Patterns of Credit Card Use Among Low- and Moderate-Income Households

Ronald J. Mann

Insuring 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 and "fringe" products like payday lending, check-cashing services, and pawnshops (Barr, this volume; Caskey 1996; Hogarth, Anguelov, and Lee 2004; Mann and Hawkins 2007). At the same time, because many of those products exploit cognitive and financial constraints, policymakers are now increasingly moving beyond concerns about access to emphasize the need for safety in the design and marketing of financial products (Warren 2007).

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 trendsetters in our society and purchase the same goods and services, at the same prices. As status in a consumer society shifts to depend more heavily on consumption (rather than family wealth or occupational status), the credit card acts as a leveler of status (Cross 2000, 169–84; Frank 1999, ch. 4). The credit card also provides a remarkably flexible safety net that can be deployed in response to unexpected financial crises (Mann 2006). That protection is particularly important in the United States, where the public safety net is more porous than it is in many peer nations (Hacker 2002; Howard 2007).

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 (Schor 1999). In previous work, I present aggregate data that suggest a significant relation between increased credit card use and consumer bankruptcy filings at a national level (Mann 2006). The

flexibility that makes the credit card so useful for households faced with unexpected difficulties is central to the danger that the product can bring to those who use it in excess (Littwin 2008a; Mann 2007; Mann and Hawkins 2007). Safety concerns are particularly important in connection with financial products for the poor (McCloud 2007).

This chapter uses data from the Federal Reserve Board's Survey of Consumer Finances (SCF) for 2004 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 (for more detail, see Mann 2007). Among other things, that trend involves the use of products aimed at LMI households that differ significantly from those aimed at middle-class households.

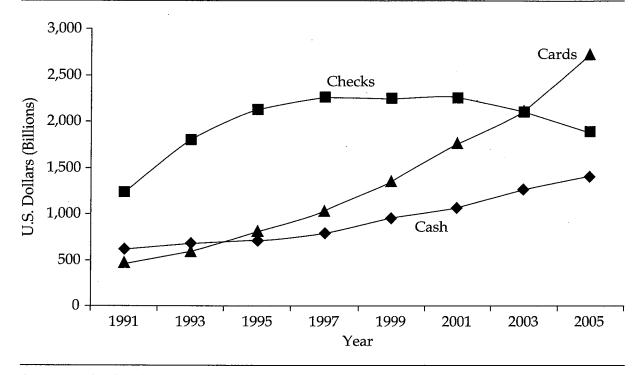
Second, I describe the use of credit cards by LMI households: the amounts of debt they carry; the types of LMI households that carry debt; and how these households differ from higher-income households that carry debt. Despite their lower incomes, LMI households use credit cards almost as often as other households do. Indeed, measured as a share of income, the credit card balances that LMI cardholders carry are substantially higher than those of higher-income households. To refine the analysis, 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 households in the overall population with credit card debt. The models I summarize here suggest that age, race, and education correlate with credit card use in the population at large. At least in these models, however, age and race become less important predictors, and education has only a marginal relation to credit card use in LMI households. In LMI households, by contrast, credit card use is most closely related to the use of other financial products: checking accounts, mortgage loans, and car loans.

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 increased from about \$800 billion in 1990 to more than \$1.7 trillion in 2006. Similarly, credit card balances increased from about \$450 billion in 1990 to more than \$750 billion in 2006 (Nilson Report; for a more detailed discussion, see Mann 2006). As figure 9.1 illustrates, the rise in spending on cards reflects a substantial shift toward cards and away from other payment devices.

What is less widely understood is the mechanism by which this has occurred. Credit card lending is by 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,

FIGURE 9.1 / Spending on Retail Payment Systems in the United States, 1991 to 2005



Source: Author's calculations based on the Nilson Report.

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 who 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 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 practice, the most effective lever the credit card lender has is the threat of damaging the credit report of the borrower. A credit card debtor who 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 is at most one of many inputs into the underwriting process. In any event, the threat of an adverse credit report is ineffective against debtors who are in serious financial distress and whose 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

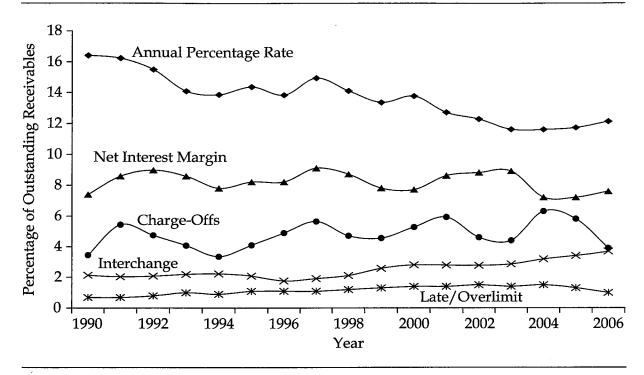
service. Interest rates were standard and relatively high, typically in the range of 18 percent. At the same time, despite those relatively high rates, the customers to whom credit card lenders could make profitable loans were a relatively small part of the middle class. The wealthy had little interest in borrowing at 18 percent, and those who had no reliable income stream were too risky. In general, most issuers had a large group of profitable customers who borrowed and paid substantial amounts of interest, a second group of generally unprofitable customers who did not borrow but instead paid their bills each month, and a third group of highly unprofitable customers who 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 1990s 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 (Johnson 2005). 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 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 percent in 1990 to 12.2 percent in 2006, 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 percent in 1990 to 7.6 percent in 2006). At the same time, however, the portfolios underwritten at that margin have become considerably riskier. For example, the rate at which issuers write off unpaid balances (charge-offs) steadily increased during this period, from 3.5 percent in 1990 to about 6 percent during 2004 to 2005. 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 who would have been unacceptably risky a few decades ago.³

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 charge-offs 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 later in this chapter. Late and overlimit fees on an annual basis were only 0.7 percent of the average outstanding balances in 1990, but doubled during the 1990s to 1.4 percent or 1.5 percent 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 percent faster than receivables, from 2.15 percent to 3.69 percent of average outstanding balances. In part, this reflects the ability of issuers, especially in recent years, to shift

FIGURE 9.2 / Cards Profitability Data



Source: Author's calculation from Cards Profitability Survey, published by Cards and Payments.

increasing numbers of cardholders to high-interchange premium and "platinum" products.4

The second stage of market segmentation involves the development of increasingly complex product attributes that tailor products to specific classes of potential cardholders. Thus, different issuers are particularly expert in superprime offerings (Chase Bank and Bank of America), affinity offerings (Bank of America's MBNA division), cobranded 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 who spend very heavily and borrow occasionally, 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 cobranded 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 the unstable incomes and poor or spotty repayment histories of many LMI families make them likely users of those products. Not surprisingly, subprime products rely heavily on interest income and fees. Indeed, a dominant share of the increase in fee revenue discussed in this chapter has come from the subprime market. In part, this reflects the reality that the stated interest rates on those products (often in the range of 18 to 24 percent per annum) are inadequate to provide a return on a portfolio with a charge-off rate in the vicinity of 15 to 20 percent. 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 receive approximately \$100 in extra revenue. Those fees add an additional 20 percent return per year on the credit line, for a total effective rate (assuming no other fees or charges) of about 35 to 40 percent.

More aggressive card issuers, targeting higher-risk customers, design products with even higher effective rates. For example, one popular subprime card has a \$300 limit and a 20 percent interest rate, with \$247 in up-front fees (\$49 annual fee, \$99 account processing fee, \$89 program participation fee, and \$10 monthly maintenance fee).8 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 5,500 percent. From a marketing perspective, this card might look attractive because it offers a grace period to cardholders who pay their entire balance. Nor is this card unique. Another successful product offers a \$250 limit and an interest rate of only 10 percent, with \$178 in up-front 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 3,000 percent. To be sure, the interest rates would fall if the cardholders took 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, these 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 percent of their customers are unprofitable, a substantial improvement from the early 1990s, 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 percent of the outstanding credit card balances, up from only 39 percent in 1994 (Nilson Report).

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 con-

siderable number of LMI households have held credit cards for some time. For example, the analysis by Edward Bird, Paul Hagstrom, and Robert Wild (1999) of the 1995 SCF cross-sectional study shows that 36 percent of households below the poverty line had a credit card, and about two-thirds were carrying balances. Similarly, Peter Yoo's (1997, 1998) analysis of the SCF cross-sectional studies between 1983 and 1995 shows 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.

Still, relatively little is known 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 (1999) have studied in some detail the holdings of checking accounts among LMI households. Their work shows that a significant number (8 percent) of LMI households that do not have checking accounts nevertheless have credit cards. So credit cards must present benefits that extend beyond simple retail transacting.

Angela Littwin's (2008b) 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. 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 precluding overlimit borrowing.

Given the rapid changes in the credit market in the last ten years, it is valuable both to update the early findings about the initial penetration of credit cards into LMI households and 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 earlier in this chapter suggests that the products that are attractive to LMI households function differently than the products that are attractive to the middle class. Thus, it would be useful to understand who chooses to use credit cards and how the choices that LMI households make differ from the parallel choices made by more financially secure households.

It is not easy to find data to investigate these questions with care. National aggregate data are useful to understand the conceptual relations between spending, borrowing, and financial distress but are of no use for this inquiry because they do not show how card use varies over the distribution of income (Mann 2006). I decided to look to the 2004 Survey of Consumer Finances, conducted by the National Opinion Research Center (NORC) for the Federal Reserve Board. The 2004 survey is based on a complex sample of U.S. households and includes data on income, assets, debt, and the demographic characteristics of respondents (for a general summary of the 2004 data, including the data on credit card use, see Bucks, Kennickell, and Moore 2006, table 11).¹¹

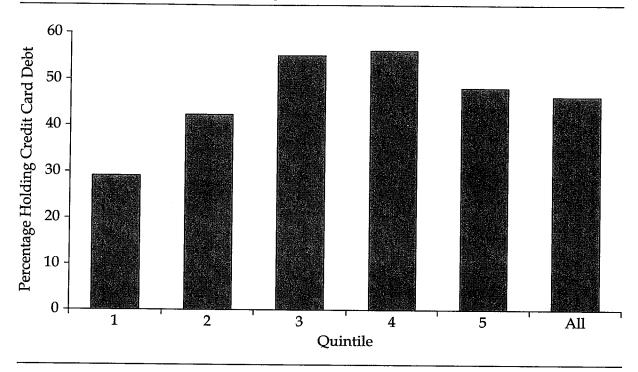
There are some problems with the use of the SCF for such an inquiry. First, the SCF is not a panel survey. Rather, investigators draw a different sample of interview subjects (and train a different set of interviewers) for each edition of the survey. This limits the value of the data for analyzing trends 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 percent, 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) (Mann 2006; Zinman 2007; for details on G.19, see Furletti and Ody 2006). 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. Jonathan Zinman's (2007) 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 relations between them.12 Yet another problem is the ambiguous relation between balances and borrowing on a revolving credit product like a credit card. This makes it particularly difficult for survey researchers to collect accurate information about debt: is the relevant figure the amount owed to the issuer at the time of the interview, the amount owed on the last statement, the amount that went unpaid on the last statement, the amount expected to go unpaid on the next statement, or some other figure entirely?13 Reasonably skeptical observers 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 that are both difficult to define and collect and known to be substantially underreported. Still, the fact remains that the SCF, despite its problems, is the best available source for householdlevel data about national patterns of card use (Kennickell 2006a).

PATTERNS OF CREDIT CARD USE

Because the purpose of this project is to understand the pattern of credit card use among LMI households (defined as the bottom two quintiles in the income distribution), I start by dividing the SCF data set into five quintiles based on income. The two lowest quintiles (quintiles 1 and 2 in the analysis that follows) end at \$18,500 and \$34,000 of annual income, respectively. Conversely, I use three distinct metrics to capture the penetration of credit card use in LMI households: the number of households that report a positive balance; the size of the balances reported by households that report a balance (CCBAL); and the ratio of the household's credit card balance to its income (CCSHARE) (Kennickell 2006a).

Penetration of the Market

The most basic question about credit card use by LMI households is how often they carry balances on cards, as compared to higher-income households.¹⁵ The answer,

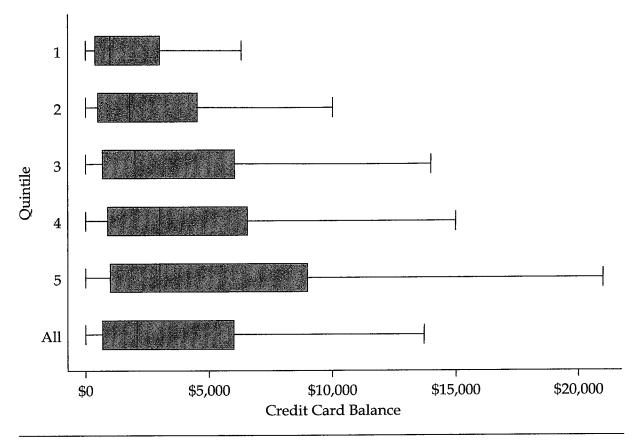


in short, is that their usage patterns are surprisingly similar. The importance of income as the primary source of repayment for credit card lenders suggests that a group of households defined by low income levels should have little or no credit card debt. On the contrary, the borrowing patterns for the four lower income quintiles are surprisingly similar.

I start with the incidence of debt—the share of households reporting that they are carrying any credit card debt at all (46 percent across the entire data set). Figure 9.3 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 percent and 56 percent) in the second and third quintiles, long considered the principal focus of credit card lending. One notable feature of the data is the robust rate of borrowing in the two LMI quintiles. First, the 43 percent 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 earlier in this chapter. 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 percent incidence of borrowing in the first quintile is considerably lower, but even that incidence is notable given the reality that the first quintile consists of households with incomes below \$23,500.

The second metric of credit card borrowing is the size of the balances carried by those households that are carrying balances.¹⁶ This metric displays the intensity

FIGURE 9.4 / Credit Card Balances, by Income Quintile

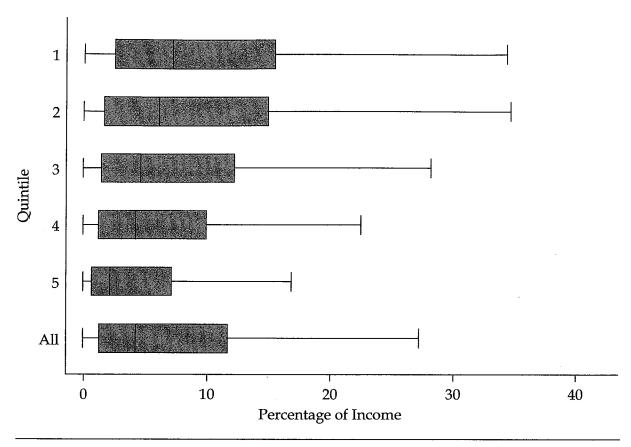


Source: Author's calculations based on Survey of Consumer Finances 2004 (excluding outliers). *Note*: Endpoints of horizontal lines show minimum and maximum; box indicates twenty-fifth and seventy-fifth percentile. Vertical line within the box indicates median (fiftieth percentile).

and regularity of borrowing by the subset of respondents who report a positive balance. To set the frame of reference, the median balance for those carrying balances in the entire data set is \$2,300, the 25 percent balance is \$700, and the 75 percent balance is \$6,300. Figure 9.4 displays a series of boxplots by quintile. These plots indicate the range of data for each quintile by vertical lines, with the boxes shading the range from the twenty-fifth to the seventy-fifty percentile and with internal vertical lines showing the median value.

Like figure 9.3, several points about the boxplots in figure 9.4 warrant emphasis. The most notable is the relative similarity 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 \$1,000. Again, combining the importance of income to credit card underwriting with the limited income of these households, it might

FIGURE 9.5 / Credit Card Balance As a Share of Income Among Those with Balances, by Income Quintiles



Source: Author's calculations based on Survey of Consumer Finances 2004 (excluding outliers). *Note:* Endpoints of horizontal lines show minimum and maximum; box indicates twenty-fifth and seventy-fifth percentile. Vertical line within the box indicates median (fiftieth percentile).

be surprising that the median balances are so high. The most likely explanation is that, even in this quintile, most of the households 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 one-tenth of their annual income than it is to know what share of customers are borrowing \$5,000. Related to the first, the ratio of credit card debt to income provides a useful tool for examining overindebtedness. Thus, Bird and his coauthors (1999) use this metric to identify customers who have borrowed excessively.

The boxplots in figure 9.5 underscore this chapter's analysis. Again, the differences among the three interior quintiles are relatively slight, with typical debt

loads of about one-twentieth of cardholders' 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 percent, median, 75 percent). Thus, using this metric, the respondents in the first quintile 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 one-quarter of the respondents have debt equal to two months' income. Moreover, the long right tail of borrowing share in that quintile suggests that it is not uncommon for people in this group to accrue substantial debts on credit cards.

Demographic Factors

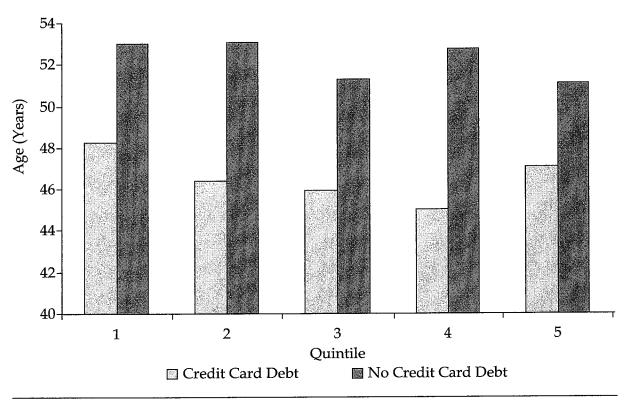
Knowing that credit cards have become a common product for LMI households tells us little about who uses them or, more importantly, whether the factors that relate to use by LMI households are the same as those that relate to use by the broader populace. For purposes of this study, I have chosen to examine four sets of demographic variables from the SCF: age, educational level, family status, and race. 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 by any particular household. The models that credit card issuers use to predict cardrelated 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 also, 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 that 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 data set. The absence of these variables necessarily limits the quality of the potential models. Even more importantly, these factors cannot predict either the demand for credit cards or individual preferences and behaviors regarding borrowing and credit card use.

Nevertheless, the data can illuminate the social role of credit cards by contributing to an understanding of demographic differences between those who borrow and those who do not. I analyze those variables in two steps. First, I present data illustrating the extent to which those variables differ for those who report carrying balances on credit cards and those who do not. For comparative purposes, I also present similar data about the financial characteristics of the households: use of other financial products (checking accounts, car loans, mortgage loans), as well as employment status and stability of income. Table 9.1 presents summary descriptive statistics for each of those variables, organized by quintile. I close the chapter with a discussion of a multivariate model designed to assess the extent to which the variables explain variations in reported credit card balances when controlling for the other variables.

TABLE 9.1 / Characteristics of Users and Non-Users of Credit Cards, by Income Quintile

| | 1 | 2 | 3 | 4 | 5 |
|--|----------|-----------|------------|------------|----------|
| Age (mean years) | | | | | |
| With credit card balance | 48 | 46 | 46 | 45 | 47 |
| Without credit card balance | 53 | 53 | 51 | 53 | 51 |
| Education (mean years) | | | | | |
| With credit card balance | 13 | 13 | 13 | 14 | 15 |
| Without credit card balance | 11 | 12 | 13 | 14 | 16 |
| White | | | | | |
| With credit card balance | 60% | 66% | 73% | 80% | 82% |
| Without credit card balance | 60 | 68 | 76 | 84 | 90 |
| Black | | | | | |
| With credit card balance | 24 | 16 | 14 | 11 | 9 |
| Without credit card balance | 23 | 23 | 15 | 7 | 3 |
| Hispanic | | | | | |
| With credit card balance | 12 | 15 | 10 | 7 | 5 |
| Without credit card balance | 14 | 15 | 6 | 4 | 1 |
| Married | | | | | |
| With credit card balance | 20 | 40 | 59 | 80 | 93 |
| Without credit card balance | 23 | 48 | 55 | 70 | 90 |
| Has children | | | | | |
| With credit card balance | 36 | 40 | 55 | 57 | 61 |
| Without credit card balance | 30 | 35 | 36 | 37 | 50 |
| Has checking account | | | | | |
| With credit card balance | 85 | 91 | 96 | 98 | 99 |
| Without credit card balance | 65 | 80 | 93 | 98 | 100 |
| Has car loan | | | | | |
| With credit card balance | 25 | 36 | . 52 | 63 | 59 |
| Without credit card balance | 8 | 20 | 33 | 32 | 34 |
| | | | | | |
| Has mortgage loan With credit card balance | 25 | 41 | 61 | <i>7</i> 5 | 86 |
| Without credit card balance | 12 | 22 | 41 | 54 | 68 |
| | 14 | | ** | O I | 00 |
| Employed | EE | 70 | 0.4 | 00 | 02 |
| With credit card balance | 55 41 | 79 57 | 84 71 | 90 74 | 93 93 |
| Without credit card balance | 41 | <i>57</i> | <i>7</i> 1 | 74 | 83 |

FIGURE 9.6 / Mean Age by Credit Card Debt Status and Income Quintile



AGE The relation between age and credit card borrowing is relatively straightforward. On the one hand, to the extent that cardholders use credit card borrowing to smooth consumption over their life cycle, I would expect to see more borrowing by relatively young cardholders and less borrowing by older cardholders. Relating the consumption cycle to income levels, I would expect that young cardholders in LMI quintiles would need to borrow more frequently than young cardholders in households with more income. Similarly, cardholders in LMI households might be less likely to repay their debts and thus more likely to continue borrowing into middle and old age.

In general, the data support that understanding of the relations between age, credit card debt, and income quintile. As table 9.1 illustrates, borrowers who carry credit card balances are younger at all income levels than those who do not; the differences in each case are significant at the 0.01 percent level. Figure 9.6 illustrates the distinction graphically, showing a gap between the mean ages of those who borrow and those who do not.

EDUCATIONAL LEVEL The relation between education and credit card borrowing is considerably harder to predict, primarily because it is difficult to be certain whether 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

FIGURE 9.7 / Mean Education by Credit Card Debt Status and Income Quintile

Credit Card Debt

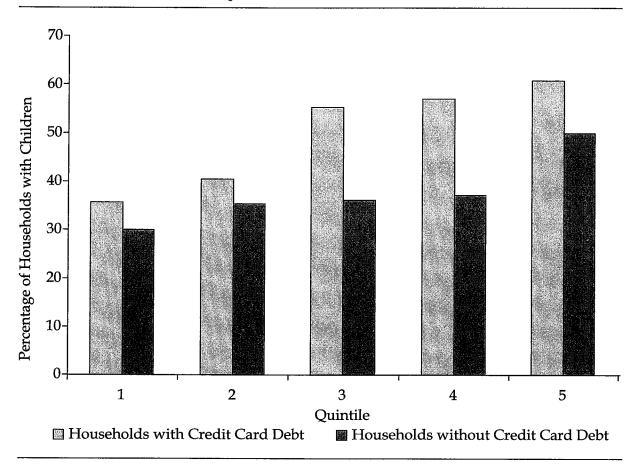
relation to credit card borrowing at different levels of income. Among LMI households, for example, it might be that only the relatively well educated would be in a position to obtain a credit card, while in households with higher income levels (where educational levels are likely to be higher across the board) credit cards might be readily available even to the relatively less educated.

No Credit Card Debt

Table 9.1 provides some support for that explanation—the mean education level of those carrying credit card balances in the LMI quintiles is higher than the education level of those who do not carry balances—but the converse is true of the highest quintile: those who carry balances tend to be less educated than those who do not. As illustrated in figure 9.7, the level of education steadily increases by quintile, but the credit card borrowers in the first two quintiles are the relatively more-educated, while borrowers are relatively less-educated in the upper 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. With respect to children, the data (in table 9.1 and figure 9.8)

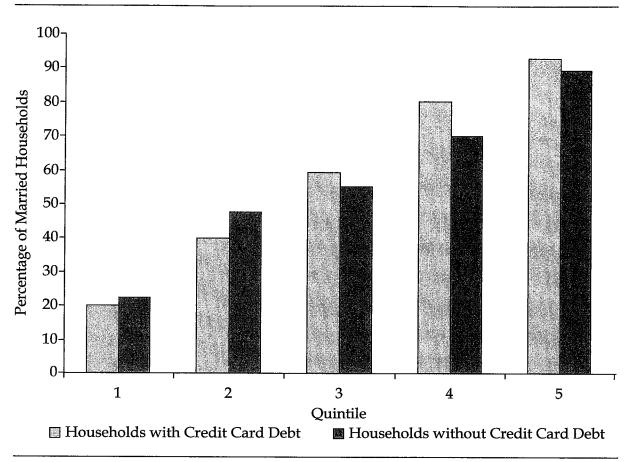
FIGURE 9.8 / Households with Children by Credit Card Debt Status and Income Quintile



suggest a relation with credit card debt; at all income levels, a greater share of households with children have credit card debt than do not. The data regarding marital status are harder to interpret. Like education, this variable seems to relate to card use differently at the LMI level than it does at higher-income levels. Thus, a lower share of LMI households in which the head is married report carrying credit card debt, while a higher share of upper-income quintiles report carrying credit card debt. Table 9.1 reports the descriptive statistics; figure 9.9 displays the data graphically.

RACE The relation between race and credit card borrowing is 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 data set, then there might be correlations between race and credit card usage. The data in table 9.1 and figure 9.10 suggest

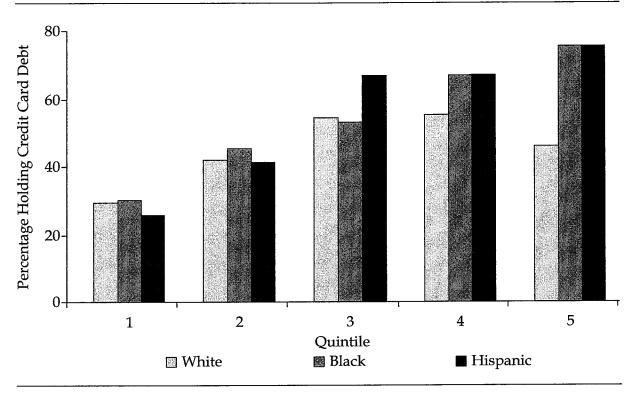
FIGURE 9.9 / Households Headed by a Married Couple by Credit Card Debt Status and Income Quintile



that whites are less likely to borrow on credit cards than African Americans and Hispanics, especially at higher income levels. To be sure, because table 9.1 and figure 9.10 control neither for income nor education, they do not suggest any causal association between race and credit card use. They do, however, provide useful information on the demographic characteristics of those who carry balances on credit cards.

USE OF OTHER FINANCIAL PRODUCTS As discussed earlier in the chapter, I also analyzed several variables related to the financial status of the household. Collectively, those variables should provide a valuable proxy for financial sophistication. If families are more likely to borrow on credit cards if they have previous experience with other banking products, then there should be a positive relation between having a checking account and carrying a credit card balance. As table 9.1 and figure 9.11 suggest, there is a significant correlation between credit card use and several of the variables summarized in table 9.1. The last column of figure 9.11 provides some support for that hypothesis by showing correlations between the

FIGURE 9.10 / Households Holding Credit Card Debt by Race, Ethnic Status, and Income Quintile



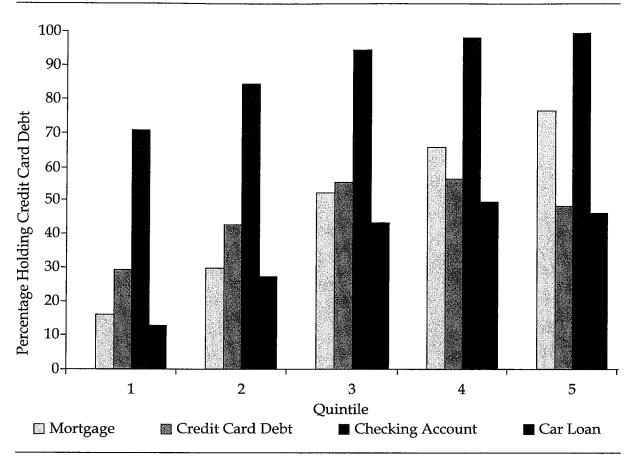
most widely used of the other products, the checking account, concentrated at the lower income quintiles, apparently because almost all households in the higher income quintiles have checking accounts.

MULTIVARIATE ANALYSIS

Given the apparent variation in the relations by income quintile, multivariate analysis would be useful to refine the relations among the variables. As explained earlier, it would be surprising if the variables in the SCF data set 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. Similarly, a model that predicts consumer behavior and preferences would include many variables beyond the straightforward demographic and financial sophistication variables used here.

To examine the relation between the different groups of variables, I started with a pair of models: one for the whole data set and one limited to the two LMI quintiles, using the demographic variables (age, age-squared, education, black, Hispanic, married, and children) as the only explanatory variables. I used the existence of

FIGURE 9.11 / Households Holding Credit Card Debt and Other Financial Products by Income Quintile



any credit card balances (a binary variable) as the dependent variable and estimated logistic regression models. The first two columns of table 9.2 report results from those models. I then estimated a second pair of models (columns 3 and 4 in table 9.2), which added the three financial sophistication variables (checking account, car loan, mortgage loan). I then estimated a pair of models (columns 5 and 6) that added employment and income shock. Finally, I estimated a pair of models (columns 7 and 8) to assess interactions among the variables. These models included seven additional variables in two groups: age interacted with black and with Hispanic, and education interacted with black, Hispanic, children, checking account, mortgage, and employment.²⁰

Turning first to the demographic variables, the analysis suggests that the quintile-by-quintile variations discussed in the preceding section reflect statistically significant relations. For example, age has an odds ratio that is statistically significant but only slightly greater than one (in the vicinity of 1.05) in all eight models, while age-squared has a statistically significant odds ratio that is only slightly below one (in the range of 0.9995) in all of the models. This suggests a slight positive increase

TABLE 9.2 / Logistic Regression Models (Dependent Variable = 1 If Household Reports Credit Card Debt; 0 Otherwise)

| | (1) All | (2) LMI | (3) All | (4) LMI | (5) All | (6) LMI | (7) All | (8) LMI |
|------------------|--|---|----------------------------------|------------------------------------|----------------------------------|---------------------------------|-------------------------------------|--------------------------------|
| Age | 1.0710*** | 1.0532*** | 1.0422*** | 1.0423** | 1.0352** | 1.0440** | 1.0274* | 1.0318 |
| Age-squared | 0.9992*** | 0.9994*** | 0.9994*** | 0.9995*** | 0.9996*** | 0.9995** | 0.9996** | 0.9996* |
| Education | (0.0001 1) 1.0454*** (0.136) | (0.00010 1) 1.1371*** (0.028) | (0.000130) 0.9857 (0.0154) | (0.000127) 1.0789*** (0.023) | (0.000133) 0.9802 (0.0155) | (0.000200) 1.07619*** | (0.000138) 1.2496*** (0.0671) | (0.000213) 1.252*** |
| Black | 1.0665 | 0.9629 | 1.3455** | 1.1498 | 1.3645*** | 1.1594 | 0.0950*** | (0.0793) 0.1552 |
| Hispanic | (0.113) 0.9924 | (U.167) 1.147 | (0.121) 1.2888* | (0.178) 1.3641 | (0.121) $1.2628*$ | (0.182) 1.2947 | (0.843) $0.1030***$ | $(1.20) \\ 0.2688$ |
| Married | (0.133) $0.8303**$ | (0.200) 1.0231 | 0.140 1.1345 | (0.212) 1.1775 | (0.140) 1.1520 | (0.211) 1.1600 | (0.816) 1.123 | (1.150) 1.2067 |
| Children | (0.0804) 1.2857*** | (0.140) 1.1448 | (0.0878) 1.1154 | (0.151) 1.0330 | (0.0885) 1.1088 | (0.150) 1.0058 | (0.0893) | (0.152) |
| Checking account | (0.0820) | (0.156) | (0.0868) 3.0771*** | (0.151) 2.8548*** | (0.0868) 2.9892*** | (0.150) 2.7566*** | (0.452) | (0.7090) $4.7185**$ |
| Car Ioan | | | (0.155) 2.3898*** | (0.181) $2.4804***$ | (0.155) 2.3432*** | (0.181) 2.3812*** | (0.713) 2.3166*** | (0.780) 2.402*** |
| Mortgage | | | (0.0830) 1.8460*** | (0.155) 2.0772*** | (0.0832) 1.7828*** | (0.155) 2.0107 *** | (0.0840) 9.612*** | (0.155) 12.513*** |
| Employed | | | (n.0865) | (0.163) | (0.115) | (0.163) 1.6782*** (0.166) | (0.467) 4.5132*** (0.502) | (0.793) 6.3662** (0.742) |

| Income shock | | | | | 0.9440 | 0.8335 | 0.9438 | 0.8205 |
|-------------------|-------|-------|-------|-------|---------|---------|------------|----------|
| | | | | | (0.125) | (0.166) | (0.125) | (0.162) |
| Age*Black | | | | | | | 1.0237*** | 1.029*** |
| | | | | | | | (0.00782) | (0.010) |
| Age*Hispanic | | | | | | | 1.0307** | 1.024 |
| | | | | | | | (0.0120) | (0.0169) |
| Educ*Black | | | | | | | 1.1246** | 1.0527 |
| | | | | | | | (0.0515) | (0.0756) |
| Educ*Hispanic | | | | | | | 1.111** | 1.0467 |
| | | | | | | | (0.0485) | (0.0704) |
| Educ*Kids | | | | | | | 0.9111*** | 0.9341 |
| | | | | | | | (0.0325) | (0.0568) |
| Educ*Chk | | | | | | | 0.8778** | 0.9533 |
| | | | | | | | (0.0610) | (0.0685) |
| Educ*Mort | | | | | | | 0.88432*** | 0.8635** |
| | | | | | | | (0.0333) | (0.0616) |
| Educ*Empl | | | | | | | 0.9235** | 0.9033* |
| | | | | | | | (0.0366) | (0.0573) |
| Pseudo-R-squared# | 0.040 | 0.035 | 0.119 | 0.105 | 0.120 | 0.111 | 0.140 | 0.124 |
| Number of | 4,519 | 1,359 | 4,519 | 1,359 | 4,519 | 1,359 | 4,519 | 1,359 |
| observations | | | | | | | | |

Source: Author's calculations based on Survey of Consumer Finances 2004.

Notes: The table reports odds ratios with standard errors in parentheses. All regressions are weighted. Similar regressions without weights (as suggested in Lindamood et al. 2007) produced generally similar results. *significant at 10 percent; **significant at 1 percent. *pseudo-R-squared calculated based on first implicates of logit regression in the incidence of credit card debt as households age, with a lessening of the rate of increase with advancing age. Odds ratios above one on the interactions between age and the race variables (columns 7 and 8 in table 9.2) suggest that the increasing incidence of credit card debt with age is more substantial for black and Hispanic households than it is for white households.

Similarly, at least in the LMI quintiles, education has an odds ratio that is significantly greater than one even after controlling for the financial variables; the results are more ambiguous in the models for the entire data set. This is consistent with the data presented in table 9.2, which suggests that education is positively related to credit card borrowing in lower quintiles but negatively related to it in higher quintiles. The analysis of interacted variables (columns 7 and 8 in table 9.2) suggests that the positive relation between credit card debt and education is even higher for black and Hispanic households.

Like the data in table 9.1, the data regarding the racial variables is somewhat more difficult to interpret. It is apparent, however, that after the financial variables are introduced as controls, both the black and Hispanic variables produce relatively stable odds ratios that are substantially greater than one. This suggests that blacks and Hispanics are more likely to carry credit card balances than whites with similar levels of use of other financial products. The interacted variables, however, suggest a different story. Once the interacted variables are included (columns 7 and 8 in table 9.2), black and Hispanic households (as compared to white households) have lower odds of having credit card balances (approximately 0.1). At the same time, the interacted variables suggest that the positive relations between age and education on credit card debt are substantially larger for black and Hispanic households than they are for white households.²¹ This suggests that the positive relation between race and credit card debt in columns 3 through 6 is driven by the use of cards by older and more educated black and Hispanic households.

The multivariate analysis for family status is less conclusive. Married households and households with children tend to have more credit card debt than unmarried households and households without children, though the models suggest, at least after controlling for the use of financial products, that these variables are not as important as the education and race variables. The most interesting finding relates to the interaction between children and education. In the final model, the odds ratio for families with children is economically and statistically significant (4.02), but the interaction between education and that variable suggests that for more-educated families the trend toward the use of credit card debt is substantially lower than it is for less-educated families. These effects seem to be about the same for LMI quintiles and for the entire data set.

The most important finding of table 9.2 is apparent in data about the financial sophistication variables in columns 3 through 8. All three of those variables (checking account, car loan, and mortgage loan) have odds ratios that are both statistically significant and (with a single exception) much higher than the odds ratios of any of the demographic variables. This suggests, at least within this data set, that the data about the use of other financial products are much more important in predicting whether a household will report credit card balances than unrelated

demographic characteristics of the household. Inclusion of the financial variables in the model also appears to alter the role of some (but not all) of the demographic variables. Thus, the odds ratios for age (and age-squared) remain relatively stable when the financial variables are added to the model. The analyses for education and race, on the other hand, change substantially with the addition of variables to control for financial sophistication. Thus, in the model for the whole data set, education has an odds ratio close to one in the model with only demographic variables, but a ratio substantially below one in columns 3 and 5 (the models that control for financial sophistication). Conversely, the odds ratios for blacks and Hispanics are substantially higher after the inclusion of financial products as controls. Interestingly, as with the interaction between education and children, the low odds ratios on the interactions between education and checking and mortgage loans (columns 7 and 8 of table 9.2) suggest that the tendency for families that use other financial products to carry credit card balances is substantially less for more-educated families than it is for less-educated families.

Columns 5 and 6 of table 9.2 reflect the addition of employment status and income shock. The income shock variable captures households in which the respondent indicated that the household's current income was at least 25 percent less than the household's normal income; the concept is that the variable might capture households for which borrowing is related to an exogenous income shock. As it turns out, the income shock variable does not appear to be economically or statistically significant in any of the models. Conversely, employment status appears to relate in a strong and positive way to carrying credit card debt; this is not surprising given the probative value that a steady job has for the lender's task of predicting the reliability of repayment. It does not appear, however, to have a substantial effect on any of the other variables, which retain odds ratios broadly similar to the odds ratios they displayed in columns 1 through 4. Like the financial variables, an interaction between education and employment status (reported in columns 7 and 8 of table 9.2) suggests that the positive relation between employment and credit card debt is less substantial for more-educated families than it is for less-educated families. The best explanation for this pattern seems to be that less-educated families with jobs are more likely to accept and use the credit cards for which their employment status qualifies them, and more-educated families are likely to refrain from using them.

CONCLUSION

This chapter provides a glimpse of the role that credit cards play in the financial lives of LMI households. Most obviously, the data show that credit cards are now a substantial factor in the economic lives of the poorest U.S. households. Indeed, at least as a share of income, the credit card debt that 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 the demographic characteristics of borrowers is intended to be suggestive, with a view to assessing the relation between those variables and the other types of variables in our data set. The variations in correlation and association by quintile suggest that sophisticated issuers might well wish to 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 that might be 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 would probably 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—those households with income below \$23,000—31 percent of the households are carrying credit card debt. Among those that carry credit card debt, half have debt equal to 10 percent of their income, and one-quarter have debt equal to 25 percent of their income (all before making mortgage payments, car payments, child support payments, and the like). As I discuss here, repaying that debt typically involves 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 percent, and only one-quarter have debt that exceeds 10 percent of their incomes. By any yardstick, credit card use among poor households has created a debt overhang that many households will bear for years, if not decades. Recognizing that the usage pattern relates so closely to the use by LMI households of other financial products, policymakers must consider the possibility that a taste for mainstream financial products is not always necessarily positive for LMI households.

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 and Adair Morse for useful comments; and Allison Mann for advice of all kinds.

NOTES

 The statistics reported in this paragraph are compiled from the annual Cards Profitability Survey published by Cards and Payments magazine (formerly Cards Management). Figure 9.2 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 and

- *Payments* data because of its consistency and availability over the entire period covered by this discussion.
- 2. There was a sharp fall shortly after the implementation of the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) of 2005, to 3.9 percent for 2006, but the rate trended steadily upward throughout 2007. It remains unclear whether the decline will be permanent.
- The most detailed evidence of that trend comes from Black and Morgan's (1999) comparison of the characteristics of credit card holders in the 1989 and 1995 crosssectional SCF studies.
- 4. 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.
- 5. The information in this paragraph is based on strategy analysis in the annual reports of large credit card issuers.
- 6. 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 those are the households that will have the unstable incomes and poor or spotty repayment histories that make them poor customers for prime or superprime card products. Conversely, those with relatively high incomes are more likely to have relatively stable income profiles and better repayment histories. There are exceptions, of course, but the pattern is useful as a generalization. For analysis of the relation between social status and consumer debt, see McCloud (2007).
- 7. Carddata.com reports that the average late fee among large issuers currently is about \$35.
- 8. This paragraph describes two cards featured at a leading card comparison website as among the most attractive subprime cards in the fall of 2007.
- 9. This fact seems surprising given the logistical difficulties of making payments on a credit card account without a checking account.
- 10. The maintenance of a continuing sense of participation in the larger economy has substantial positive spillover effects (see Phelps 1997).
- 11. 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 (see Kennickell 2006b).
- 12. 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, however, that those problems produce random errors.
- 13. The SCF attempts to ascertain the amount that went unpaid on the last statement. As of 2004, the relevant question (X413) asked: "After the last payments were made on these accounts, roughly what was the balance still owed on these accounts? WE WANT THE TOTAL AMOUNT OWED, NOT THE MINIMUM PAYMENT."

- 14. 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.
- 15. As discussed earlier, the SCF collects data only on the outstanding balance at any given time. Although this obviously is not a perfect measure of credit card debt, it is the best that the SCF has to offer, and for simplicity of exposition I refer to it as "credit card debt" throughout this chapter.
- Like most scholars who write about the SCF, I emphasize the size of balances among those who carry any balance at all (see, for example, Bucks, Kennickell, and Moore 2006).
- 17. For example, there is reason to believe that differing attitudes about debt explain a great deal of the difference in borrowing by those of different races (McCloud 2007). The effects of education and occupation on borrowing also are likely to differ for those of different races, at least in part because of differing levels of wealth (Conley 1999; McCloud 2007).
- 18. 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 a cardholder's 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).
- 19. I also estimated tobit and ordinary least squares (OLS) models of credit card balances, using a similar set of variables as explanatory variables. The variables were much less closely related to the dependent variable in those models, presumably because of the substantial measurement error in self-reported survey data about the level of credit card balances.
- 20. I separately tested first-order interactions among all of the independent variables. Columns 7 and 8 reflect the addition to the model of the interactive variables that were economically and statistically significant in any of the models.
- 21. The conclusion that education has a different effect on nonwhite households than it does on white households is not a new one. See note 17.

REFERENCES

Bird, Edward J., Paul A. Hagstrom, and Robert Wild. 1999. "Credit Card Debts of the Poor: High and Rising." *Journal of Policy Analysis and Management* 18(1): 125–33.

Black, Sandra E., and Donald P. Morgan. 1999. "Meet the New Borrowers." Current Issues in Economics and Finance 5(3): 1–6.

Bucks, Brian K., Arthur B. Kennickell, and Kevin B. Moore. 2006. "Recent Changes in U.S. Family Finances: Evidence from the 2001 and 2004 Survey of Consumer Finances." *Federal Reserve Bulletin* 92 (Mar.): A1–38.

Cards Profitability Survey. 1990–2007. Cards and Payments. Source Media, Inc.

- Caskey, John P. 1996. Fringe Banking: Check-Cashing Outlets, Pawnshops, and the Poor. New York: Russell Sage Foundation.
- Conley, Dalton. 1999. *Being Black, Living in the Red: Race, Wealth, and Social Policy in America*. Berkeley: University of California Press.
- Cross, Gary. 2000. An All-Consuming Century: Why Commercialism Won in Modern America. New York: Columbia University Press.
- Frank, Robert H. 1999. Luxury Fever: Money and Happiness in an Era of Excess. New York: Free Press.
- Furletti, Mark, and Christopher Ody. 2006. "Measuring U.S. Credit Card Borrowing: An Analysis of the G.19's Estimate of Consumer Revolving Credit." Payment Cards Center discussion paper 06-03. Philadelphia: Federal Reserve Bank of Philadelphia.
- Hacker, Jacob S. 2002. The Divided Welfare State: The Battle over Public and Private Social Benefits in the United States. Cambridge: Cambridge University Press.
- Hogarth, Jeanne M., Christoslav Anguelov, and Jinkook Lee. 2004. "Why Don't Households Have a Checking Account?" *Journal of Consumer Affairs* 38(1): 1–34.
- Hogarth, Jeanne M., and Kevin H. O'Donnell. 1999. "Banking Relationships of Lower-Income Families and the Governmental Trend Toward Electronic Payment." Federal Reserve Bulletin 85(July): 459–73.
- Howard, Christopher. 2007. The Welfare State Nobody Knows: Debunking Myths About U.S. Social Policy. Princeton, N.J.: Princeton University Press.
- Johnson, Kathleen W. 2005. "Recent Developments in the Credit Card Market and the Financial Obligations Ratio." Federal Reserve Bulletin 89(Aug.): 473–86.
- Kennickell, Arthur B. 2006a. *Codebook for 2004 Survey of Consumer Finances*. Washington: Board of Governors of the Federal Reserve System (February 9). Available at: http://www.federalreserve.gov/PUBS/oss/oss2/2004/codebk2004.txt (accessed January 22, 2009).
- ———. 2006b. "How Do We Know if We Aren't Looking? An Investigation of Data Quality in the 2004 SCF." Paper presented to the annual meetings of the American Statistical Association. Seattle (August 7–10).
- Lindamood, Suzanne, Sherman D. Hanna, Lan Bi, Jeanne M. Hogarth, Darryl E. Getter, and Sandra J. Huston. 2007. "Using the Survey of Consumer Finances: Some Methodological Considerations and Issues." *Journal of Consumer Affairs* 41(2): 195–222.
- Littwin, Angela. 2008a. "Beyond Usury: A Study of Credit Card Use and Preference Among Low-Income Consumers." *Texas Law Review* 86(3): 451–506.
- ——. 2008b. "Testing the Substitution Hypothesis: Would Credit Card Regulation Force Low-Income Borrowers Into Less Desirable Lending Alternatives?" Working paper. Available at: http://bdp.law.harvard.edu/pdfs/papers/Littwin/Testing-Substitution.pdf (accessed January 22, 2009).
- Mann, Ronald J. 2006. Charging Ahead: The Growth and Regulation of Payment Card Markets Around the World. Cambridge: Cambridge University Press.
- ——. 2007. "Bankruptcy Reform and the 'Sweat Box' of Credit Card Debt." *Illinois Law Review* 2007(1): 375–404.
- Mann, Ronald J., and Jim Hawkins. 2007. "Just Until Payday." UCLA Law Review 54(4): 855–912.
- McCloud, Laura. 2007. "Charging into Hardship: The Effect of Social Location, Permanent Income, and Status Inconsistency on Consumer Debt." Paper presented to the annual meeting of the American Sociological Association. New York (August 11–14). Available

at: http://www.allacademic.com/meta/p_mla_apa_research_citation/1/8/4/6/5/ p184657_index.html (accessed January 22, 2009).

Nilson Report. 1990–2007. Carpinteria, California: The Nilson Report.

Phelps, Edmund S. 1997. Rewarding Work: How to Restore Participation and Self-Support to Free Enterprise. Cambridge, Mass.: Harvard University Press.

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

HarperCollins.

Warren, Elizabeth. 2007. "Unsafe at Any Rate." Democracy: A Journal of Ideas 5(Summer): 8-19. Yoo, Peter S. 1997. "Charging up a Mountain of Debt: Accounting for the Growth of Credit Card Debt." Federal Reserve Bank of St. Louis Review 79(2): 3-14.

Federal Reserve Bank of St. Louis Review 80(1): 19–28.

Zinman, Jonathan. 2007. "Where Is the Missing Credit Card Debt? Clues and Implications." Federal Reserve Bank of Philla Payment Cards Center Discussion Paper No. 07-11. Available at: http://www.dartmouth.edu/~jzinman/Papers/Zinman_MissingCardDebt_ sep07.pdf (accessed January 22, 2009).