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"Credit Cards and Household Demand for Monetary Assets:
A Cross-Sectional Study"

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Abstract

This study investigates credit card holding and the household demands for several monetary assets in a simultaneous equations framework. It exploits the detailed data on household assets, as well as demographic and preference characteristics in the 1983 Survey of Consumer Finances. A key finding is that, consistent with theory, a higher probability of credit card ownership implies lower demand for liquid money balances with no effect on small time deposit balances.

JEL Classification Codes: E41, E50, D12

Over the past two decades, the use of credit cards in the United States has increased dramatically, as reflected in the level of credit card debt and the proportion of the population with credit cards.[1] Nevertheless, there have been few empirical studies of the effect of credit cards on money demand. Using the 1970 Survey of Consumer Finances (SCF), Mandell (1972) found that families with credit cards had smaller demand deposit balances than those without, but that the difference was statistically insignificant. Using data from one bank, White (1976) found evidence that credit card usage had a statistically significant effect on household demand deposit balances.

There are some empirical problems, however, with these cross-sectional studies. First, at the time of these and other published cross-sectional studies of money demand (e.g., Feige (1964, 1974) and Lee (1966)) were undertaken, empirical methods were not yet developed to handle the self-selection bias that arises when only deposit owners are sampled and the potential for simultaneity bias if credit card ownership depends on money demand. Second, neither study controlled for the impact of wealth or total assets on money demand (Mandel did not use such variables and White's data set did not include them). Furthermore, White's data set did not include information on the total holdings of demand deposits of account holders at all depositories. Finally, White's findings may be skewed toward reflecting the behavior of higher income households, since he had no data on balances at thrift institutions, where lower income households tended to have deposits.

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1. From yearend 1969 to yearend 1989, revolving consumer credit outstanding, deflated by the PCE deflator, grew about 1600%. Over the shorter period 1977 and 1983, credit card ownership increased from 62.9% to 67.6% of surveyed households in the 1977 and 1983 SCFs, respectively.

The current study addresses these deficiencies using newer empirical techniques developed since these earlier studies along with data on opportunity costs, household balances at all depositories, and household asset holdings. To avoid selectivity and simultaneity biases, a multi-stage estimation procedure is employed. In the first step, probit models of deposit account and credit card ownership are estimated. A non-zero covariance of the probit and money demand errors indicates that a two-stage approach is necessary to obtain consistent parameter estimates. In the second stage, constructed variables from the account probits are used to correct money demand regressions for selectivity bias, and the estimated probability of card ownership is used as an instrument for card ownership.

The study contributes to literature on money demand in other ways. There have been few cross-sectional studies of money demand, and the data sets available to earlier researchers (e.g., Feige (1964, 1974) and Lee (1966)) did not have the extensive demographic and preference information available on the 1983 SCF. Controlling for these additional influences, the current study conducts cross-sectional tests of income and assets as scale variables--an issue which Feige and Lee were unable to address. Furthermore, in contrast to previous studies, this paper uses cross-sectional data after the deregulation of most deposit interest rates, and after an explosive period of growth of both credit cards and of new liquid financial instruments for households.

This study is organized as follows. Section 1 begins with a brief theoretical discussion. The second section presents the

estimation method and Section 3 discusses the data. Results are reviewed in Section 4, and the final section presents conclusions.

1. Credit Cards and Money Balances in Theory

The ensuing empirical analysis could be related to an infinite horizon problem in which households maximize the utility of lifetime consumption, subject to the constraint that a medium of exchange must be used to complete any transaction. Payment media are currency, checks, or credit cards, each of which has different transaction costs across goods purchases.[2] In addition, transaction costs are incurred in transferring funds among various monetary components and other financial assets.

The model would be enriched, though likely made intractable, by incorporating institutional constraints related to particular transactions (which might be time-varying). For instance, certain types of transactions may require payment with currency , while others may require checks. Also, a three-check per month limit may apply to money fund accounts.

The costs and benefits of account or credit card ownership, and the optimal balances in the various account types, thus depend on the structures of transaction costs, institutional restrictions, and relative interest rates. Liquidity constraints related to imperfect capital markets may also affect who owns credit cards. The decision to own an account or credit card would of course involve comparing the

2. Whitesell (1990) develops a theoretical model with a simplified structure of transaction costs in which consumers minimize the sum of transaction and holding costs across these three media of exchange.

discounted net benefit of prospective use with the fixed cost of obtaining the card or account. The terms of offer of credit cards and account facilities by retailers and banks could also be important to model, particularly in the presence of local market power.

As pointed out by Marcus (1960) and White (1976), the effect of credit cards on transaction balances may be ambiguous. Credit card ownership could be associated with smaller checking account balances for the following reasons:

(1) A credit card owner likely holds lower precautionary money balances to the extent that the card can be used for emergency payments.

(2) While awaiting the credit card bill, funds could be held in an asset earning higher returns than a checking account.

(3) Cardholders may synchronize payments so that the card bill is paid shortly after receiving a paycheck.

Also, Cuthbertson (1985, p. 208) mentions that credit cards may reduce transactions balances by providing a "buffer stock" of liquidity.

On the other hand, credit card ownership could be associated with larger checking account balances for the following reasons:

(1) Reduced withdrawals of currency from checking accounts may occur if credit cards substitute for currency.

(2) When cards substitute for checks, funds may stay idle in the checking account for a longer time, awaiting the credit card bill. Transaction costs may eliminate potential profits from shifting temporarily idle funds to assets with higher returns.

(3) Card ownership may reveal a higher propensity to consume out of income and wealth. Apparently, this effect has not been mentioned

previously in the literature. It is particularly relevant for cross-section studies with income or wealth proxying for spending levels.

The propensity-to-consume effect can be illustrated simply by adopting a standard assumption that credit cards offer a net variable benefit of "b" per dollar when compared with checks, but only "p" percent of spending is with merchants who accept cards. Using a single-period analysis, a household will obtain a credit card if the fixed cost of owning it, q, is less than the total benefit, bpcY, where c is the propensity to consume out of permanent income, Y. Suppose income is constant across a population, but different preferences lead to two subpopulations with propensities to consume, c_1 and c_2, where:

$$c_2 > \frac{q}{bpY} > c_1.$$

Group 2 therefore owns credit cards, while group 1 does not. If no funds are held in checking accounts to pay credit card debts, total check spending and thus, checking account balances, of the cardholding group are nevertheless larger than the balances of the non-card group, *ceteris paribus*, if $(1-p)c_2Y > c_1Y$, or if:

$$\frac{c_2 - c_1}{c_1} > \frac{p}{1 - p}.$$

The percentage difference in propensities to consume must be larger than the ratio of card to check spending for this effect to induce a positive correlation between card ownership and checking account balances.

In a Baumol-Tobin money demand framework similar to that of Akhand and Milbourne (1986), card ownership would not affect the income

or interest elasticity of the demand for money of individuals.[3] Rather, using the above framework in a regression of the log of money demand, the constant term of the cardholder group would differ from that of the noncard group by:

$$\frac{1}{2}[\log((1-p)c_2) - \log(c_1)]$$

2. Estimation Method

The structural model employed in this study is:

$$M^* = X_1\beta_1 + u_1,$$

$$M_r = X_2\beta_2 + u_2, \text{ and}$$

$$\text{Card}^* = X_3\beta_3 + u_3,$$

where the β_i are parameter matrices, M^* is a vector of latent variables representing the desired levels of various monetary components, and Card* is a latent variable for credit card ownership. The u_i follow a joint normal distribution with covariance matrix:

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & 0 \\ \sigma_{31} & 0 & \sigma_{33} \end{bmatrix}.$$

Furthermore, it is assumed that u_3 is a standard normal variable ($\sigma_3 = 1$). The reason is that the Card* equation is estimated with a probit model, which can only estimate the ratio, β_3/σ_3, and $\sigma_3 = 1$ is the usual normalization.

M_r is a matrix of reservation money balances across households and account types. M_r is defined to be the level of deposits at which a

3. Although the Akhand and Milbourne (1986) model implies this result for individuals, they stress that credit card use affects the interest and income elasticities of total money demand when they aggregate across card and noncard holders using an assumed density function for income.

household's net benefit from account services just equals the fixed cost of establishing an account. Actual deposit balances, M, is a censored variable since we observe $M = M^*$ if $M^* \geq M_r$, but $M = 0$ otherwise. Of course, M_r is also unobserved.

In addition, Card* is unobserved, but the dichotomous variable Card is observed (and is a component of X_1), where:

$$\text{Card} = 1 \text{ if } \text{Card}^* > 0,$$

indicating credit card ownership, and Card = 0 otherwise. The condition, Card* > 0, is equivalent to $u_3 > -X_3\beta_3$. Credit card ownership affects the desired level of money balances, but not the threshold level required for deposit account ownership.

The estimation of this model is complicated by selectivity and simultaneity problems. Selectivity bias arises because money holdings are observed only for households who have accounts. A sample restricted to account owners is biased since $E(u_1 | M^* > M_r) \neq 0$. Including non-account-owners is inappropriate, since their desired money holdings are are less than their reservation level, M_r, but not necessarily zero. The standard two-step procedure that is used to correct for selectivity bias is as follows [see, e.g., Heckman (1979) or Lee (1982)].

First, let A be a matrix of dummy variables, with an entry of one if a household has a particular type of account. Then, define the following variables:

$$Z\gamma \equiv \frac{X_1\beta_1 - X_2\beta_2}{\sigma}, \quad u \equiv \frac{u_2 - u_1}{\sigma}, \quad \text{and} \quad \sigma^2 \equiv \text{Var}(u_2 - u_1) = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12}.$$

Account ownership is then equivalent to the following events:

$$A = 1, \quad M^* \geq M_r, \quad \text{and} \quad u \leq Z\gamma.$$

Defining the latent variables, $A^* \equiv M^* - M_r$, a probit model for account ownership could estimate $\hat{\gamma}$. For each household, it would then be possible to compute the hazard rate or inverse Mill ratio, $\frac{\phi(Z\hat{\gamma})}{\Phi(Z\hat{\gamma})}$, where Φ is the standard normal distribution function, and ϕ is the density. Subtracting this hazard rate from u_1 leaves zero-mean errors.

In this case, however, the above procedure has to be modified because of the presence of two types of simultaneity bias along with selectivity bias. Because ownership of a transaction account may be required for credit card ownership, the endogenous variable A is a component of X_3. Furthermore, ownership of a credit card affects desired money holdings. Because the endogenous variable Card is a component of X_1, it is also a component of Z.[4]

The probit equations for card and account ownership are estimated as a block, since money holdings do not enter as explanatory variables in that bivariate system.[5] Instruments for Card and transaction account ownership[6] that enter into regressions of money balances are estimated by probit regressions involving all exogenous variables. Money balances do not enter into the Card probit, and the Card/Money equation system is therefore recursive. Nevertheless, simultaneity bias arises because the Card probit and the money equation

4. The presence of both dichotomous variables in a bivariate latent variable model leads to a well-known logical inconsistency [e.g., see Maddala (1983), page 119]. However, in this case, Card is insignificant in the account probit equation, implying no inconsistency.

5. Probit estimation was undertaken with the GQOPT4/I nonlinear optimization package (version 4.03), developed by Goldfeld and Quandt. To ensure convergence, a number of optimization algorithms were employed, including GRADX (see Goldfeld and Quandt (1972)), POWELL (see Powell (1964)), and DFP (see Powell (1971)).

6. Defined as owning a checking or a money fund/MMDA account, or both.

errors are correlated ($\sigma_{13} \neq 0$).[7] This correlation could reflect the existence of omitted and unobserved household preference variables that help explain both money holdings and card ownership. For instance, a higher propensity to consume out of income or wealth could lead to both larger money holdings and a greater propensity to obtain a credit card.

The standard two-step correction for simultaneity bias of this nature is to substitute the estimated probability of card ownership for the credit card dummy variables in the money regressions. The final money demand equations are then estimated by OLS, after making this substitution, and after including the appropriate hazard rate to correct for simultaneity bias. The resulting covariance matrix of the estimators is very complicated, but the standard errors in such models can be consistently estimated using White's (1980) correction for heteroskedasticity.[8]

The final equations for money components must be considered semi-reduced forms, because interdependence among balances held in different types of accounts is ignored. Because the data set is unlikely to yield good predictions of the precise structure of holdings among monetary components, a two stage least squares procedure is not employed for the money runs. Instead, equations for various aggregates are estimated, including transaction balances (checking and money funds/MMDAs), nontransactions deposits (savings and CDs), liquid

7. This correlation was found by constructing a hazard rate for the Card variable, and adding it to the error term in the money demand equations. Then regressions using data only from Cardowners give an estimate of σ_{13} from the coefficient on the Card hazard rate.

8. Intuitively, the use of estimated explanatory variables (and an error term whose variance depends on the hazard rate) does not result in nonzero covariances of errors among households. Because the error covariance matrix remains diagonal, White's estimator is consistent.

balances (checking, money funds/MMDAs, and savings), and all components combined (called household M2 deposits). Each of these aggregations internalizes substitution across accounts with some similar features.

In principle, one could estimate the entire system of equations with maximum likelihood techniques. This technique was not employed, however, due to the computational difficulty of evaluating multiple integrals for each iteration of the likelihood function.

3. Data and Variables

The main data source for this study is the cleaned and imputed version of the 1983 Survey of Consumer Finances (SCF) produced by the Federal Reserve Board staff (see Avery and Elliehausen (1988)).[9] From the representative sample of this survey, a subsample of 3516 households is used, excluding any observations with relevant missing variables and households with zero assets or income.[10] Given the availability of data in the 1983 SCF, four individual deposit components were estimated: checking, passbook-type savings, money market mutual funds (MMMFs) plus MMDAs, and small time deposits.[11] MMDAs and MMMFs were combined because the introduction of MMDAs in late 1982 and early 1983 induced households to switch from MMMFs to MMMDAs, and most households in the 1983 SCF were interviewed during this period. In

9. The 1986 SCF was not used because its data were not as disaggregated by type of account. Indeed, savings and checking accounts are lumped together, as are small time and MMDA/MMMF accounts; in each case, a deposit with transactions features is combined with a savings vehicle.
10. 308 households from the representative sample were dropped under these two criteria. Households with zero income or assets were excluded because log-linear money demand specifications were used.

Also note that the impact of credit cards on deposit holdings was not sensitive to outliers; results were qualitatively similar in runs which excluded households with income or assets of $1 million or more.
11. Data on currency holdings were not collected on the SCF.

addition, as mentioned in the preceding section, four aggregations of these components were investigated.

In addition to determinants of money demand, variables reflecting the supply and demand for credit cards were included in the reduced form probit models of credit card and account ownership. A household was classified as having a credit card if it had a retail (nongasoline) credit card or a general credit/travel card (e.g., Visa, Mastercard, or American Express).[12]

3a. Money Demand Variables

A variety of independent variables, including measures of preferences, were used to assess the relevance of different theories of money demand. These variables fall into four categories: opportunity cost, scale/employment, precautionary/savings demand, and demographic.

Scale/Employment Variables

According to the transactions approach to money demand, the appropriate scale variable is a proxy for transactions, whereas portfolio theories imply that wealth should be used instead. Straddling these two approaches, Friedman (1956) emphasizes that human and nonhuman wealth determine the demand for money. Two different scale variables were tried: the logs of total assets (LASSETS) and total household income (LINCOME).[13] Household income includes interest and realized

12. Gasoline or airline travel cards were not counted as credit cards, in part because they are much poorer substitutes for deposits. Gasoline cards were also treated this way because they mainly affect the use of currency and currency data were not collected in the 1983 SCF.
13. In principle, permanent income proxies could be constructed for some households using income data from the 1986 SCF over the period 1983-1985. However, doing this reduces the sample by one-third, since many

(Footnote continued on next page.)

capital gains on assets. Regressions also included dummies reflecting whether the household head was a student not currently employed (STUDENT), and whether the household head was unemployed but neither retired nor a student (UNEMPLOY)--both equal 1 if yes.

Opportunity Cost Variables

In this cross-sectional study, observable variation in opportunity costs arises from variation across time resulting from different interview dates (ranging from February to August). Similar to Moore, Porter, and Small (1990), opportunity cost measures were defined as the difference between the three-month Treasury bill rate and the own-rate on the relevant monetary variable (OWNCOST). A weighted-average opportunity cost for MMDAs and MMMFs was computed, using national quantities to calculate weights for each month. A similar weighted-average opportunity cost for checking accounts was computed, using the ratio of OCDs to household demand deposits. Household demand deposits were imputed by applying the proportion of individual to total demand deposits from the national Demand Deposit Ownership Survey to demand deposits (not seasonally adjusted). Weighted averages of opportunity costs were again computed for transactions, nontransactions, and household M2 deposits. Because of lags in the response of money demand to interest rate changes, three-month moving averages of

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(Footnote is continued from previous page.)
households on the earlier panel could not be contacted for the 1986 panel, and the sample from 1986 is prone to selection bias because it was easier to find homeowners who answered the 1983 sample than renters.

The log of net worth was not used as a scale variable because a good portion of the sample had zero or negative net worth. By contrast, only 3% of households had zero assets. In runs not reported, the qualitative results with respect to credit cards and money balances were similar when net wealth was used in place of assets in a more restricted sample.

opportunity costs were used in the regressions, using data over the three months ending just prior to the month of the interview.

Unfortunately, the estimates of the opportunity cost elasticities that are obtained here are not really meaningful for two reasons. First, opportunity costs only vary over the short time period over which interviews were conducted. Second, this problem is compounded by time series evidence that there are lags in the adjustment of money balances to changes in opportunity costs. Thus, including opportunity cost terms in this study only serves the purpose of minimizing any omitted variable bias effects on other estimated coefficients.

Precautionary Demand/Savings Variables

Miller-Orr (1966) models of money demand imply that greater variation in income or expenditures induces households to hold more money balances.[14] To control for variation in such factors across households, several dummy variables were included. One indicated whether the household could rely on family or friends for emergency funds (EMER), and the other, whether medical expenses were one of the households' two most important reasons for saving (SAVMED), both coded as 1 if yes. Two preference dummies were included to control for differences in risk aversion. The first reflected whether the family would take any risk in investing its savings in exchange for above average returns (AVERSE=1 if no). The second indicated whether the household was willing to tie up funds for a period of time in exchange for above average returns (ILLIQ=1 if no). Precautionary theories and

14. The Miller-Orr model implies that the variability of net cash outflows (expenditures less income) increases the demand for money and to a greater extent as the cost of shortfalls (i.e., the disutility) rises.

inventory models including preference weightings on funding shortfalls suggest that families that are more averse to risk or illiquidity and those unable to rely on others in an emergency would have a larger demand for money, implying positive coefficients on AVERSE, EMER, ILLIQ, and SAVMED.[15] Also included were dummies indicating whether the household did not save (DONTSAVE), used professional advice on investments (SOPH), and owned a home (OWNHOME), all coded as 1 if yes.

Demographic Variables

These included marital status (MARR=1, if married), sex of household head (SEX=1, if male), log of household size (LHSIZE), age of household head (e.g., AGE3544), education of household head (NOHIGH=1, if did not attend high school; HIGH=1, if only graduated from high school; and COLLEGE=1, if graduated college),[16] and race of household head (RACE=0, if white).

3b. Additional Credit Card Variables

In the probit models of credit card ownership, a number of variables from the money demand regressions were included. Among these were the log of income, the log of total assets, and most of the demographic variables.[17] Income and total assets may be positively associated with having a credit card not only because families with higher income and assets may have a greater demand for transactions media, but also because such households are more apt to meet the credit standards used by lenders in approving credit card applications or in

15. A positive coefficient on AVERSE may also reflect an increased precautionary motive to save in general, particularly in the form of small time deposits.
16. The omitted group are those with only some high school education.
17. Quadratic log terms of income and assets were statistically insignificant in probits not reported in tables.

preapproving households for credit cards. (For similar reasons, demographic variables may also reflect both supply and demand factors.)

Other variables were included in the probit models of credit card ownership to pick up other factors affecting the supply of or demand for having a credit card. On the demand side, a dummy variable was included to control for household attitudes toward using debt. This variable indicated whether the household thought that using debt was bad (DEBTBAD), coded as 1 if yes. Also included was a dummy indicating whether the household lived in a rural area (NONRURAL=1, if lived inside of an SMSA), on grounds that the demand for transactions media in rural areas may be lower than elsewhere, ceteris paribus, because shopping is less convenient or because rural households may have different preferences.

Several supply-side variables reflecting the creditworthiness of households were included that often appear on credit card applications (some of which were used by Duca and Rosenthal (1991)). Among these were dummies for whether the household had problems repaying debt on time (BADHIST), did not have a credit history outside of a credit card (NOHISTORY), and received public assistance (WELFARE), all coded as 1 if yes. [18] Studies on the quality of consumer loans have found that such variables are significantly related to the probability of loan defaults (e.g., Boyes, Hoffman, and Low (1989) and Orgler (1970)). Another variable used was the log of median county family income in 1982 (LMEDINC) on grounds that banks often target promotional efforts and preapproved offers of cards to high income areas.

18. Homeowners with mortgages were treated as having a credit history.

A dummy (CONSTRAIN) was included that equaled 1 if the household had either: (1) been denied a loan or received a smaller than desired loan during the period 1980-1983 or (2) did not apply for a loan because they did not think that they would be approved.[19] Although this variable is multicollinear with other variables reflecting creditworthiness, as suggested by the findings of Duca and Rosenthal (1991), including it may control for additional supply factors not captured by the other variables. In particular, CONSTRAIN may tend to pick up households that were actually turned down for credit cards. The other creditworthiness variables may control for households that were not preapproved for credit cards, which can be important insofar as preapprovals increase the demand for credit cards by reducing the shopping/transactions costs of obtaining credit cards from the point of view of households.[20]

4. Results

Since what determines credit card and deposit account ownership is an interesting topic, the first two subsections present results from "short" probit models of credit card and account ownership, in which only relevant r.h.s. variables are included. The last two subsections present money demand runs which incorporate first stage results from reduced form probit models that include all the exogenous variables.

4a. Results from the Short Probit Model of Having a Credit Card

19. Note: for those indicating the source of information that led them to believe this, over half listed lenders, retailers, or credit ratings.
20. Banks often preapprove households based on information such as income, homeownership, and a household's credit history.

The short probit model of credit card ownership performs reasonably well (see Table 1). First, it correctly classified 78% of all households, 88% of credit card holders, and 60% of noncard holders. Second, the log-likelihood ratio is very significant.

Most coefficients for the estimated probability index had the expected signs and were significant. The financial advice, income, and wealth variables were positive and very significant. Among the demographic variables, households with heads who were over 65, male, or who lived in rural areas were significantly less likely to have a card, whereas households with heads who were married, high school graduates, or college graduates were significantly more likely to have a credit card. Household size was negatively related to having a credit card. This may reflect the fact that larger households have less per capita income/wealth, and for this reason, may be less likely to qualify for credit cards or have less demand for a credit card.

As to variables more associated with the supply of credit, households that had no credit histories, perceived themselves as credit constrained, or received welfare benefits were significantly less likely to have credit cards. Having a bad credit history was marginally significant, but was significant in runs that excluded CONSTRAIN. These results suggest that lenders use credit standards based on observable characteristics in approving credit cards, consistent with "screening" models of credit rationing (e.g., Stiglitz and Weiss (1981), part IV), rather than, in general, arbitrarily approving some observationally equivalent households but not others (as in Stiglitz and Weiss (1981), parts II and III). These findings are consistent with the loan quality

results of Boyes, Hoffman and Low (1988), Canner and Luckett (1990), and Orgler (1970), and with results about who is credit constrained obtained by Duca and Rosenthal (1991) and Jappelli (1990).[21]

4b. Results from Short Probit Models of Deposit Account Ownersip

Results from "short" probit models of account ownership are provided in Tables 2A and 2B. In these models, the same set of r.h.s. variables were used, including only variables that either were precautionary in nature or were significant for at least one account type with sensible signs.[22] Several patterns emerge across the different types of accounts. First, several socio-demographic variables are important; among these, households with heads who were white, female, married, college or high school educated were significantly more likely to have accounts. Second, the financially-related variables also were generally significant with the expected signs. Account ownership was positively related to using financial advice (SOPH) and levels of income and assets, but negatively related to household size, being unemployed or receiving public assistance.[23] Third, the probit model for money fund/MMDA account ownership does poorly in terms of correctly predicting actual account status better than a naive prediction that no one had a money fund/MMDA account. Fourth, many preference variables were insignificant. However, households that were averse to being

21. Using a data from the Atlanta area, Lindley, Rudolph, and Selby (1989) found that homeownership was significantly related to having a credit card, but their data did not include other supply-side variables.
22. Opportunity cost terms were generally insignificant, except in a regression of checking plus money funds, where the opportunity cost term had a significant, but positive sign. As discussed in the text, there are good reasons to discount opportunity cost findings in this cross-section study.
23. Quadratic income and assets terms were insignificant in other runs.

illiquid were less likely to have accounts; this may reflect that such preferences are held by families with low income/wealth. Finally, coefficients on the age dummies, which are not shown in order to conserve space, generally were significant and indicated that the likelihood of having an account tended to increase with age.

4c. Results Concerning Credit Cards and Money Demand

Table 3 summarizes findings on whether credit card ownership affects money demand as a separate variable in a log-linear specification using income and assets as scale variables.[24] The first column reports the coefficients on a Mill's ratio term from a credit card probit model that was entered into money demand regressions for a sample restricted to card holders. The significance of this term in runs for deposits with transactions features attests to a non-zero covariance of the probit and money demand errors, which in turn indicates that a two-stage approach is necessary to obtain consistent

24. The qualitative results with respect to PROBCARD were qualitatively similar in other runs that used only income as a scale variable, with the exception that the significance of PROBCARD for passbook savings fell to the 90 percent confidence level.

Other regressions tested whether scale elasticities differ for credit card holders. Although interactive terms were significant in runs using income and assets, the signs of the interactive income and wealth terms are opposite in each case, suggesting that a bizarre form of multicollinearity among the four scale terms may be creating spurious correlations. In runs using only income or assets as scale variables, the scale elasticities are somewhat higher, with the difference being significant. However, the model that tends to provide the best fit includes the logs of both income and assets with the estimated probability of having a credit card as a noninteracted variable.

In other tests, the observed interest elasticity of money demand is significantly and substantially different for credit card holders. However, for each definition of money, the coefficient on the noninteracted opportunity cost terms was of roughly equal magnitude, but of opposite sign. This result, coupled with the lack of much variation in the opportunity cost terms and time series evidence on the lagged impact of opportunity cost changes on money holdings, suggests that interest rate elasticity estimates should be viewed with a great deal of caution.

parameter estimates. The second column reports coefficients on the estimated probability of having a credit card (PROBCARD) in money demand regressions. The third column provides the coefficients obtained using the incorrect procedure of using a dummy variable for credit card ownership status (CARD).

The estimated probability of having a credit card (PROBCARD) is negatively and significantly associated with checking, total transactions, passbook saving, and money fund balances, but is insignificant for small time deposits and for total household M2 deposits. This finding is consistent with the view that credit cards enable households to minimize transactions deposits. It is worth noting that these qualitative results were also obtained in other regressions which excluded families with $1 million in income or assets and/or which excluded total assets as a scale variable. Notice in comparing columns 2 and 3 that CARD is generally insignificant for transactions-type deposits while PROBCARD is significant. This difference may reflect simultaneity bias arising from the endogeneity of money balances and credit card ownership. Alternatively, this result may stem from the existence of omitted, unobservable variables that help explain money holdings and card ownership; biased estimates can plausibly arise when a credit card dummy is used because households with credit cards likely have a higher demand for media of exchange, and thus may hold a higher level of balances than otherwise similar families if they did not have

credit cards.[25] In this way, our study suggests that Mandell's (1972) finding that a dummy for card ownership had an insignificant (and negative) coefficient in regressions of demand deposit balances likely reflected a selectivity bias. Indeed, this interpretation is suggested by Mandell's finding that credit card holders in the 1970 SCF wrote more checks than noncard holders after controlling for a number of factors.

4d. More General Money Demand Results

Results from money demand runs using income and assets as scale variables are presented in Tables 4A and 4B.[26] Both income and assets significantly affect money balances, however defined, except that income is insignificant when assets are included in the nontransaction deposit regression. The income coefficients are relatively larger for the transactions components (checking and MMDA+MMMF deposits), while the asset coefficients are relatively larger for the savings components (passbook savings, small time, and M2-type deposits). This pattern is consistent with the view that the demand for transactions media should be scaled by a good proxy for spending, while the demand for savings vehicles should be scaled by a good proxy for total assets. In

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25. Note that the effect of having a credit card on small time balances changes from being negative and significant using a credit card dummy to being negative and insignificant using the fitted probability. This result may reflect that credit card holders may have less demand for illiquid savings instruments within M2 than non credit card holders owing to unobservable differences in preferences; using a fitted probability in place of dummy variable corrects for this problem.

26. To conserve space, results using income as the only scale variable are provided in a separate appendix, available upon request from the authors. Most of these results are similar to those in Tables 4A and 4B, with two explainable differences. First, the income coefficient is larger and more significant, reflecting some multicollinearity between income and assets. Second, the age coefficients are larger in the absence of assets, likely reflecting that the age variables likely proxy for the accumulation of assets over the life cycle in these runs.

regressions with income as the only scale variable, the estimated income elasticities of transactions and M2 accounts were near unity. This result is broadly consistent with Feige (1964, 1974) and Lee (1966), who found that the income elasticity of demand deposits was not significantly different from 1 in an era prior to deposit deregulation. The opportunity cost terms are insignificant for each of the four deposit components and for M2-type balances, but are significant and negative for the transactions deposit aggregation. For reasons mentioned earlier, these estimates should not be viewed as definitive and are only presented for completeness.

In general, the precautionary variables (AVERSE, SAVMED, and UNEMPLOY) were insignificant; one exception was ILLIQ, which tended to have a negative sign. By contrast, the savings preference variables, DONTSAVE and OWNHOME were significant and negative, suggesting that overall savings preferences affect money demand and that renters partly use money balances in place of owner-occupied housing as an alternative form of holding wealth.

In general, demographic variables were significant. Households headed by males, nonmarried households, and larger households tended to have lower money balances across the board, while college graduates tended to hold more transactions balances and fewer deposits in passbook savings accounts. In general, younger families had smaller money holdings, controlling for assets and income, and since the age dummies for age groups up to 65 were negative, the results imply that families with heads aged 65 and over had larger deposit balances, particularly in nontransactions deposits. This evidence suggests that life-cycle

influences affect the demand for different deposits and thus, that demographic shifts may affect the aggregate demand for money.

Finally, the account ownership selection or inverse Mill's ratio terms (SELECTION) tend to be negative, indicating that households with a greater-than-predicted propensity to own a particular type of account have, on average, larger balances in that type of account. These selectivity terms were significant for passbook savings and small time deposits, and for the nontransactions, liquid, and M2 deposit aggregations. In the absence of the account selectivity terms, results from regressions not reported in table form differ in several noteworthy ways from those in Tables 4A and 4B. First, the estimated income and asset elastities are bigger for money funds, passbook savings, and small time deposits, while the income elasticity for the sum of savings and small time deposits is smaller. Second, the estimated magnitude of the coefficient on PROBCARD is somewhat smaller (but still significant) for checking and money funds separately, but somewhat larger (and still significant) for the sum of these two account types. Third, the coefficient on PROBCARD for passbook savings changes from negative and significant to positive and significant when the account selection term is dropped. This is the only instance in which any of the qualitative results with respect to the effect of credit cards on money demand was different. Nevertheless, the high degree of significance of the account selection term in the passbook savings regression indicates that the regression in Table 4B is preferable, and by implication, that credit card ownership likely lowers passbook savings balances. In sum, these

results indicate that controlling for account selection effects is important in cross-sectional work on money demand.

5. Conclusion

This study sheds light on issues relating to credit card ownership, the effects of credit card ownership on household deposit balances, and the determinants of deposit account ownership. Results indicate that both demand and supply factors affect who has a credit card, with household attitudes toward using debt being significant. In addition, evidence also suggests that lenders offer or approve credit cards using credit standards based on observable characteristics related to default risk, consistent with "screening" models of credit rationing.

Results indicate that credit card ownership reduces the demand for transactions deposits, with little effect on small time and total deposits. These findings are consistent with the view that credit card use can help minimize the need for deposits that serve as transactions media.

This study contributes to the money demand literature in two other ways. First, it provides cross-sectional evidence that both income and assets are significant scale variables for transactions deposits, but that income may not be an appropriate scale variable for small time deposits. Second, our findings indicate that controlling for selection effects can be empirically important for cross-sectional analysis of money demand.

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Table 1: Results from the "Short" Probit Model of Credit Card Ownership

Variables	Coefficients	Variables	Coefficients
Constant	-8.0011**	SOPH	0.1872**
	(-6.00)		(3.02)
LASSETS	0.1079**	UNEMPLOY	-0.4478**
	(5.90)		(-3.75)
LINCOME	0.3946**	RACE	-0.1059
	(8.61)		(-1.38)
WELFARE	-0.4983**	SEX	-0.3984**
	(-4.88)		(-4.61)
CONSTRAIN	-0.3329**	LHSIZE	-0.1491*
	(-4.59)		(-2.22)
NOHISTORY	-0.3644**	MARR	0.4146**
	(-5.69)		(4.69)
BADHIST	-0.1334	COLL	0.7657**
	(-1.66)		(7.72)
DEBTBAD	-0.4441**	HIGH	0.3033**
	(-7.49)		(3.99)
NONRURAL	0.3540**	NOHIGH	-0.1558
	(5.23)		(-1.66)
LMEDINC	0.3630**	STUDENT	-0.5928*
	(2.63)		(-2.20)
AGE24	-0.0207	AGE2534	-0.1171
	(-1.80)		(-1.13)
AGE3544	-0.0480	AGE4554	0.0017
	(-0.45)		(0.02)
AGE5564	0.2593**		
	(2.71)		

Summary Statistics

EFRON R-sq:	0.361	# Card Holders:	2281
% Wrong Predictions:	.214	Of these predicted	2017
Log Likelihood	-1578.0	# Without Cards	1232
		Of these predicted	744
Likelihood Ratio:	1395.98**		

(T statistics are in parentheses)
* denotes significant at the 95% level and ** at the 99% level.

Table 2A

Results from "Short" Probit Models of Liquid Deposit Account Ownership

Variables	Checking	Money Fund & MMDA	Passbook Savings	MMMF+MMDA+ Checking
Constant	-3.2444**	-5.6740**	-2.3180**	-3.4876**
	(-7.60)	(-11.46)	(-6.84)	(-8.02)
LASSETS	0.1476**	0.2169**	0.0595**	0.1541**
	(8.02)	(7.41)	(3.66)	(8.30)
LINCOME	0.3178**	0.2465**	0.1915**	0.3416**
	(6.55)	(4.33)	(4.91)	(6.94)
LHSIZE	-0.1938**	-0.2471**	0.0086	-0.2214**
	(-2.76)	(-4.52)	(0.15)	(-3.12)
UNEMPLOY	-0.4207**	-0.1822	-0.2108*	-0.4099**
	(-3.69)	(-0.87)	(-2.00)	(-3.58)
WELFARE	-0.5056**	-0.1886	-0.4060**	-0.4847**
	(-5.53)	(-0.84)	(-4.59)	(-5.29)
STUDENT	1.4451**	0.3420	0.2525	1.4699**
	(3.48)	(0.88)	(0.96)	(3.52)
MARR	0.1249	0.0593	-0.0177	0.1310
	(1.51)	(0.61)	(-0.26)	(1.57)
COLL	0.6297**	0.4610**	-0.0017	0.6379**
	(5.69)	(3.85)	(-0.21)	(5.62)
HIGH	0.3136**	0.0797	0.2354**	0.3026**
	(3.84)	(0.72)	(3.35)	(3.66)
NOHIGH	-0.2556*	-0.0323	-0.1429	-0.2606*
	(-2.60)	(-0.23)	(-1.64)	(-2.62)
SOPH	0.1630*	0.1680*	0.0437	0.2292**
	(2.25)	(2.61)	(0.82)	(3.06)
NONRURAL	-0.1322*	0.2227**	0.0995*	0.1285*
	(-2.09)	(3.08)	(1.96)	(2.00)
DONTSAVE	-0.0823	-0.6812*	-0.8147**	-0.0877**
	(-0.50)	(-1.96)	(-5.01)	(-5.29)
AVERSE	0.0903	0.2584**	0.0173	0.0734
	(1.37)	(3.57)	(0.33)	(1.10)
ILLIQ	-0.2148**	-0.2471*	-0.1244*	-0.2083**
	(-3.11)	(-2.59)	(-2.12)	(-2.99)
EMER	0.0698	0.0191	0.0871	0.0767
	(1.18)	(0.31)	(1.86)	(1.28)
Correct Predict.	84.3%	86.7%	68.7%	84.8%
EFRON R-sq:	.261	.179	.115	.269
Likelihood Ratio	820.3**	602.8**	400.4**	853.9**

(AGE variable coefficients are omitted from table to conserve space.)

Table 2B

"Short" Probit Results for NonTransactions and Household M2 Accounts

	Small Time	Savings + Small Time	Liquid Deposits	Household M2 Accts.
Constant	-3.5070**	-2.6869**	-3.5521**	-3.6587**
	(-8.03)	(-7.56)	(-6.99)	(-7.10)
LASSETS	0.2811**	0.1088**	0.0896**	0.0967**
	(10.40)	(6.56)	(4.18)	(4.46)
LINCOME	0.0719	0.2370**	0.4628	0.4731**
	(1.43)	(5.80)	(8.03)	(8.12)
LHSIZE	-0.0821	-0.0568	-0.3091**	-0.3360**
	(-1.08)	(-0.94)	(-3.71)	(-3.99)
UNEMPLOY	-0.2212	-0.1725	-0.2962*	-0.2830*
	(-1.18)	(-1.61)	(-2.36)	(-2.22)
WELFARE	-0.5359*	-0.3755**	-0.4868**	-0.4914**
	(-2.77)	(-4.23)	(-5.00)	(-5.03)
STUDENT	0.1467	0.2382	6.6609	6.6994
	(0.37)	(1.01)	(0.05)	(0.05)
MARR	-0.1655*	-0.0628	0.0489	0.0929
	(-1.90)	(-0.87)	(0.49)	(0.69)
COLL	0.0357	0.0283	0.4972**	0.4655**
	(0.34)	(0.32)	(3.66)	(3.35)
HIGH	-0.0274	0.2296**	0.4648**	0.4384**
	(-0.29)	(3.16)	(4.84)	(4.49)
NOHIGH	-0.1957	-0.2485**	-0.1613	-0.1920
	(-1.69)	(-2.79)	(-1.45)	(-1.69)
SOPH	0.1018	0.0666	0.2427*	0.2565*
	(1.68)	(1.18)	(2.53)	(2.61)
NONRURAL	-0.1213*	0.0486	-0.0238	0.0108
	(-1.94)	(0.91)	(-0.31)	(0.14)
DONTSAVE	-1.3838**	-0.9020**	-0.4883**	-0.5009**
	(-3.11)	(-5.53)	(-2.87)	(-2.93)
AVERSE	0.1297*	0.0211	0.0146	0.0192
	(2.03)	(0.38)	(0.18)	(0.23)
ILLIQ	-0.8499**	-0.2240**	-0.1800*	-0.1892*
	(-9.63)	(-3.74)	(-2.15)	(-2.23)
EMER	-0.0412	0.0881	0.1217	0.1254
	(0.73)	(1.80)	(1.62)	(1.64)
Correct Predict.	82.3%	74.1%	91.1%	91.3%
EFRON R-sq:	.234	.161	.224	.232
Likelihood Ratio	850.6**	103.6**	500.4**	615.5**

(AGE variable coefficients are omitted from table to conserve space.)

Table 3

Impact of Credit Cards on Money Demand
Coefficients on selected variables from regressions with the same set of other r.h.s. variables.[1]

Monetary Actual Asset	Inverse Mill's Ratio[2]	Estimated Probability of Having Card	Dummy for Credit Card Status
Checking	0.527**	-0.820**	-0.067
	(.184)	(.256)	(.057)
MMMFs+MMDAs	1.047*	-1.717**	-.530**
	(.484)	(.564)	(.201)
Savings	0.140	-.923**	-.120
	(.283)	(.362)	(.087)
Small Time	-0.153	-.180	-.227*
	(.358)	(.384)	(.112)
Checking+ MMMFs+MMDAs	0.450*	-.653*	-.084
	(.215)	(.303)	(.072)
Checking+MMMFs +MMDAs+Savings	-.084	0.158	0.046
	(.206)	(.259)	(.064)
Savings + Small Time	0.612**	-1.584**	-.238**
	(.260)	(.324)	(.087)
Checking+MMMFs +MMDAs+Savings + Small Time	0.059	-.176	-.006
	(.213)	(.269)	(.066)

1. The coefficients are from regressions that include both income and assets as scale variables. Note that, by construction, the Mill's ratio should generally have an opposite sign than that of PROB or CARD.
2. These coefficients are on inverse Mill's ratio terms from credit card probits and from money demand regressions which include the standard set of other r.h.s. variables for a sample restricted to account and credit card holders only. The other columns provide coefficient estimates for account holders, including households without credit cards.

* denotes significant at the 95% level.
** denotes significant at the 99% level.
Standard errors are in parentheses.

Table 4A: Money Demand Results for Transactions and Passbook Deposits

Variables	Checking	Money Fund & MMDA	Passbook Savings	MMMF+MMDA+ Checking
Constant, Selectivity Bias, and Credit Card Variables				
Constant	2.968	4.596*	2.470*	-2.715**
	(1.11)	(1.99)	(2.18)	(-4.67)
PROBCARD	-0.820**	-1.717**	-0.923*	-0.653*
	(3.20)	(-3.04)	(-2.55)	(-2.15)
SELECTION	-0.374	-0.604	-2.905**	0.132
	(-1.43)	(-1.32)	(-6.82)	(0.47)
Scale/Employment Variables				
LINCOME	0.433**	0.372*	0.189*	0.593**
	(8.95)	(2.47)	(2.46)	(10.40)
LASSETS	0.361**	0.318*	0.346**	0.505**
	(14.62)	(2.11)	(10.24)	(17.70)
STUDENT	0.499	0.833	-0.883*	0.890**
	(1.84)	(1.07)	(-2.12)	(2.66)
UNEMPLOY	-0.128	0.729*	-0.251	-0.156
	(-1.03)	(2.06)	(-1.24)	(-1.04)
Opportunity Cost Variables				
OWNCOST	-0.603	-0.182	0.750**	0.016
	(-1.18)	(-0.73)	(2.99)	(0.42)
Precautionary/Saving Variables				
AVERSE	-0.049	0.333*	-0.055	-0.130*
	(-0.94)	(1.95)	(-0.72)	(-1.99)
DONTSAVE	-0.749**	0.657**	-0.151	-0.928**
	(-4.01)	(4.86)	(-0.33)	(-4.38)
EMER	-0.021	-0.150	-0.112	-0.008
	(-0.46)	(-1.22)	(-1.62)	((-0.13)
ILLIQ	-0.152*	-0.329	0.071	-0.263**
	(-2.45)	(-1.12)	(0.76)	(-3.63)
OWNHOME	-0.492**	-0.305	-0.523**	-0.707**
	(-6.65)	(-1.39)	(-4.82)	(-7.71)
SAVMED	0.036	0.097	0.151	0.070
	(0.57)	(0.54)	(1.55)	(0.85)

Table 4A Continued

SOPH	0.190**	0.106	0.036	0.308**
	(3.59)	(0.84)	(0.48)	(4.52)
	Socio-Demographic Variables			
LHSIZE	-0.344**	0.020	-0.211*	-0.540**
	(-5.26)	(0.09)	(-2.31)	(-6.60)
MARR	-0.050	-0.023	-0.089	0.032
	(-0.59)	(-0.09)	(-0.68)	(0.28)
RACE	-0.010	0.309	0.032	-0.230
	(-0.83)	(1.03)	(0.30)	(-1.73)
COLL	0.441**	-0.094	0.341*	0.698**
	(4.77)	(-0.29)	(2.34)	(6.00)
HIGH	0.095	-0.013	-0.143	0.120
	(1.23)	(-0.05)	(-1.24)	(1.24)
NOHIGH	0.015	0.371	0.533**	0.015
	(1.10)	(1.19)	(3.63)	(0.12)
AGE24	-1.023**	-0.982*	-1.471**	-1.273**
	(-9.59)	(-2.58)	(-10.49)	(-9.66)
AGE2534	-1.177**	-0.710**	-1.035**	-1.493**
	(-13.26)	(-2.70)	(-10.80)	(-13.53)
AGE3544	-0.893**	-0.615*	-1.035**	-1.085**
	(-9.55)	(-2.40)	(-10.80)	(-9.37)
AGE4554	-0.735**	-0.233	-0.859**	-0.922**
	(-7.85)	(-1.00)	(-6.43)	(-7.87)
AGE5564	-0.326**	-0.221	-0.410**	-0.521**
	(-3.57)	(-1.08)	(-3.03)	(-4.53)
Summary Statistics				
$\bar{R}^2$	.3633	.2231	.3121	.3974
# Acct. Owners	2862	487	2235	2873

(corrected standard errors in parentheses)
*--denotes significant at the 95% level.
**--denotes significant at the 99% level.

Table 4B: Money Demand Results for Other Deposits

	Small Time	Savings + Small Time	Liquid Deposits	Household M2 Accts.
Constant, Selectivity Bias, and Credit Card Variables				
Constant	5.053**	6.565**	-1.150*	-1.104*
	(4.10)	(7.09)	(-2.19)	(-2.12)
PROBCARD	-0.180	-1.584**	0.158	-0.176
	(-0.47)	(-4.89)	(0.61)	(-0.66)
SELECTION	-1.532**	-3.970**	-0.639*	-0.827**
	(-6.01)	(-10.40)	(-2.07)	(-2.64)
Scale/Employment Variables				
LINCOME	0.236*	0.149	0.511**	0.529**
	(2.31)	(1.82)	(9.70)	(9.67)
LASSETS	0.252**	0.393**	0.475**	0.547**
	(3.26)	(10.40)	(20.13)	(21.75)
STUDENT	-0.273	-0.754	0.516	0.471
	(-0.62)	(-1.68)	(1.66)	(1.48)
UNEMPLOY	-0.350	-0.248	-0.150	-0.220
	(-0.65)	(-1.20)	(-1.07)	(-1.52)
Opportunity Cost Variables				
OWNCOST	-2.358	-0.127**	-0.041	-0.047
	(-1.59)	(-2.61)	(-0.041)	(-0.57)
Precautionary/Saving Variables				
AVERSE	0.099	0.023	-0.106	-0.033
	(1.11)	(0.30)	(-1.78)	(-0.53)
DONTSAVE	1.586**	0.248	-1.165**	-1.328**
	(4.24)	(0.51)	(-5.37)	(-5.72)
EMER	0.003	-1.166*	0.027	0.001
	(0.04)	(-2.40)	(0.52)	(0.02)
ILLIQ	0.570*	-0.065	-0.213**	-0.4467**
	(2.32)	(-0.66)	(-3.08)	(-6.51)
OWNHOME	-0.413**	-0.305	-0.609**	-0.529**
	(-2.94)	(-1.39)	(-5.48)	(-6.06)
SAVMED	-0.012	0.097	0.037	-0.063
	(-0.10)	(0.54)	(0.39)	(-0.81)

Table 4B Continued

SOPH	-0.082 (-0.93)	0.128 (1.71)	0.232** (3.92)	0.284** (4.66)
	Socio-Demographic Variables			
LHSIZE	-0.228 (-1.73)	-0.197* (-2.08)	-0.335** (-4.50)	-0.374** (-4.86)
MARR	-0.050 (-0.30)	-0.086 (-0.66)	-0.127 (-1.25)	-0.137 (-1.32)
RACE	0.504* (2.42)	0.076 (0.65)	-0.165 (-1.68)	-0.248 (-2.39)
COLL	0.024 (0.14)	0.386** (2.76)	0.406** (3.77)	0.364** (3.27)
HIGH	-0.051 (-0.37)	-0.192 (-1.70)	0.067 (0.73)	0.007 (0.08)
NOHIGH	0.128 (0.73)	0.619** (4.37)	0.164 (1.45)	0.005 (0.05)
AGE24	0.041 (0.15)	-1.539** (10.00)	-1.151** (-9.55)	-1.493** (-11.89)
AGE2534	-0.123 (-0.51)	-1.660** (-12.80)	-1.3731** (-13.94)	-1.796** (-17.87)
AGE3544	0.038 (0.16)	-1.098** (-7.75)	-1.003** (-7.28)	-1.413** (-13.06)
AGE4554	0.032 (0.16)	-0.849** (-6.07)	-0.859** (-8.28)	-1.223** (-11.50)
AGE5564	0.099 (0.72)	-0.247 (-1.79)	-0.621** (-6.14)	-0.742** (-7.09)
Summary Statistics				
R^2	.3774	.4447	.4686	.5239
# Acct. Owners	722	2428	3176	3184

(corrected standard errors in parentheses)
*--denotes significant at the 95% level.
**--denotes significant at the 99% level.

Table 5

Definitions of Independent Variables

Income and Wealth Variables

LASSETS = log of household total assets in 1982 in current dollars.

LINCOME = log of total household income in 1982 in current dollars.

LMEDINC = log of the median 1980 income for county of residence.

STUDENT = a dummy equal to 1 if the household head was a student who was not employed.

UNEMPLOY = a dummy equal to 1 if the household head was unemployed, not a student, and not retired.

Savings and Precautionary Demand Variables

AVERSE = a dummy equal to 1 if the household were not willing to take on any risk in investing family savings.

DEBTBAD = a dummy equal to 1 if the household thinks that using debt is a "bad" thing to do.

DONTSAVE = a dummy equal to 1 if the household does not save.

ILLIQ = a dummy equal to 1 if the household were not willing to tie up any family savings in exchange for higher asset returns.

SAVMED = a dummy equal to 1 if the household's first or second most important reason to save is for medical expenses.

SOPH = a dummy equal to 1 if the household relied upon some sort of professional for investment advice.

Creditworthiness and Debt Preference Variables

BADHIST = a dummy equal to 1 if the household had problems making loan payments in the last three years.

CONSTRAIN = a dummy equal to 1 if in the past 3 years a household either:

a) was denied a loan or offered a loan smaller than it desired and did not successfully reapply for a loan at another lender,

or

b) thought about applying but did not because it thought that it would not get the loan. (Note: for those indicating the source of information that lead them to believe this, over half indicated lenders, retailers, or credit ratings.

DEBTBAD = a dummy equal to 1 if the household views buying items with installment credit as a "bad" thing.

NOHISTORY= a dummy equal to 1 if the household has no credit history other than having a credit card.

OWNHOME = a dummy equal to 1 if the household owns a home.

WELFARE = a dummy equal to 1 if the household received public assistance in 1982.

Demographic Variables

AGE24 = a dummy equal to 1 if head's age is less than 25.

AGE2534 = a dummy equal to 1 if head's age is between 25 and 34.

AGE3544 = a dummy equal to 1 if head's age is between 35 and 44.

AGE4554 = a dummy equal to 1 if head's age is between 45 and 54.

AGE5564 = a dummy equal to 1 if head's age is between 55 and 64.

COLL = a dummy equal to 1 if the head graduated from college.

HIGH = a dummy equal to 1 if the head only finished high school.

NOHIGH = a dummy equal to 1 if the head did not attend high school.

LHSIZE = log of the number of people in the household.

MARR = a dummy variable equal to 1 if married.

NONRURAL = a dummy variable equal to 1 if does not live in an SMSA.

RACE = a dummy equal to 1 if the household head is nonwhite.

SEX = a dummy variable equal to 1 if the household head is male.

Appendix Table A: Money Demand Results for Transactions and Passbook Deposits With Income As the Only Scale Variable

Variables	Checking	Money Fund & MMDA	Passbook Savings	MMMF+MMDA+ Checking
Constant, Selectivity Bias, and Credit Card Variables				
Constant	5.364*	5.710*	2.695*	-0.773
	(1.95)	(2.57)	(2.35)	(-1.26)
PROBCARD	-0.816**	-1.549*	-0.604	-0.645*
	(-2.81	(-2.54)	(-1.60)	(-2.06)
SELECTION	-0.709*	-0.563	-2.570**	-0.370
	(-2.59)	(-1.18)	(-6.36)	(1.36)
Scale/Employment Variables				
LINCOME	0.653**	0.588*	0.423**	0.903**
	(12.34)	(3.35)	(5.33)	(14.21)
STUDENT	0.283	0.767	-0.942*	0.561
	(0.97)	(0.68)	(-2.09)	(1.56)
UNEMPLOY	-0.074	0.742*	-0.310	-0.090
	(-0.55)	(1.95)	(-1.44)	(-0.55)
Opportunity Cost Variables				
OWNCOST	-0.787	-0.120	0.933**	0.188
	(-1.49)	(-0.48)	(3.56)	(0.60)
Precautionary/Saving Variables				
AVERSE	-0.078	0.263	-0.084	-0.169*
	(-1.44)	(1.43)	(-1.08)	(-2.50)
DONTSAVE	-0.703**	0.502	-0.191	-0.896**
	(-3.48)	(1.85)	(-0.42)	(-4.01)
EMER	-0.042	-0.156	-0.137*	-0.036
	(-0.88)	(-1.23)	(-1.94)	(-0.59)
ILLIQ	-0.230*	-0.159	-0.023	-0.373**
	(-3.53)	(-0.50)	(-0.24)	(-4.81)
OWNHOME	0.137*	0.045	0.035	0.188*
	(2.17)	(0.26)	(0.37)	(2.40)
SAVMED	0.023	0.073	0.154	0.053
	(0.33)	(0.39)	(1.55)	(0.61)

Appendix Table A Continued

SOPH	0.279**	0.168	0.159*	0.421**
	(5.03)	(1.17)	(2.09)	(5.90)
	Socio-Demographic Variables			
LHSIZE	-0.305**	0.014	-0.126*	-0.489**
	(-4.37)	(0.06)	(-1.33)	(-5.62)
MARR	-0.081	-0.038	-0.190	-0.004
	(-0.89)	(-0.14)	(-1.40)	(-0.03)
RACE	0.052	0.249	-0.035	-0.160
	(0.41)	(0.76)	(-0.30)	(-1.11)
COLL	0.502**	0.021	0.306*	0.778**
	(5.18)	(0.06)	(2.04)	(6.38)
HIGH	0.135	0.055	-0.142	0.178
	(1.64)	(0.19)	(-1.19)	(1.78)
NOHIGH	-0.013	0.418	0.406**	-0.016
	(-0.12)	(1.30)	(2.68)	(-0.12)
AGE24	-1.324**	-1.469**	-1.765**	-1.673**
	(-11.83)	(-3.43)	(-10.66)	(-11.92)
AGE2534	-1.462**	-1.072**	-1.785**	-1.873**
	(-16.09)	(-3.51)	(-12.73)	(-16.21)
AGE3544	-1.131**	-0.872**	-1.312**	-1.402**
	(-11.72)	(-3.16)	(-9.44)	(-11.62)
AGE4554	-0.919**	-0.414	-1.049**	-1.166**
	(-9.24)	(-1.62)	(-7.77)	(-9.31)
AGE5564	-0.397**	-0.329	-0.580**	-0.611**
	(-4.16)	(-1.50)	(-4.25)	(-5.03)
Summary Statistics				
$\bar{R}^2$	.3049	.1789	.2702	.3337
# Acct. Owners	2862	487	2235	2873

(corrected standard errors in parentheses)
*--denotes significant at the 95% level.
**--denotes significant at the 99% level.

Appendix Table B: Results for Other Deposits
With Income As the Only Scale Variable

	Small Time	Savings + Small Time	Liquid Deposits	Household M2 Accts.
Constant, Selectivity Bias, and Credit Card Variables				
Constant	5.312**	7.918**	0.153	0.438
	(4.51)	(8.44)	(0.27)	(0.78)
PROBCARD	-0.540	-1.518**	0.460	0.136
	(-1.29)	(-4.32)	(1.63)	(-0.46)
SELECTION	-1.328**	-3.864**	-0.696*	-0.933**
	(-4.99)	(-10.16)	(-2.52)	(-3.27)
Scale/Employment Variables				
LINCOME	0.470**	0.421**	0.818**	0.882**
	(4.35)	(4.83)	(13.97)	(14.38)
STUDENT	-0.783	-0.933*	0.405	0.335
	(-0.80)	(-1.86)	(1.12)	(0.89)
UNEMPLOY	-0.260	-0.312	-0.187	-0.256
	(-0.52)	(-1.41)	(-1.19)	(-1.57)
Opportunity Cost Variables				
OWNCOST	-3.408*	-0.129*	-0.002	0.042
	(-2.23)	(-2.50)	(-0.04)	(0.46)
Precautionary/Saving Variables				
AVERSE	0.050	-0.014	-0.133	-0.065
	(0.52)	(-0.18)	(-2.12)	(-0.97)
DONTSAVE	1.737**	0.432	-1.106**	-1.247**
	(4.49)	(0.87)	(-4.91)	(-5.14)
EMER	-0.008	-0.209**	0.004	-0.025
	(-0.09)	(-2.91)	(0.07)	(0.43)
ILLIQ	0.511*	-0.163	-0.334**	-0.606**
	(1.84)	(-1.57)	(-4.60)	(-7.94)
OWNHOME	-0.229**	-0.026	0.288**	0.461**
	(-1.43)	(-0.22)	(-3.94)	(-5.95)
SAVMED	-0.032	0.045	0.071	-0.057
	(-0.25)	(0.46)	(0.88)	(-0.68)

Appendix Table B Continued

SOPH	0.008	0.282**	0.367**	0.441**
	(0.08)	(3.60)	(4.91)	(6.77)
	Socio-Demographic Variables			
LHSIZE	-0.116	-0.102	-0.285**	-0.316**
	(-0.82)	(-1.02)	(-3.63)	(-3.81)
MARR	-0.135	-0.200	-0.163	-0.179
	(-0.73)	(-1.44)	(-1.49)	(-1.57)
RACE	0.375	0.043	-0.285**	-0.377**
	(1.59)	(0.34)	(-2.65)	(-3.30)
COLL	0.109	0.402**	0.460**	0.431**
	(0.60)	(2.70)	(3.99)	(-3.55)
HIGH	-0.015	-0.204	0.096	0.040
	(-0.10)	(-1.68)	(0.99)	(0.40)
NOHIGH	0.107	0.484**	0.107	-0.060
	(0.57)	(3.22)	(0.88)	(-0.47)
AGE24	-0.334	-1.964**	-1.576**	-1.984**
	(-1.08)	(-12.08)	(-12.37)	(-14.79)
AGE2534	-0.553*	-2.057**	-1.776**	-2.260**
	(-1.98)	(-15.48)	(-17.23)	(-21.20)
AGE3544	-0.380	-1.479**	-1.360**	-1.824**
	(-1.44)	(-10.16)	(-12.65)	(-16.25)
AGE4554	-0.246	-1.116**	-1.133**	-1.537**
	(-0.99)	(-7.71)	(-10.32)	(-13.44)
AGE5564	0.028	-0.427**	-0.769**	-0.910**
	(0.18)	(-2.96)	(-7.29)	(-8.14)
Summary Statistics				
R^2	.2983	.3887	.3989	.4483
# Acct. Owners	722	2428	3176	3184

(corrected standard errors in parentheses)
*--denotes significant at the 95% level.
**--denotes significant at the 99% level.

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