Understanding Credit Card Liquidity

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Abstract

This paper considers the growth of credit card liquidity in explaining household credit card use. With data from the 2004 Survey of Consumer Finances we identify key predictors of new credit card charges for households. The data suggest credit card spending appears motivated by low-cost access to credit card liquidity. This is consistent with previous research arguing credit card use is rational, but is contrary to research that emphasizes liquidity constraints in explaining credit card behavior. New credit card charges are primarily predicted by the amount of available liquidity on the card (the limit minus the balance) for all households, controlling for income and other factors. The data also show that credit card spending is primarily done by the more educated and wealthier households, at all income quintiles, and that liquidity constraints have little to do with credit card use.

1. Introduction

Though much attention has been paid to credit card borrowing (see Gross and Souleles (2002), Zinman (2007), Telyukova (2006) for examples), less has been said about the increase of credit card liquidity, the available credit on a credit card line. To be sure Castranova and Hagstrom (2004) ask how important the limit on a credit card is and conclude that the demand for the limit actually drives borrowing behavior (a household will first demand an increase in the limit, and then borrow). Indeed, a significant number of households in the United States revolve high levels of credit card debt from month to month, with a mean balance of $5100 in 2004.[1] This is relative to the mean total limit per household of almost $25,000.[2] However, less understood about credit card behavior is the *increase* in the available liquidity (the difference between the balance and the limit) relative to the balance. The increase is evident from the growth of aggregate available liquidity or "unused portions" of credit card lines, which, as shown in Figure 1, has risen from under $500 billion in 1990 to over $3 trillion by 2007.[3]

The growth of credit card liquidity may have important consequences for understanding not only credit card behavior, but for how this behavior affects the business cycle. For example, a conventional story is that credit card use is a function of liquidity constraints facing households (as noted by Gross and Souleles (2002)). And a liquidity-constrained household may demand a higher limit in order to charge more purchases, consistent with Castranova and Hagstrom (2004). If constrained households rely on credit cards for credit, then such households, laden with high-interest debt, may be more vulnerable to economic shocks and, in fact, exacerbate those shocks. This expectation is reasonable, as household balance sheets are cited as an important source for the propagation of shocks and the amplification of their effects (see Bernanke, Gertler and Gilchrist (1996), and Mishkin (2007)).

[1] Figure is in 2004 dollars and reported in the 2004 Survey of Consumer Finance. The survey also shows that approximately 75 percent of households surveyed in 2004 had a credit card, up from about half since 1983. Almost 50 percent of card using-households carry a balance on their primary credit card from month to month (as opposed to using the card for strictly transactions purposes).

[2] The actual amount, calculated by the authors, is just over $24, 800. This is based on the balance reported in Bucks *et al.* (2006), the balances on the last bill received (and excluding new charges after that bill).

[3] As reported in the Call Reports of all commercial banks in the U.S. See the discussion in Section 3 for more discussion on this data. Figures expressed are in 2000 dollars.

On the other hand, Figure 1 suggests that the supply of credit card liquidity has increased primarily independent of balances which show a more modest increase. Indeed, Gross and Souleles (2002) note that limits on credit cards are primarily driven by pre-determined rules set by the lender. In other words, with more at their disposal households may exploit credit card liquidity for consumption smoothing purposes, and households' apparent reliance on credit cards may be a manifestation of that strategy. In this sense, aggregate credit card borrowing may have more benign consequences for the business cycle.

In this paper, we seek to better understand the implications of credit card liquidity in explaining households' credit card use. To do so we exploit information on credit card use from the 2004 Survey of Consumer Finances (SCF). For a sample of 3,476 households that have at least one credit card, we estimate using linear regression the significance of a household's available credit card liquidity—defined as the difference between the household's total credit card balance and the total limit—in predicting the level of the household's new credit card charges as reported in the survey.[4] In doing so, we control for a number of factors that may be important in explaining the household's decision to incur new charges. These include the total credit card balance before the new charges are made, the highest interest rate the household pays on a credit card, the balance on any non-credit card consumer loan, any available liquid assets such as non-pension stock and savings accounts, and income and demographic information such as education and age.

In addition to the overall sample of households, we estimate for each income quintile (as delineated by the U.S. Census Bureau). And for each regression, we consider additional information on the household's credit history and their revealed attitudes towards using credit (meant to capture any remaining unobserved heterogeneity in the sample). We also consider consumption smoothing motives revealed in the survey, including unusually low income and a projection of future income, which may account for the new charges independent of the factors already listed. Finally, given the potential for endogeneity among the regressors, we estimate with both ordinary least squares and

[4] Credit cards are defined as bank type credit cards, such as Visa or Mastercard and not including Discover, American Express, or department store cards. The data are discussed in more detail in Section 4 of the paper.

instrumental variables. We use information in the survey to asses and test the exogeneity of our regressors, using a number of instruments available in the survey for the latter (using traditional Hausman-type tests of exogeneity).

The results from this combination of estimation reveal at least two insights. First, the higher the available credit card liquidity, the higher predicted level of new charges for a household. This effect is statistically and economically significant across all specifications and across all income quintiles. Moreover, the credit card liquidity effect overrides, so to speak, the liquidity available from savings accounts and non-pension stock holdings. The level of savings is not a significant factor in explaining new charges, while the level of stock is, in fact, a positive and significant predictor of new charges.

This credit card liquidity effect may help in understanding credit card behavior. That is, the liquidity effect in the 2004 SCF data is consistent with Brito and Harvey (1995) in that straightforward cost-benefit analysis may best explain the decision to use a credit card. Brito and Harvey (1995) stress the liquidity "services" of credit cards and the low cost of access (where the service might be avoiding the opportunity cost of holding money). [5] The regression results in this paper are consistent with the notion that households weigh the benefits of accessing credit card liquidity as greater than the loss of paying interest on the card relative to the interest earned on savings or on (non-pension) stock holdings (or against the perceived cost of depleting savings). Indeed, the card interest rate is not a statistically significant predictor of new charges, nor is the level of savings, while the level of stock is a positive predictor, as mentioned.

On a related note, the second insight one can draw from the analysis in this paper is that credit card use is simply not the province of the young, the dumb, or the liquidity-constrained. Instead, educated households characterize the typical credit card user. Education is a positive and significant predictor of new charges in the majority of the regressions (while age is statistically insignificant). And controlling for education, households appear to act sensibly (in a manner one would expect of rational agents) given

[5] Alternative explanations include recent papers by Telyukova (2006) and Zinman (2007). Both seek to understand households' willingness to hold both liquid assets (such as a savings account) and revolve a credit card balance month-to-month. Telyukova (2006) reasons this is indicative of some sort of mental or payment accounting, where the households uses liquid assets for some payments and credit cards for others, while Zinman (2007) emphasizes the value the household places on the liquid assets.

the existing balance on the credit card—a higher balance predicts a lower level of new charges. The statistical and economic significance of this result is robust across all income quintiles.

Moreover, there is little support in the data for the notion that liquidity constraints explain the choice to incur new credit card charges. In the least, we infer this from comparing the behavior of households across the income quintiles and for sub-sets of households that may have particular consumption smoothing motives. For the primary sample of all card-holders, and across income quintiles, the coefficient on the level of income is statistically insignificant; whereas one might expect a strong response to a change in income if liquidity-pinched households rely on credit cards. Only for the bottom quintile is the coefficient negative and statistically significant. While certainly one might expect this for the poorest households, additional evidence suggests even for this group this result is not robust. This effect is no longer statistically significant when only those that revolve balances month-to-month are considered.

For an additional perspective, the results for a sample of households that report a bout of unusually low income do not differ substantially from the broader samples, and income itself is not statistically significant. In the least, households suffering a level of income below normal do not incur new charges in a manner different from the rest. In contrast, for households that report they have a good sense of their income in the next year, the level of income is a positive and significant predictor of new charges. This latter result is evocative of consumption smoothing; or in the least, the result evokes forward-looking consumers incurring new charges instead of desperately-charging households motivated by liquidity constraints.

These general insights have implications for not only research on consumer behavior, but also for economic policy that affects or purports to affect consumer behavior. With respect to research, this paper is a modest complement to Gross and Souleles (2002), Castranova and Hagstrom (2004) and Brito and Harvey (1995). The data analyzed here suggest that the relationship between the limit and the balance has arguably changed relative to the time periods those papers considered; in the least, the relationship between new charges and available liquidity is not indicative of liquidity constraints as it could be interpreted to be so in previous work. Instead, the data is consistent with Brito and Harvey's (1995) framework for understanding the costs and benefits of credit cards.

Also, this paper has direct implications for economic policy. For example, for fiscal policy, a liquidity-constrained household should act differently than a non-constrained household (see Coronado *et al.* (2005), and Johnson *et al.* (2004), for analysis of recent fiscal stimuli). In the aggregate, the effect of on the former should be economically larger than the effect on the latter, who, with access to credit, are already consumption smoothing. Similar reasoning applies to the case of monetary policy. Liquid, credit card-using households should be better able to smooth consumption in the face of monetary policy-induced credit crunches. Credit channels well-studied by monetary economists such as the lending channel should certainly be less potent, while even balance sheet channels may be muted (see Bernanke and Gertler (1995) for a review).

The remainder of this paper discusses these topics further. The next section briefly reviews recent research pertaining to consumer behavior and credit card use. The sections thereafter describe credit card use as revealed by the 2004 SCF and the regression analysis based on that data. The last section concludes.

2. Credit Card use and Consumer Behavior

The purpose of this section is to provide a brief survey of recent attempts to understand consumer credit card use. More to the point, this discussion provides the motivation for the data analysis in Section 4.

Reasons for consumers' preference for using credit cards run the gamut, from it's nothing to be overly concerned with since it's rational (despite the high interest rates), to less-than-rational reasons such as rule-of-thumb or mental accounting behavior, to credit card use is rational given certain conditions such as credit market constraints. In a theoretical and empirical exploration of the latter, Ludvigson (1999) incorporates a time-varying credit constraint into the representative consumer's optimal intertemporal problem. The constraint varies with income (which is uncertain) and generates, in Ludvigson's model, the long-held empirical result that consumption is "excessively" sensitive to current income (see Carroll (2001) for a survey). Ludvigson (1999) also shows that both revolving and non-revolving credit growth predicts consumption growth, which is inconsistent with optimizing behavior.[6] That is, if households were not constrained in credit markets, then the "excess sensitivity" would not be evident in the data.

Ludvigson's (1999) results are consistent with Gross and Souleles (2002). In a study of individual credit card accounts, the authors' conclude that credit card behavior is indicative of credit constraints (in particular, how balances respond to an exogenous increase in the card limit). Agarwal, Liu, and Souleles (2007) bolster this finding by showing that credit card spending after the 2001 tax rebates increased for constrained consumers (and declined for those designated as unconstrained).

Along a similar vein, others emphasize various forms of less-than-rational behavior to understand credit card use. For example, Angeletos *et al.* (2001) invoke time-inconsistent preferences, while Telyukova (2006) and Zinman (2007) focus on consumers' willingness to hold both high-interest credit card balances and low-interest bearing savings account. Telyukova (2006) argues this is motivated by a sort of mental accounting, where the household reserves its savings balances for purchases that cannot be made with a credit card (such as a mortgage payment).

Other the hand, the rational consumer is not forgotten in credit card studies. Brito and Harvey (1995), in particular, provide a model of credit card use that is motivated by a relative lack of transaction costs. That is, credit card use is optimal if there are even small transaction costs, relative to credit cards, to accessing alternative sources of credit. In his study, Zinman (2007) offers a related perspective for understanding the lend-low, borrow-high behavior of credit card use. The liquidity value of savings accounts offsets the interest rate differential, suggesting credit card use may be more rational than at first glance.

Given the variety of approaches to understanding credit card use and the particular objective of this paper, how can one synthesize the literature thus far to make sense of the data from the 2004 SCF analyzed in the next section? That is, what are the key factors that determine the consumer's choice to use a credit card? If we consider the optimal decision of a representative agent, say that maximizes intertemporal consumption, one

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[6] Bacchetta and Gerlach (1997) provide similar analysis and reach similar conclusions with international data.

might conjecture the consumer will decide to use a credit card given a budget constraint that includes the interest rate on the card; the interest rate on the card relative to other forms of credit; the interest rate on the card earned on liquid assets, again, a relative interest rate (à la Telykukova (2006) and Zinman (2007); the level of existing liquid assets; the level of existing debt and the regular payment on that debt; and, of course, current or lifetime time resources including income.

A analogous setup to understand the consumer's choice is Hurst and Stafford's (2004) model of the consumer's problem to access home equity given an existing mortgage and other assets (including the home). Analogous to their model, for a credit card, the consumer may choose to draw off its credit card loan given an existing level of debt and liquid assets on the balance sheet. The consumer may choose to add to its credit card balance instead of drawing down its liquid assets given the low cost of accessing the card relative to perceived cost of depleting the liquid asset in the given period (again, a trade-off motivated by Telyukova (2006) and Zinman (2007)). That the costs of using a credit card might be low enough to make credit card use rational is a point made by Brito and Harvey (1995).[7]

Given this background, the objective of this paper is to understand what the data says about the decision to use a credit card. In addition to data on income and demographics, the 2004 SCF, in particular, provides information on the levels of liquid assets held by a household, its total credit card balance, its total available liquidity on the sum of its credit card accounts (the difference between the balance and the limit), and the amount of new charges, independent of its existing balance at the time of the survey. From this information, we attempt to understand what predicts the new charges and what this reveals about the motives, rational or otherwise, of households' and their credit card use.

3. Descriptive Statistics

To further understand credit card behavior, a sensible step is to look at some descriptive information on credit card use. From such a look, it is not difficult to see that credit card use has expanded at both the aggregated and disaggregated levels. At the aggregate level,

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[7] Calibrating an intertemporal model for credit card use in the mold of Hurst and Stafford (2004) is the objective of joint ongoing research by this author and Kristin A.Van Gaasbeck.

revolving consumer credit has increased from less than $20 billion (constant 2000 dollars) in 1970 to almost $800 billion as of April 2008 (see Figure 2). That represents an increase in the revolving component as a share of total consumer credit of less than three percent to 37 percent.[8]

In addition to aggregate balances, it is also useful to compare the level of balances to the available "unused portions" remaining on credit card lines—that is, the available liquidity available to credit card holders. The Call Reports for commercial banks reveal that the amount of available liquidity on credit cards dwarfs the level of balances—as measured on and off bank balance sheets (collected and made available by the Federal Deposit Insurance Corporation).[9] In the second quarter of 2007 the amount of the unused portion of credit card loans in the aggregate was just over three trillion dollars (constant 2000 dollars), while combined on and off-sheet balances totaled just over seven hundred billion 2000 dollars for the same quarter. This utilization rate of just over twenty percent is consistent since approximately 2000. Again, Figure 1 displays the comparison since 1990.[10]

For a different perspective, the 2004 Survey of Consumer Finances shows that 74.9 percent of families have a credit card, and of that subset, approximately 46 percent carry a balance. Of those families that carry a balance, the median dollar value (in 2004 dollars) was $2,200, up from approximately $1,300 in 1989. The mean value for this group was $5,100 in 2004, up from approximately $2,800 in the 1989 survey.

Table 1 shows credit card use by income percentile from 1989 to 2004 (that is, the percentage of families with credit card debt), as well as the mean and median dollar values for each percentile.[11] A few general facts of credit card use by income stand out. Higher income households are more likely to carry credit card debt; however, the poorer households show the largest increases in the percentage of their numbers that do so.

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[8] Consumer credit series are available from the Federal Reserve Board, statistical release H.19. Series are seasonally adjusted and deflated using the personal consumption expenditures deflator (2000 = 100). Revolving credit is predominately comprised of bank card type credit cards, though also includes department store cards and American Express and Discover cards.

[9] This information is taken from the FDIC's "Graph Book" available at http://www2.fdic.gov/QBP/Index.asp.

[10] See the FDIC's Graph Book tables, "Expansion of Commercial Bank Credit Card Lines" and "Utilization Rates of Loan Commitments."

[11] Data is from the 2004 SCF. The 2004 values can be found in Table 11 of Bucks et al. (2006). The data for 1989 is approximated (rounded off) from the time series charts available in the 2004 SCF Chartbook.

Also, the median and mean values of credit card balances (among those who carry balances) have increased across all income groups. The greatest relative percentage increase in the averages, though, has been for lower income households.

3.1 Credit Cards by Income

For the highest four income groups, the percentage of households with credit card debt has remained fairly steady for the over the fifteen year period. This is true for those in the middle income groups, in the 40 to 79 percentile range, as well as for the income percentiles above 80 percent. Though the amount carried on average has increased. For middle income households, both the median and mean balances have essentially doubled. For households above the 80th percentile, the averages have also increased, but at a slower rate than the middle income households.

For the lowest two income groups— below the 40th percentile—the percentage of households with credit card debt has increased noticeably, especially relative to the higher income groups. For households below the 20th percentile, the median balance has more than doubled, while the mean has more than tripled (percentage increases of 150 and 238 percent, respectively). For the next group, both averages have at least doubled.

3.2 Credit Cards by Age

The percentage of families with credit card balances by the age of the household head has not changed that drastically. At the ends of the spectrum, the percentage of young households aged 35 and younger with credit card debt has been steady, while the most notable growth in participation is for senior citizens, aged 75 and older. The increases in the median and mean for this latter group is the largest of all cohorts (well over 200 percentage increases for both statistics), while for the youngest group, the changes are more modest, with no change in the median and a $1000 increase in the mean. For middle-aged households and up there are significant increases in both the medians and means of credit card holdings.

3.3 Credit Cards by Education

The education level of households does not appear to matter that much for credit card use. There is a noticeable difference between those without a high school diploma and those with at least a high school diploma. However, for those with at least a high school diploma there is not much difference in the percentage of families with debt across education levels. Each group too, shows fairly similar increases in both the median and mean holdings.

These statistics reveal some interesting facts about credit card use—facts which, on the one hand make sense, but on the other hand, do not necessarily jibe with the conventional picture of the liquidity-constrained household described in economic research.

4. Econometric Analysis of Credit Card Behavior

Motivated by the data in Table 1, in this section we provide econometric analysis on credit card use. Specifically, we regress a household's new credit card charges on the level of liquid assets held by the household; the level of outstanding debt; the available liquidity on the card (the amount available under the limit); and controlling for demographic characteristics.

The data on credit card use is based on a sample of 4519 households from the 2004 Survey of Consumer Finances (discussed in section 3; see also Bucks *et al* (2004) provide a detailed discussion on the 2004 SCF). Our analysis focuses on Bank Cards, which includes Visa, MasterCard and Discover. The category excludes American Express, store cards or gas cards. We exclude, also, households that declared they had zero credit (bank) cards. This leaves a sample of 3,476 households. In addition, due to concerns with over-sampling of wealthy households in the SCF, we report results after excluding households in the sample that make over $150,000 dollars, which leaves a sample of 2,310.[12] And to understand better credit card use across the income spectrum (which varies as suggested by Table 1) we estimate separately for each income quintile as determined by the U.S. Census Bureau.

We also extend the primary regression to incorporate two related issues. First we attempt to control for any unobserved heterogeneity that may exist across households, and second, we attempt to gauge the affects of consumption smoothing motives on credit card use. To capture any remaining unobserved heterogeneity across households, we add to the list of regressors the households' revealed attitudes towards using credit as well as

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[12] See Bucks et al. (2006) for discussion of the over-sampling issue. The $150,000 delineation eliminates households in the top 5 percentile for income in the United States (U.S. Census).

financial background information, such as frequency of paying off debt late (these variables are discussed in more detail below).

To capture a possible consumption smoothing motive we consider two household statements. First, we estimate a regression only on those households that claim to be suffering unusual income shortfalls. Second we estimate a regression for households who feel they have a good idea of their level of income in the future. Whether real or imagined, the shortfall or the projection may inspire consumption smoothing and help predict their credit card charges.

Again, the estimation is conducted on households that have credit cards. Given the set of card-holding households, we consider households that have either a positive or zero balance on their credit cards before the new charges were made. As a final alternative, however, we consider only those households with a positive balance before the new charges were made. While approximately two-thirds of households surveyed in the SCF have a credit card, about 45 percent revolve a balance from month to month. We consider the latter separately to see if they behave differently from the former.

Ultimately we report results from ordinary least squares estimation. Tests of exogeneity derived from two-state least squares estimation reveal ordinary least squares is appropriate; we describe in detail those tests below after we discuss the regression analysis in more detail.

4.1 NEW CREDIT CARD CHARGES

The dependent variable is defined as *New Charge*. The variable is defined by the household's answer to the SCF question, "on your last bill roughly how much were the new charges made to this account(s)." In this question, "this account(s)" refers to the household's total number of credit cards (again, bank cards).

We estimate the following baseline equation for *New Charge* for household *i*:

$$NEWCHARGE_i = \beta_o + \beta_1 INCOME + \beta_2 DEMOG + \beta_3 DEBT + \beta_4 ASSETS + u_i \,, \quad (1)$$

where the blocks of right-hand side variables include a number of household-specific data capturing the budget constraint and characteristics of each household.

Before we describe each right hand-side variable, it is important to mention that many of the chosen regressors may be endogenous. In particular, the levels of new charges and some of the assumed independent variables may be made simultaneously (and we are ignoring some omitted factor behind that choice). To address this we consider both timing evidence from the survey ("narrative" information) and statistical tests of exogeneity. As we define each variable, we will discuss the former narrative information and then take up the tests of exogeneity later. In particular, the regressors are,

INCOME

- *Income* is the total income reported by the household. This includes the household's total income from wages and salaries, capital gains or any other source (received pre-tax—the data appendix contains more details). We interpret this as the level of income the household has when making the choice to add a new charge to their credit card (and is not determined simultaneously).[13]

DEMOG

- *Age* is the year of the household head's birth. Age and credit card use appears to be correlated with the life cycle. As shown in Table 1, the heaviest credit card use takes place in the middle-aged years, with less use below the age of 35 and after the age of 65. We assume the age of the respondent is exogenous.
- *Education* is a dummy variable indicating if the household head has a college degree (equaling 1 if they do). Moreover, this is the level of education the household head has obtained at the time of survey, and is exogenous to *new charges*.

DEBT

- *Balance* is the amount the household still carries after making the last payment (this is not the minimum payment for the revolving balance). As this variable is reported in the SCF, it includes the amount the household includes as "new charges." Hence, in the estimation, the *Balance* variable is the amount reported minus the amount of new charges. In other words, this represents the balance held by the household *before* the new charges were made. Given this timing, we

[13] It is possible this level of income is somehow higher or lower than what the household perceives as normal. This is a question asked in the survey and we consider this possibility in an additional regression discussed later.

assume the level of balances is exogenous. Of course, it might still be argued that the level of balances the household chooses to hold and the amount of new charges it makes are somehow determined simultaneously—and the survey questions do not reveal this subtle choice. Hence, we test the exogeneity assumption statistically.

- *Other Consumer Loan* is the amount of the household's installment consumer loan (independent of the credit card account). This excludes education and vehicle loans. If credit cards are substitutes for traditional, lower-interest loans, we expect this to have a negative effect on balances. However, if credit card use is a complement to installment loans, this variable will be positively associated with on balances.
- *Rate* is the highest interest rate charged on any of the household's credit cards.

ASSETS

- *Liquid Savings Value* is the dollar amount of the total savings held in a savings or money market account (independent of pension accounts or certificates of deposit). For this liquid asset and the asset immediately below, *stock value*, one cannot be certain if this value is determined at the same time new charges are made. A household may make a new charge at the same time they decide to adjust their level of savings or even cash in on some stock holdings (to pay off the new charges, perhaps).
- *Stock Value* is the dollar amount of the household's publicly traded stock (that is not held as part of a pension account).
- *Limit* is the amount of available liquidity on the credit card with which the household has made the new charge. This is calculated as the limit as reported by the household minus the balance on the card as defined above. The survey question simply asks "what is the maximum amount you could borrow on these accounts; that is, what is your total credit limit." We make the assumption that a

line increase as not occurred at the same time the household made the new charges.[14]

4.1 Estimation and Results

We estimate first using ordinary least squares (OLS) assuming that all regressors are exogenous. In practice, before resting on the final specification estimated with OLS, we estimated with instrumental variables in order to test for potential endogeneity. Ultimately we conclude that endogeneity is not plaguing our results; we discuss our final results using OLS and then discuss the details of exogeneity tests and the instruments employed in those tests.

Table 2 displays the results for the overall samples and the samples stratified by income quintiles. The first column in Table 2 displays for the entire sample of card holders; the second column displays the results for only those with incomes up to $150,000; and the remaining columns display the results for the quintiles.[15] In discussing the results displayed in Table 2 we first compare the results across the income groups then contrast the results. One should note that all variables in dollars have been transformed by taking the natural log.

Across all income groups (columns one through seven) the common predictors of new charges are the existing balance and the available limit. In each regression the level existing balance is negatively (and statistically significant) related to new charges; existing balances are a deterrent for all households, all else equal, in making new charges. Both the dependent variable and the level of balances are estimated in the natural log, so the coefficients can be interpreted as the percentage change if the values displayed in the table are multiplied by 100. For the fifth quintile, an increase of balances by one percent leads to a 17 percent decrease in the predicted level of new charges.

The available liquidity positively predicts new charges (and is statistically significant) for all income groups. The economic significance is similar and large across the income

[14] Given research on credit card limits, this assumption is reasonable. Credit card line increases are typically made at predetermined intervals and at the prerogative of the lender, as opposed to by request of the borrower (see Gross and Souleles (2002) and Castronova and Hagestrom (2004)).
[15] The SCF uses multiple imputations to eradicate issues with missing data, as discussed in Bucks *et al.* (2006) and Montalto and Sung (1992). This has been accounted for in the estimation, as recommended by the latter authors.

quintiles. This relatively large and statistically significant effect suggests households are sensitive to changes in the liquidity on the card, irrespective of income and controlling for other factors. Even households in the bottom two quintiles, who might reasonably be characterized as constrained in credit markets, behave similarly to their upper quintile counter parts with respect to available liquidity.

Given the information in Table 1, one might expect a positive relationship between income and credit cards spending in the sample. This is the case for all but the first quintile, those with less than $20,000 in total income, and the fifth quintile. Only for the poorest quintile is the negative coefficient statistically significant. Otherwise, income is a significant and positive predictor of new charges for the entire sample (that includes the wealthiest households) and for the second quintile. For the latter, statistically significant at the ten percent level, the economic effect is large (a 145 percent increase, which may suggest an outlier or unobserved heterogeneity is affecting the estimate).

The lack of significance in the remaining quintiles for income may not be surprising given the delineation by income defining the sub-regressions (removing much of the variability that otherwise might occur in the income variable); however, this is also case in the sample excluding the top five percent of income earning households (this excludes 1,166 households). It would seem that for households below the top five percent, once other factors are accounted for income is not a statistically important predictor of new credit card charges.

As for those other factors, college is a positive and statistically significant predictor in all the regressions except for the second quintile. This general result accords with the data displayed Table 1. Even for the poorest quintile, all else held constant, the more educated incur higher levels of new charges. Age is a positive and statistically significant predictor in all but two of the cases, though the economic significance is small compared to the variables discussed thus far.

With respect to the remaining balance sheet regressors, the level of savings is not statistically significant in any of the regressions. The level of stock, however, is statistically significant in the two larger samples (columns one and two) and for the fourth quintile, those making between $60,000 and $97,000 a year. This suggests that perhaps there is a non-linear wealth effect for credit card spending, where only for the upper middle class is the accumulation of stock wealth significant enough to predict higher credit card charges. However, for the statistically significant coefficients the economic significance is less than the other factors. For example, if one is to compare the sources of liquidity from the credit card accounts to the savings accounts and the stock funds together, credit card liquidity dominates in terms of economic significance in explaining the level of new charges.

Finally, the balance on a household's installment consumer loan is not a significant predictor in any of the regressions. And only for the lowest quintile is the credit card interest rate a negative and statistically significant predictor of new charges. Overall, the first quintile behaves similarly to other income groups with the exception of the significance of the interest rate and the negative and significant coefficient on the level of income.

These conclusions are tentative at this point, in so far as unobserved heterogeneity may be affecting the results as might the endogeneity of some of the regressions. We address these in turn, beginning with the latter.

4.1.1 Endogenous Regressors and Instruments

To consider potential endogeneity, we test whether the level of balances, the available liquidity, the other loan, stock and savings are endogenous (all might be determined simultaneously driven by some unaccounted for factor). For the two-stage least squares estimation necessary for testing for endogeneity, we use the numerous additional information on each household contained in the SCF to build a set of instruments; variables that are redundant in our main regression specification and uncorrelated with the error term. The instrument set includes the following variables:

- *Number of Credit Cards*: The current estimation is based on the total balance on the household's credit cards. The survey asks of each household how many credit cards it has, and the number of new cards. This variable excludes new accounts.
- *Amount of Typical Payment on the Other Consumer Loan*: The amount of the typical payment the household makes on the loan designated as the primary other consumer loan. This is correlated with the total loan, and is set before the

decision to take on new credit card charges (in other words, this variable is not simultaneously chosen when new charges are chosen).

- *Other Loans prior to the Survey Data*: The surveys for the 2004 SCF took place over 2003 and early 2004. The date the consumer loan originated is identified in the data set. Hence, we define affirmative responses for *Other Loans* to only those originated in 2002 and before.
- *Number of Savings Accounts*: This is the number of total savings and money market accounts held by the household.
- *Other Line of Credit*: This variable is the most recent amount borrowed off of a non-credit card line of credit (such as secured by home equity).
- *Other Line of Credit Payment:* The variable represents the monthly payment on that line of credit balance.
- *Balance of Store Cards*: This is the total balance of all department store cards for the household.
- *Balances of American Express Card:* This is the total balance of all American Express and Diners cards for the household.
- *Number of Cars owned*: The number of cars owned by the household.
- *Luxury Cars owned*: A dummy variable if the household's primary car is a sports utility vehicle (SUV) or a collector's or classic car.

The potential list of instruments could go on given the detail of the SCF. However, the current list offers a parsimonious set of instruments that are correlated with the potential endogenous variables, but redundant in the main equation. For brevity we discuss the results for tests on the first two regressions shown in Table 2 (the largest samples). The findings were similar for the quintiles so we eschew discussing those results.

The first-stage F-tests for the explanatory power of the group of instruments for each potentially endogenous variable are statistically significant at the five percent level.[16]

[16] For brevity, we do not report the test statistics. The weakest correlation is for the value of stock, with a first-stage F-stat below 5. The F-stats for the other regressors are above ten and most are actually significant at the one percent level.

Moreover, for the Hansen-Sargan test of over-identifying restrictions, we fail to reject the null hypothesis that the set of instruments are not correlated with the residuals (from the TSLS estimation).[17]

Given this reasonable confidence in the instrument set, we perform two tests of exogeneity, the Durbin-Wu-Hausman test and the Wu-Hausman test. For both tests, we fail to reject the null hypothesis that there is no statistically significant difference between the OLS and IV estimates (at conventional levels of significance). Accordingly, we focus on the OLS output in this application.

4.1.2 Unobserved Heterogeneity: Credit History and Attitudes

An additional issue arises with respect the specification estimated above. The demographic variables may not be enough to capture other heterogeneous aspects that define household behavior. Perhaps one household has a more liberal view of using credit cards to finance consumption, while another believes that credit cards should only be used in emergency. Such household preferences may exist given age, education or income level (and may be correlated with those variables). Ignoring this heterogeneity may bias the reported coefficients above.

To attempt to capture the unobserved behavior of similar households, we use a number of variables representing the behavior and attitude of the household with respect to using credit (perhaps not captured by the initial regressors). This group of variables reveals a past behavior with credit use and reveals explicitly how the household feels about using credit. The behavior and attitudes may explain why new charges increase, *ceteris paribus*, relative to another household. The variables are the following:

- *Applied for Credit*: The household responds "yes" if either they or their spouse has applied for any type of credit in the last five years (this includes pre-approved applications the household has accepted). All else remaining equal, a household with a history of using credit may have a higher level of new charges.

[17] For the Sargan statistic (assuming no conditional heteroskedasticity) the decision is clear (with a probability value for the statistic of 0.40). For the Hansen J statistic (still consistent if heteroskedasticity is present), the potential for a type II error is greater, as we fail to reject at the five percent level of significance, but reject at the ten percent level.

- *Turned Down for Credit*: This question identifies a household that has been turned down for credit, or not approved for the requested amount, at least once in the last five years. The household may now be more likely to use a credit card to access credit (if the previous denial was for cheaper, installment credit)**.**
- *Missed Payments*: Identifies a household that has missed a payment or made a late payment on any type of loan in the last year**.** All else remaining equal, a household with a spottier credit record may have a higher level of new charges (perhaps revealing a more reckless attitude towards using credit). A similar point applies to the next variable.
- *Bankruptcy*: Identifies a household that has filed for bankruptcy (the head of the household or the spouse at any point).
- *Credit is good*: Identifies households that respond it is "a good idea" to buy things on installment credit plans (the other two options included "good in some ways, bad in others," and simply, "bad idea"). All else remaining equal, a household with liberal attitudes towards credit use may have a higher level of new charges. The same can be said for the next two attitude variables.
- *Credit okay for Vacations***:** Identifies households that agree it is okay to borrow money to "cover expenses of a vacation trip" (other options included the purchase of a car and for education).
- *Credit okay for a Fur Coat or Jewelry***:** Identifies households that agree it is okay to borrow money to "finance the purchase of a fur coat or jewelry."

We include this set of "behavior and attitude" variables in the regressions we first reported in Table 2. Table 3 displays the coefficient estimates from our primary regressions with the behavior and attitude variables included in the regressions. The estimated coefficients are not much different from those displayed in Table 2 and in the majority of cases we are not led to change our decision for the null hypothesis on each coefficient estimate. The results displayed in Table 3 suggest that overall the exclusion of these variables are not causing undue bias in the estimates displayed in Table 2.

It is not the case either that the robust standard errors are improved much from the inclusion of the attitude and behavior regressors. Table 3 also displays the F-tests on the significance joint explanatory power of the behavior and attitude variables as group. Only for the largest sample is the explanatory power of the group significant.[18] Broadly speaking, the main regressors appear to be sufficient for capturing heterogeneity across households.

4.1.3 Consumption Smoothing Motives: Income Shortfalls and Expectations

An additional form of unobserved heterogeneity may be of interest, information on each household that may suggest a need for consumption smoothing. For example, new charges may be driven by a desire to smooth consumption given a spell of unemployment, lower than normal income, or the expectation that income will be lower than normal. Fortunately, the SCF identifies the level of income as "normal," "unusually high," or "unusually low." Also, expectations at the time of the survey for future income may explain the new charges. New charges may increase given a projection of permanent or longer term income. Such a projection is included in the survey data.

We control for the first factor by running a separate regression for households reporting their level of income as being "unusually low." If a significant response to income is evident for this sample of households, this may indicate that households use credit cards if they perceive current income is low relative to their conception of permanent income level. For brevity, we focus on the primary largest sample, which includes all households except the top five percent according to reported total income.

For this sample of 448 households, the results displayed in the first two columns of Table 4 show these households do not behave much differently than the larger sample represented by column two in Table 2. The income variable is not statistically significant and the magnitudes of the statistically significant coefficients do not change appreciably. Though for this sample, neither stock nor age are significant predictors of new charges.[19] The second column shows that including the behavior and attitude variables do not change the coefficient estimates to an important degree (enough to change the decisions on any the null hypotheses).

[18] We eschew reporting the individual coefficient estimates for the behavior and attitude variables; the majority were statistically insignificant.

[19] As an alternative, we included dummy variables in the first two regressions (columns 1 and 2 in Table 2) for both "unusually low" income and "unusually high" income levels. The estimated coefficients were not statistically significant.

The third and fourth columns of Table 4 displays the results for considering households who claim to have “a good idea of their income “next year”—suggesting they have a good sense of their permanent, or at least, medium term level of income. For this sample of 1625, the only apparent difference relative to column 2 in Tabl2 is the level of income is statistically significant, with a higher coefficient estimate. Again, including the behavior and attitude variables does not change the inference.

4.1.4 Households that Revolve Balances Month-to-Month

Lastly, this section considers the oft-quoted statistic that almost 50 percent of households revolve their credit card balances. While the samples above considered new credit card charges for households with either a zero or positive balance, perhaps those who revolve are somehow different from those “responsible” enough to pay off the balance each month. Perhaps these responsible households are masking important information between the dependent and independent variables in the results discussed thus far.

On balance, the results displayed in Table 5 for those revolving balances reveal a few interesting insights. First, the coefficient estimates for the available liquidity are all still statistically significant with similar magnitudes to those displayed in Table 2 (though for the fifth quintile this significance comes at the ten percent level). That is, the level of new charges predicted by the available liquidity is not appreciably different if we isolate the “revolvers” in the sample. On the other hand, the coefficient estimates for the level of balances are economically larger for the “revolvers” than for the broader sample that includes households with both zero and positive balances at the time the new charges are made. That is, for the “revolvers,” the level of new charges will be lower relative to all households.

Some other differences of note are the coefficients on age are now statistically insignificant in each sample, and the coefficient estimates for the bottom two quintiles are no longer statistically significant. Also, for the largest two samples (columns one and two), the interest rate is now statistically significant (though for the income quintiles this is not the case). Aside from those differences, however, the decisions on the null hypothesis of most of the coefficient estimates do not change when we isolate the "revolvers" in the sample.[20]

5. Conclusion and Implications

Overall, the two most important factors in predicting new credit card charges for the households surveyed in the 2004 SCF are the level of balances and the available liquidity provided by their credit cards. Indeed, new charges are predictably lower the higher the level of balances, especially so for those that carry a balance month-to-month. New charges, however, are predictably higher given credit card liquidity. The qualitative and quantitative significance of the latter result is the same for all households. This is true, too, across income quintiles, where households in the lower quintiles do not appear much different from those in the upper quintiles with respect to these factors.

Also notable is the lack of economic and statistical significance of the level of savings in determining the level of new charges. This result in general accords with the behavior noted by Telyukova (2007) and Zinman (2007), the level of savings does not deter a positive balance. Here, the level of savings is not important in predicting the choice to make new charges on the credit card.

Similarly, the level of non-pension stock does not deter new charges. Instead, the level of stock is positively related to the level of new charges. This suggests a sort of wealth of effect for credit card spending, though this effect is not consistent across income quintiles (with little to no effect for the bottom two quintiles). Taken together the results for both the level of savings and the level of stock are interesting since they provide a source of liquidity to households in competition with the available liquidity on a the credit card accounts. The results from these regressions seem clear. Credit card liquidity dominates in terms of economic significance in explaining the level of new charges.

Why would a household prefer to draw down its credit card liquidity instead of accessing its savings or stock? One explanation is the household is irrational or

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[20] Given the lack of import, qualitatively and quantitatively, of the behavior and attitude variables in our inference up to this point, we do not report the results for regressions on the "revolvers" including those additional controls. Also, no new insight was provided by regressions for "revolvers" with consumption smoothing motives (akin to the results displayed in Table 4). Hence, we do not report and discuss those results.

somewhat less than rational. A household may have time inconsistent preferences as reasoned by Angeletos *et al.* (2001), or they use different accounts for different types of purchases, as suggested by Telyukova (2006). Alternatively, this behavior is rational in so far as the benefits of using the credit card are higher than the cost of accessing the credit and accruing more charges on the card. This possibility is pointed out by Brito and Harvey (1995), and the data analyzed here appear consistent with that story.

The most economically significant predictor of new charges is, in fact, the available liquidity which is costless to access. As for one measurable cost of accruing additional charges, the interest rate is not a factor in determining the level of new charges for most households, though is more so for households carrying balances from month-to-month. Economically, the effect is relatively small (at most 2.8 percent for the sample of "revolvers," relative to the magnitudes of 26 percent and 37 percent for balances and card liquidity, respectively, in column 2 of Table 5). Overall, this result is consistent with previous findings that credit card spending is generally inelastic to the interest rate (see the references in section 2). While the methods in this paper do not provide a way of measuring the benefits of credit card use, in the least, the data support the notion that the relevant costs of doing so are apparently less than the benefit perceived by households.

To be sure, the perceived benefits of credit card use may be misunderstood by households, or over-estimated by those that may be considered liquidity-constrained. However, the results in this paper suggest otherwise. Controlling for income, the level of education is a positive and statistically significant predictor of new charges. The better educated are more likely to incur new charges. Also, the poorer households do not appear to use, or rely on, credit cards more than the higher income quintiles. While there is some evidence of this for the poorest households, this result is not robust. Also, the results controlling for a unusual shortfall of income and a good idea of income next year, respectively, are consistent with consumption smoothing more so than liquidity constraints.

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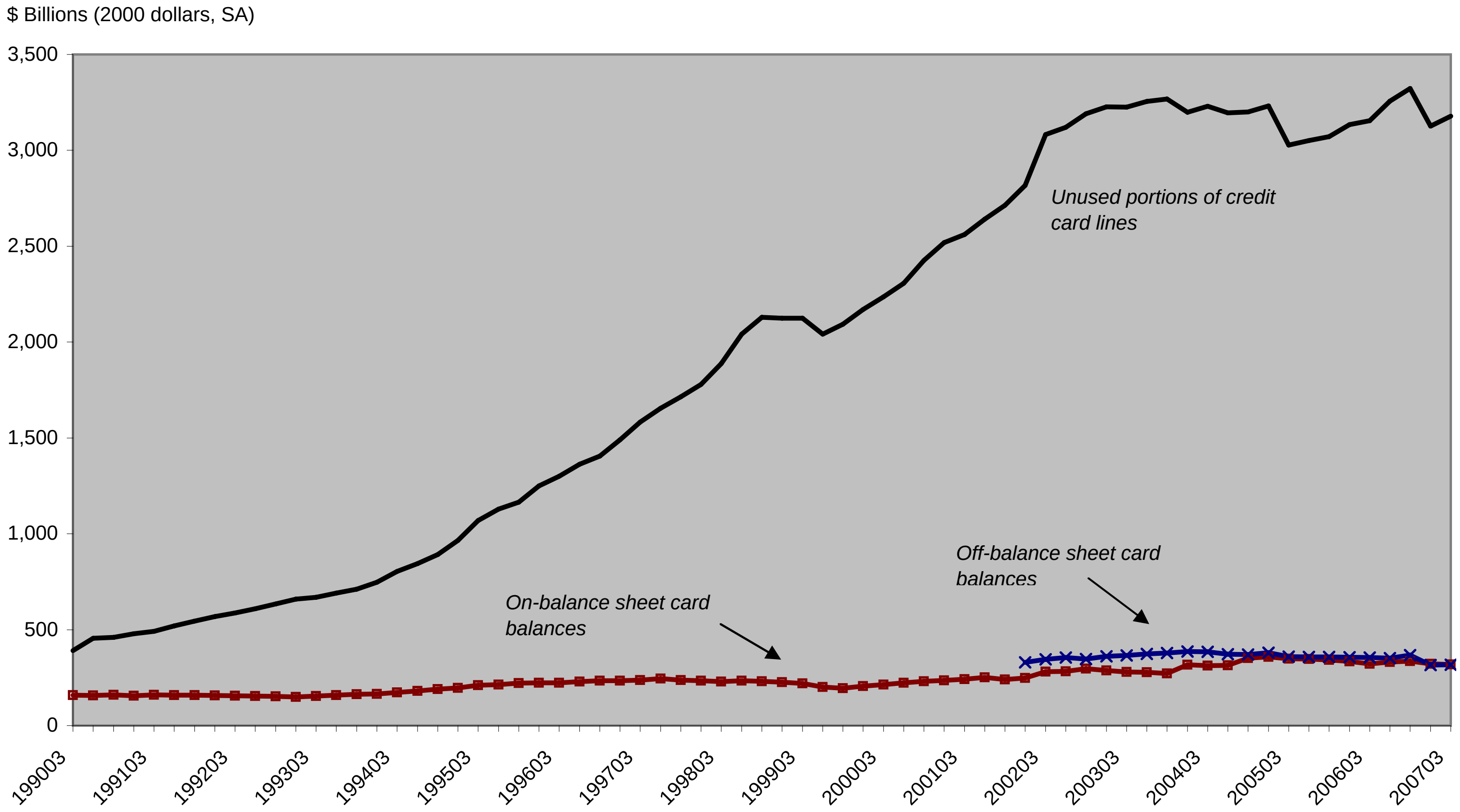
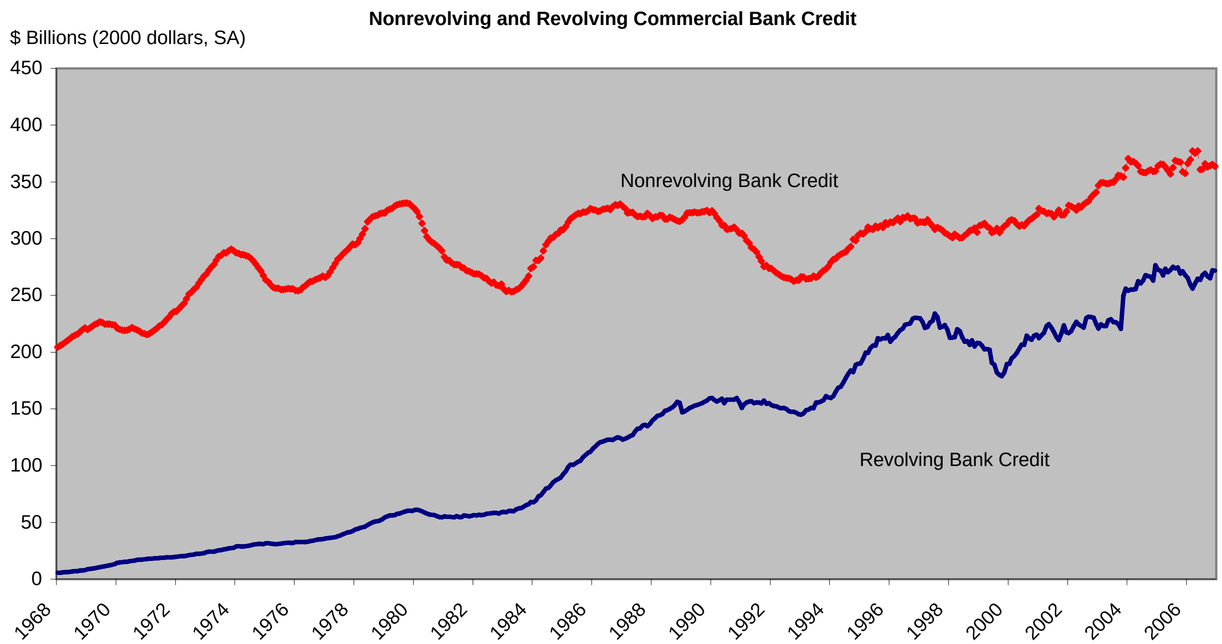
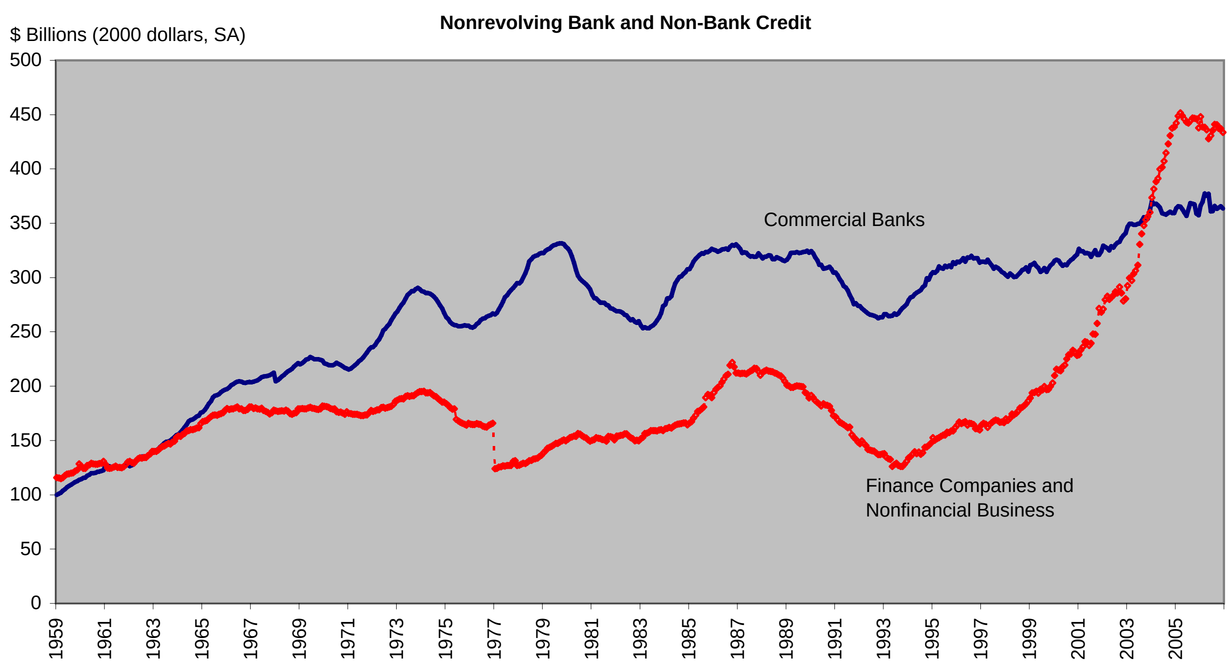
Figure 1: Commercial bank Credit Card Balances and Liquidity: Unused Credit Card Lines



Notes: Data series are calculated from the Call Reports for all FDIC-insured commercial banks (and made available by the FDIC). The series are deflated by the personal consumption expenditures deflator and seasonally adjusted. The off-balance sheet series is available through www.fdic.gov.

Figure 2: Bank and Non-Bank Consumer Credit Loans





Notes: Consumer credit series are from the Federal Reserve Board's G.19 release. The data has been deflated using the personal consumption expenditures deflator (Bureau of Economic Analysis) and seasonally adjusted. The non-bank component includes finance companies and nonfinancial business.

Table 1: Credit Card Use by Income and Demographics

A. Credit Card use by Income

Income Percentile	Percent of families with Credit Card debt		Median		Mean	
	1989	2004	1989	2004	1989	2004
Less than 20	15.0	28.8	400	1,000	800	2,700
20 to 39.9	27.0	42.9	900	1,900	1,700	3,800
40 to 59.9	49.0	55.1	1,200	2,200	2,400	5,200
60 to 79.9	57.0	56.0	1,500	3,000	2,700	5,500
89 to 89.9	58.0	57.6	2,100	2,700	3,100	6,500
90 to 100	41.0	38.5	3,100	4,000	5,600	8,500

B. Credit Card use by Age

Age of Family Head	Percent of Families with Credit Card debt		Median		Mean	
	1989	2004	1989	2004	1989	2004
Less than 35	44.0	47.5	1,500	1,500	2,700	3,700
35 to 44	51.0	58.8	1,600	2,500	2,900	5,200
45 to 54	49.0	54.0	1,500	2,900	3,100	6,200
55 to 64	33.0	42.1	1,500	2,200	2,600	5,700
65 to 74	27.0	31.9	800	2,200	1,800	5,400
75 and above	10.0	23.6	300	1,000	900	4,300

C. Credit Card use by Education

Education of Family Head	Percent of Families with Credit Card debt		Median		Mean	
	1989	2004	1989	2004	1989	2004
No high school diploma	24.0	29.0	900	1,200	2,100	3,600
High school diploma	41.0	48.0	1,300	1,900	2,300	4,500
Some college	51.0	54.0	1,200	2,200	2,600	5,300
College degree	46.0	47.0	1,800	2,700	3,500	6,000

Notes: Income percentiles expressed in thousands. Median and Mean expressed in actual amount, 2004 dollars. The 2004 values can be found in Table 11 of Bucks *et al* (2004). The data for 1989 is approximated (rounded off) from the time series charts available in the 2004 SCF Chartbook. The charts show the values for each survey from 1989 to 2004.

Table 2: Least Squares Estimation of *New Credit Card Charges* in the 2004 Survey of Consumer Finances

	All Households	Households with Income < $150k	5th Quintile	4th Quintile	3rd Quintile	2nd Quintile	1st Quintile
	n = 3476	*n = 2310*	*n = 380*	*n = 566*	*n = 578*	*n = 465*	*n = 320*
Income	0.332	0.062	-0.404	1.124	0.035	1.453	-0.188
	9.280	1.300	-0.384	1.310	0.044	1.764	*-3.720*
Balance	-0.146	-0.125	-0.170	-0.120	-0.122	-0.117	-0.091
	-11.707	*-8.936*	*-4.945*	*-4.412*	*-4.139*	*-3.582*	*-2.288*
Available Limit	0.405	0.415	0.529	0.438	0.293	0.395	0.385
	14.062	*14.061*	*3.147*	*4.834*	*5.485*	*7.327*	*5.647*
Interest Rate	-0.004	-0.011	-0.003	-0.006	-0.021	0.003	-0.045
	-0.545	-1.271	-0.121	-0.343	-1.042	0.142	*-2.096*
Other Consumer Loan	0.013	0.006	0.033	-0.046	0.071	-0.006	-0.089
	0.817	0.266	0.597	-0.852	1.461	-0.109	-1.275
Savings	-0.002	-0.003	-0.004	-0.005	-0.021	-0.049	0.052
	-0.287	-0.234	-0.156	-0.206	-0.726	-1.453	1.400
Stock	0.050	0.047	0.031	0.049	0.036	0.030	0.002
	6.402	*4.032*	1.388	*2.121*	1.277	0.878	0.044
Age	0.006	0.006	0.003	0.016	-0.015	0.006	0.012
	2.004	*1.812*	0.293	*1.963*	*-1.965*	0.863	1.636
College	0.705	0.679	0.660	0.580	0.530	0.129	1.049
	7.489	*6.346*	*2.172*	*2.454*	*2.353*	0.494	*3.921*
R^2	0.400	0.230	0.22	0.17	0.18	0.18	0.29

Notes: The dependent variable for each regression is *New Charges* since the last payment. T-statistics are shown below the coefficient estimates (calculated with robust standard errors). *Italics* indicates statistical significance at the five percent level. Sample sizes includes all households with a credit card, with either a zero or positive balance at the time of the new charge. The quintile ranges accord with the U.S. Census Bureau delinations for 2007. The fifth quintile includes all incomes above $97,030 and excludes households with incomes greater than $150,000. The fourth quintile includes households making $97,030 down to those making just above $60,000; the third quintile includes households making $60,000 down to those making more than $37,771; and the second quintile includes $37,771 down to those making more than $20,032.

Table 3: Least Squares Estimation of *New Credit Card Charges* in the 2004 Survey of Consumer Finances: Controlling for Household Heterogeneity

	All Households	Houeholds with Income < $150k	5th Quintile	4th Quintile	3rd Quintile	2nd Quintile	1st Quintile
	n = 3476	*n = 2310*	*n = 380*	*n = 566*	*n = 578*	*n = 465*	*n = 320*
Income	0.3337	0.0542	-0.582	1.133	0.084	1.400	-0.184
	9.3050	1.1544	-0.556	1.311	0.102	1.725	*-3.417*
Balance	-0.1531	-0.1338	-0.182	-0.112	-0.125	-0.124	-0.116
	-11.9518	*-9.2743*	*-5.134*	*-3.830*	*-4.030*	*-3.909*	*-2.756*
Available Limit	0.4040	0.4202	0.484	0.387	0.313	0.447	0.406
	13.1913	*13.1186*	*2.963*	*4.005*	*5.238*	*7.545*	*5.502*
Interest Rate	-0.0040	-0.0113	0.002	-0.005	-0.026	-0.004	-0.047
	-0.5794	-1.3371	0.087	-0.248	-1.310	-0.202	*-2.173*
Other Consumer Loan	0.0077	-0.0002	0.037	-0.046	0.062	-0.019	-0.114
	0.4771	-0.0081	0.653	-0.890	1.254	-0.357	-1.570
Savings	-0.0020	-0.0013	-0.004	-0.009	-0.015	-0.056	0.060
	-0.2557	-0.1049	-0.164	-0.347	-0.505	-1.651	1.620
Stock	0.0494	0.0467	0.031	0.049	0.035	0.037	-0.008
	6.3658	*3.9739*	1.418	*2.155*	1.215	1.054	-0.183
Age	0.0024	0.0031	0.003	0.018	-0.016	-0.002	0.010
	0.7998	0.8758	0.254	*2.054*	*-1.955*	-0.231	*1.279*
College	0.6864	0.6714	0.550	0.541	0.491	0.136	1.107
	7.2473	*6.2591*	*1.852*	*2.273*	*2.172*	0.522	*3.978*
F-test of Block	2.120	1.332	1.662	0.956	0.858	3.684	1.148
p-value	0.038	0.230	0.117	0.463	0.540	0.001	0.333
R^2	0.41	0.23	0.25	0.18	0.19	0.20	0.31

Notes: *See* notes for Table 2. "Block" includes a set of variables that controls for households' past use of credit and attitudes towards using credit (see the text for a complete list and descriptions).

Table 4: Least Squares Estimation of *New Credit Card Charges* in the 2004 Survey of Consumer Finances: Consumption Smoothing Motives

	Households with Unusually Low Income	Low Income and Unobserved Heterogeneity	Households with "Good Idea" of Future Income	Future Income and Unobserved Heterogeneity
	n = 448	*n = 448*	*n = 1625*	*n = 1625*
Income	0.003	-0.0123	0.164	0.1583
	0.044	-0.2123	*1.974*	*1.9190*
Balance	-0.127	-0.1296	-0.141	-0.1475
	-4.275	*-4.2056*	*-8.280*	*-8.3715*
Available Limit	0.433	0.4219	0.407	0.4153
	8.642	*7.8294*	*10.824*	*9.9139*
Interest Rate	0.009	0.0127	-0.007	-0.0078
	0.410	0.5985	-0.640	-0.7164
Other Consumer Loan	0.012	0.0132	-0.020	-0.0240
	0.242	0.2687	-0.691	-0.8346
Savings	0.027	0.0277	-0.017	-0.0155
	1.009	1.0227	-1.190	-1.0880
Stock	0.038	0.0389	0.051	0.0515
	1.418	1.4254	*3.688*	*3.7193*
Age	0.005	0.0027	0.008	0.0054
	0.732	0.3401	*2.081*	1.2700
College	0.702	0.6890	0.610	0.6128
	2.867	*2.7839*	*4.658*	*4.6590*
F-test of Block	-	1.268	-	0.7
p-value	-	0.260	-	0.670
R^2	0.290	0.300	0.230	0.230

Notes: *See* notes to Table 2. Columns 1 and 2 represent a sample of households statting current income was "unusually low." Columns 3 and 4 represent a sample of households stating they have "a good idea of their income next year." Columns 2 and 4 display results that include the block of variables controlling for past credit use and attitudes towards credits. *See* the notes to Table 3.

Table 5: Least Squares Estimation of *New Credit Card Charges* in the 2004 Survey of Consumer Finances: Households Revolving Balances

	All Households	Households with Income < $150k	5th Quintile	4th Quintile	3rd Quintile	2nd Quintile	1st Quintile
	n = 1461	*n = 1316*	*n = 172*	*n = 310*	*n = 346*	*n = 296*	*n = 190*
Income	0.234	0.113	0.374	0.434	0.563	0.743	-0.097
	3.303	1.618	0.245	0.437	0.572	0.819	-1.103
Balance	-0.249	-0.264	-0.243	-0.283	-0.267	-0.302	-0.217
	-16.450	*-16.001*	*-6.207*	*-8.351*	*-7.632*	*-7.835*	*-3.773*
Available Limit	0.394	0.377	0.370	0.405	0.332	0.364	0.402
	11.870	*11.042*	1.750	*3.722*	*5.683*	*6.303*	*5.010*
Interest Rate	-0.025	-0.028	-0.031	-0.030	-0.029	-0.023	-0.036
	-2.506	*-2.667*	-0.766	-1.273	-1.296	-1.194	-1.326
Other Consumer Loan	-0.006	-0.009	0.014	-0.108	0.076	-0.029	-0.071
	-0.204	-0.311	0.169	-1.605	1.449	-0.509	-0.788
Savings	-0.012	-0.011	-0.022	0.030	-0.041	-0.090	0.050
	-0.802	-0.619	-0.493	0.790	-1.095	*-2.233*	0.886
Stock	0.050	0.045	0.067	0.030	0.015	0.018	-0.021
	3.270	*2.502*	1.597	0.956	0.372	0.341	-0.266
Age	0.001	0.003	-0.026	0.032	-0.015	0.002	0.012
	0.211	0.606	-1.504	0.997	-1.403	0.308	1.249
College	0.528	0.494	-0.032	0.530	0.544	0.131	0.879
	3.986	*3.584*	-0.088	1.881	*1.882*	0.429	*2.392*
R^2	0.30	0.26	0.20	0.25	0.24	0.28	0.29

Notes: *See* notes for Table 2. The results displayed here are based on a sample households that carries a credit card balance from month-to-month (excluding households that reported having a zero balance before new charges were made).

Table 6: Least Squares Estimation of *New Credit Card Charges* in the 2004 Survey of Consumer Finances: Consumption Smoothing Motives and positive balance

	Households with Unusually Low Income	Low Income and Unobserved Heterogeneity	Households with "Good Idea" of Future Income	Future Income and Unobserved Heterogeneity
	n = 270	*n = 270*	*n = 891*	*n = 891*
Income	0.069	0.031	0.279	0.268
	0.596	0.277	*2.049*	1.965
Balance	-0.229	-0.228	-0.273	-0.279
	-6.097	-5.746	*-13.334*	*-13.343*
Available Limit	0.403	0.390	0.372	0.380
	7.098	6.703	*8.292*	7.754
Interest Rate	-0.004	0.005	-0.023	-0.023
	-0.173	0.222	*-1.682*	-1.654
Other Consumer Loan	0.000	0.020	-0.020	-0.023
	0.006	0.349	-0.598	-0.697
Savings	0.005	0.002	-0.031	-0.029
	0.114	0.048	-1.468	-1.372
Stock	0.071	0.066	0.030	0.031
	1.806	1.596	1.350	1.356
Age	0.015	0.014	0.004	0.002
	1.404	1.233	0.649	0.294
College	0.233	0.212	0.424	0.428
	0.745	0.679	*2.467*	*2.477*
F-test of Block	-	1.210	-	1.38
p-value	-	0.297	-	0.215
R^2	0.29	0.32	0.25	0.26

Notes: The dependent variable is *New Charges* since the last payment. T-statistics are shown below the coefficient estimates (calculated with robust standard errors). *Italics* indicates statistical significance at at least the five percent level. Sample s