2008

Patterns of Credit Card Use Among Low and Moderate Income Households

Ronald J. Mann
Columbia Law School, rmann@law.columbia.edu

Patterns of Credit Card Use Among Low and Moderate Income Households

Ronald J. Mann[*]

Ensuring that the poorer segments of the population have access to financial products and services has taken on increased significance as policymakers have come to understand the broad social ramifications of inclusive financial regimes. Access not only promotes savings but also enables the poor to manage cash flows and to meet basic needs such as health care, food, and housing. In the United States, the last few decades have seen remarkable progress on that front, as low- and moderate-income ("LMI") households increasingly use both mainstream products like deposit accounts[1] and "fringe" products like payday lending, check-cashing services, and pawnshops.[2] At the same time, because many of those products exploit cognitive and financial constraints, policymakers now increasingly move beyond concerns about access to emphasize the need for safety in the design and marketing of financial products.[3]

Credit cards cut across those concerns. With respect to access, the credit card is a profoundly democratizing instrument. It is only a slight exaggeration to say that any person with a Visa or MasterCard product can walk into the same stores and restaurants as the most elite trend-setters in our society and purchase the same goods and services, at the same prices. As social status in our consumer society shifts to depend on consumption rather than wealth or family status, the

---

* Professor of Law, Columbia Law School. I thank Karen Pence for gracious assistance with programming to interpret data from the Survey of Consumer Finance, James Carlson for assistance with statistical analysis, David Hogan for useful comments, and Allison Mann for advice of all kinds.

1 Barr (this volume); Hogarth et al. 2004.

2 Barr (this volume); Caskey 1996; Mann & Hawkins 2007.

3 Warren 2007.

credit card has become the great leveler of social hierarchies.[4] The credit card also provides a remarkably flexible safety net, ready for deployment in response to the most unexpected financial crises.[5] That protection is particularly important in the United States, where the public safety net is more porous than it is in many of our peer nations.[6]

At the same time, the credit card is singled out as one of the most perilous consumer financial products. The prevalence of credit card use raises concerns that consumer spending is leading to overindebtedness.[7] Studies of national aggregate data suggest a significant relation between increased credit card use and consumer bankruptcy filings.[8] The flexibility and unpredictability that make the credit card so useful for households faced with unexpected difficulties are central to the danger the product can bring to those who use it recklessly.[9] The financial precariousness of LMI households makes those concerns particularly telling for those concerned about financial products for the poor.

This chapter uses data from the Federal Reserve Board's Survey of Consumer Finances for 2004 (the "SCF") to examine the penetration of credit cards into LMI markets. The chapter has two purposes. First, I discuss the rise of the modern credit market, emphasizing the segmentation of product lines based on behavioral and financial characteristics of customer groups.[10] Among other things, that trend involves the use of products aimed at LMI households that differ significantly from those aimed at middle-class households.

---

[4] Frank 1999 ch. 4; Cross 2000:169-84.

[5] Mann 2006.

[6] Howard 2007; Hacker 2002.

[7] Schor 1999.

[8] Mann 2006.

[9] Mann 2007; Mann & Hawkins 2007; Littwin 2008a.

[10] For more detail, see Mann 2007.

Second, I describe the extent to which LMI households borrow on credit cards, the types of LMI households that borrow, and how they differ from the more affluent households that borrow. Despite lower incomes, credit card use is almost as common among LMI households as it is among more affluent households. Indeed, measured as a share of income, the credit card balances that LMI cardholders carry are substantially higher than those of more affluent households. To check the robustness of those results, the chapter closes with the results of a multivariate regression analysis of the characteristics of LMI households with credit card debt. Generally, those results suggest that the demographic characteristics of LMI households that have credit card debt are different in material ways from the characteristics of those with credit card debt in the overall population. The models that I summarize here suggest that age, race, and education are important predictors of credit card use in the population at large. At least in these models, however, age and race become insignificant and education is only marginally important in predicting credit card use in LMI households. In LMI households, by contrast, the most significant predictors of credit card use are employment status, the use of other financial products (checking accounts, mortgage loans, and car loans), and marital status.

The Modern Credit Card Market

The rise of the credit card to dominance in American payment and lending transactions is well known. The total value of credit card transactions has increased from about $800 billion in 1990 to more than $1.7 trillion in 2006. Similarly, credit card balances have increased from about $450 billion in 1990 to more than $750 billion in 2006.[11] As Figure 1 illustrates, the rise in spending on cards reflects a substantial shift toward cards and away from other payment devices.

---

[11] Nilson Report. For a more detailed discussion, see Mann 2006.

What is less widely understood is the mechanism by which this has occurred. Credit card lending is by its nature risky. Unlike the home mortgage lender or the car lender, the credit card lender has no collateral to which it can look for repayment. Moreover, several factors combine to leave the credit card lender with no practical device for collecting payment. First, in most American jurisdictions unsecured lenders have no practical remedy other than litigation, either because garnishment is illegal (the rule in some States), or because it is ineffective, especially against debtors that do not have regular incomes or bank accounts. Most jurisdictions also have schedules of exempt assets that are not subject to seizures by unsecured creditors, even when they hold unpaid judgments. Thus, exemptions in many cases will cover all assets in the household. Finally, the availability of a discharge in bankruptcy means that debtors who are pushed too far normally can discharge their obligations to the credit card lender.

In truth, the most effective lever the credit card lender has is the threat of damaging the credit report of the borrower. A credit card debtor that does not pay will suffer a substantially lower credit rating. Although the lower credit card rating will have only a limited impact on the debtor's access to credit card debt, it will substantially increase the cost of subsequent borrowing. This is particularly true for mortgage lenders, which continue to use crude underwriting systems that rely directly on the credit rating system. For the sophisticated credit card lender, in contrast, the credit rating will be at most one of many inputs into the underwriting process. In any event, the threat of an adverse credit report will be ineffective against debtors in serious financial distress, where the credit rating already has been compromised because of missed payments to other creditors.

Because of the riskiness of the credit card business model, the industry, in its infancy, used a unitary business model. The product offerings of the different issuers were similar, so competition occurred mainly through marketing and customer service. Interest rates were standard and relatively high, typically in the range of 18%. At the same time, despite those relatively high rates, the customers to whom credit card lenders could make profitable loans were a relatively small slice of the middle class. The wealthy would have no interest in borrowing at 18% and those without reliable income streams were too risky. In general, most issuers had a large group of profitable customers that borrowed and paid substantial amounts of interest, a second group of generally unprofitable customers that did not borrow, but instead paid their bills each month, and a third group of highly unprofitable customers that borrowed and did not repay their debts. Profitability came from maximizing the number of customers in the first group and minimizing the number in the second and third groups.

The advent of technological underwriting tools in the 1990's changed everything. The most capable lenders developed increasingly complex statistical models that predicted more accurately the spending and repayment behavior of smaller slices of the potential cardholding population. The result has been a steady segmentation and specialization of the market. The first stage involved differential pricing, in which low risk customers received lower interest rates (to encourage borrowing), and in which high risk customers received higher interest rates (to provide a margin for delinquencies).

Differential pricing has not led to a decline in net interest margins. Although the effective annual interest rate has fallen in the last fifteen years from about 16.4% in 1990 to 12.2% in 2006,[12] a parallel decrease in the cost of funds means that the net interest margin has not changed substantially during that period (rising from 7.4% in 1990 to 7.6% in 2005). At the same time, however, the portfolios underwritten at that margin have become considerably riskier. For example,

---

12 The statistics reported in this paragraph are compiled from the annual Cards Profitability Survey published by Cards & Payments (formerly Cards Management). Figure 2 presents a detailed time series of the relevant information. Other sources suggest higher borrowing rates at the early end of this period, but I use the Cards & Payments data because of its consistency and availability over the entire period covered by this discussion.

the rate at which issuers write off unpaid balances ("chargeoffs") steadily increased during this period from 3.5% in 1990 to about 6% during 2004-05.[13] Essentially, improved underwriting technologies allowed the successful credit card lenders to develop reliable predictions about the repayment behavior of increasingly unreliable customers. This capability has allowed those lenders to acquire profitable portfolios filled with cardholders that would have been unacceptably risky a few decades ago.[14]

The maintenance of a relatively constant net interest margin suggests a balance of increased borrowing at lower rates by relatively creditworthy customers against new borrowing by relatively risky customers at higher rates. The ability to profit with flat interest margins despite the increase in chargeoffs suggests that the card issuers have developed new revenue sources. The first is an increased reliance on fees, particularly in the subprime product lines discussed below. Late and overlimit fees on an annual basis were only 0.7% of the average outstanding balances in 1990, but doubled during the 1990's to 1.4% or 1.5% of the average outstanding balances, a plateau at which they remained until they began to decline in 2005 and 2006. The second increased revenue source is fees paid by merchants that accept cards ("interchange"), which has risen about 70% faster than receivables, from 2.15% to 3.69% of average outstanding balances. In part, this reflects the ability of issuers, especially in recent years, to shift increasing numbers of cardholders to high-interchange premium and "platinum" products.[15]

---

[13] There was a sharp fall shortly after the implementation of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA), to 3.9% for 2006, but the rate trended steadily upward throughout 2007. It remains unclear whether the decline will be permanent.

[14] The most detailed evidence of that trend comes from Black & Morgan's comparison of the characteristics of credit cardholders in the 1989 and 1995 cross-sectional SCF studies.

[15] Premium cards typically bear higher interchange rates than subprime and prime cards, even though premium cardholders present lower risk to the issuer and their transactions involve no offsetting benefit for the merchant.

The second stage of market segmentation involves the development of increasingly complex product attributes that tailor products to specific classes of potential cardholders.[16] Thus, different issuers are particularly expert in superprime offerings (Chase Bank and Bank of America), affinity offerings (Bank of America's MBNA division), co-branded offerings (Chase Bank), relational offerings (Wells Fargo), subprime offerings (Capitol One), and foreign offerings (CitiBank). Each issuer tailors its products carefully to make them both profitable and attractive, with a different mix of anticipated revenue streams based on the type of customer. Superprime offerings, for example attract a portfolio of customers that spend very heavily and borrow occasional primarily for convenience. Issuers rely heavily on interchange and episodic interest payments, balanced against the large losses that come when a customer with a five-figure credit line becomes insolvent. Affinity products (bearing logos of universities, sports teams, or the like) are more likely to balance interchange against limited payments to sponsors, while co-branded offerings (bearing logos of airlines or leading retailers) are likely to balance annual fees and interchange against relatively high payments to sponsors. Relational offerings are part of a strategy in which a bank strives to provide many products to each customer, with a view to lowering the customer's price sensitivity on particular products.

For a study of LMI households, subprime issuers are the most interesting, because they are the issuers whose products are most likely to be seen commonly in LMI households.[17] Not surprisingly, subprime products rely heavily on interest income and fees. Indeed, a dominant share of the increase in fee revenue discussed above has come from the subprime market. In part, this

---

[16] The information in this paragraph is based on strategy analysis in the annual reports of large credit card issuers.

[17] This is not because subprime products are designed for LMI households. Product design depends much more on stability of income and on past repayment patterns than on the amount of current income. Subprime products are more likely to appear in LMI households because LMI households are more likely to have unstable incomes and poor or spotty repayment histories.

reflects the reality that the stated interest rates on those products (often in the range of 18%-24% per annum) are inadequate to provide a return on a portfolio with a chargeoff rate in the vicinity of 15-20%. Fee revenue provides a simple way to substantially increase the effective interest rate. Take, for example, a typical subprime $500 credit card line that has been fully extended. If the cardholder incurs three late or overlimit fees per year (not an unreasonable estimate), the issuer is likely to get approximately $100 in extra revenue.[18] Those fees add an additional 20% return per year on the credit line, for a total effective rate (assuming no other fees or charges) of about 35%-40%.

More aggressive card issuers, targeting customers of greater risk, design products with even higher effective rates. For example, one popular subprime card[19] has a $300 limit and a 20% interest rate, with $247 in upfront fees ($49 annual fee, $99 account processing fee, $89 program participation fee, and a $10 monthly maintenance fee). The fees are charged against the card when the cardholder receives it, leaving an available credit line of $53. If a cardholder makes a $53 purchase on the date the card arrives (thus expending the entire remaining available balance), and repays the balance in one month, the effective interest rate would be about 5500%. From a marketing perspective, this card might look attractive because it offers a grace period to cardholders that pay their balance in the entirety. Nor is that card unique. Another successful product offers a $250 limit and an interest rate of only 10%, with $178 in upfront fees ($29 account setup fee, $95 program fee, $48 annual fee, $6 participating fee). If that cardholder spends the entire available credit ($72) on the first day, and repays the balance at the end of the first month, the effective interest rate would be about 3000%. To be sure, the interest rates would fall if the cardholders took

---

[18] Carddata.com reports that the average late fee among large issuers currently is about $35.

[19] This paragraph describes two cards featured at a leading card comparison Web site as among the most attractive subprime cards in the fall of 2007.

longer to repay their balances, but the large share of fees compared to the maximum amount of available credit ensures that the effective interest rate will remain substantially higher than the stated interest rate.

Collectively, those market segmentation strategies are highly effective, at least for lenders that are able to employ cutting-edge technology. Large issuers say privately that only about 25% of their customers are unprofitable, a substantial improvement from the early 1990's when about half of the customers in a typical portfolio would be profitable to the issuer. One final corollary of the increasing importance of sophisticated underwriting technology is the rapid concentration of the lending market. Issuers that do not invest heavily in technology quickly fall behind, losing the ability to compete against those that do. As of 2006 the top five issuers held more than 70% of the outstanding credit card balances, up from only 39% in 1994.[20]

The changes in the credit card market raise important questions about the role of credit cards in the finances of LMI households. It is clear, of course, that a considerable number of LMI households have held credit cards for some time. For example, the analysis by Edward Bird and his coauthors of the 1995 SCF cross-sectional study shows that 36% of households below the poverty line had a credit card and about two-thirds were carrying balances.[21] Similarly, Peter Yoo's analysis of the SCF cross-sectional studies between 1983 through 1995 show that the share of households with credit cards and credit card debt has been increasing over time. Most importantly for present purposes, he shows that the rates of increase vary across deciles of the SCF's respondent population.[22]

---

[20] Compiled from the Nilson Report.

[21] Bird et al. 1999.

[22] Yoo 1997; Yoo 1998.

Still, we know relatively little about the extent of borrowing or the characteristics of LMI households that use credit cards. Existing research shows that credit cards play a different financial and social role in LMI households than they do in middle-class households. For example, Jeanne Hogarth and Kevin O'Donnell have studied in some detail the holdings of checking accounts among LMI households. Their work shows that a significant number (8%) of LMI households that do not have checking accounts nevertheless have credit cards.[23] So, credit cards must present benefits that extent beyond simple retail transacting.

Angie Littwin's research is particularly enlightening. Based on interviews with women in Boston housing projects, Littwin shows how credit cards provide a lifeline that facilitates access to or lower prices for a variety of mainstream transactions. She explains that the credit card helps LMI households remain a part of the mainstream economic community.[24] At the same time, these households have a deep-seated recognition of the risks they face if they borrow. Generally, Littwin suggests, these products would be more attractive to LMI households and also safer for them if they included a hard-credit line, thus limiting impulsive borrowing.[25]

Given the rapid changes in the credit market in the last 10 years, it is valuable both to update the early findings about the initial penetration of credit cards into LMI households and also to analyze the available data in more detail. For example, scholars have not examined which LMI households are most likely to hold credit cards or to borrow heavily with them. The segmentation and proliferation of product models discussed above suggests that the products that will be attractive to LMI households will function differently than the products that are attractive to the

[23] Hogarth & O'Donnell 1999. This fact seems surprising given the logistical difficulties of making payments on a credit card account without a checking account.

[24] The maintenance of a continuing sense of participation in the larger economy has substantial positive spillover effects. Phelps 1997.

[25] Littwin 2008.

middle class. Thus, it would be useful to understand who chooses to use those products and how the choices that LMI households make differ from the parallel choices that more financially secure households make.

It is not easy to find data to investigate those questions with care. National aggregate data are useful to understand the conceptual relations among spending, borrowing and financial distress,[26] but are of no use for this inquiry because they do not show how card use varies over the distribution of income. I decided to look to the 2004 survey of the Survey of Consumer Finances, conducted by NORC for the Federal Reserve Board. The 2004 survey is based on a complex sample of U.S. households[27] and includes data on income, assets, debt, borrowing, and the demographic characteristics of respondents.

There are some problems with the use of the SCF for such an inquiry. First, the SCF is not a panel survey. Rather, investigators draw a different sample of interview subjects (and train a different set of interviewers) for each edition of the survey. This limits the value of the data for analyzing trends over time – such as the changes in credit card use since 1990. Another well-known problem is the tendency of survey respondents to underreport stigmatizing behavior. Credit card borrowing, for example, is understated by about 30%, at least as compared to the Federal Reserve's G-19 statistics (which rely for the most part on call reports submitted by financial institutions to regulators).[28] At first glance, the large underreporting problem seems difficult to overcome, given the likelihood that the factors that cause the underreporting will create a selection bias in the data.

---

[26] Mann 2006.

[27] The SCF uses a dual sampling technique that includes a probability sample collected in specified geographic regions and a sample from the tax list provided by the Internal Revenue Service. The resulting sample oversamples higher wealth groups, but weighting of the data can be used to obtain estimates applicable to the U.S. population as a whole. Kennickell 2006.

[28] Mann 2006; Zinman 2007. For details on G.19, see Furletti & Ody 2006.

Jonathan Zinman's work, however, suggests that the underreporting is random with respect to other variables – so that the underreporting will affect only the weights of variables rather than the relation among them.[29] Reasonably skeptical observers, however, will worry that use of the SCF to analyze card-related behavior is a dubious enterprise. This is particularly true for a project that focuses directly on data known to be substantially underreported. Still, the fact remains that the SCF, despite its problems, is the best available source for household-level data about national patterns of card use.[30]

Patterns of Credit Card Use

Because the purpose of this project is to understand the role that credit card borrowing plays among LMI households (defined as the bottom two quintiles in the income distribution), I start by dividing the SCF dataset into five quintiles based on income. The two lowest quintiles (Quintiles 1 and 2 in the analysis below) end at $18,500 and $34,000 of annual income respectively.[31] Conversely, I use three distinct metrics to capture the penetration of credit card lending into LMI households: the number of households with any credit card debt at all (those carrying a positive balance); the size of the balances carried by households that are carrying balances ("CCBAL"); and the ratio of the household's credit card balance to its income ("CCSHARE").[32]

---

[29] Zinman 2007. Of course, the measures of credit card debt have other problems, particularly the difficulty of identifying outstanding credit card debt at the time of the interview and the fact that the outstanding debt at any particular point in time might not be representative of a person's average credit card debt. It is plausible to believe, though, that those problems will produce random errors.

[30] Kennickell 2006a.

[31] The descriptive statistics in this section reflect weighting of the data to compensate for the oversampling of high-income households, as well as averaging of the five implicates for each household.

[32] Kennickell 2006a.

Penetration of the Market

The most basic question about credit card use by LMI households is how often they borrow on cards, as compared to more affluent households. The answer, in short, is that their usage patterns are surprisingly similar. The importance of income as the primary source of repayment for credit card lenders suggests that a group of households defined by low income levels should have little or no credit card debt. On the contrary, it is startling how similar the borrowing patterns are for the four lower income quintiles.

I start with the incidence of debt – the share of households that report that they are carrying any credit card debt at all (46% across the entire dataset). Figure 3 breaks down that data by quintile. Several things about this figure are interesting. First, as expected it shows the highest rate of card balances (55%) in the middle-class quintile long considered the principal focus of credit card lending. The most intriguing feature of the data is the robust rate of borrowing in the two LMI quintiles. First, the 43% rate of borrowing by households in the moderate-income quintile is very close to the rates in the higher quintiles. This is a graphic illustration of the broadening of the traditional credit card demographic discussed above. The data here display a highly similar incidence of borrowing across the interior three quintiles of the populace – with incomes ranging from $23,500 (the top of the first quintile) to $90,000 (the bottom of the fifth quintile). To be sure, the 29% incidence of borrowing in the first quintile is considerably lower, but it is somewhat sobering given the reality that the first quintile consists of households with income below $23,500.

The second metric of credit card borrowing is the size of the balances carried by those households that are carrying balances. This metric provides considerably more information about borrowing than the first metric because it displays the intensity and regularity of borrowing. To set the frame of reference, the median balance for those carrying balances in the entire dataset is $2300, the 25% balance is $700, and the 75% amount is $6300. Figure 4 displays a series of boxplots by quintile, which show the complete range of the data as well as the 25 percentile, median, and 75 percentile values.[33]

Like Figure 3, several points about the boxplots in Figure 4 warrant emphasis. The most notable is the relative stability of balances across the three interior quintiles. To be sure, the amounts borrowed are staggered by quintile, but the differences are relatively insignificant. Finally, the level of debt in the first quintile is surprisingly high. Press reports and industry publicity suggest that credit limits of $500 are typical for low-income households. But these data suggest that most of the lower-income (first quintile) households that are carrying credit card balances have balances greater than $1000. Again, combining the importance of income to credit card underwriting with the limited income of these households, it is quite surprising that the typical balances could be so high. The most likely explanation is that, even in this quintile, most of the households that are carrying balances are using more than one card.

The third metric of credit card borrowing is the amount of the credit card balance as a share of income. For purposes of descriptive comparison, this metric has two advantages over the preceding metrics. First, given the role that income plays in credit card underwriting, it facilitates useful cross-quintile comparisons. To compare the extent to which customers in different quintiles are heavy borrowers, it is more useful to know what share of customers are borrowing a tenth of their annual income than it is to know what share of customers are borrowing $5000. Related to the first, the ratio of credit-card debt to income provides a useful tool for examining overindebtedness. Thus, Edward Bird and his co-authors use this metric to identify customers who have borrowed excessively.[34]

---

[33] The boxplots in Figures 2 and 3 exclude a number of statistical outliers.

[34] Bird et al. 1999.

The boxplots in Figure 5 underscore the analysis above. Again, the differences among the three interior quartiles are relatively slight, with typical debt loads of about one-twentieth of a customer's annual income. Again, this suggests a relatively homogeneous willingness to take and use credit cards within these quintiles. For another, the charts show an interesting and steady decline on each of the measurement points (25%, median, 75%). Thus, when we use this metric, we can see that respondents in the first quintile in fact borrow more intensively than respondents in the higher quintiles. The median borrowing share of about one-twelfth of annual income is higher than the median for the other quintiles. Half of the respondents have debt equal to a month's income, and a quarter of the respondents have debt equal to two months income. Moreover, the long right tail of borrowing share in that quintile suggests that creditors routinely write relatively extensive credit lines for people in this group.

Demographic Factors

Knowing that credit cards have become a common product for LMI households tells us little about who uses them, or, more importantly, whether the factors that relate to use by LMI households are the same as those that relate to use by the populace more broadly. For purposes of this study, I have chosen to examine five sets of demographic variables from the SCF: age, educational level, family status, race, and use of other financial products. My goals for this analysis are modest. I do not believe, for example, that a model based on these variables can reliably predict the level of credit card use. The models that credit card issuers use to predict card-related behavior are much more sophisticated, including dozens of variables for each potential cardholder. These variables are related not only to demographic factors like the ones included here, but more importantly to indicators of financial activity and creditworthiness that are not easily replicated in a survey like the SCF. To put it another way, the most important variables issuers use to identify the persons to whom they will extend credit (and the terms on which they will extend it) are missing from this dataset. The absence of those variables necessarily limits the quality of the potential models. Even more importantly, those factors cannot predict either the demand for credit cards or individual preferences and behaviors regarding borrowing and credit card use.

Nevertheless, we learn two things from investigating the demographic characteristics of credit card users. First, the model illuminates the social role of credit cards by contributing to an understanding of demographic differences between those that borrow and those that do not. Second, the model provides indirect evidence regarding to the hypothesis that the business models for the products that are marketed to LMI households differ substantially from those offered to more affluent households. If the factors that distinguish those that do and do not borrow (or among those that borrow) vary across quintiles, we might infer that the products being sold to customers in those quintiles differ in substantial ways. I analyze those variables in two steps. First, I present pairwise data comparing each of these variables to metrics of credit card use.[35] Second, I close the paper by presenting the results of efforts to create models fitting those demographic variables to the various credit card metrics discussed above.

Age

At least in the univariate analysis, the relation between age and credit card borrowing is relatively straightforward. On the one hand, to the extent cardholders use credit card borrowing to smooth consumption over their lifecycle, we should see more borrowing by relatively young cardholders and less borrowing by relatively old cardholders. As for the relation between this age effect and LMI households, we might expect that young cardholders in LMI quintiles would need to

[35] The demographic and regression analyses in this section examine only the existence of credit card debt and the amount of credit card debt. Because the relation between credit card balance and income relates directly to income, it is not useful to use it in regression models in which income will be one of the control variables.

borrow more frequently than young cardholders in more affluent households. Similarly, we might expect that cardholders in LMI households would be less likely to repay their debts and thus more likely to continue borrowing into middle and old age.

In general, the univariate data support that simple understanding of the relations among age, credit card debt, and income quintile. Table 1 shows the results of simple pairwise correlations between age and the existence of credit card debt. The coefficients are negative for each quintile, and in each case significant at the 0.01% level. Thus, the coefficients suggest that in each quintile people with credit card debt tend to be younger than those without credit card debt. Finally, the coefficient is weakest in the first quintile (where the credit card is least likely to be used for consumption smoothing) and strongest in the fourth quintile, where consumption smoothing is most likely. Figure 6 illustrates the distinction graphically, showing a gap between the mean ages of those who do borrow and those who do not, with the widest gap in the fourth quintile.

Educational Level

The relation between education and credit card borrowing is considerably harder to predict, primarily because it is difficult to be certain whether that increased financial sophistication would lead to a greater or lower incidence of credit card debt. Similarly, it is possible that education would have a different relation to credit card borrowing at different levels of affluence. Among LMI households, for example, it might be that only the relatively well-educated would be in a position to obtain a credit card, while in more affluent households (where educational levels are likely to be higher across the board) credit cards might be readily available even to the relatively less educated.

The correlations between educational level and credit card borrowing do little to dispel the ambiguity of the relationship suggested above. For the first four quintiles the coefficients steadily fall from a strongly positive coefficient in the first quintile to a strongly negative coefficient in the fourth quartile. There is no significant difference in the fifth quintile, apparently because there is relatively little variation in education. As illustrated graphically in Figure 7, the level of education steadily increases by quintile, but the credit card borrowers in the first two quintiles are the relatively more educated, while they are the relatively less educated in the third and fourth quintiles.

Family Status

The next demographic variables are family status variables – specifically whether the head of the household is married and whether there are children in the household. As with educational level, it is easy to discern conflicting possible relations. On the one hand, married families and those with children might be more stable, and thus less likely to need credit card borrowing. On the other hand, the greater level of stability and higher level of consumption might make them more attractive customers. Interestingly, the data suggest that having children and being married have different effects on the likelihood of credit card borrowing. As Figure 8 illustrates, having children correlates with having credit card debt, and the correlation is significant both overall and at each of the five quintiles. Figure 9, on the other hand, illustrates the more nuanced effect of marriage – the married who are in the two LMI quintiles are less likely to borrow on credit cards. Households with a married head of household in the more affluent quintiles, by contrast are more likely to borrow.

Race

The effects of race on credit card borrowing are most difficult to predict because of two directly conflicting intuitions. On the one hand, if markets function rationally, race would not be a useful predictor of either creditworthiness or financial behavior. On the other hand, if the effects of discrimination are present in lending or borrowing markets, or if race correlates substantially with important variables that are missing from this dataset, then we would find correlations between race and credit card behavior. The data in Table 1 suggest that whites are less likely to borrow on credit cards than blacks and Hispanics.

On the other hand, as the lower rows of that table illustrate, the significant correlation with race appears only in the more affluent quintiles; there are no significant correlations between race and the incidence of credit card debt in the LMI quintiles. The pattern is apparent in Figure 10. In the first two quintiles, all races have approximately the same incidence of credit card debt. But in the more affluent quintiles, blacks and Hispanics are much more likely to be carrying credit card debt.

Use of Other Financial Products

The last variable is the household's use of other financial products. This is not, strictly speaking, a demographic variable, but it seems important to include it in the model because it provides a valuable proxy for financial sophistication. If we think families are more likely to borrow on credit cards if they previous experience with other banking products, then we should expect a positive relation between having a checking account and carrying a credit card balance. The last column of Table 1 shows correlations between the most widely used of the other products (the checking account), which provide some support for that hypothesis, concentrated at the lower-income quintiles, apparently because almost all households in the more affluent quintiles have checking accounts.

Multivariate Analysis

Given the large number of variables that exhibit pairwise association, multivariate analysis is necessary to test the robustness of the associations. As explained above, it would be surprising if the variables in the SCF dataset explained most of the pattern of credit card borrowing. Credit card lenders rely on proprietary statistical models that aggregate dozens of variables from numerous sources, many of which are not in the public domain much less in the SCF.[36] Similarly, a model that predicts consumer behavior and preferences would include many variables beyond the straightforward demographic variables and financial sophistication variables used here.

Model for the Entire Dataset

The first step was to estimate models for the entire dataset. I estimate a logistic model for the binary credit card variable (whether the household has credit card debt) and an ordinary least squares model for the credit card balances variable (logged because of the skewness of the data). The function for the linear model is:

$$\text{Log}\mathit{CCBAL} = \beta_0 + \beta_1 \mathit{age} + \beta_2 \mathit{agesq} + \beta_3 \mathit{education} + \beta_4 \mathit{black} + \beta_5 \mathit{hispanic} + \beta_6 \mathit{logincome} + \beta_7 \mathit{incomeshock} + \beta_8 \mathit{empl} + \beta_9 \mathit{checking} + \beta_{10} \mathit{vehicle} + \beta_{11} \mathit{mortgage} + \beta_{12} \mathit{married} + \beta_{13} \mathit{children} + \beta_{14} \mathit{educlogincome} + \beta_{15} \mathit{blacklogincome} + \beta_{13} \mathit{hispaniclogincome} + \mathrm{u}$$

I use the RII method to reflect the multiple implicates for each household in the SCF dataset. Because of the controversy regarding the propriety (or necessity) of using weighting in regressions from the SCF dataset, I report alternate runs with and without weighting.[37] I separately tested first-order interactions among all of the independent variables and retained in the model the interactive variables that were economically and statistically significant in any of the models. As summarized in Columns 1 and 2 of Tables 2 and 3, the results of the multivariate analysis are substantially different from the results suggested by the univariate descriptions in the preceding section.

---

[36] Credit card lenders rely heavily, for example, on information about past spending and repayment patterns, much of which is far more detailed than the information available from credit reporting agencies. The information is proprietary, in part, because of its competitive value. The issuer familiar with years of spending, borrowing, and repayment history has a considerable advantage in designing and pricing products over an issuer that has never had a relationship with the cardholder. Among other things, consumers face high switching costs when competing issuers are less well placed to extend credit than their existing card issuer. This contributes, in turn, to the ability of issuers to charge higher prices to LMI customers (and other customers in distress).

[37] Lindamood et al. 2007.

Turning first to the demographic variables, although age was inversely correlated to debt in the univariate analysis presented above, the multivariate analysis suggests that the effect of age is much more ambiguous, with an inverse relation to the existence of debt and a positive relation to the amount of debt).[38] Similarly, blacks and Hispanics (more likely to have credit card debt in the univariate analysis) appear in the multivariate analysis only marginally more likely to have credit card debt, but at the same time significantly likely to have much less of it (at least in the unweighted models).[39] Income is inversely related to the existence of debt (because those at higher income levels are less likely to have debt), but positively related to the amount of debt. Similarly, education has little or no relation to the existence of debt but has a strong positive relation to the amount of debt. Finally, marital status and the existence of children are unimportant in the multivariate model, presumably because the other variables in the model data regarding age, education, and race capture the features of households most likely to relate to credit card borrowing.

I also use a series of financial controls that collectively indicate the creditworthiness and financial sophistication of the household: employment, having a checking account, car loan, or mortgage loan).[40] Not surprisingly, all of these variables relate positively to the existence and amount of credit card debt and all are significant at the 1% level.[41]

[38] Because the effect of age appears to be nonlinear, the OLS model includes agesquared and a number of interactive variables.

[39] Significant positive coefficients on black*logincome and hisp*logincome suggest that the effects of increasing income to increase credit card debt are more pronounced for blacks and Hispanics than they are for Caucasians.

[40] The variables for having a vehicle or mortgage loan likely measure creditworthiness, because the standards for underwriting those loans are somewhat more rigorous, even recognizing the secured nature of those loans. But, they also measure a tolerance for borrowing and a willingness to use financial products and services. The ambiguity in the measure, thus, makes it somewhat difficult to interpret the results. Nevertheless, using those measures permits a more nuanced analysis of credit card borrowing and lending practices.

[41] Four interactive variables indicate that the effects of other variables are related to income. First, the interactions with race are discussed in footnote 39. Second, significant negative coefficients on

I also tested an "income shock" variable, which indicates whether the household's current income is 25% less than the household's "normal" income as described in survey responses. If credit card borrowing compensates for a shock to the household's income, this variable should relate positively to credit card borrowing. If income shock causes households to borrow less, and thus pay down their obligations, this variable should relate negatively to credit card borrowing. Somewhat to my surprise, the variable has a negative coefficient in all four models, and is related to the existence of debt at the 1% level, albeit only in the unweighted model.

Model for the Two LMI Quintiles

Finally, I estimated the same models for the two LMI quintiles.[42] To ease comparison between the overall dataset and the LMI quintiles, Table 2 reports all four of the models regarding the existence of credit card debt (with the results for LMI households in Columns 3 and 4); Table 3 reports all four of the models regarding the amount of credit card debt (with the results for LMI households in Columns 3 and 4).

The principal difference between the two sets of models is that the demographic variables are much less important in the LMI model. For example, race, children, and income are wholly insignificant in those models. The only demographic variable with a robust relation in this model is age, which has a strong positive relation to the amount of credit card debt in LMI households (thought not to the existence of debt). Education now has a weakly positive relation on both the

---

educ*logincome suggest that the positive effects of increasing income and education are mitigated when *both* income and education increase. Finally, marginally significant coefficients on logincome*incomeshock suggest that the negative effects of the income shock variable on credit card debt are mitigated at higher levels of income.

[42] I also estimated separate models for each of those two quintiles. Although the magnitude of most of the coefficients in those models was similar, it was more difficult to discern significant relations because of the smaller sample size.

existence and amount of debt, and marital status has a significant positive relation in the unweighted models (although not in the weighted models).

Conversely all of the financial variables (employment, checking accounts, car loan, and mortgage loan) remain significant at the 1% level across all specifications. Interestingly, this suggests that even at the lowest levels, the amount of income is much less relevant to credit card lending than the reliability of the income (as evidenced by employment). The most apparent explanation of the strong effects for the other financial products variables is that the model reflects a "taste" for financial products: households that are integrated into the financial institutions of society (as evidenced by their use of one of those products) are much more likely to be using other products as well.

Finally, the income shock variable is much less important in the LMI quintiles than in the overall model. This suggests, interestingly enough, that the level and existence of credit card debt for the lower quintiles is relatively unaffected either by income or by changes in income level. It is not clear what to make of this finding. One possibility of course is that the dataset is too small or has insufficient variation to reveal a relation that in fact exists. Another possibility, as with the findings related to financial products, is a "taste" for financial products, which leaves the choice to use credit card debt unrelated to income shocks.[43]

Conclusion

This chapter provides a glimpse of the role that credit cards play in the financial life of LMI households. Most obviously, the data show that credit cards are now a major part of the economic life of the poorest U.S. households. Indeed, at least as a share of income, the credit card debt that

[43] None of the interactive variables are significant in the LMI models.

LMI households carry is higher than that of more affluent households. The data also illustrate the patterns by which credit card borrowing is distributed based on age, race, and other demographic factors.

The statistical analysis of demographic characteristics of borrowers is intended to be suggestive, with a view to showing how rational lenders that specialize in different markets would target entirely different groups of customers. The variations in correlation and association by quintile provide strong evidence of the reasons why sophisticated issuers should design and market different products to households at different income levels. The data do not, however, provide reliable information on the actual factors that credit card issuers use to underwrite their loans. Moreover, data limitations aside, the absence of panel data means that the SCF simply cannot provide the temporal evidence useful for examining causal effects. Given the difficulties of using surveys to collect panel data on that question, the best source for research of that nature likely would be data from the portfolio of a major credit card issuer.

Returning to the focus on access and safety with which the chapter began, the data provide stark evidence about the high incidence and level of debt among the poorest families. Looking at the lowest quintile alone – with income below $23,000 – 31% of the households are carrying credit card debt. Among those that carry credit card debt, half have debt equal to 10% of their income and a quarter have debt equal to 25% of their income (all before making mortgage payments, car payments, child support payments and the like). As I discuss, the process of repaying that debt typically will involve high interest rates and considerable fees. By comparison, among the middle class borrowers who are so widely bemoaned for their rampant spending and overindebtedness, the median debt share is only 5% and only a quarter have debt that exceeds 10% of their incomes. By any yardstick, we must acknowledge that credit card use among poor households has created a debt overhang that many households will bear for years, if not decades.

Bibliography

Bird, Edward J. et al. Credit Card Debts of the Poor: High and Rising, 18 J. Pol'y Analysis & Management 125 (1999)

Black, Sandra E. & Donald P. Morgan. Meet the New Borrowers, 5 Current Issues in Economics & Finance No. 3 (Fed. Reserve Bank of New York Feb. 1999)

Cards & Payments. Statistics about credit card profitability and expenses over time are compiled from the annual cards profitability surveys published by Cards & Payments (formerly Cards Management).

Caskey, John P. Fringe Banking: Check-Cashing Outlets, Pawnshops and the Poor (1996).

Cross, Gary. An All-Consuming Century: Why Commercialism Won in Modern America (2000).

Frank, Robert H. Luxury Fever: Money and Happiness in an Era of Excess (1999).

Furletti, Mark & Christopher Ody. Measuring U.S. Credit Card Borrowing: An Analysis of the G.19's Estimate of Consumer Revolving Credit (Payment Cards Center Discussion Paper, Fed. Reserve Bank of Philadelphia Apr. 2006).

Hacker, Jacob S. The Divided Welfare State: The Battle over Public and Private Social Benefits in the United States (2002).

Hogarth, Jeanne M. et al. Why Don't Households Have a Checking Account?, 38 J. Consumer Affairs 1 (2004).

Hogarth, Jeanne M. & Kevin H. O'Donnell. Banking Relationships of Lower-Income Families and the Governmental Trend toward Electronic Payment, Fed. Res. Bull, July 1999, at 459.

Howard, Christopher. The Welfare State Nobody Knows: Debunking Myths About U.S. Social Policy (2007).

Kennickell, Arthur B. Codebook for 2004 Survey of Consumer Finances. Washington, DC: Board of Governors of the Federal Reserve System (2006).

Kennickell, Arthur B. How Do We Know If We Aren't Looking? An Investigation of Data Quality in the 2004 SCF (American Statistical Ass'n 2006).

Lindamood, Suzanne et al. Using the Survey Method of Consumer Finances: Some Methodological Considerations and Issues, J. CONS. AFFAIRS, Winter 2007, at 195.

Littwin, Angela. Beyond Usury: A Study of Credit Card Use and Preference Among Low-Income Consumers, 86 TEXAS L. REV. 451 (2008).

Littwin, Angela. Comparing Credit Cards: An Empirical Examination of Borrowing Preferences Among Low-Income Consumers (2008 working paper).

Mann, Ronald J. Charging Ahead: The Growth and Regulation of Payment Card Markets Around the World (Cambridge U. Press 2006).

Mann, Ronald J. Bankruptcy Reform and the "Sweat Box" of Credit Card Debt, 2007 Ill. L. Rev. 375.

Mann, Ronald J. & Jim Hawkins. Just Until Payday, 54 UCLA L. Rev. 855 (2007).

Nilson Report: I use a variety of national aggregate statistics reported in the Nilson Report.

Phelps, Edmund S. Rewarding Work (1997).

Schor, Juliet B. The Overspent American: Why We Want What We Don't Need (1999).

Warren, Elizabeth. Unsafe at Any Rate, DemocracyJournal.Org, Summer 2007.

Yoo, Peter S. Charging up a Mountain of Debt: Accounting for the Growth of Credit Card Debt, Fed. Res. Bank of St. Louis Review, Mar./Apr. 1997, at 3.

Yoo, Peter S. Still Charging: The Growth of Credit Card Debt Between 1992 and 1995, Fed. Res. Bank of St. Louis Review, Jan./Feb. 1998, at 19.

Zinman, Jonathan. Where Is the Missing Credit Card Debt? Clues and Implications (Sept. 2007 working paper).

Appendix

Figure 1 – Spending on Retail Payment Systems (U.S.)

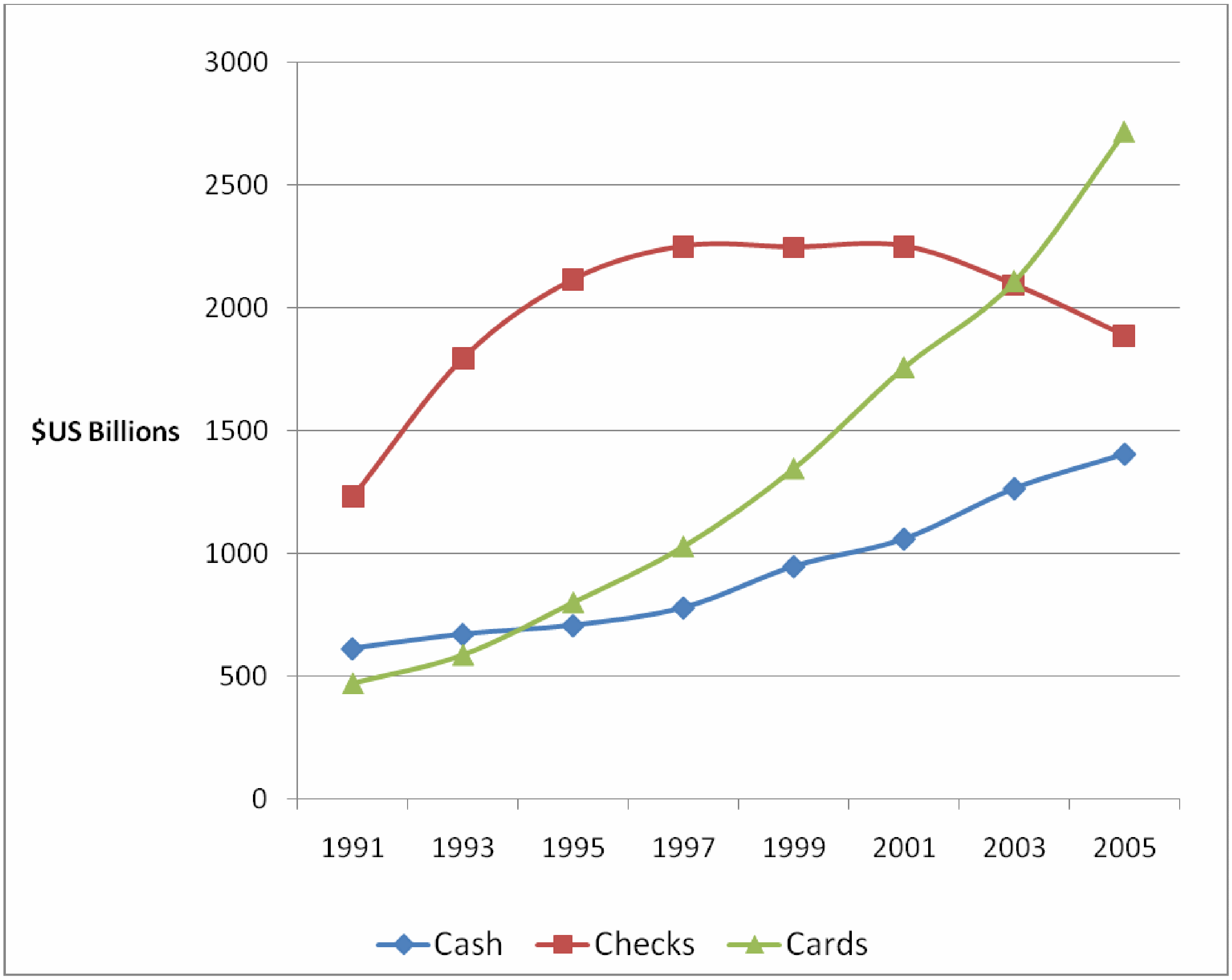

Figure 2 – Cards Profitability Data

(Percentages of Outstanding Receivables)

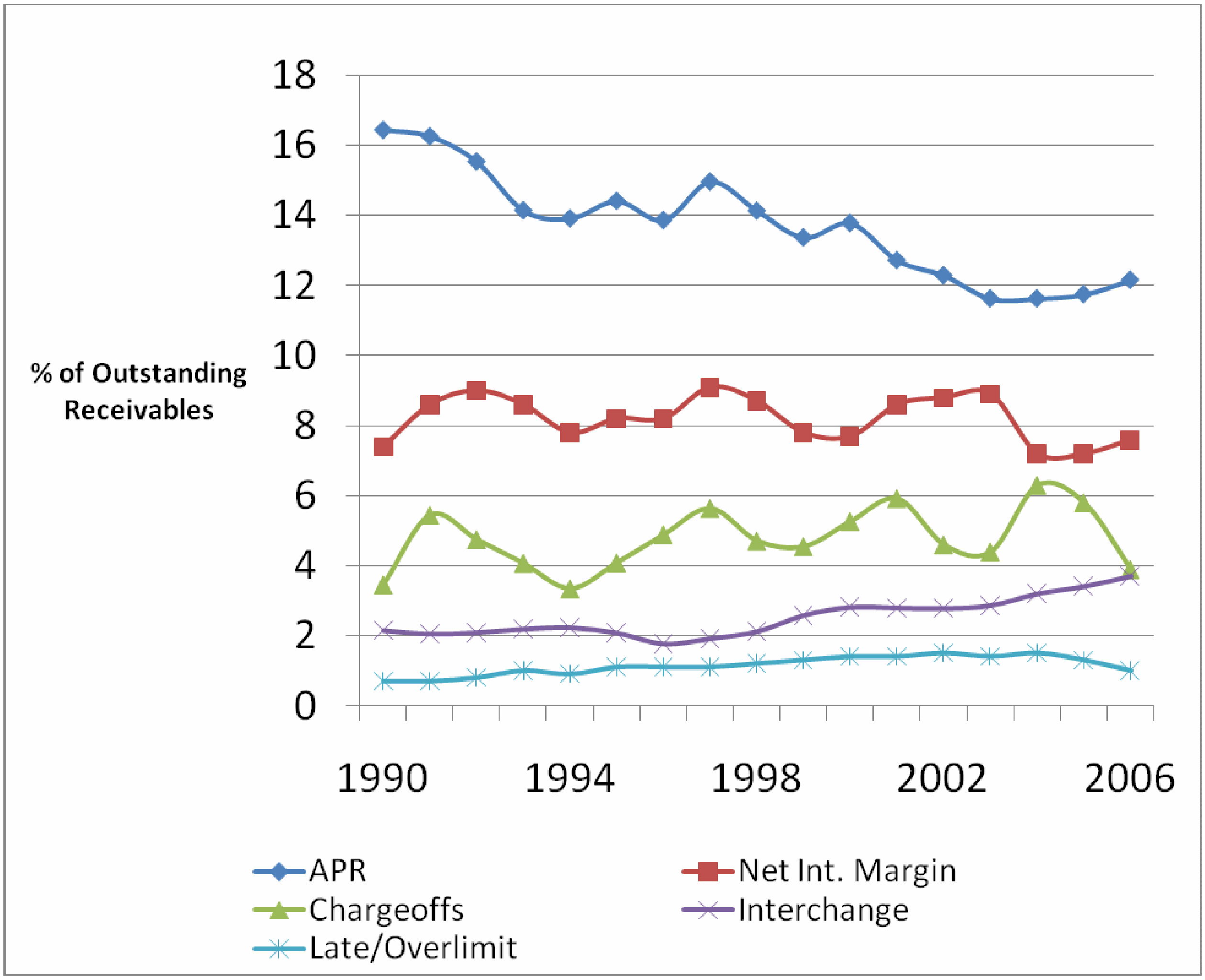

Figure 3: Percent of Households Holding Credit Card Balances

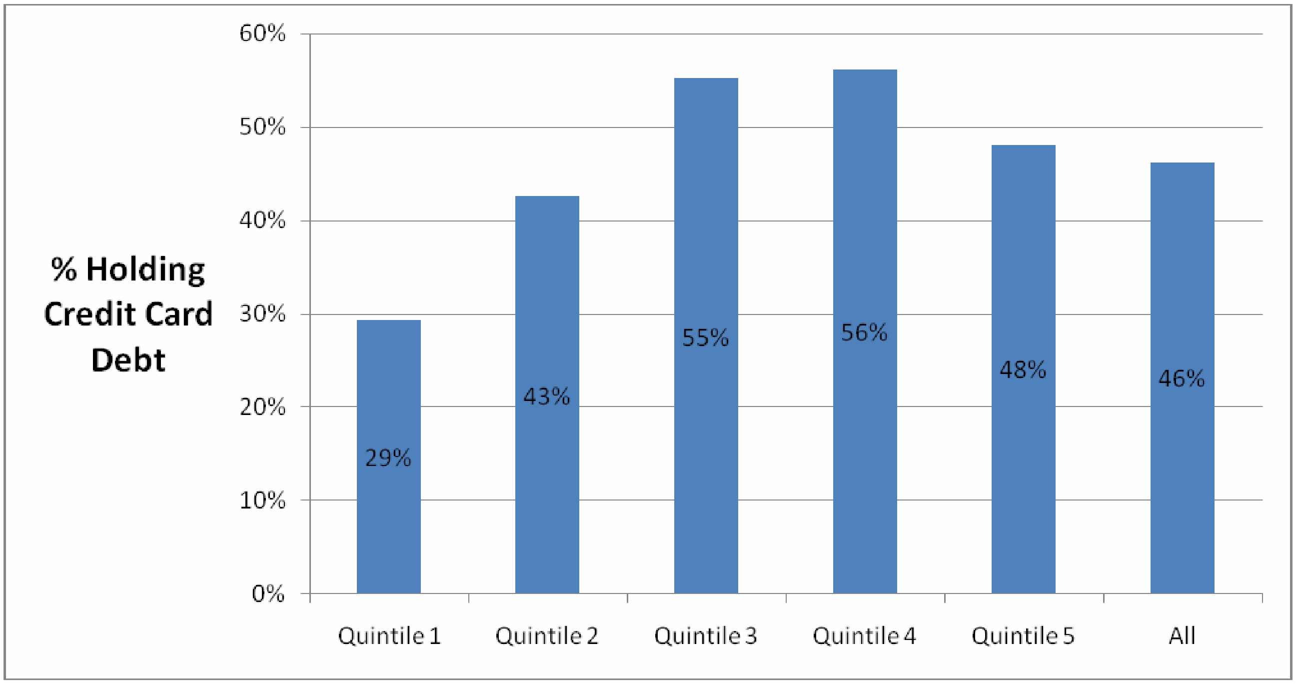

Figure 4: Credit Card Balances (by Quintile)

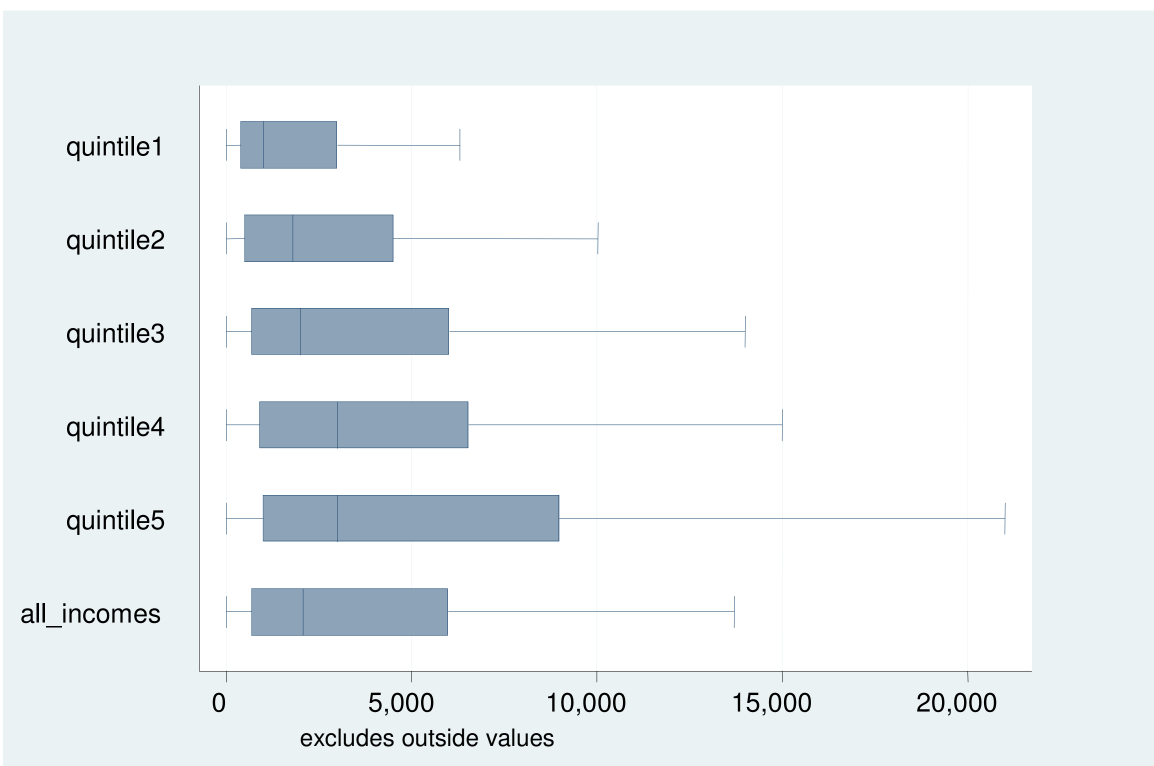

Figure 5: Credit Card Balance as a Share of Income (by Quintile)

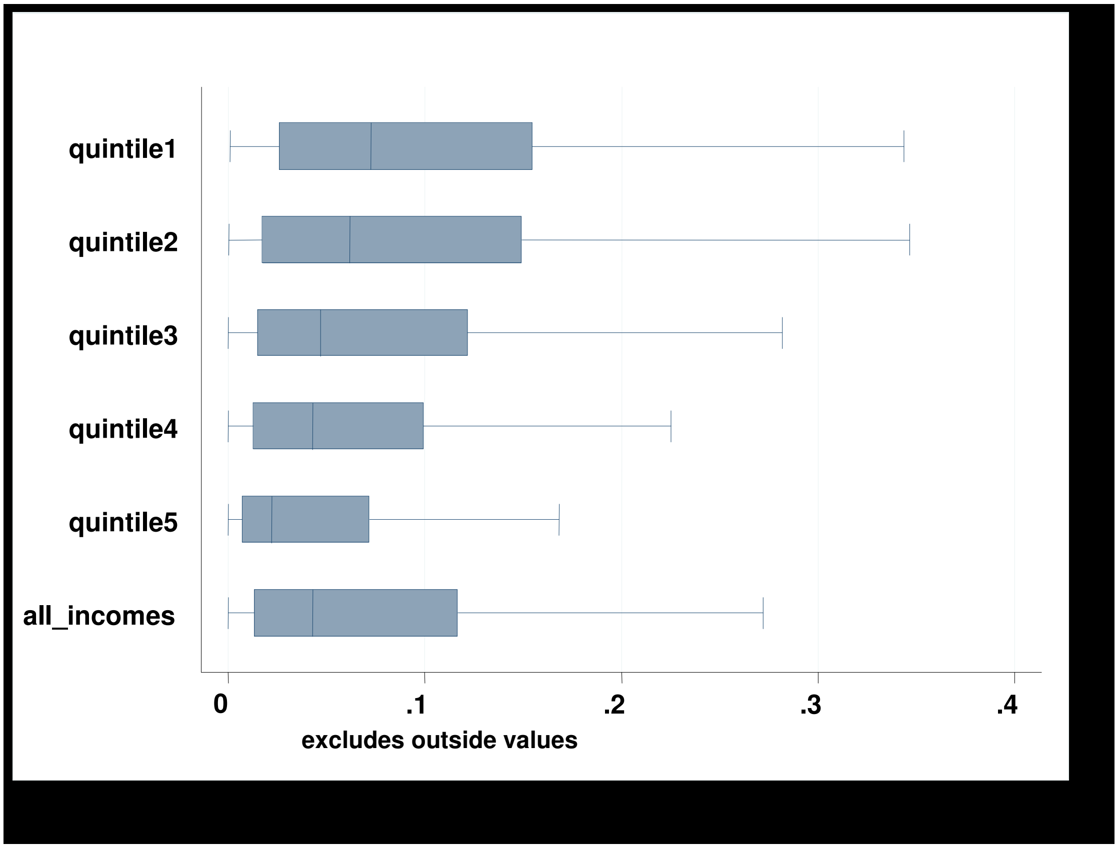

Figure 6: Mean Age and Credit Card Debt (by Quintile)

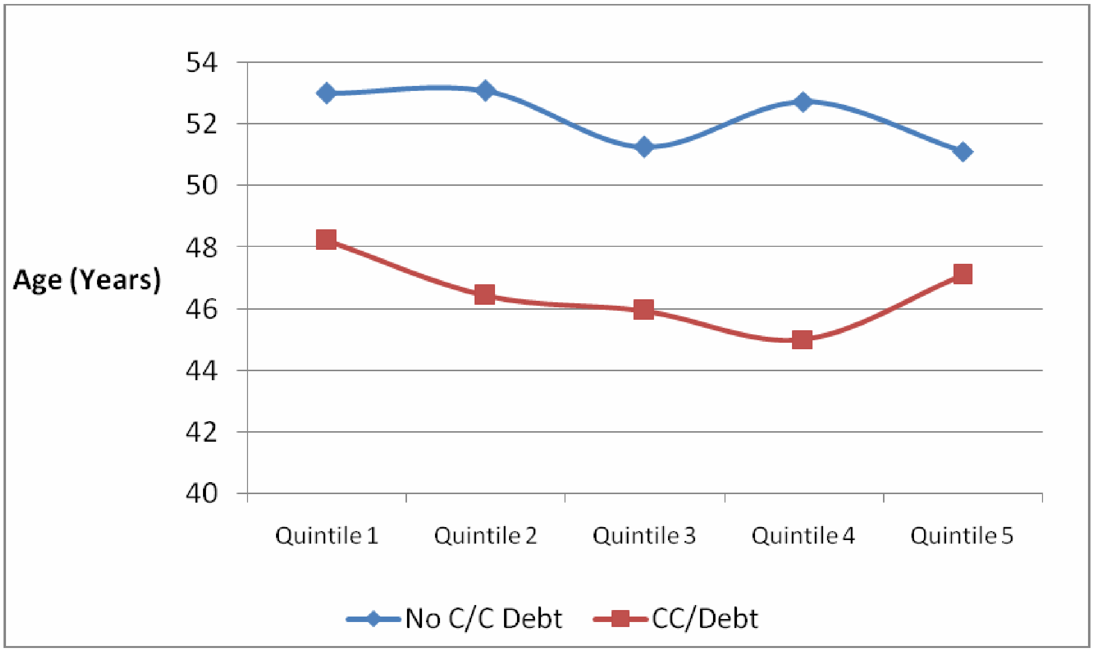

Figure 7: Mean Education and Credit Card Debt (by Quintile)

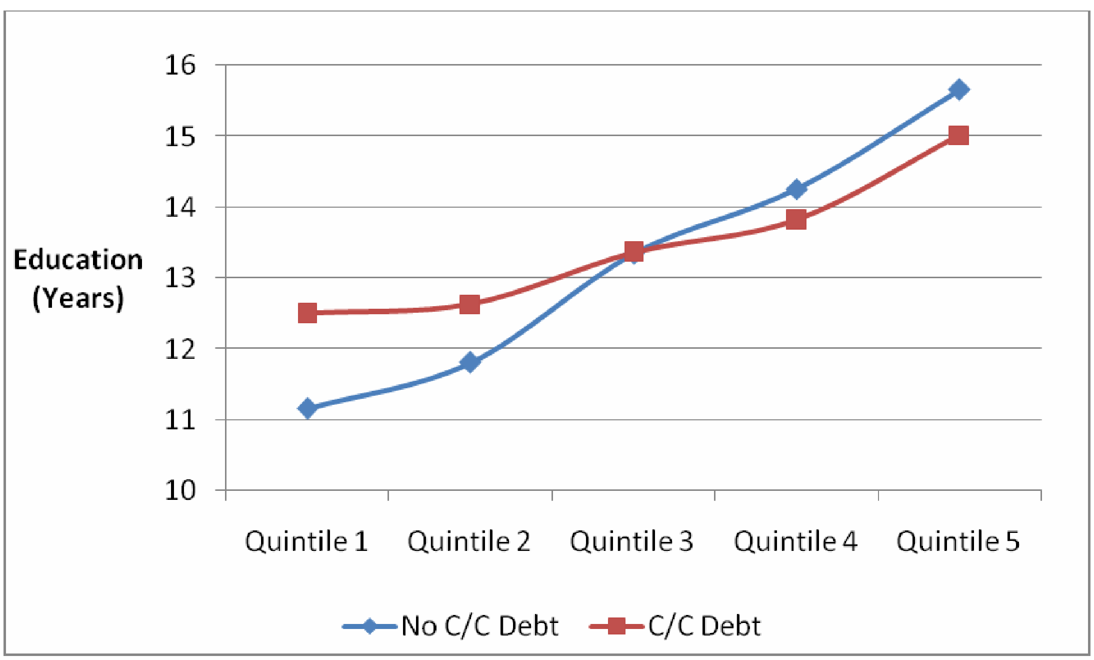

Figure 8: Children in the Household and Credit Card Debt

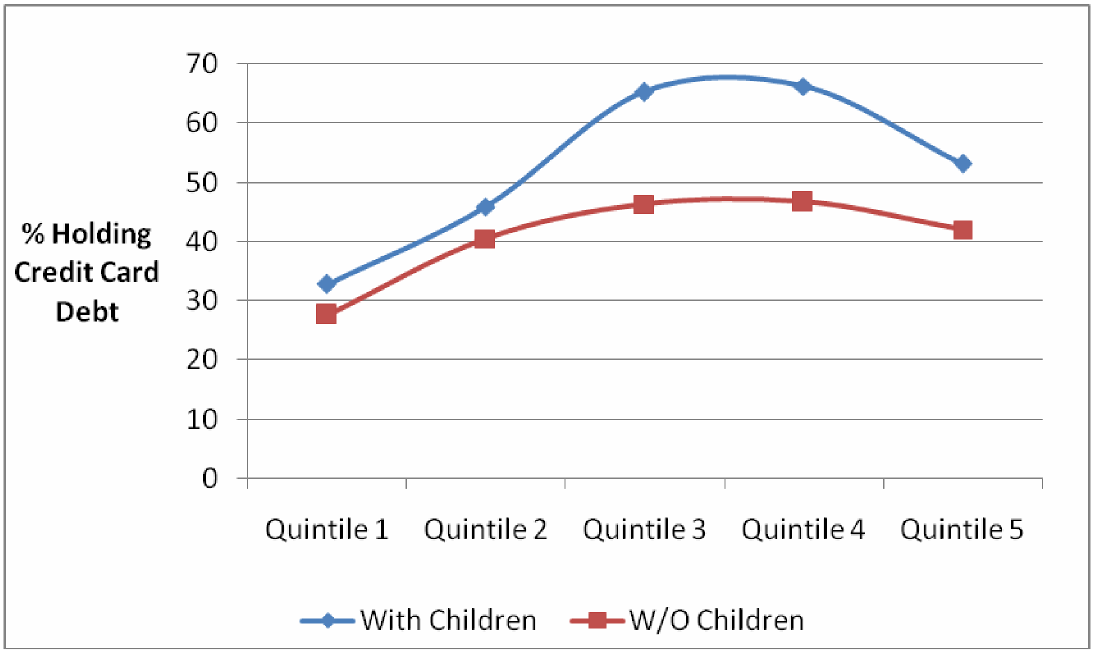

Figure 9: Marital Status and Credit Card Debt

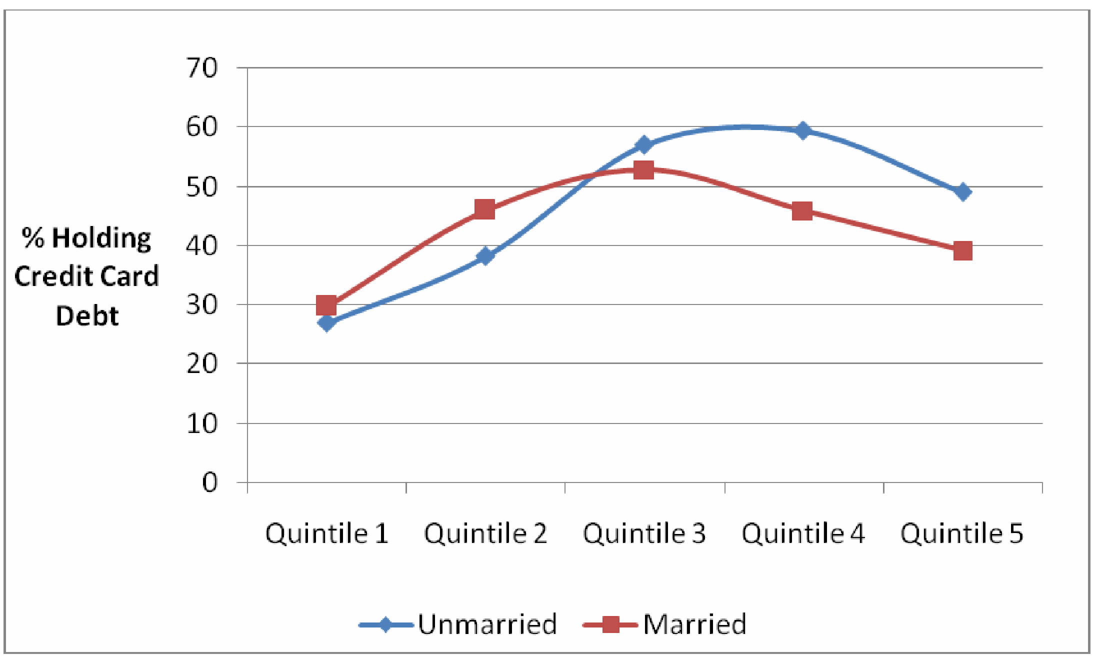

Figure 10: Credit Card Debt (by Race and Quintile)

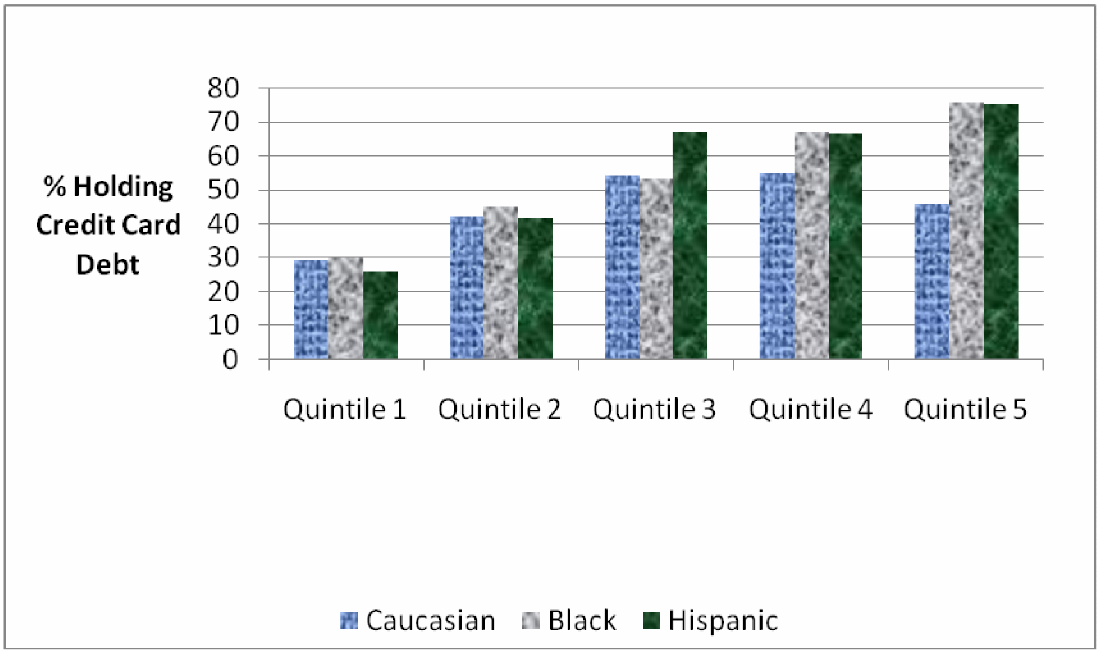

Figure 11: Credit Card Debt and Other Financial Products

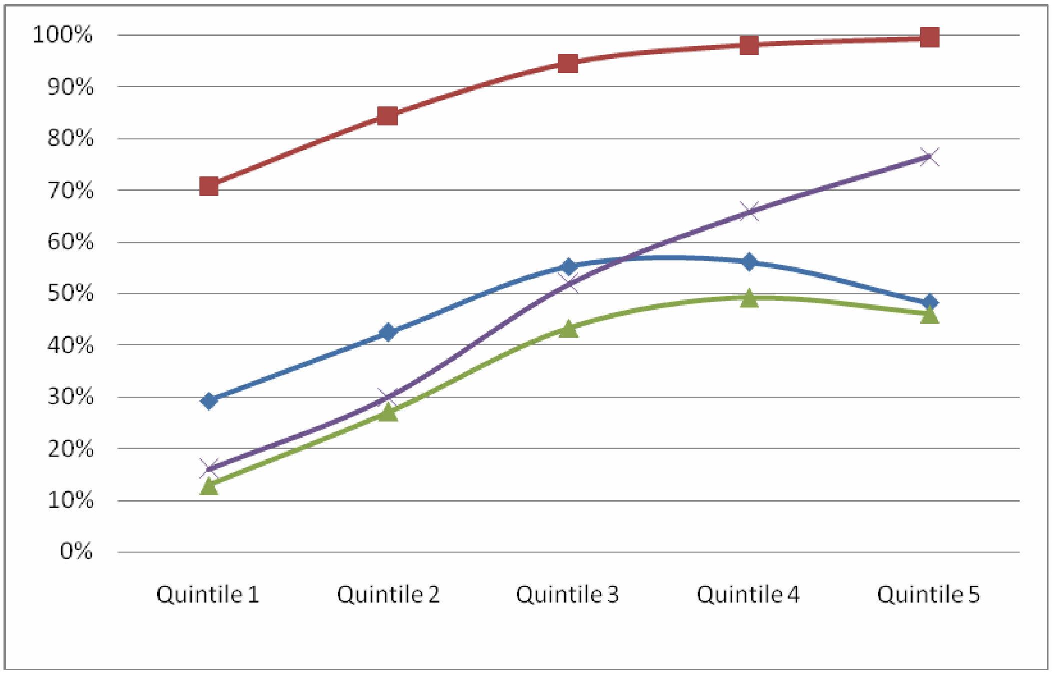

Table 1: Correlations between Demographic Variables and Borrowing on Credit Cards

Quintile	Age	Educ.	Married	Children	Cauc.	Black	Hisp	Checking Account
Overall	-.17***	.09***	-.09***	.15***	-.004	.01	.005	.16***
1	-.10**	.19***	.03	.05	.001	.01	-.03	.20***
2	-.17***	.14***	.08*	..05	-.02	.02	-.01	.16***
3	-.16***	.003	-.04	.19***	-.03	-.02	.07*	.06
4	-.26***	-.09**	-.12***	.20***	-.05	.07	.05*	.03
5	-.17***	-.17***	-.06	.11***	-.12***	.13***	.1***	-.01

* - 5% ** - 1% *** - .1%

The table reports correlations with the binary variable for the existence of credit card debt. Thus, positive correlations suggest that the characteristic is positively related to borrowing on credit cards; negative correlations suggest the converse.

Table 2 – Logistic Regression Models for Households Holding Credit Card Debt

	(1)	(2)	(3)	(4)
	All	All Weighted	LMI	LMI Weighted
age	0.989***	0.992***	0.995	0.995
	(0.003)	(0.003)	(0.004)	(0.004)
educ	0.973*	0.994	1.068***	1.078***
	(0.015)	(0.016)	(0.025)	(0.026)
black	1.305**	1.359**	1.052	1.192
	(0.119)	(0.122)	(0.168)	(0.181)
hisp	1.349**	1.269*	1.331	1.303
	(0.134)	(0.140)	(0.205)	(0.211)
logincome	0.717***	0.905***	1.062	1.020
	(0.039)	(0.036)	(0.053)	(0.053)
incomeshock	0.743***	0.895	0.862	0.878
	(0.115)	(0.128)	(0.155)	(0.167)
empl	1.696***	1.714***	1.636***	1.751***
	(0.107)	(0.115)	(0.161)	(0.168)
chk	3.770***	3.019***	2.573***	2.627***
	(0.159)	(0.156)	(0.177)	(0.181)
vehlbin	2.596***	2.382***	2.356***	2.380***
	(0.074)	(0.083)	(0.149)	(0.156)
mortbin	2.036***	1.954***	2.010***	2.143***
	(0.075)	(0.086)	(0.150)	(0.161)
married	1.050	1.059	1.305*	1.172
	(0.090)	(0.092)	(0.140)	(0.150)
kidsbin	1.124	1.163*	1.035	1.061
	(0.076)	(0.086)	(0.142)	(0.149)
Pseudo R2	0.145	0.111	0.107	.116
Observations	4519	4519	1359	1359

Table reports odds ratios with standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
Adjusted R-squared calculated based on first implicates.

Table 3 – OLS Regression Models for the Level of Credit Card Balances

	(1)	(2)	(3)	(4)
	All	All Weighted	LMI	LMI Weighted
age	0.068***	0.081***	0.082***	0.077***
	(0.019)	(0.021)	(0.026)	(0.026)
agesquared	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
educ	0.809***	1.147***	0.241	0.451*
	(0.129)	(0.189)	(0.264)	(0.267)
black	-3.430***	-1.649	1.158	0.837
	(1.031)	(1.112)	(1.412)	(1.400)
hisp	-4.699***	-3.470*	-0.837	-0.756
	(1.576)	(1.913)	(1.968)	(2.046)
logincome	0.718***	1.313***	0.321	0.513
	(0.185)	(0.272)	(0.392)	(0.403)
incomeshock	-0.234	-0.070	-0.088	-0.073
	(0.176)	(0.212)	(0.231)	(0.249)
empl	0.664***	0.758***	0.674***	0.807***
	(0.146)	(0.188)	(0.234)	(0.249)
chk	1.546***	1.416***	1.358***	1.368***
	(0.193)	(0.203)	(0.219)	(0.221)
vehlbin	1.586***	1.523***	1.305***	1.285***
	(0.132)	(0.148)	(0.248)	(0.256)
mortbin	1.002***	1.228***	1.137***	1.214***
	(0.119)	(0.152)	(0.257)	(0.268)
married	0.138	0.105	0.372*	0.228
	(0.131)	(0.153)	(0.207)	(0.220)
kidsbin	0.143	0.237	-0.098	0.002
	(0.121)	(0.147)	(0.211)	(0.222)
educlogincome	-0.078***	-0.110***	-0.015	-0.036
	(0.012)	(0.018)	(0.028)	(0.028)
blacklogincome	0.360***	0.192*	-0.127	-0.074
	(0.101)	(0.110)	(0.149)	(0.149)
hisplogincome	0.504***	0.378**	0.124	0.108
	(0.151)	(0.186)	(0.210)	(0.217)
Constant	-8.433***	-14.907***	-5.831	-7.572*
	(2.031)	(2.823)	(3.824)	(3.920)
R2	0.188	0.167	0.140	0.151
Observations	4519	4519	1359	1359

Standard errors in parentheses
Pseudo R2 calculated based on first implicates.
*** significant at 10%; ** significant at 5%; *** significant at 1%**