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The Credit-Constrained Consumer: An Empirical Study of Demand and Supply in the Loan Market

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This article presents an empirical analysis of credit-constrained households in which models of both demand and supply sides of the market for loans are simultaneously estimated. We develop a discrete-choice logit model of the consumers' decision on whether or not to apply for credit. Combining this with a reduced-form logistic model for the banks' credit-granting decision, we then estimate the model with cross-sectional data, as a nonlinear, ordered, sequential logit. Our findings shed light on the criteria used by banks in assessing credit applications and reveal the strong dependence of preferences on demographic characteristics. The results also suggest that agents face significant fixed costs in applying for loans. The fact that we jointly estimate models of both supply and demand sides of the credit market enables us to examine whether particular groups in the population are more frequently credit rationed because they tend to demand more loans or because they are viewed as bad credit risks by lenders.

KEY WORDS: Application cost; Credit rationing; Loan demand; Logistic regression.

1. INTRODUCTION

Capital-market imperfections, including quantity constraints on consumer borrowing from banks, are likely to have drastic consequences for several of the more familiar neutrality results of modern macroeconomics. For example, Bernanke (1983) and Blinder and Stiglitz (1983) argued persuasively that monetary policy will have pronounced real effects in economies in which liquidity constraints are widespread, and Heller and Starr (1979), Webb (1981), and Yotsuzuka (1987) examined the impact of liquidity or credit constraints on Ricardian debt neutrality as expounded by Barro (1974). Understanding the operation and incidence of credit rationing within financial markets is, therefore, an important subject of empirical research.

The present study takes as its starting point the information collected by the Federal Reserve in 1983 on the finances of 2,700 U.S. households. Among other questions, households were asked whether they had been turned down for credit in the recent past or whether they had failed to apply through fear of being refused. Using figures on households' existing portfolios of consumer loans, we were also able to infer whether or not households wished to borrow in the first place. Together with the extensive demographic, wealth and income data also collected by the Federal Reserve, this quite unique data set enables us to develop a pair of sequential discrete-choice models that explain both the consumers' decision whether or not to apply for credit and the decision of "banks" whether to accept the application. (The data set did not allow one to distinguish between bank borrowing and loans from other financial institutions. Throughout the article, we use the term "bank" as shorthand for "credit institutions".)

Our results suggest interesting conclusions about the way in which banks assess prospective borrowers. Black skin, male head of household, bad health, and large city dwelling are all shown to be distinct handicaps to someone applying for credit. We are also able to identify marked demographic influences on preferences. In particular, the race and sex of the head of household turn out to be highly significant. Finally, we find that the utility cost incurred by agents when they apply for loans depends strongly on demographic characteristics.

As an example of our results, we find that Blacks are less prone to want credit than Whites, though this is partially offset by their relatively low costs of application. Conditional on application, however, Blacks are more likely to be refused credit than Whites with the same level of income and net worth, even after controlling for a large number of other demographic effects. Whether this finding reflects a genuinely rational evaluation of credit risk rather than racial bias is beyond the scope of this article. Among other interesting results, we find that individuals face highly significant fixed utility costs in applying for credit. Wilcox (1989) argued that such costs could potentially explain his finding that fully anticipated increases in Social Security benefits only give rise to increased consumption after they have actually been paid out. To our knowledge, the present study is the first to estimate the potential disutility of applying for credit.

Our results may be contrasted with those of the few previous studies in this area that are directly comparable to ours. Using a low-income sample, Avery (1981) attempted to identify demand and supply effects, employing a switching-regressions approach, and found that, in explaining individuals' ability to secure credit, racial effects dominated other influences to a degree that Avery himself described as "implausible at best."

Another relevant study is that of Jappelli (1990). Using the same data set as we did (tables of descriptive statistics for the data set can be found in his article), he found several roughly similar results. He did not, however, estimate costs of applying for credit, and, moreover, his reduced-form approach did not allow him to distinguish between supply and demand effects in the market for loans. The disentangling of supply and demand factors is what previous studies—with the exception of that of Avery (1981)—had not attempted and is what this data set now makes possible. As an example, Jappelli found that level of education has a significant influence on one's chances of being refused credit. In fact, as our estimates show, this conclusion reflects the dependence of loan application cost on educational level. Banks' decisions on whether to grant credit are actually independent of applicants' educational achievement.

The conclusions we reach may have implications for other branches of the empirical literature on the life-cycle hypothesis and credit rationing. The majority of such studies (see King [1985] and Hayashi [1987] for surveys) have analyzed the time series behavior of aggregate consumption and income to see if current consumption is more sensitive to innovations in disposable income than would be predicted by the strict life-cycle hypothesis. Some notable works are those of Hall (1978), Flavin (1981), Deaton (1987), and Blinder and Deaton (1985). Departures from the life-cycle model are then interpreted as indicating the presence of liquidity constraints. Our work suggests that the dependence of preferences on demographic factors may be systematic and substantial. By ignoring such factors, the aggregate time series studies just described lay themselves open to the danger of aggregation bias.

A further group of studies has attempted to test for liquidity constraints using panel data (see, for example, Hall and Mishkin 1982; Hayashi 1985; Zeldes 1989a). These works, however, have been hampered by the lack of satisfactory data, their authors being obliged, for example, to proxy full consumption by food expenditure. These studies also allowed for a smaller range of demographic influences than we do.

An article that is close in spirit to this article is that of Mariger (1987). He estimated a model of credit rationing using cross-sectional data from the Federal Reserve Survey of 1962–1963. His study however, relied on consumption data and was thus unable to analyze the supply and demand effects that are the particular innovation of this article. (On the other hand, this allowed Mariger to formulate a more general model of the demand side than the one that will be estimated in this article.)

Of course, consumers' own reports of whether or not they are credit rationed may not be entirely reliable. The accuracy of survey-question responses may well vary across different demographic groups, thereby hampering attempts to estimate the dependence of credit rationing on demographic factors. Studies such as ours should therefore be regarded as supplemental or complementary to the more usual consumption-data-based studies rather than as strict substitutes. In fact, it is reassuring that most such studies (see for example Hall and Mishkin 1982; Mariger 1987) conclude that 20% of consumers are credit rationed, a figure quite close to the fraction reporting themselves credit rationed in our data set.

We will point out one important difference between credit constraints as they are treated in this article and the consumption-based tests for credit constraints. Our data contain information about whether consumers were able to obtain credit when they applied for it, which will not correspond exactly to whether they were able to smooth consumption over time. For example, a consumer might not be able to obtain a credit card for various reasons–even if he or she possesses illiquid assets like stocks. In our data, such a consumer will be observed as turned down for credit, but he or she may nevertheless be able to smooth consumption by selling illiquid assets. This article does not treat the question of whether a consumer was ultimately able to obtain the desired degree of consumption smoothing.

An important feature of the model that we adopt is that it is built to match the data. Thus we impose quite restrictive assumptions in which the data are weak and allow for more general assumptions in which the data are more informative and therefore "able to speak for themselves." We do not regard it as sensible to try to extract information that is not in the data and instead prefer to impose assumptions that, although stringent, at least leave readers with the possibility of evaluating the potential biases on their own rather than presenting somewhat spurious results from an overambitious estimation model. This philosophy guides our choice of utility function and time horizon in Section 2.

On the plus side the data set contains the answer to the question, "Have you at any time during the last few years thought of applying for a loan but changed your mind because you thought you might be turned down?" This quite unique observation gives us the possibility of modeling consumers' disutility of applying for credit and, more interestingly, whether particular demographic groups are more easily dissuaded than others. This is particularly relevant if one wishes to estimate both the demand and supply side of the credit market, because it enables one to see whether the fact that some demographic groups tend to be turned down for credit more often than others is a reflection of low costs of applying for credit in these particular groups.

The remainder of the article is organized as follows. Section 2 describes the basic model and the derivation of estimable forms. Section 3 provides an account of the data set, and Section 4 discusses estimation. Section 5 summarizes the results and their interpretation, and Section 6 concludes the article, drawing out the relevance of the results for a number of broader economic issues. Finally, the Appendix provides a detailed description of the data.

2. THE MODEL

The intertemporal optimization problem of an infinitely lived individual in the case of perfect capital markets is

$$\max_{\{C_t\}} \sum_{t=0}^{\infty} \frac{1}{(1+\delta)^t} U(C_t)$$

such that

$$\sum_{t=0}^{\infty} \frac{C_t}{(1+r)^t} = \sum_{t=0}^{\infty} \frac{Y_t}{(1+r)^t} \equiv W.$$

Here, W is lifetime income, C_t is consumption of the single homogeneous good at time t, δ is the rate of time preference, r is the real rate of interest, Y_t is labor income at $t = 1, 2, \ldots,$ and Y_0 is the value of nonhuman wealth plus labor income at $t = 0$. We assume that the same constant rate of interest, r, applies to lenders and savers and is the same across demographic groups. This assumption is perhaps the most stringent that we adopt, but our data contain no information on interest rates paid or received, so it is not possible to relax it. If some demographic groups are particularly prone to apply for loans from, say, high-interest-rate finance companies, this might bias the results. The problem is somewhat alleviated by the fact that we treat borrowers, who report having obtained credit after first having been turned down for credit as being credit constrained. In principle, one could model multiple credit applications, but given the relatively few reapplications and the problems of identifying who were turned down several times, it does not appear empirically feasible. If the purpose of the present study was to evaluate the effects of credit rationing on consumption, one would, of course, change the focus to whether credit is eventually obtained or not. On the savings side the most important place in which the interest rate appears is in the calculation of the unconstrained individuals' human wealth, where the main effect of the simplification is to introduce measurement error in our wealth series.

For reasons that we will explain later, we assume quadratic utility of the form $U(C_t) \equiv [\lambda_{\alpha 1} C_t - C_t^2]$. The α subscript on $\lambda_{\alpha 1}$ indicates that the parameter potentially depends on the demographic characteristics of the individual. This dependence permits one to investigate demand-side demographic effects.

An important feature of value functions derived from quadratic, time-separable optimal control problems is that they in turn are quadratic in form. In our problem, the quadratic value function is

$$V(W) = \mu_{\alpha 0} + \mu_{\alpha 1} W - \left(1 - \frac{(1+\delta)}{(1+r)^2}\right) W^2,$$

where $\mu_{\alpha i}$ $(i = 0, 1)$ are constants whose exact values will be immaterial here.

Suppose that in deciding whether or not to apply for a loan, the consumer is influenced by two considerations. First, banks ration credit by only accepting a fraction of the applications from a given demographic group or cohort. The implied probability of acceptance (P_α) for a given individual will, in general, be a function of the agent's demographic characteristics (including income and net financial worth). We assume that individuals are either accepted or rejected unconditionally, even though the adverse selection model of Jaffee and Russell (1976) implies that banks ration credit by offering contracts that specify both interest rate and loan size. Our data set does not contain size of loan contracts or interest rates and, more importantly, 87% of the consumers who experienced difficulties in satisfying their credit needs were turned down unconditionally rather than being offered less credit than they wanted.

Second, applying for a loan entails a direct loss of utility $(d_{\alpha 1})$ on the part of the consumer. This assumption is necessary to model the fact that the data set contained households who desired credit and yet did not apply. Again, this disutility may depend on the demographic characteristics of the individual concerned.

To simplify our model, we assume that consumers do not consider the possibility of being rationed in future periods, in effect formulating a two-period model. This assumption reflects our strategy of matching the model to the data. Not only is our data set cross-sectional and therefore not well suited for more genuine multiperiod modeling but our observation of the exact time that the credit-rationed consumer encountered rationing is not available, making an attempt to model the timing of potential credit rationing as done by Mariger (1986, 1987), unappealing. He employed the concept of varying effective planning horizons, modeling the fact that people might consider possible rationing in future periods.

If consumers do consider the possibility of future rationing, it seems that the model's predictions will be biased. In particular, one could expect savings to exceed systematically the level implied by a "myopic" model. The model we estimate, however, may still yield consistent estimates of the probability of loan application if one reinterprets the value function parameterized previously as an approximation to the true value function that takes into account the possibility of future rationing. (In this case, note that our estimate of δ can no longer be viewed as a consistent estimate of the rate of time preference.)

We suppose that the consumer is a von Neumann–Morgenstern utility maximizer who compares his or her expected utility of consumption in the situations in which he or she applies or does not apply for credit. We shall say that the consumer *wants credit* if the optimal unconstrained level of consumption in period 0, C_0^* that maximizes $U(C_0) + 1/(1 + \delta)V((W - C_0)(1 + r))$ is larger than the amount of disposable resources Y_0. From the first-order condition, one finds C_0^* to be

$$C_0^* = \frac{1}{2}\frac{1 + \delta}{(1 + r)^2}\left[-\lambda_{\alpha 1} + \mu_{\alpha 1}\frac{1 + r}{1 + \delta}\right] + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W \equiv \lambda_{\alpha 3} + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W$$

(with $\lambda_{\alpha 3}$ being defined by the second equality). Now the expected utility, for a consumer who both wants and applies for credit is

$$V_a = P_\alpha\left[U(C_0^*) + \frac{1}{(1 + \delta)}V((W - C_0^*)(1 + r))\right] + (1 - P_\alpha)\left[U(Y_0) + \frac{1}{(1 + \delta)}V((W - Y_0)(1 + r))\right] - d_{\alpha 1}.$$

The value function for a consumer who decides not to apply is

$$V_n = U(Y_0) + \frac{1}{(1 + \delta)}V((W - Y_0)(1 + r)).$$

Here, $d_{\alpha 1} \geq 0$ is the disutility the consumer suffers when he applies for credit and P_α is the probabilty of being accepted by the bank. In general, P_α will be a complicated function of the individual's observable lifetime wealth, demographic characteristics, and current disposable wealth Y_0. Boyes, Hoffman, and Low (1989) reported that banks use demographic indicators *and* the personal evaluation of the loan officer in making their credit evaluations. In their words, "However, most lenders maintain that credit scoring is only one aspect of the credit assessment process and that loan officers also allow subjective assessments to enter the loan granting decision. Presuming that these assessments are not simply a different deterministic function of observed attributes, they add an element of randomness to the loan granting process . . . " (p. 5). From the viewpoint of the bank management and the econometrician, this personal evaluation could be seen as random.

Our model implies that consumers fall into three categories: (1) individuals who do not want credit, (2) individuals who want credit but are discouraged from applying by the cost of application, and (3) those who do apply for credit. Category (3) may be further broken down into those who the bank accepts (3a) and those who are refused (3b).

It would be helpful if we could express the inequality $V_a > V_n$ as a function of C_0^* and Y_0. The direct approach of multiplying out components and rearranging involves some rather tedious algebra. Fortunately, a simpler argument is available. First, note that $V_a > V_n$ iff

$$U(C_0^*) + \frac{1}{(1 + \delta)}V((W - C_0^*)(1 + r)) - U(Y_0) - \frac{1}{(1 + \delta)}V((W - Y_0)(1 + r)) > \frac{d_{\alpha 1}}{P_\alpha}.$$

But the left side of this equality represents the gain in lifetime utility from consuming C_0^* in the current period instead of Y_0, and the right side reflects application costs weighted by the inverse probability of getting accepted for credit. (Note that the right side of the preceding inequality tends to infinity as P_α goes to 0. Individuals with very low acceptance probabilities will, therefore, almost never apply for credit.) Hence, given the quadratic nature of U and V, the gain in utility is a second-order polynomial in Y_0, which is always strictly positive except at $Y_0 = C_0^*$, where there is a double root. Using this fact, it is easy to show that $V_a > V_n$ iff

$$\frac{(1 + r)^2}{(1 + \delta)}(C_0^* - Y_0)^2 > \frac{d_{\alpha 1}}{P_\alpha}.$$

Thus we may state the inequalities corresponding to our three categories as

Category (1): $C_0^* - Y_0 \leq 0$

Category (2): $C_0^* - Y_0 > 0$,
$$C_0^* - Y_0 \leq \left[\frac{d_{\alpha 1}(1 + \delta)}{P_\alpha(1 + r)^2}\right]^{1/2}$$

Category (3): $C_0^* - Y_0 > 0$,
$$C_0^* - Y_0 > \left[\frac{d_{\alpha 1}(1 + \delta)}{P_\alpha(1 + r)^2}\right]^{1/2},$$

or, substituting for C_0^*, and defining $d_\alpha = [d_{\alpha 1}(1 + \delta)/(1 + r)^2]^{1/2}$,

Category (1): $\lambda_{\alpha 3} + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W - Y_0 \leq 0$

Category (2): $\lambda_{\alpha 3} + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W - Y_0 > 0$,
$$\lambda_{\alpha 3} + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W - Y_0 \leq d_\alpha/P_\alpha^{1/2}$$

Category (3): $\lambda_{\alpha 3} + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W - Y_0 > 0$,
$$\lambda_{\alpha 3} + \left[1 - \frac{1 + \delta}{(1 + r)^2}\right]W - Y_0 > d_\alpha/P_\alpha^{1/2}.$$

Which category a consumer falls into is a deterministic function of Y_0 and W. For the econometrician observing the consumers' choice of category, it is, however, not a deterministic function. The primary reason for this is measurement error in W. Since our data include details of individuals with given demographic characteristics but different ages, we are able to build up figures for lifetime wealth (as is standard in cross-sectional work) by estimating what a particular individual will earn in later years, based on the current income of older members of his cohort.

We therefore model the difference between true lifetime wealth W (or, more precisely, lifetime wealth as estimated by the consumer) and constructed wealth W' (lifetime wealth as estimated by us) through the equation $W = W' + \varepsilon_c$, where ε_c is a random error assumed to be independent of W'. Note that we depart here from the usual approach to measurement error under which such errors are taken to be orthogonal to the true value. In contexts in which the observed variable is a forecast of the true quantity, our approach appears to be the more natural. In the current model, for example, it is not unreasonable to assume that the expectation of ε_c given W' is 0, as W' is constructed from linear forecasts of future income. Actual independence is of course a purely simplifying assumption, although it is not innocuous, since heteroscedasticity will render the estimates inconsistent. The model's size and nonlinearity, however, mean that robust but computationally demanding estimators, like Manski's (1975) maximum score estimator, are less appealing.

To estimate the model, we solve for the stochastic term ε_c by substituting in the expression for W and reordering:

Category (1): $\varepsilon_c \le \xi Y_0 + \lambda_\alpha - W'$

Category (2): $\xi Y_0 + \lambda_\alpha - W' < \varepsilon_c \le d_\alpha / P_\alpha^{1/2} + \xi Y_0 + \lambda_\alpha - W'$

Category (3): $d_\alpha / P_\alpha^{1/2} + \xi Y_0 + \lambda_\alpha - W' < \varepsilon_c$,

where $\xi = (1 + r)^2/((1 + r)^2 - (1 + \delta))$ & $\lambda_\alpha = \xi \lambda_{\alpha 3}$.

Since ε_c appears additively in these inequalities, one may implement the system as a standard discrete-choice model. If one further assumes that ε_c follows a logistic distribution, then the model may be estimated as a nonlinear, ordered logit. The model is "ordered" because the three options correspond to successive ranges of the random variable ε_c.

Now, consider once again the model of the banks' behavior. We suppose that there exists a simple, linear, reduced form for the banks' evaluation of whether to grant credit. This also reflects our objective of building the model to match the data. The direct information we have on the rationing faced by consumers is the answer to the question, "Have you had a request for credit turned down by a particular creditor or lender in the past few years, or have you been unable to get as much as you applied for?" We do not think that this answer gives a satisfactory basis for an elaborate estimation model for the behavior of credit-giving institutions, building on, for example, the well-known theoretical articles on credit rationing by Jaffee and Russell (1976) or Stiglitz and Weiss (1981). Thus we assume that a bank decides to accept an individual belonging to the group indexed by α iff $\gamma_\alpha + \varepsilon_b < 0$, where γ_α is a function of demographic characteristics and ε_b is a scalar random variable.

Furthermore, assume that ε_b possesses a logistic distribution and is independent of ε_c. It then follows that the banks' decision to accept or reject a loan application may be modeled as a simple linear logit. We adopt a logit approach because the logit model is much less computationally demanding than its main competitor, the probit model. We would have liked to give some indication of the sensitivity of our results to this assumption, but even using logistic distributions, the model is already highly demanding in computational cost. Given our assumptions, combining the consumer model [which places individuals in categories (1), (2), and (3)] together with the banks' model [which subdivides category (3) into (3a) and (3b)] yields a sequential, ordered logit model.

Note that our formulation of the banks' method of evaluating loan applications implies a relatively simple parameterization for the probability of acceptance—namely,

$$P_\alpha \equiv F(-\gamma_\alpha) \equiv \frac{1}{1 + \exp(\gamma_\alpha)},$$

where $F(s)$ is the cumulative distribution function of a logistically distributed random variable. If we suppose that consumers are rational, in the sense of fully understanding the process by which banks process loan applications, then we may substitute this expression wherever P_α appears in the consumer part of the model. (The fact that P_α enters the consumers' choice has limited overidentifying value in our model, since we assume that application costs are demographically varying and P_α and d_α only appear in the likelihood function in the form of a ratio. In fact, it is hard to imagine a model of the same general form as ours that could clearly differentiate between the possibility that a consumer tends to underestimate the probability of acceptance from the possibility that the individual's application costs are low.)

We will end this section by discussing some aspects of the choice of model that we make. One important choice was the use of a quadratic utility function. Our reason for selecting this functional form was the fact that human-wealth figures had to be constructed by forecasting agents' income using a simple linear forecasting rule. This procedure unavoidably entails quite serious measurement error, which is generally quite intractable in nonlinear settings. One way to resolve this difficulty is to assume preferences for which the decision rules are linear in human wealth since the measurement errors then enter the model linearly. One may thus derive a discrete-choice model based on closed-form inequalities. The problem with this approach is that quadratic utility functions have several well-known drawbacks. They decrease outside a certain range and they imply increasing absolute risk aversion and zero prudence. Since other commonly applied utility functions, such as constant relative risk aversion (CRRA) functions, would not allow one to cope with the measurement-error problem, we regarded these drawbacks of the quadratic utility function as a lesser evil. (Zeldes [1989b] examined the effect of assuming quadratic utility functions when the true utility function is CRRA.) It might be argued, however, that the most stringent and probably most counterfactual assumption adopted in many studies is that all agents possess the same simple utility function.

Adopting a reduced form for the banks' randomization rule means that we cannot impose the additional overidentifying restrictions that one would expect to find between the decision rules of consumers and banks. Deriving a fully structural model of the banks' behavior, however, would require strong restrictions on the distribution of default costs in different demographic cohorts. Information on default probabilities is available (see Boyes et al. [1989], who studied the dependence of default probabilities on demographic characteristics among the credit-card customers of a single major bank). It would be difficult, however, to combine such information in a consistent manner with the data used in this article. For all of these reasons, the simpler "semi-structural" approach taken here seems preferable.

3. THE DATA

The data used in our study are all drawn from the 1983 Survey of Consumer Finances, carried out by the U.S. Federal Reserve. The basic sample comprises 3,824 U.S. households chosen so as to be approximately representative of the U.S. population as a whole. The Federal Reserve also surveyed a further 438 high-income households selected from federal income tax returns, but we thought it better not to include these in our study. Inclusion of the high-income group would have made our sample unrepresentative of the economy as a whole, and the presence of some *very* rich people in the high-income group would have made the likelihood estimation numerically more difficult. Furthermore, the few credit-rationed observations among high-income households would appear as outliers, which could have had an unreasonably large influence on the results.

Interviewing for the survey took place between February and August of 1983. The sampling methodologies and procedures were described at length by Avery and Elliehausen (1986). Elaborate imputation and consistency checks were performed by Federal Reserve staff to clean up the raw data. Again, these procedures were described by Avery and Elliehausen (1986). One hundred and fifty-nine observations were dropped because of excessively high numbers of missing variables. We also decided to exclude the 965 observations for which the household head was over 60 years old. In estimating the model, it simplified matters considerably to use value functions for infinitely lived agents. We regarded this as no more than an approximation to the true value functions, since we actually calculated human wealth for a finite working life. The approximation, however, was likely to prove unreliable for households with older household heads, and indeed preliminary runs of the model suggested that the model did not describe this age group very well. It therefore seemed sensible to omit these observations, leaving a final sample of 2,700 observations. Moreover, including individuals over 60 years old would probably make it more important to model explicitly difficult aspects of the consumers' planning problem such as bequests, retirement decisions, and planning horizon.

Information on households' existing portfolios of consumer debt, together with the responses to questions 1 and 2 given in the Appendix were used to partition the sample into four basic categories: (1) those who do not want credit, (2) those discouraged from applying, (3a) those who apply and are accepted, and (3b) those who apply and are rejected. Families were assumed to *want* credit if they belonged to one of two groups, those with positive levels of total consumer debt and those with zero debt levels who reported being turned down for credit or discouraged from applying. Households were classified as discouraged from applying if they reported themself as such and at the same time did not have consumer debt or had been rejected. Loan applicants were subdivided into accepted and not accepted by classifying everybody that reported having been rejected as a rejected applicant (even if credit had been obtained before or after).

One problem with the survey questions employed was that the date of rejection of a family's loan application was not specified, respondents being asked instead whether they had been turned down "in the last few years." For simplicity, we assumed, in specifying our model, that the rejections had occurred within the previous year. We took households to be "turned down" if they had been refused credit or if they had been offered less than they wanted. The fact that we consider current wealth and income, although credit rationing may have occurred in earlier periods, may bias our results in the direction of overestimating the probability of credit rationing if some households that had been credit constrained in the past were no longer constrained at the time of the interview. This may have some impact on the estimated effects of unemployment, but most other variables are more slowly changing, suggesting that the timing issue is not critical for the estimation of the effect of those variables.

We should perhaps comment on our use of total consumer debt as an indicator of household credit needs. The main form of borrowing that this aggregate excludes is loans for house purchase. Such loans seemed to us qualitatively different from the kind of consumer debt that is the subject of this article. Families that buy houses on a mortgage may be regarded as borrowing to acquire a form of asset rather than to bring consumption forward in time. The collateral provided by a house is so good that it is hard to imagine significant numbers of families "successfully" defaulting on their mortgages. Such collateral arguments might, of course, be applied to other forms of debt—for example, car loans. We thought it a reasonable approximation, however, to draw the line at mortgage debt and to regard all other loans as unsecured.

We defined current disposable wealth as current income plus liquid assets. An important choice we made was not to include stocks and bonds in liquid resources Y_0—in effect, assuming that a consumer who needs cash will apply for credit prior to selling illiquid assets. Of course, this will not be true in general, and a fully satisfactory approach would include yet another choice—namely, selling illiquid assets versus applying for credit. Such an approach seems overambitious based on the present data set, and we take the simpler approach of assuming that the consumer first applies for credit, based on the observation that consumers who owned illiquid assets were observed to want credit to the same degree as consumers who did not own illiquid assets. More precisely, 64% of the consumers in our sample who did not own "bonds" (bonds, savings deposits, etc.) or equity wanted credit, whereas 70% of the consumers who held bonds but not equity wanted credit, and 64% of the consumers who held both bonds and equity wanted credit.

In estimating the model, we assumed that all individuals faced the same real interest rate of 8%. We chose the figure of 8% for the interest rate because it seemed a reasonable compromise between average consumer credit rates and rates available on small deposits in 1983. In principle, agents face different discount rates depending on whether or not they are credit constrained. We felt, however, that the added complications of including multiple rates outweighed the benefits. In these circumstances, 8% seemed like a sensible figure.

Total lifetime wealth was taken to be the sum of net worth (as defined in the Appendix) and human wealth. The construction of human wealth is also documented in the Appendix.

Note that the Federal Reserve Survey contained further information concerning credit availability that, for various reasons, we did not employ in our study. In particular, households who reported being turned down for loans were asked whether they had reapplied and what the outcome had been. Of those turned down, only 24% had reapplied and received the credit they had wished for.

Although our model might well be extended to allow some limited number of repeated applications, the resulting likelihood function would have been extremely complicated. We therefore preferred to adopt the simpler specification that we actually estimated.

Finally, the Federal Reserve Survey also reported the factors that banks had cited to refused credit applicants as the most important reasons for the rejection of their application. These data were limited in scope because only a very few refused applicants gave more than a single reason for their rejection. Moreover, most of the reasons quoted by the banks were covered by the detailed demographics that we introduced into the bank model. Since our aim was to uncover the banks' implicit credit-scoring system, which would depend, for example, on the subjective evaluations of individual loan officers and which banks would presumably be unwilling or unable to report to rejected applicants, we thought it best not to make use of the banks' claimed rejection criteria.

4. ESTIMATION

The model described in Section 3 constitutes a nonlinear, ordered, sequential logit. Basic references for such models are Maddala (1983), McFadden (1984), and Amemiya (1985). Ordered logits were first considered by Cox (1970), and sequential logits have been widely used in the qualitative response literature.

The categories we consider are the following (with the number of households in each category given in brackets): (1) those who do not want credit (551), (2) those dissuaded from applying (59), (3a) those whose application was granted (1,577), and (3b) those whose application was rejected (513). The form of the likelihood in our model is

$$(1 - D_1(i))\frac{\exp\{\xi Y_{i0} - \lambda_\alpha - W_{i0}\}}{1 + \exp\{\xi Y_{i0} - \lambda_\alpha - W_{i0}\}} + D_1(i)$$

$$(1 - D_2(i))\left[\frac{\exp\{Y_{i0} - \lambda_\alpha - W_{i0} + d_\alpha(1 + e^{\gamma_\alpha})^{1/2}\}}{1 + \exp\{Y_{i0} - \lambda_\alpha - W_{i0} + d_\alpha(1 + e^{\gamma_\alpha})^{1/2}\}}\right.$$

$$\left. - \frac{\exp\{\xi Y_{i0} - \lambda_\alpha - W_{i0}\}}{1 + \exp\{\xi Y_{i0} - \lambda_\alpha - W_{i0}\}}\right]$$

$$+ \frac{D_1(i)D_2(i)}{1 + \exp\{\xi Y_{i0} - \lambda_\alpha - W_{i0} + d_\alpha(1 + e^{\gamma_\alpha})^{1/2}\}}$$

$$\times \left[D_3(i)\frac{1}{1 + \exp\{\gamma_\alpha\}} + (1 - D_3(i))\frac{\exp\{\gamma_\alpha\}}{1 + \exp\{\gamma_\alpha\}}\right],$$

where i index observations and $D_1(i)$, $D_2(i)$, and $D_3(i)$ are dummy variables whose values are determined by the following conditions:

$D_1(i) = 1$ if the ith observation wants credit;

0 otherwise

$D_2(i) = 1$ if the ith observation applies;

0 otherwise

$D_3(i) = 1$ if the ith observation is accepted;

0 otherwise.

We allow dependence of demographic characteristics indexed by a vector of real numbers $(\alpha_1, \ldots, \alpha_n)$ by letting λ_α, d_α, and γ_α be linear functions of those:

$$\lambda_\alpha = \beta_{10} + \beta_{11}\alpha_1 + \cdots + \beta_{1n}\alpha_n$$

$$d_\alpha = \beta_{20} + \beta_{21}\alpha_1 + \cdots + \beta_{2n}\alpha_n$$

$$\gamma_\alpha = \beta_{30} + \beta_{31}\alpha_1 + \cdots + \beta_{3n}\alpha_n,$$

where the β_{ij}'s are parameters to be estimated.

The fact that not all demographic variables that, for example, affect the banks' decision process influence consumers' application costs (e.g., income) is accounted for in the preceding notation by setting some coefficients equal to 0 a priori. We allowed λ_α to depend on variables, such as age, that are not constant over the life cycle. To the extent that these are significant, they may indicate that the consumers consider the possibility of future rationing. In that case the consumers' value function must be considered an approximation as previously explained. In choosing which variables to include in the banks' equation and the consumers' utility functions, we limited ourselves as much as possible to demographic and other variables that might be regarded as exogenous. For example, such variables as car ownership could not be included in the banks' model, first, because households would then have an incentive to influence decisions on loan applications by buying more cars and, second, because car ownership might itself depend on the household's ability to secure credit. The dividing line between exogenous and endogenous variables, in this sense, was inevitably somewhat delicate. Belt codes were included in both consumer and bank models despite the fact that families might conceivably move house to increase their chances of getting credit. We estimated relatively few parameters for application cost because of the low number of households that were dissuaded from applying for credit. Instead of listing which demographic variables we allowed for the bank and the consumer, respectively, we refer readers to the tables of results.

5. RESULTS AND INTERPRETATION

The main results are contained in Tables 1, 2, and 3. Table 1 gives parameter estimates for the banks' decision whether or not to reject loan applications. Positive parameters mean that an individual having the corresponding characteristic is more likely to be rejected for credit. Table 2 sets out the estimated parameters for the consumer demand for credit. In general, the parameter estimates seemed convincing. Being healthy, married, white, a houseowner, from a suburban or rural part of the north central United States, with a large current disposable income and a managerial or administrative job, all make it easier to get credit. Education exhibited a clear linearity in the paramaters, with individuals finding it slightly harder to get credit as their education level increased, although the parameter estimates were not significant.

The belt-code dummies similarly showed a very marked linearity in the parameters suggesting that the nearer one was to a large city the more difficult it was to secure a loan. Among the more surprising results that emerged from our study was the insignificance of the labor-force-participation dummies and the fact that households with female heads found it easier to secure credit. The only anomalous result is the finding that after allowing for the level of current, disposable resources, higher net financial wealth seems to damage houseowners' chances of obtaining credit. It is hard to guess why this result comes about. Possibly it reflects some left-out higher order interaction effects in the model.

The parameter estimates for the consumer model were also quite plausible. Loan demand appeared highly sensitive to demographic effects, and the parameter estimates were quite precise. Sex, race, marital status, and household size all had highly significant coefficients. Being black, unmarried, unemployed, and in a small household with a male household head all contributed to less demand for loans. To the degree that unemployment is independent of the utility function, the significance of the employment parameters can be interpreted as saving to avoid future rationing. Moreover, the group of dummy variables for household size showed a very clear linear pattern, with parameter values increasing smoothly as family size rose. Region had little influence on preferences, and the belt code was only significant for households who lived in the outer suburbs of large cities. Educational level had a large and very significant impact on preferences, with highly educated households tending to demand less credit.

The parameters of the application costs in Table 3 generally showed very high levels of significance. Westerners without a college degree living in rural areas (or inner cities) with large families and a female household head found it particularly costly to apply for credit. Finally, white households had significantly higher cost of application. It is conceivable that the significance of the application cost parameters reflects agents' wrong assessments of the probability of being accepted. A glance at the likelihood function reveals that these different effects will be hard to distinguish. Our discussion therefore presupposes rationality on the part of consumers.

Of course, statisical significance cannot be equated with economic significance. Because of nonlinearity it is not possible to interpret the estimated parameter values in our model directly in terms of probabilities. For a given set of demographic characteristics, however, it is possible to calculate the marginal change in the probability of a particular outcome that results from altering a given characteristic. Since it has stimulated a fair amount of controversy, we shall consider, as an example, the effects of race. We take as base cases, first, a suburban married couple with children, and, second, an unmarried man living in the city.

For a typical married couple living in the suburbs with more than two children, the probabilities forecast by our model are shown in Table 4. The precise category we choose is that of families satisfying the following criteria: age 40, male household head, married, both employed, some college, professional, child under six years old (life cycle stage 3), four or more in household, suburb of large city, houseowners, Northeast, good health, no previous repayment problems, average risk

Table 1. Parameters of the Bank Model

Name	Description	Value	Std. err.
Late payments	Problems repaying loans (385) (d.)	.45	.13
	Other (2,315) (o.d.)	—	—
Health	Excellent or good (2,296) (d.)	−.40	.17
	Fair or poor (404) (o.d.)	—	—
Employment	Head only household, unemployed (254) (d.)	−.03	.26
	Head only household, employed (725) (o.d.)	—	—
	Head and spouse household, both unemployed (86) (d.)	.17	.35
	Head and spouse household, one employed (684) (d.)	.01	.16
	Head and spouse household, both employed (951) (o.d.)	—	—
Sex	Household head male (2,094) (d.)	.42	.21
	Household head female (606) (o.d.)	—	—
Race	Household head white (2,158) (d.)	−.45	.15
	Household head black, Hispanic or other (363) (o.d.)	—	—
Education	Household head 0–8 grades (206) (d.)	−.22	.30
	Household head 9–12 grades (341) (d.)	−.13	.23
	Household head school diploma (955) (d.)	−.01	.18
	Household head, college, no degree (513) (d.)	.17	.18
	Household head, college degree (685) (d.)	—	—
Life cycle stage	Head <45 yrs, unmar., no child. (443) (d.)	−.91	.36
	Head <45 yrs, mar., no child. (276) (d.)	−.23	.66
	Head <45 yrs, mar., youngest child <6 yrs (505) (d.)	−.14	.66
	Head <45 yrs, mar., youngest child >6 yrs (376) (d.)	−.21	.66
	Head >45 yrs, mar., has child. (260) (d.)	−.24	.64
	Head >45 yrs, mar., no child., retired (34) (o.d.)	—	—
	Head >45 yrs, mar., no child., working (272) (d.)	−.39	.65
	Head >45 yrs, unmar., no child., retired (56) (d.)	−.44	.68
	Head >45 yrs, unmar., no child., working (153) (d.)	−.85	.51
	Head any age, unmar., has child (325) (o.d.)	—	—
Age	Age of head (i.v.)	.00	.05
	Age of head squared (i.v.)	−.0005	.0007
Household size	One (528) (d.)	.62	.40
	Two (616) (d.)	.03	.25
	Three (547) (d.)	.10	.16
	Four or more (1,009) (o.d.)	—	—
Occupation of head	Professional, technical, etc. (413) (d.)	.15	.28
	Managers and administrators (321) (d.)	−.58	.33
	Self-employed managers (169) (d.)	.27	.36
	Sales, clerical etc. (325) (d.)	−.10	.28
	Craftsmen, protective services, etc. (529) (d.)	.19	.26
	Operatives, laborers, service wkers. (764) (d.)	.21	.25
	Miscel. (hswives, students, soldiers, never wked) (179) (d.)	—	—
Region of the country	Northeast (546) (d.)	−.22	.18
	North central (729) (d.)	−.47	.18
	South (948) (d.)	−.25	.17
	West (477) (d.)	—	—
Belt code	City, >2 million pop. (238) (d.)	1.10	.26
	City, <2 million pop. (489) (d.)	1.00	.21
	Suburbs of large city (394) (d.)	1.03	.24
	Suburbs of small city (550) (d.)	.77	.20
	Outside suburbs, inside 50 miles (602) (d.)	.61	.21
	Outlying areas (427) (d.)	—	—
Marital status	Married (1,721) (d.)	−.40	.68
	Never married, separated, divorced, or widowed (979) (o.d.)	—	—
House ownership	House owner (1,692) (d.)	−.70	.68
	No house (1,008) (o.d.)	—	—
Constant	Constant	.36	1.02
Financial status	Net financial wealth—houseowner (c.v.) (mill. $)	.48	.29
	Net financial wealth—not houseowner (c.v.) (mill. $)	−1.70	3.05
	Disposable income (c.v.) (mill. $)	−17.05	4.52

NOTE: Positive parameters imply that households with the indicated characteristic are less likely to be given credit. d. indicates dummy variable; o.d., omitted dummy; i.v., integer-valued variable; and c.v., continuous valued variable. The number of observations in each category is given in parentheses after the variable descriptions. In the categories for life cycle stage, two dummies were omitted rather than just one because otherwise the presence of the marital status dummy would have led to collinearity.

Table 2. Parameters of the Consumers' Model

Name	Description	Value	Std. err.
Time preference	"δ"	−.02	.04
Risk	Take substantial risks (173) (d.)	.01	.21
	Take above average risks (324) (d.)	−.03	.18
	Take average risks (1,140) (o.d.)	−.02	.12
	Never take risk (1,063) (d.)	—	—
Health	Excellent or good (2,296) (d.)	−.08	.15
	Fair or poor (404) (o.d.)	—	—
Employment	Head only household, unemployed (254) (d.)	−.20	.21
	Head only household, employed (725) (o.d.)	—	—
	Head and spouse household, both unemployed (86) (d.)	−.98	.26
	Head and spouse household, one employed (684) (d.)	−.67	.15
	Head and spouse household, both employed (951) (o.d.)	—	—
Sex	Household head male (2,094) (d.)	−.47	.18
	Household head female (606) (o.d.)	—	—
Race	Household head white (2,158) (d.)	.30	.15
	Household head black, Hispanic or other (363) (o.d.)	—	—
Education	Household head 0–8 grades (206) (d.)	1.15	.26
	Household head 9–12 grades (341) (d.)	.88	.23
	Household head school diploma (955) (d.)	1.32	.19
	Household head, college, no degree (513) (d.)	1.25	.20
	Household head, college degree (685) (d.)	—	—
Life cycle stage	Head <45 yrs, unmar., no child. (443) (d.)	.24	.29
	Head <45 yrs, mar., no child. (276) (d.)	−.06	.49
	Head <45 yrs, mar., youngest child <6 yrs (505) (d.)	−.56	.49
	Head <45 yrs, mar., youngest child >6 yrs (376) (d.)	−.42	.49
	Head >45 yrs, mar., has child. (260) (d.)	−.70	.44
	Head >45 yrs, mar., no child., retired (34) (o.d.)	—	—
	Head >45 yrs, mar., no child., working (272) (d.)	−.35	.43
	Head >45 yrs, unmar., no child., retired (56) (d.)	−.26	.40
	Head >45 yrs, unmar., no child., working (153) (d.)	.26	.33
	Head any age, unmar., has child (325) (o.d.)	—	—
Age	Age of head (i.v.)	.08	.04
	Age of head squared (i.v.)	−.0013	.0005
Household size	One (528) (d.)	−1.34	.29
	Two (616) (d.)	−1.17	.21
	Three (547) (d.)	−.74	.16
	Four or more (1,009) (o.d.)	—	—
Occupation of head	Professional, technical, etc. (413) (d.)	.29	.27
	Managers and administrators (321) (d.)	.10	.28
	Self-employed managers (169) (d.)	−.69	.28
	Sales, clerical etc. (325) (d.)	.66	.26
	Craftsmen, protective services, etc. (529) (d.)	.32	.24
	Operatives, laborers, service wkers. (764) (d.)	.28	.22
	Miscel. (hswives, students, soldiers, never wked) (179) (d.)	—	—
Region of country	Northeast (546) (d.)	.22	.18
	North central (729) (d.)	.09	.16
	South (948) (d.)	.10	.16
	West (477) (d.)	—	—
Belt code	City, >2 million pop. (238) (d.)	.03	.21
	City, <2 million pop. (489) (d.)	.24	.17
	Suburbs of large city (394) (d.)	−.19	.20
	Suburbs of small city (550) (d.)	−.17	.18
	Outside suburbs, inside 50 miles (602) (d.)	−.68	.17
	Outlying areas (427) (d.)	—	—
Marital status	Married (1,721) (d.)	1.09	.50
	Never married, separated, divorced, or widowed (979) (o.d.)	—	—
House ownership	House owner (1,692) (d.)	.16	.13
	No house (1,008) (o.d.)	—	—
Constant	Constant	−.41	.79

NOTE: Positive parameter values imply that households with the indicated characteristic have relatively high loan demand for given income and wealth. d. indicates dummy variable; o.d., omitted dummy; i.v., integer valued variable; and c.v., continuous valued variable. The number of observations in each category is given in parentheses after the variable descriptions. In the categories for life cycle stage, two dummies were omitted rather than just one because otherwise the presence of the marital status dummy would have led to collinearity.

Table 3. Application Cost Parameters

Name	Description	Value	Std. err.
Sex	Household head male (2,094) (d.)	−.19	.07
	Household head female (606) (o.d.)	—	—
Race	Household head white (2,158) (d.)	.21	.08
	Household head black, Hispanic or other (363) (o.d.)	—	—
Education	Household head 0–8 grades (206) (d.)	1.38	.17
	Household head 9–12 grades (341) (d.)	1.18	.15
	Household head school diploma (955) (d.)	1.17	.14
	Household head, college, no degree (513) (d.)	1.00	.13
	Household head, college degree (685) (d.)	—	—
Household size	One (528) (d.)	−.67	.11
	Two (616) (d.)	−.61	.11
	Three (547) (d.)	−.64	.09
	Four or more (1,009) (o.d.)	—	—
Region of country	Northeast (546) (d.)	−.21	.12
	North central (729) (d.)	−.03	.07
	South (948) (d.)	−.37	.10
	West (477) (d.)	—	—
Belt code	City, >2 million pop. (238) (d.)	.04	.12
	City, <2 million pop. (489) (d.)	−.03	.07
	Suburbs of large city (394) (d.)	−.37	.10
	Suburbs of small city (550) (d.)	−.54	.09
	Outside suburbs, inside 50 miles (602) (d.)	−.75	.14
	Outlying areas (427) (d.)	—	—
Marital status	Married (1,721) (d.)	−.12	.07
	Never married, separated, divorced, or widowed (979) (o.d.)	—	—
Constant	Constant	.15	.10

NOTE: Positive parameters indicate that households with the indicated characteristic incur a higher cost in applying for loans. See notes to Tables 1 and 2.

attitude, and net worth and current income corresponding to 1.5 times the population (under 60) average.

Our second example (see Table 5) is that of a single man without children. Again, to be precise, our chosen category is the following: age 40, male, unmarried, employed, some college, professional, no children, one person in household, lives in city, not houseowner, Northeast, good health, no previous repayment problems, average risk attitude, and net worth and current income corresponding to the population (under 60) average.

These results show that our estimated parameters are also highly significant in an economic sense. The effect of race on the probability of getting credit is about 10% in typical cases, and this is after controlling for the large number of demographic characteristics shown in Table 3. In commenting on the effect of race on credit-acceptance probabilities, note also, from looking at Table 1, the interesting fact that the marginal increase in one's probability of getting credit due to living in a rural area is 2.5 times larger than the decline due to being non-Caucasian. As this example shows, a dummy variable coefficient of .5 will typically translate into a 10% change in acceptance probabilities. This rule of thumb provides a rough indication of the economic significance of other estimated parameters. For example, one can infer that an increase in disposable income of 30,000 dollars will also increase the acceptance probability by around 10%.

An important additional question that our model can answer which previous studies do not address is whether non-Whites tend to be refused in large numbers because of a higher rate of application. Our estimates suggest a clear "no" to this question since, if anything, non-Whites are slightly less prone to want credit. One can also notice the interesting fact that the impact of having a male versus a female head of household is almost the same as that of having a black rather than a white household head in all three tables.

Whether inclusion of even more demographic factors would eliminate the racial effect that we find is, of course, an open question. We would tend to doubt it, given the magnitude of the effect and the large number of demographic factors for which we are able to control.

Table 4. Probabilities for Suburban Couples

Probabilities	White	Nonwhite
Probability of wanting credit	.96	.95
Probability of applying for credit	.93	.93
Probability of getting credit (cond. on appl.)	.81	.73

NOTE: The probability of getting credit is conditioned on application and thus is not restricted by the size of the application probability.

Table 5. Probabilities for Urban, Single Men

Probabilities	White	Nonwhite
Probability of wanting credit	.71	.64
Probability of applying for credit	.61	.60
Probability of getting credit (cond. on appl.)	.63	.52

6. CONCLUSIONS

Our empirical results have several implications. Our finding that preferences and access to credit depend on demographic factors may imply problems with previous time series studies of the life-cycle hypothesis. Aggregation biases might very well explain the poor statistical performance of time series, Euler-equation models noted by Hansen and Singleton (1982) and Deaton (1987).

Second, our results lend support to the idea that credit rationing may have a significant, if not substantial, impact on the performance of the U.S. economy. Fifteen percent of the consumers in our sample reported having been turned down for credit or refused the size of loan they had asked for. The fact that our model explains the behavior of banks and consumers so convincingly lends credence to these figures. (One might note that our 15% figure is in line with the estimate of 17% reported by Hayashi [1982]. On the other hand, our figure falls a long way short of the somewhat controversial 45% that Campbell and Mankiw [1987] argued is the proportion of national income accruing to credit-constrained individuals.)

A third set of implications following from our results concerns the criteria used by banks in allocating loans. It is possible that banks are acting rationally in refusing certain types of borrowers much more often than others. Since we estimate a reduced form for the banks' decision, however, one may equally well interpret the banks' rule as being irrational. Either way, our results provide evidence of strong racial, sexual, regional, and other biases on the part of banks, and our results reveal that these biases are not merely a reflection of different propensities to apply for credit.

Finally, the strong significance of "application costs" and their strong dependence on education and so forth raises some interesting questions for economic modeling. The fact that consumers do incur a cost of applying for credit implies that consumers may not necessarily smooth out "bumps" in consumption that are small (or close in time, as found by Wilcox [1989]).

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APPENDIX: DATA

The following appendix provides details of the data set employed in our study. Section A.1 states the survey questions as posed, and the second section describes the construction of the lifetime wealth variable.

A.1 The Survey Questions

1. TURNED DOWN FOR CREDIT IN LAST FEW YEARS Question: The respondents were asked if they (or their spouse) 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 they had applied for. Responses: (i) Yes, turned down (440); (ii) yes, unable to get as much credit as they wanted (66); (iii) not turned down (2,187); (iv) NA (7).

2. DISSUADED FROM APPLYING FOR CREDIT Question: respondents were asked if there had been any time in the last few years that they (or their spouse) had thought about applying for credit at a particular place, but had changed their mind because they thought they might be turned down. Responses: (i) yes (337); (ii) no (2,350); (iii) DK (1); (iv) NA (3).

3. MARITAL STATUS Question: marital status. Responses: (i) married (includes couples living together) (1,721); (ii) separated (115); (iii) divorced (361); (iv) widowed (90); (v) never married (411); (vi) married but spouse not present (2).

4. RISK Question: which of the following statements on this card comes closest to the amount of financial risk you are willing to take when you save or make investments? Responses: (i) take substantial financial risks expecting to earn substantial returns (173); (ii) take above average financial risks expecting to earn above average returns (324); (iii) take average financial risks expecting to earn average returns (1,101); (iv) not willing to take any financial risks (1,063); (v) DK (17); (vi) NA (22).

5. LATE PAYMENTS Question: now thinking of all types of debts, were all payments made the way they were scheduled during the last year, or were payments on any of the loans sometimes made late or missed? Responses: (i) all paid as scheduled (996); (ii) sometimes got behind or missed payments (385); (iii) other including "payments not due yet" (13); (iv) NA (180); (v) INAP no consumer loans (1,126).

6. HEALTH OF HOUSEHOLD HEAD Question: health as self reported. Responses: (i) excellent (1,228); (ii) good (1,068); (iii) fair (290); (iv) poor (114).

7. LABOR FORCE PARTICIPATION Question: labor force particpation. Responses: (i) head only household, not in labor force (254); (ii) head only household, in labor force (725); (iii) head and spouse household, neither in labor force (86); (iv) head and spouse household, one in labor force (684); (v) head and spouse household, both in labor force (951).

8. SEX OF HOUSEHOLD HEAD Question: sex of head of household. Responses: (i) male (2,094); (ii) female (606).

9. RACE OF HOUSEHOLD Variable is observed race of survey respondent. All missing values imputed using census data and other sources. Categories: (i) Caucasian except Hispanic (2,158); (ii) black except Hispanic (353); (iii) Hispanic (95); (iv) American Indian or Alaskan native (8); (v) Asian or Pacific Islander (31); (vi) NA (45).

10. EDUCATION OF HOUSEHOLD HEAD Question: education of household head. Responses: (i) 0–8 grades (206); (ii) 9–12 grades, no high school diploma (341); (iii) high school diploma or equivalent, no college

(955); (iv) some college, no college degree (513); (v) college degree (685).

11. LIFE CYCLE STAGE Question: life cycle stage. Responses: (i) head under 45, unmarried, no children (443); (ii) head under 45, married, no children (276); (iii) head under 45, married, youngest child under 6 years (505); (iv) head under 45, married, youngest child 6 years or above (376); (v) head age 45 and over, married, has children (260); (vi) head age 45 and over, married, no children, head retired (34); (vii) head age 45 and over, married, no children, head in labor force (272); (viii) head age 45 and over, unmarried, no children, head retired (56); (ix) head age 45 or over, unmarried, no children, head in labor force (153); (x) head any age, unmarried, has children (325).

12. AGE OF HEAD Question: age by date of birth, at last birthday of head of household. All missing values imputed. (Range: 16 to 60.)

13. HOUSEHOLD SIZE Question: total number of persons in household. Responses: (i) 1 (528); (ii) 2 (616); (iii) 3 (547); (iv) 4 (579); (v) 5 (270); (vi) 6 (99); (vii) 7 (36); (viii) 8 (17); (ix) 9 (6); (x) 11 (2); (xi) 13 (0).

14. OCCUPATION OF HEAD Question: occupation of household head. Response: (i) professional, technical and kindred workers (413); (ii) managers and administrators (except farm) (321); (iii) self-employed managers (121); (iv) sales, clerical and kindred workers (325); (v) craftsmen, protective service, and kindred workers (529); (vi) operatives, laborers, and service workers (764); (vii) farmers and farm managers (48); (viii) miscellaneous (mbrs. of armed service, housewives, students, never worked and other occupations) (179).

15. REGION OF THE COUNTRY Question: region of the country. Responses: (i) northeast (Maine, Massachusetts, Connecticut, New York, New Jersey, Pennsylvania) (546); (ii) north central (Ohio, Indiana, Illinois, Michigan, Wisconsin, Minnesota, Missouri, Nebraska, Iowa, South Dakota) (729); (iii) south (Virginia, North Carolina, South Carolina, Georgia, Florida, Alabama, Mississippi, Louisiana, Arkansas, Tennessee, Texas, Oklahoma, Kentucky, Maryland, District of Columbia, West Virginia) (948); (iv) west (Colorado, Utah, Arizona, California, Oregon, Washington) (477).

16. BELT CODE This variable was coded according to the 1970 Census with additions from census population reports. Question: belt code. Responses: (i) central cities of the two standard consolidated areas plus the ten largest SMSA's (those over 2,000,000 population—New York, Los Angeles, Chicago, Philadelphia, Boston, Washington, Baltimore, Detroit, San Francisco, St Louis, Cleveland, Pittsburgh) (238); (ii) central cities of SMCA's with fewer than 2,000,000 population (489); (iii) suburbs of the two SCA's or ten largest SMSA's. Suburbs are defined as all the urbanized areas within the SMSA exclusive of the central city plus the remainder of any county containing a central city or part of a central city or part of a central city (394); (iv) suburbs of othe SMSA's (550); (v) adjacent areas (adjacent area includes all territory beyond the outer boundary of the suburban belt, but within fifty miles of the central business district of a central city) (602); (vi) outlying areas (an outlying area includes all territory more than fifty miles from the central business district of a central city) (427).

17. LIQUID ASSETS Total dollar value of liquid assets. Equals sum of checking accounts, money market accounts, savings accounts, IRA's and keoghs, CD's, and savings bonds owned by household. (Range: 0 to 369,000.)

18. INCOME Total dollar value 1982 gross pretax household income. (Range: −24,062 to 385,000.)

19. NET WORTH Total dollar value of gross assets excluding pensions minus total debt. (Range: −73,400 to 16,977,100.)

A.2 Estimation of Lifetime Wealth

For a member of the α cohort with demographics given by a vector of dummy variables, X, human wealth at time 0 is defined as follows:

$$W_{\alpha 0} \equiv \sum_{t=0}^{T} \frac{w_{\alpha t}(1 - \tau_t)}{(1 + r)^t} \equiv \sum_{t=0}^{T} \frac{Y_{\alpha t}}{(1 + r)^t}, \quad (A.1)$$

where $w_{\alpha t}$ is labor income at t, τ_t is the average rate of personal income tax, and r is the discount rate. Assume that members of cohort α of age n will earn m years from now what members of the α cohort of age $n + m$ are currently earning. Assume that this holds for any two positive integers n and m. Thus $w_t \equiv f(\text{age}_t, X)$, where age_t is the age of the person at t. Specify f as linear in demographics and quadratic in age_t. X includes dummies for level of education, occupation, sex of household head, region of the country, race, and labor-force participation. We omitted variables such as the belt-code dummies that cannot be expected to be constant over the life cycle. The preceding equation was estimated using ordinary least squares with 3,665 observations. Given the parameter values generated by this estimation, W_0 was calculated using Equation (A.1). We assumed a constant tax rate equaling the 1982 implicit, average, personal income tax rate of .1883493 and took r to be 8%. T was set to be 91, which was higher than the age of the most elderly person in the sample. The negative parameter on age_t^2 meant that, for high t, w_t was sometimes negative. In that case, we assumed that the person concerned retired at that age, and w_t was set to 0 for subsequent years. Finally, we did not allow for productivity growth in our forecast of human wealth, though this would have been simple to do. Income growth in the 1980's was modest and the high discount rate that we adopted meant that productivity adjustments would have had little impact on the results.

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