PENINC	.107798	1.451	.126793	1.592	.213046	.389
UNEMP	-.569004E-02	-3.413	-.593543E-02	-3.346	-.205065E-01	-1.738
ED	.200220E-01	.640	.299459E-01	.888	.626434	2.873
SEX	.506923E-01	2.504	.340333E-01	1.226	.108654	.753
RACE	-.464992E-01	-1.317	-.477976E-01	-1.435	.208511	.887
MARR	-.768645E-02	-.246	.140007E-01	.340	.686764E-01	.313
HSIZE	.242861E-01	2.550	.275198E-01	2.844	.195488	2.888
AVERSE	-.191822E-01	-.953	-.159661E-01	-.733	.303752E-01	.213
CONSUMP	-.458077E-01	-1.717	-.412947E-01	-1.457	-.816847E-01	-.439
LUX	.379140E-01	1.757	.467654E-01	1.916	.250718	1.635
DUR	.840479E-02	.209	.581330E-01	.880	.545033	1.905
EMERG	.100745E-01	.356	.100973E-02	.031	.127080E-02	.006
$\lambda(xa)$	-	-	.233961	.917	-	-
$\lambda(zg)$	.258802E-01	.329	-	-	-1.92042	-3.649
σ_1	.24300		.26731		1.9266	
R^2	.38572		.38635		.409131	
F	27.197		27.270		29.9905	
SSR	41.708		41.665		1437.64	
Obs	710		710		710	

*All demand functions were estimated by OLS using only unconstrained households with positive debt. T-ratios are corrected for selection effects. $\lambda(s)$ is the Mill's ratio evaluated at s.

TABLE IV
Tobit Debt Demand Models for Constrained Households and the Full Sample

Variable	Constrained Coefficient	Constrained T-ratio	Full Sample Coefficient	Full Sample T-ratio
CONST	-.762262E-01	-1.202	-.212091	-4.637
WHAT	.226857	3.906	.167208	4.732
INC82	.106502	.420	.742339	5.279
INCSQ82	.437017	1.196	-.165884	-1.423
PENINC	.200106	1.989	.180170	3.158
UNEMP	-.222517E-03	-1.345	-.460102E-03	-3.693
ED	.340417E-01	1.199	.318645E-01	1.405
SEX	.261860E-01	1.266	.245941E-01	1.587
RACE	-.247446E-01	-1.076	-.504362E-01	-2.429
MARR	.638379E-01	2.437	.503060E-01	2.478
HSIZE	-.555534E-02	-.689	.118878E-01	1.824
AVERSE	.201294E-01	1.013	-.183389E-02	-.120
CONSUMP	-.103641E-01	-.436	-.322621E-01	-1.659
LUX	.129617E-01	.613	.339844E-01	2.070
DUR	.298052E-01	.727	.604459E-01	2.106
EMERG	-.372371E-01	-1.237	-.151401E-01	-.681
σ	.165264	23.305	.234773	44.041
Log-L	46.290		-125.16	
Mean of D	.088576		.159644	
Std. Dev. of D	.170461		.267568	
Obs.	376		1224	

FIGURE I
Distribution of Impacts on 376 Constrained Households
In 100,000 Dollar Units (1982 dollars)
(Dual Selectivity-Adjusted Model - Column (1) of Table II)

Mean Impact = .047, Median Impact = .045

Lower limit	Upper limit	Frequency	Cumulative Frequency
-.2571	-.1378	9 (.0239)	9 (.0239)
-.1378	-.0914	24 (.0638)	33 (.0878)
-.0914	-.0450	49 (.1303)	82 (.2181)
-.0450	.0013	56 (.1489)	138 (.3670)
.0013	.0477	67 (.1782)	205 (.5452)
.0477	.0941	57 (.1516)	262 (.6968)
.0941	.1404	45 (.1197)	307 (.8165)
.1404	.1868	28 (.0745)	335 (.8910)
.1868	.2332	19 (.0505)	354 (.9415)
.2332	.6436	22 (.0585)	376 (1.0000)

```
Frequency  ---------------------------------------------------------------------
     .178 |                             **                                     |
          |                             **                                     |
          |                             **                                     |
          |                      **     **     **                              |
          |                      **     **     **                              |
     .134 |               **     **     **     **                              |
          |               **     **     **     **                              |
          |               **     **     **     **     **                       |
          |               **     **     **     **     **                       |
          |               **     **     **     **     **                       |
     .089 |               **     **     **     **     **                       |
          |               **     **     **     **     **                       |
          |               **     **     **     **     **     **                |
          |        **     **     **     **     **     **     **            **  |
          |        **     **     **     **     **     **     **     **     **  |
     .045 |        **     **     **     **     **     **     **     **     **  |
          |        **     **     **     **     **     **     **     **     **  |
          | **     **     **     **     **     **     **     **     **     **  |
          | **     **     **     **     **     **     **     **     **     **  |
          | **     **     **     **     **     **     **     **     **     **  |
          |--------------------------------------------------------------------
          -.14   -.09   -.04    .00    .05    .09    .14    .19    .23    .64  Impact
```

FIGURE II

Distribution of Impacts on 376 Constrained Households
In 100,000 Dollar Units (1982 dollars)
(OLS Model - Column (2) of Table II)

Mean Impact = .095, Median Impact = .120

Lower limit	Upper limit	Frequency	Cumulative Frequency
-.5921	-.1667	25 (.0665)	25 (.0665)
-.1667	-.1013	7 (.0186)	32 (.0851)
-.1013	-.0359	20 (.0532)	52 (.1383)
-.0359	.0294	45 (.1197)	97 (.2580)
.0294	.0948	64 (.1702)	161 (.4282)
.0948	.1602	86 (.2287)	247 (.6569)
.1602	.2256	67 (.1782)	314 (.8351)
.2256	.2909	42 (.1117)	356 (.9468)
.2909	.3563	12 (.0319)	368 (.9787)
.3563	.6782	8 (.0213)	376 (1.0000)

```
Frequency -----------------------------------------------------------------------------------------------------
     .229 |                                                   **                                              |
          |                                                   **                                              |
          |                                                   **                                              |
          |                                                   **                                              |
          |                                                   **        **                                    |
     .172 |                                         **        **        **                                    |
          |                                         **        **        **                                    |
          |                                         **        **        **                                    |
          |                                         **        **        **                                    |
          |                                         **        **        **                                    |
     .114 |                               **        **        **        **        **                          |
          |                               **        **        **        **        **                          |
          |                               **        **        **        **        **                          |
          |                               **        **        **        **        **                          |
          | **                            **        **        **        **        **                          |
     .057 | **                  **        **        **        **        **        **                          |
          | **                  **        **        **        **        **        **                          |
          | **                  **        **        **        **        **        **        **                |
          | **        **        **        **        **        **        **        **        **        **      |
          | **        **        **        **        **        **        **        **        **        **      |
          |-----------------------------------------------------------------------------------------------------
           -.17      -.10      -.03       .03       .09       .16       .23       .29       .36       .70     Impact
```

FIGURE III
Distribution of Impacts on 376 Constrained Households
In 100,000 Dollar Units (1982 dollars)
(Tobit Model - Column (3) of Table II)

Mean Impact = .216, Median Impact = .200

Lower limit	Upper limit	Frequency	Cumulative Frequency
-.2102	.1159	14 (.0372)	14 (.0372)
.1159	.1410	10 (.0266)	24 (.0638)
.1410	.1662	34 (.0904)	58 (.1543)
.1662	.1913	83 (.2207)	141 (.3750)
.1913	.2165	77 (.2048)	218 (.5798)
.2165	.2416	63 (.1676)	281 (.7473)
.2416	.2667	39 (.1037)	320 (.8511)
.2667	.2919	19 (.0505)	339 (.9016)
.2919	.3170	17 (.0452)	356 (.9468)
.3170	.6324	20 (.0532)	376 (1.0000)

```
Frequency ------------------------------------------------------------
     .221 |                    **
          |                    **    **
          |                    **    **
          |                    **    **
          |                    **    **
     .166 |                    **    **    **
          |                    **    **    **
          |                    **    **    **
          |                    **    **    **
          |                    **    **    **
     .110 |                    **    **    **
          |                    **    **    **    **
          |              **    **    **    **    **
          |              **    **    **    **    **
          |              **    **    **    **    **
     .055 |              **    **    **    **    **    **          **
          |              **    **    **    **    **    **    **    **
          |  **          **    **    **    **    **    **    **    **
          |  **    **    **    **    **    **    **    **    **    **
          |  **    **    **    **    **    **    **    **    **    **
          |------------------------------------------------------------
            .12   .14   .17   .19   .22   .24   .27   .29   .32   .70   Impact
```

FIGURE IV
Distribution of Impacts on 376 Constrained Households
In 100,000 Dollar Units (1982 dollars)
(Log-linear Model - Column (4) of Table II)

Mean Impact = ****, Median Impact = .550

Lower limit	Upper limit	Frequency	Cumulative Frequency
-.2338	.0000	2 (.0053)	2 (.0053)
.0000	.2500	93 (.2473)	95 (.2527)
.2500	.5000	85 (.2261)	180 (.4787)
.5000	.7500	52 (.1383)	232 (.6170)
.7500	1.0000	29 (.0771)	261 (.6941)
1.0000	2.0000	49 (.1303)	310 (.8245)
2.0000	3.0000	25 (.0665)	335 (.8910)
3.0000	+ ∞	41 (.1090)	376 (1.0000)

```
Frequency  ---------------------------------------------------
     .247 |        **                                        |
          |        **                                        |
          |        **    **                                  |
          |        **    **                                  |
          |        **    **                                  |
     .186 |        **    **                                  |
          |        **    **                                  |
          |        **    **                                  |
          |        **    **                                  |
          |        **    **    **          **                |
     .124 |        **    **    **          **                |
          |        **    **    **          **          **    |
          |        **    **    **          **          **    |
          |        **    **    **          **          **    |
          |        **    **    **    **    **          **    |
     .062 |        **    **    **    **    **    **    **    |
          |        **    **    **    **    **    **    **    |
          |        **    **    **    **    **    **    **    |
          |        **    **    **    **    **    **    **    |
          |  **    **    **    **    **    **    **    **    |
          |--------------------------------------------------
            -.24  0.0   .25   .50   .75   1.0   2.0   3.0    Impact
```

APPENDIX A
SELECTIVITY VARIABLES

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 (DbtO=1) can be written as,

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

while the conditional expectation of D* is,

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

Based on work by Rosenbaum (1961), Fishe et al (1981), and Maddala (1984), for $k_1 = -xa$ 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 $u_2 < -zg$.[43] 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,

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

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

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

When calculating impacts based on the Tobit model in Table II, 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 II.

---

[43]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 $m_{1,u2}$) which eliminates one form of truncation, while 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 AND SUMMARY STATISTICS

Cr equals a dummy variable equal to 1 if not credit constrained and 0 otherwise.

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

Wealth equals household net worth (A - D) in 1982 in current dollars (in 100,000 dollar units).

What equals the fitted value from the Wealth regression (in Appendix C).

Assets equals total non-pension household real and financial assets in 1982 dollars (in 100,000 dollar units).

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

INCSQ82 equals total household income in 1982 squared (INC82 squared).

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.

SEX 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.

OWNHIST 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.

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.

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	.88576E-01	.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
ASSETS	.22332	.42945	.54674	.82158	.62126	.84176	.44739	.73912
INC82	.16254	.11570	.23993	.17590	.25862	.17815	.21616	.16373
INCSQ82	.39768E-01	.65274E-01	.88471E-01	.17087	.98577E-01	.18033	.73510E-01	.14843
PENINC	.73584E-01	.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
SEX	.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
OWNHIST	.10904	.31211	.26061	.43923	.30000	.45858	.21405	.41033
SOMHST	.84574	.36167	.87382	.33225	.84930	.35801	.86520	.34165
WELFARE	.24468	.43047	.82547E-01	.27536	.64789E-01	.24633	.13235	.33901
CHECK	.61436	.48739	.77241	.41953	.82535	.37993	.72386	.44727
FULLTIME	.59043	.49241	.67925	.46704	.69859	.45919	.65196	.47654
EXPINHER	.19947	.40013	.24057	.42768	.24507	.43043	.22794	.41968
INHERIT	.10638	.30874	.77830E-01	.26806	.76056E-01	.26528	.86601E-01	.28136
FULLINC	.11455	.13402	.17716	.18552	.19131	.18998	.15793	.17372
EXPINC	.37928E-01	.92106E-01	.64397E-01	.14830	.70184E-01	.15773	.56266E-01	.13410

APPENDIX C
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	.358908E-01	.819
SEX	-.144051E-01	-.461
RACE	-.590050E-01	-1.455
MARR	-.323001E-01	-.799
HSIZE	.228435E-01	1.699
AVERSE	-.580367E-01	-1.945
CONSUMP	-.326270E-01	-.847
LUX	-.463826E-01	-1.420
DUR	.125476E-01	.232
EMERG	-.275956E-01	-.617
CUREMP	.269413E-01	5.668
BADHST	-.693045E-01	-1.953
OWNHIST	.331459	8.892
SOMHST	.756476E-01	1.827
WELFARE	-.199662E-01	-.404
CHECK	.364597E-01	.963
FULLTIME	.168308E-01	.326
EXPINHER	.162771E-01	.284
INHERIT	-.674185E-01	-1.340
FULLINC	-.347664	-1.811
EXPINC	.771757	4.006

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

APPENDIX D

TABLE D.1
Bivariate Probit Model of Who is Not Credit Constrained and Who Would Like to Hold Positive Debt Excluding Dissuaded Families

	Holding Positive Debt (Dbt0 = 1)		Not Being Credit Constrained (Cr = 1)	
Variable	Coefficient	T-ratio	Coefficient	T-ratio
CONST	.108347	.311969	1.07811	1.42060
WHAT	.406110	1.10102	.151037	.261408
INC82	1.84916	1.43447	.197556	.105440
INCSQ82	-1.61929	-1.35104	.725258	.300416
PENINC	.885629	1.52142	.915146	1.38256
UNEMP	-.526200E-02	-.642962	-.125020E-01	-1.33085
ED	.135812	.817534	-.344723	-2.19178
SEX	-.309258	-2.51812	.662640E-01	.483753
RACE	-.148497	-.956429	-.302589	-1.93738
MARR	.472660	2.91481	.232197	1.07545
HSIZE	.242890E-01	.424069	-.390380E-01	-.832864
AVERSE	.834740E-01	.672191	-.114935	-1.05456
CONSUMP	.314220E-01	.202149	-.162031	-1.28616
LUX	.162011	1.16856	-.703900E-01	-.590060
DUR	.601666	3.36851	-.332608	-.996719
EMERG	-.213610	-1.11116	-.393200E-01	-.239733
CUREMP	-	-	.202510E-01	.935554
BADHST	-	-	-.250516	-2.08348
OWNHIST	-	-	.319244	1.33853
SOMHST	-	-	.651170E-01	.466762
WELFARE	-	-	-.415624	-2.51584
CHECK	-	-	.115951	.928797
$\sigma_{u1,u2}$	-.188330	-.167319		

Log-Likelihood..... -974.15

Observations 1101

TABLE D.2
Selectivity-Adjusted Linear Demand Function
Excluding Dissuaded Families
(Based on Bivariate Probit Estimates From Table D.1)

Variable	Coefficient	T-ratio
CONST	-.280886	-1.558
WHAT	.139834	2.023
INC82	1.05316	4.381
INCSQ82	-.332934	-1.615
PENINC	.154452	1.481
UNEMP	-.605689E-02	-3.355
ED	.216755E-01	.571
SEX	.382676E-01	1.354
RACE	-.639474E-01	-1.673
MARR	.257474E-01	.546
HSIZE	.242170E-01	2.436
AVERSE	-.170227E-01	-.761
CONSUMP	-.468734E-01	-1.616
LUX	.438323E-01	1.840
DUR	.436410E-01	.651
EMERG	.559748E-03	.016
$M_{1,u1}$	.185828	.748
$M_{1,u2}$	.687418E-01	.414

TABLE D.2
Distribution of Impacts on 253 Constrained Households
In $100,000 (1982 $) Units Based on the OLS Model (Column (2) of Table II)

Mean Impact = .090, Median Impact = .120

Lower limit	Upper limit	Frequency	Cumulative Frequency
-.5504	-.1740	19 (.0751)	19 (.0751)
-.1740	-.1079	4 (.0158)	23 (.0909)
-.1079	-.0418	15 (.0593)	38 (.1502)
-.0418	.0243	25 (.0988)	63 (.2490)
.0243	.0904	44 (.1739)	107 (.4229)
.0904	.1565	58 (.2292)	165 (.6522)
.1565	.2226	45 (.1779)	210 (.8300)
.2226	.2887	28 (.1107)	238 (.9407)
.2887	.3548	8 (.0316)	246 (.9723)
.3548	.6404	7 (.0277)	253 (1.0000)

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FIELD	OFFICER	ECONOMISTS	ASST & ASSOC ECONOMISTS
Money/Macro	Cox	Koenig Duca Haslag Wynne Emery Becsi	Ozment
Banking	O'Driscoll	Clair	Yeats
Intl Finance	Cox		
Intl Trade		Gould	
North-South	O'Driscoll	Gruben	Sigalla
Economic Growth		Wynne	
Public Finance	Brown	Yucel Taylor	Sigalla
Energy	Brown	Yucel	
Urban/Regional		Gilmer Taylor Phillips	
Labor		Taylor	