The Credit Card Debt Puzzle: The Role of Preferences, Credit Access Risk, and Financial Literacy

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Abstract

We use the 1979 National Longitudinal Survey of Youth to revisit what is termed the credit card debt puzzle: why consumers simultaneously co-hold high-interest credit card debt and low-interest assets that could be used to pay down this debt. Relative to individuals with no credit card debt but positive liquid assets, borrower-savers have very different perceptions of future credit access risk and use credit cards for precautionary motives. Moreover, changing perceptions about credit access risk are essential for predicting transitions among the two groups. Preferences and the composition of financial portfolios also play a role in these transitions.

JEL Classifications: D14, D91, E21, G02.

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1 Introduction

The credit card debt puzzle describes the phenomenon of consumers rolling over unsecured high-interest credit card debt while simultaneously holding low-interest monetary assets that could be used to pay down this revolving debt—see Morrison (1998) for an early discussion. This behavior has been well-documented in proprietary datasets and in publicly available ones, including the Survey of Consumer Finances (SCF) and the Consumer Expenditure Survey (CEX). For example, in the 2010 SCF, the proportion of households exhibiting this behavior was around 40.5 percent.

There have been many explanations offered for why the credit card debt puzzle exists. A natural explanation is that this behavior is simply an accounting phenomenon relating to the measurement of revolving credit card debt and liquid asset holdings (a timing mismatch): liquid asset holdings may already be committed to forthcoming expenses. Gross and Souleles (2002) dismiss this reasoning since they find that more than one-third of credit card borrowers keep more than one full month of family income in liquid assets while rolling over credit card debt. Other explanations include self-control problems (see Laibson, Repetto, and Tobacman 1998; Haliassos and Reiter 2007; Bertaut, Haliassos, and Reiter 2009) or strategic preparation for bankruptcy—Lehnert and Maki (2007). Telyukova and Wright (2008) and Telyukova (2013) stress the need for liquidity and rationalize the credit card debt puzzle as a situation where consumers keep liquid assets to pay for cash-only expenditures. More recently, Fulford (2015) and Druedahl and Jorgensen (2018) emphasize the insurance value of revolving credit card balances against possibly binding future credit constraints. When consumers face adverse shocks, they may not be able to tap new sources of credit and/or may face reduced credit limits on currently available sources. However, credit card lenders cannot demand immediate repayment of outstanding balances. For this reason, some consumers could choose not to pay balances in full to conserve cash, or may take advantage of cash advances on credit cards to build a cash buffer in anticipation of future expenses exceeding income.

We revisit the credit card debt puzzle using the 1979 National Longitudinal Survey of Youth (NLSY79). The longitudinal nature of this dataset makes it suitable to study, not previously examined, transitions into and out of the puzzle group, and the future financial costs associated with this behavior. Moreover, it allows us to go beyond well-documented reasons such us impulsiveness, and explore the role of credit access risk. We define *credit access risk* as the likelihood that credit access might be limited or reduced in the future. To our knowledge, we are the first to document that credit access risk plays a key role in this behavior (consistent with Fulford 2015; Druedahl and Jorgensen 2018), and that changes in credit access risk drive the transitions into and out of the borrower-saver (puzzle) group. More generally, our paper contributes to an expanding literature on household finance, improving our understanding of the way households make financial decisions by differentiating between mistakes and strategic choices.

The NLSY79 is a particularly useful dataset to measure revolving credit card debt. After being asked about having credit cards or credit card debt, respondents must answer the following question: *"After the most recent payment, roughly what was the balance still owed on all of these accounts together? If you paid off all of these accounts, please report $0."* Respondents are also asked to report their holdings of low-interest liquid monetary assets: *"Total amount in checking, savings and money market accounts."* Based on the amount of revolving credit card debt and liquid monetary assets an individual holds (abstracting from other assets, liquid and illiquid, and liabilities for now), we classify NLSY79 respondents into four groups: (1) borrower-saver (puzzle), with positive holdings of both debt and assets, (2) borrower, with no assets but positive debt, (3) neutral, with zero holdings of debt and assets, and (4) saver, with assets and no debt.

Compared to respondents in the neutral and borrower categories, individuals in the borrower-saver group have more education, higher Armed Forces Qualification Test (AFQT) scores (a proxy for intelligence), higher financial literacy scores, and more financial resources (income and wealth). They are less present biased and report having a better sense of how to spend money in general. Relative to savers, borrower-savers have higher discount rates, are more likely to have middle levels of risk aversion, have slightly lower financial literacy and AFQT scores, fewer years of formal education, and significantly larger holdings of all types of debt.

We construct a measure of perceived credit access risk (whether an individual was denied credit in the past or did not apply for credit because he/she thought credit would be denied), and document that credit access risk matters for explaining the puzzling behavior. Moreover, respondents whose credit access risk increases over time are more likely to transition from being savers to being borrower-savers and *vice versa*. Fixed effect regressions—which control for time-invariant traits such as time preferences, impulsiveness, financial literacy and other characteristics that could affect demand for consumer credit—confirm that changes in credit access risk are a key driving force behind the transitions between groups. This result remains true even when instrumenting for credit access risk.

An extensive literature documents that physical bank branches are important for credit access (see for example, Gilje, Loutskina, and Strahan 2016; Cortés and Strahan 2017). Our instrument is based on Nguyen (2017), who shows that bank branch closings cause a sharp and persistent reduction in the local credit supply. In other words, when the number of people served by a given bank branch changes, credit availability to these individuals is affected. Thus, we instrument for credit access risk with the growth rate in the number of people served by a bank branch at the county level. One may be concerned that an increase in population per branch may be the result of poor economic conditions, which cause both bank branch closings (the main determinant of number of people per branch) and the puzzling behavior. However, the precautionary motive explanation of the credit card debt puzzle relies on consumers perceiving that credit tightens when they need it the most. Observing bank branch closings may make it more salient for consumers that credit may get tighter in the future. Nevertheless, to lessen these concerns, we also control for the general state of the local economy in our regressions. Conditional on county-level controls for economic conditions and other factors, credit access shocks, as measured by changes in population per branch, have an economically and statistically significant impact on the borrower-saver behavior. Our results speak to the importance of the precautionary borrowing motive as a relevant explanation for the borrower-saver behavior, distinct from explanations relating to self-control issues and poor financial literacy.

The borrower-savers that comprise the puzzle group are a very heterogenous group of individuals. We provide clear evidence that a non-trivial fraction of financially-literate individuals in this group act rationally given their preferences and credit access risk perceptions: they can simultaneously hold revolving credit card debt and liquid assets for extended periods of time without getting into financial trouble. Yet some borrower-savers do not fit this description. In fact, compared to savers, borrower-savers in 2008 were significantly more likely to declare bankruptcy or go through foreclosure sometime between 2009 and 2012.[1]

The rest of the paper is organized as follows. In Section 2, we define and characterize the borrower-saver group relative to the other three groups in the NLSY79. Section 3 presents the main theoretical explanations for the existence of the credit card debt puzzle offered in the literature. We formally test the precautionary borrowing hypothesis along with other theories in Section 4, and analyze transitions into and out of the borrower-saver group in Section 5. In Section 6, we present estimates of the financial burden borrower-savers actually face from the interest payments on their revolving balances, and then examine whether this borrower-saver behavior increases the likelihood of bankruptcy and foreclosure. Section 7 presents our conclusions.

2 The Borrower-Saver Group in the NLSY79

The NLSY79 follows a cohort of 12,686 male and female respondents who were 14–22 years-old in 1979. These individuals were interviewed annually until 1994 and biennially thereafter. Because the NLSY79 oversampled the poor and members of the military, we dropped these subsamples to concentrate our analysis on the random sample that is more broadly representative of the U.S. population.

The NLSY allows for a detailed examination of respondents' behavior by collecting a variety of

[1]Athreya, Mustre-del Rio, and Sanchez (2017) use panel credit bureau data to show that most episodes of financial distress can be accounted for by a small proportion of individuals. They show this finding can be explained in a model with heterogeneity in time preferences. We document that such heterogeneity indeed exists.

personal data that ranges from current financial assets and liabilities to health indicators. Compared to the SCF and the CEX, the other U.S. datasets employed to investigate the credit card debt puzzle, the NLSY's longitudinal dimension allows for respondents' behavior to be observed before, during, and after being in the borrower-saver group. While credit card data was not collected in the NLSY until 2004, the starting point of our analysis, a variety of other variables are available since 1979 for each respondent, thus offering a unique opportunity to look backwards as well as forwards for factors that could contribute to being a borrower-saver.

Credit card data is available in 2004, 2008, and 2012 only, and our analysis focuses on this period. Our sample consists of approximately 2,700 respondents per year when including all nonmissing controls and restricting the analysis to the random sample. Respondents are 39–47 years-old in 2004.

2.1 The Distribution of Respondents

Based on the reported holdings of revolving credit card debt and liquid monetary assets, we classify the NLSY79 respondents into four groups: (1) borrower-saver (or baseline puzzle), with positive holdings of revolving credit card debt and liquid monetary assets; (2) borrower, with no assets but positive credit card debt; (3) neutral, with zero holdings of both; and (4) saver, with liquid monetary assets and no credit card debt.

Table 1 shows that in 2004, 48.4 percent of the NLSY79 respondents are in the borrower-saver group, 4.6 percent fall in the pure borrower category, 35.6 percent are in the saver group, and 11.4 percent are in the neutral group. These figures are similar to comparable statistics calculated using the SCF. In 2004, 49.3 percent of respondents in the SCF revolve credit card debt and keep positive liquid assets.

Over time, the proportion of respondents in the borrower-saver group declines and the share of savers rises. By 2012, 40.5 percent of respondents are in the borrower-saver group, and 41.3 percent are in the saver group. The overall number of consumers with revolving credit card debt goes down by 8 percentage points (from 53 percent to 45 percent), consistent with the documented deleveraging of consumer debt during the Great Recession. Respondents get older over time, and it is also possible that debt simply declines when respondents hit their peak earning years. However, the size and the evolution of the borrower-saver group do not seem to be very sensitive to the age distribution. In the SCF, representative of the U.S. population, the borrower-saver group is slightly larger but also declines after 2008; see Figure 1.

Alternative Definitions

To make sure our results are robust as to how the borrower-saver group is constructed, we consider alternative definitions. In particular, carrying small balances on credit cards may not be very costly, and/or some of the current balances in liquid assets may already be committed to upcoming expenses. We reclassify individuals initially placed in the baseline puzzle group as savers or borrowers depending on the specific alternative definition used, but we keep the definition of the neutral group unchanged. The distribution of respondents based on other variations in debt-savings thresholds are presented in Table 2. For example 20.1 (23.2) percent of respondents are borrower-savers (savers) in 2004 when defining the puzzle group as having at least $500 in credit card debt and one month of annual income in monetary assets —a definition that will be used in our robustness analysis and labelled *strict* puzzle from now on. These numbers are similar to those from the SCF, where 17 percent of respondents are borrower-savers in 2004 when using the strict definition. As with the baseline definition, the proportion of respondents in the strict borrower-saver group declines over time.

2.2 Comparisons across the Four Groups

Table 3 provides a quick summary of the differences across groups in 2004. Detailed definitions of all variables used in the paper can be found in the online appendix.

We find that borrower-savers are very similar to savers in many ways: they have similar AFQT scores, levels of education, financial literacy, and financial knowledge. On the other hand, borrower-savers and savers have much higher levels of AFQT scores, education levels, and financial literacy scores than borrowers and individuals in the neutral group. Borrower-savers have slightly lower family income and lower wealth than savers, but they are notably wealthier than borrowers and neutrals.

When comparing the borrower-savers in the puzzle group to the saver group, what most distinguishes the former is their appetite for credit (borrower-savers have the highest loan application rates among all groups and are more likely to hold loans of all types), time preferences (borrower-savers have higher time discount rates than savers), and higher credit access risk (measured with a dummy for whether respondents had applied for credit in the last five years and were denied, or did not applied because they thought they would be denied).

We reach similar conclusions when comparing borrower-savers and savers using the strict puzzle definition. Compared to baseline savers, the different characteristics between the two groups (in terms of formal and financial knowledge, time preferences and resources) lessen or disappear. This implies that the behavior associated with the credit card debt puzzle may be strategically informed; i.e., there is some financial sophistication informing these choices at least among some subset of the borrower-saver group.

2.3 Evolution over Time

The longitudinal nature of the NLSY79 allows us to analyze how persistent or transitory group membership is. Table 4 contains information on transitions over time across the four different respondent categories (borrower-saver, borrower, neutral, and saver). In the first panel, the first four entries can be read as follows: under the baseline definition, 70.2 percent of members of the borrower-saver group in 2004 remain in the borrower-saver group in 2008, 5.7 percent of them transition to the borrower group, 3.2 percent transition to the neutral group, and 20.9 percent switch to the saver category. Other rows in this panel and other panels should be read similarly except the last one, which reports the percentages of respondents who remain in the same group during all three periods: 48.5 percent of borrower-savers in 2004 are also borrower-savers in 2008 and 2012, 7 percent of respondents are always borrowers, 47.5 percent are always in the neutral category, and

48.3 percent are always savers. Being in the puzzle group seems to be quite a stable condition, comparable to being in the neutral and saver categories.

When using the strict definition, ($500 of credit card debt, one month of saved annual income), the picture is somewhat different. From 2004 to 2008, 43.9 percent of respondents in the borrower-saver group stay there, while 18.1 percent become savers; 58.1 percent of savers remain savers, while 12.9 percent of savers transition into the borrower-saver group. Overall, belonging to the puzzle group appears to fluctuate, with 21.2 percent of borrower-savers in 2004 remaining borrower-savers during the whole period, compared to 43.7 percent of savers who always stay savers. This finding indicates that it is important to consider alternative definitions of the credit card debt puzzle going forward, while acknowledging that a nontrivial fraction of individuals are in the puzzle category during all three sample periods, even when a stricter definition is considered.

While liquid savings increase over time for both savers and borrower-savers, credit card balances increase from 2004 to 2008 and decrease from 2008 to 2012 (savers have zero credit card debt by definition). Arbitrage, or the difference between liquid assets and credit card debt, increases over time. Interestingly, strict borrower-savers and baseline savers have very similar levels of net liquid assets (see the online appendix).

Figure 2 depicts the evolution of the credit access risk measures used in our regressions: (1) a dummy equal to one if a respondent has been denied credit in the past five years, and zero otherwise; and (2) a dummy equal to one if a respondent has been denied credit in the past five years, or decided not to apply for credit because he/she thought the application would be denied, and zero otherwise. On average, credit expanded during the 2004–2007 period, only to get tighter after 2008. Importantly, borrower-savers are more likely to have been denied credit than savers.

In sum, some borrower-savers are fairly wealthy and seem to have good access to credit compared to other groups (the strict puzzle group in particular). It is possible that the reason why these individuals simultaneously hold credit card debt and liquid assets is because they are offered favorable credit card rates (at least temporarily), and they simply take advantage of them. However, more borrower-savers (relative to savers) have been denied credit in the past, so access (or perception of access to) credit may play an important role in the borrower-saver behavior.

3 Theoretical Explanations for the Borrower-Saver Behavior

Four distinct explanations for the credit card debt puzzle stand out in the literature. First, individuals or couples may have self-control issues when it comes to shopping that they recognize needs to be dealt with. Bertaut, Haliassos, and Reiter (2009) propose an accountant-shopper model. The rational accountant (self or partner) has a motive not to fully pay credit card balances to limit spending by a more impatient shopper (self or partner)—upper limits on credit cards would be reached more quickly if balances are not paid for in full, and this restrains spending.[2] This accountant-shopper theory suggests that borrower-savers would tend to be more impatient than others (or have relatively more impatient partners), but not necessarily financially illiterate. Using survey data from the United Kingdom, Gathergood and Weber (2014) provide empirical support for models that stress managing self-control problems as an explanation for the puzzle (as opposed to explanations based on a misunderstanding of basic personal finance). They find that households that co-hold credit card debt and assets tend to be impulsive shoppers with higher levels of financial literacy than other households. Although direct information on shopping-related impulsiveness is not available in the NLSY79, we are able to circumvent this problem by examining a fixed-effects specification that removes impulsiveness and time preferences (under the assumption that these variables are time invariant), allowing us to look into explanations beyond these factors.

Second, Lehnert and Maki (2007) find that states with higher asset protection from bankruptcy have both higher bankruptcy rates and more borrower-saver households. Mankart (2014) builds an explanatory model of the credit card debt puzzle around the idea that bankruptcy laws in the

[2]This behavior is different from hyperbolic discounting and present bias—Laibson (1997). We do not expect present-biased individuals to belong to the puzzle group, as such individuals (when recognizing their bias) would tend to hold credit card debt and illiquid assets (as a commitment device) instead of liquid assets.

United States create an incentive for individuals who may default in the near future to hold debt and assets simultaneously: when filing for bankruptcy, debts are forgiven (under Chapter 7) and assets can be kept up to an exemption level. His model, however, does not deliver a strong positive relationship between exemption levels and default rates; the reason is that borrowers who default in the model do not own much wealth so very few households are affected by increases in the exemption level. This implication is consistent with the findings in Lefgren and McIntyre (2009), who document that state bankruptcy rate differentials reflect the relative costs of filing for formal bankruptcy protection versus informal default, rather than differences in exemption levels. While individuals preparing for bankruptcy may strategically want to hold positive balances on credit card debt and liquid assets, such incentives should not be present with foreclosure. If we see a differential effect on bankruptcy and foreclosure, strategic behavior may be at play. In contrast, if borrower-savers go bankrupt and are also foreclosed on their properties more often than others, this may indicate a poor understanding of financial matters rather than strategic behavior. The NLSY79 allows us to explore whether borrower-savers are more likely to declare bankruptcy or be foreclosed on their properties.

Third, Telyukova (2013) explains the borrower-saver puzzle as a need for liquidity: certain expenses can only be paid for in cash (e.g., mortgage or rent, utilities, babysitting, child/elder care services, or taxes). Her explanation could be interpreted as cash being committed for future expenses that require liquid payment, a hypothesis that combines the timing-mismatch explanation and the precautionary borrowing explanation of the credit card debt puzzle (discussed next). Unfortunately, the NLSY79 contains very limited information on spending, except for information on mortgages and other types of debt (like car loans and student debt), and we are not able to formally test her model. One implication of Telyukova's model is that the size of the puzzle group should decline as credit cards usage becomes more widespread, a pattern observed in the NLSY79. However, there are several alternative explanations for this trend over our sample period (2004–2012), such as the overall reduction in credit supply during and following the financial crisis, and/or possible side effects related to the Credit Card Act of 2009.

Finally, Fulford (2015) and Druedahl and Jorgensen (2018) stress the precautionary motive for revolving credit card balances. Access to new debt may be limited when facing adverse shocks (income/wealth, health, and so on), but (under current U.S. law) lenders cannot demand immediate payment of outstanding balances. Future credit reductions could come in many forms, including being unable to open a new line of credit, or more relevantly, losing access to currently available sources. Using the Federal Reserve Bank of New York Consumer Credit Panel data, Fulford (2015) documents that credit limits vary over time, and that there is a significant and positive probability of experiencing a credit limit reduction. Moreover, this credit reduction is observed across consumers of all credit quality levels.[3] This credit access risk (not being able to borrow or use currently available credit in the future), in combination with legal credit card holder rights (lenders cannot demand early repayment of outstanding balances on unsecured debt), may be what potentially motivates some individuals to revolve their credit card balances while keeping some liquid assets on hand. Druedahl and Jorgensen (2018) provide a complete catalog of what is needed to generate a large borrower-saver group in their augmented buffer-stock model of savings. Individuals have to be impatient enough, have the right degree of risk aversion, and they must perceive income and credit access risk as positively correlated. Their theoretical model also predicts that the borrower-saver behavior that defines the puzzle group is most optimal for individuals with intermediate levels of net worth. The richness of the NLSY79 allow us to formally test the predictions of this model. We refer to this explanation as the precautionary borrowing hypothesis.

[3]Similarly, VantageScore Solutions (2011) reports that as a response to the Credit Card Act of 2009, many lenders reduced credit limits and closed lines of credit on existing customers to reduce their exposure to market risk. Importantly, this credit reduction was seen across all levels of initial credit quality. Credit card holders in the lowest (highest) Vantage score range, 501–600 (901–990), had their limits reduced by 58 (56) percent.

4 Explaining the Borrower-Saver Behavior

The rest of the paper examines what factors determine the probability of becoming a borrower-saver, where we try to disentangle the different reasons motivating this behavior. We are the first to formally test the precautionary borrowing hypothesis. We also examine the role played by individual preferences (discount factors and risk aversion), formal education, financial literacy, and self-assessed financial knowledge in predicting the borrower-saver phenomenon.

We pool all three years of credit card data together (2004, 2008, and 2012), and estimate weighted linear probability regressions (WLS) of the form:

$$\boldsymbol{P_{ist}} = \alpha + \boldsymbol{N_i}\theta + \boldsymbol{M_i}\gamma + \boldsymbol{X_{it}}\beta + \boldsymbol{F_{it}}\eta + \mu\boldsymbol{L_{it}} + \nu\boldsymbol{\sigma^{Y}_{it}} + \boldsymbol{C_{i,t}}\xi + \lambda_t + \lambda_s + \boldsymbol{\epsilon_{i,t}}, \qquad (1)$$

where $\boldsymbol{P_{ist}}$ is a dummy variable equal to one if individual i who lives in state s at time t is in the borrower-saver (puzzle) group, and is zero otherwise. The matrix $\boldsymbol{N_i}$ measures the respondent's intelligence as proxied by the AFQT score, level of completed education, financial literacy and self-assessed financial knowledge (the last two are dummies for being above or below the median).[4] The matrix $\boldsymbol{M_i}$ measures personal traits that may affect the desire for credit such as risk aversion (being in the middle group vs. the rest) and time preferences (being below or above the median discount rate and the median present-bias measure).[5] The matrix $\boldsymbol{X_{it}}$ measures demographics including age, race, gender, marital status, and the presence of children in the household. $\boldsymbol{F_{it}}$ is a financial information matrix: it includes a standardized measure of net worth (zero mean and a standard deviation of one), and dummy variables for the respondent's past demand for credit. The vector $\boldsymbol{L_{it}}$ denotes credit access risk, and is measured with a dummy equal to one if, in the past

[4]We use detailed questions administered by the NLSY79 in 2012 to assess respondents' financial literacy and self-assessed financial knowledge. See the online appendix for details.

[5]The appendix describes how these measures are computed. We follow Barsky et al. (1997) to construct a risk aversion measure, and Courtemanche, Heutel, and McAlvanah (2015) to measure discount rates.

five years, the respondent applied for and was denied credit, or was discouraged from applying because she thought she would be denied credit, and is zero otherwise—the assumption is that individuals who were denied credit in the past, or thought they would be denied, are more likely to expect rejection in the future. The vector $\boldsymbol{\sigma}_{it}^{Y}$ denotes income volatility. Our measure is based on detailed work histories. In particular, we use answers to the question *"What is the main reason you happened to leave this job?"* to create a *job shock* variable equal to the total number of times since the previous interview that a respondent lost his/her job for unexpected reasons (such as being discharged or fired, laid off, job eliminated, business closings, business bankruptcies, and/or failure, quits for disabilities or health reasons). We experimented with other measures of income uncertainty and found our results to be similar (see the online appendix).

We include measures of changes in local economic conditions, $\boldsymbol{C}_{i,t}$, to control for the possibility that these conditions affect the decision to become a borrower-saver. We measure $\boldsymbol{C}_{i,t}$ with the change in the unemployment rate and the growth rate of house prices, both at the county level. We also include time fixed effects, λ_t, to control for aggregate economic conditions, and state fixed effects, λ_s, to control for differences in personal bankruptcy regulations across states, along with any other time-invariant differences across states that may affect the probability of being in the puzzle group. Standard errors are clustered by respondent in all regressions.

In Table 5, columns (1)–(4), we present results for the baseline puzzle definition (positive balances on credit card debt and liquid savings), while columns (5) and (6) focus on the strict puzzle definition, ($500 in credit card debt and one month of annual income in liquid savings). According to the summary statistics, borrower-savers are very similar to savers, so in the main text we present results comparing borrower-savers to savers. Multinomial logistic regressions, comparing borrower-savers to all other groups are in the online appendix.

In column (1), we control for demographics, time preference parameters, risk aversion, intelligence, formal and financial knowledge, credit access risk, income uncertainty, financial information, local economic conditions, and aggregate shocks. Relative to savers, individuals who more heavily discount the future are 6 percentage points more likely to be borrower-savers. Also, individuals falling in the middle of the risk aversion spectrum are almost 4 percentage points more likely to be borrower-savers. Present bias does not seem to have a statistically significant effect, as expected. The effect of impatience is consistent with the accountant-shopper model of Bertaut, Haliassos, and Reiter (2009). The fact that both discount rates and risk aversion matter for placement in the puzzle group is in accord with the model of precautionary borrowing posited by Druedahl and Jorgensen (2018).

Turning to the effect of intelligence, education and financial literacy, individuals with more formal and informal knowledge are less likely to be borrower-savers. Having a college degree lowers the probability of being a borrower-saver by almost 5 percentage points. Having above-median financial literacy decreases the probability of being in the puzzle by 4 percentage points, while having above-median self-assessed financial knowledge does not have an additional effect beyond the previous controls. This result differs from Gathergood and Weber (2014), who find no differences in financial literacy scores between borrower-savers and savers. Interestingly, higher AFQT scores are associated with a higher probability of being in the puzzle, all else constant—a one standard deviation higher AFQT score increases the probability of being a borrower-saver by almost 3 percentage points.

Changes in the unemployment rate at the local level do not seem to affect puzzle membership (conditional on individual-specific job shocks and other controls), while recent local house-price appreciation decreases puzzle membership—consumers may use potentially less expensive home equity lines of credit when house prices are increasing. The probability of being a borrower-saver has been declining over time, a development that might reflect changes in credit card availability and costs following the Credit Card Act of 2009, or more general credit supply restrictions enacted during the Great Recession. We revisit credit card borrowing costs in Section 6.1.

Moving on to credit access risk and the precautionary borrowing hypothesis, we find that respondents with higher levels of credit access risk are significantly more likely to belong to the puzzle group. Keeping all else constant, a one standard deviation increase in the probability of being denied credit is associated with a 3 percentage point increase in the likelihood of being a borrower-saver. Income volatility does not have an independent, statistically significant effect in these regressions. The income volatility result is similar to that of Gathergood and Weber (2014), who control for a subjective measure of future income shocks.

In column (2), we include state fixed effects and financial controls. Adding these variables does not change our main results, however the regression predictive power (as measured by the adjusted R^2) increases from 0.03 to 0.10. Not surprisingly, net worth matters: a one standard deviation increase in net worth, reduces the likelihood of being a borrower-saver by 7 percentage points. On the other hand, having other types of debt results in a higher probability of being a borrower-saver. These results may speak to liquid savings already being earmarked for certain expenditures, consistent with Telyukova (2013), or to debt repayment prioritization by the respondents.

To rule out the possibility that our findings are driven by timing mismatch—the reality where liquid assets are already committed to expenses, though it appears that respondents have funds available to repay revolving credit card debt—we focus on the strict borrower-saver definition in column (5). The number of observations is lower because under this definition there are fewer respondents in both the borrower-saver group and the saver category. Our main results on the importance of time preferences, formal education, financial literacy, and credit access risk for predicting the borrower-saver behavior, remain unchanged. The main difference is that the effect of risk aversion goes away in favor of present bias.

Predicting Credit Access Risk

So far, we have used information on whether a respondent was credit constrained or discouraged from applying in the past five years to measure their expectations about the availability of future credit, or credit access risk. Our working assumption has been that individuals who were constrained in the past are more likely to expect some non-zero probability of future rejection. This backward-looking measure is potentially problematic since it may be correlated with unobserved heterogeneity terms. In fact, the measure could be conflating the inherent appetite for credit that borrower-savers seem to exhibit with the strategic behavior we are testing for. For example, one might worry that the likelihood of being turned down for credit is just a signal of poor financial management, which could also be an explanation for the borrower-saver behavior. To deal with this potential endogeneity problem, we instrument for credit access risk.

We postulate that credit availability, and therefore credit access risk, is a function of local credit conditions. Access to physical bank branches plays an important role in the local supply of credit. Nguyen (2017) documents the causal impact of bank branch closings during the 2000s on local access to credit. She shows that areas with physical branch closings experienced a sharp and persistent reduction in small business lending, and to a smaller extent, mortgage lending, especially in low-income neighborhoods. Theoretically, if physical bank branches did not matter for lending, bank funding inflows (or outflows) would be spread evenly across counties. However, Gilje, Loutskina, and Strahan (2016) show that banks receiving funding windfalls expand lending only in markets where they have a branch presence. Moreover, Cortés and Strahan (2017) illustrate that in response to higher demand for loans in some markets, banks cut lending in markets where they have no branch presence. Célerier and Matray (2017) further document that an exogenous increase in the number of bank branches (due to deregulation of interstate banking) significantly reduces the number of unbanked households. Consumer loans, just as small business lending, are an information-intensive market and the physical presence of banks allows lenders to get to know areas better and channel resources to the people who can manage them best.

We use the four-year growth rate in the average number of people served by a typical branch in a given county as a plausibly exogenous instrument for credit access risk. The evolution of the number of people served by a bank branch over time is determined by bank branch closings/openings and by population growth to a lesser extent. The exclusion restriction requires our instrument to have an impact on the borrower-saver membership only through its effect on credit access risk. One may be concerned that branch closings may be the result of poor economic conditions, which are causing both the closings and the borrower-saver behavior—thus, potentially failing the random assignment requirement. However, the precautionary motive explanation of the credit card debt puzzle relies on consumers perceiving that credit tightens when they need it the most. Observing bank branch closings may make it more salient for consumers that credit may get tighter in the future. Nevertheless, to alleviate further concerns regarding the correlation of branch closings and economic conditions, we control for the general state of the local economy with the change in the local unemployment rate and the growth rate of house prices in the area (both measured at the county level). The identifying assumption is that, conditional on local economic conditions, the growth rate in the number of people served by a bank branch is plausibly exogenous to the individual decision on whether to behave as a borrower-saver. In other words, by using a county-level measure, we are able to remove idiosyncratic unobserved components from our measure of credit access risk.

To predict credit access risk, in addition to these county-level variables and the controls already included in estimation of Equation (1), we control for whether the respondent applied for credit any time during the past five years. We pool all three years of data together, and include time fixed effects to control for time-varying needs for liquidity, and state fixed effects to account for time-invariant differences across states that may affect individuals' demand or access to credit.

Table 6 summarizes the results from the first stage regression. In column (1) we include variables that appear in Equation (1), i.e. included instruments; column (2) presents results with the addition of excluded instruments; and column (3) adds individual fixed effects to the controls in column (2). As the table shows, our excluded instruments are strong with Anderson Rubin F-statistics of 83.8 and 28.1 in columns (2) and (3), respectively. We find that a 1 percentage point increase in the population served by an average branch increases the probability of being denied credit by 0.1 percentage points, consistent with our hypothesis that the probability of being denied credit depends on the number of consumers served by a bank branch. Respondents with higher levels of income volatility are more likely to be denied credit. Not surprisingly, those who apply for credit are more likely to be rejected. According to the results in column (2), the impact of credit application on the probability of rejection is of the same order of magnitude as the impact of local credit supply. However, once individual fixed effects are included, column (3), the effect of bank access becomes more important for loan rejections.

Finally, we re-estimate the baseline specification given by Equation (1) using predicted credit access risk instead of the original measure. Standard errors are bootstrapped with 1000 repetitions and clustered at the individual level to account for the fact that predicted credit access risk is a generated regressor. We find clear support for the precautionary borrowing hypothesis (Table 5 columns (3) and (4) for our baseline borrower-saver definition and column (6) for the strict definition). The coefficient on predicted credit access risk is between 0.08 and 0.109, depending on the definition and specification used, and precisely estimated. This means that increasing credit access risk by one standard deviation, increases the probability of being a borrower-saver by 10 percentage points, keeping all else constant. Other results remain virtually unchanged. The only exception is that the effect of income risk, as measured by the exogenous job shock variable is statistically significant under the baseline borrower-saver definition, is small and statistically insignificant when using the strict definition. Unless stated otherwise, the remaining regressions in the paper use the predicted credit access risk measure instead of the raw measure.

Further Results

We find that financially literate respondents are more likely to be borrower-savers than savers when facing credit access risk. In particular, we estimate Equation (1), including an interaction of financial literacy and credit access risk. Panel A of Table 7 shows these results. The more financially literate respondents are almost 6 percentage points more likely to belong to the borrower-saver group than to the saver group as their credit access risk rises by one standard deviation above the mean. In results not shown for brevity, we further explore this result by focusing on the interaction of credit access risk and a dummy variable for whether a respondent answers a question on compound interest correctly. Respondents who understand the concept of compound interest and have one standard deviation higher credit access risk than the mean are between 4 and 6 percentage points, depending on the definition used, *more* likely to be borrower-savers, all else equal.

We also test the stability of our results to the inclusion of forward ($t+4$) measures of predicted credit access risk and income uncertainty. These results are presented in Panel B of Table 7. By including expected ($t+4$ forward) credit access risk in the regression, we measure whether today's knowledge of the local financial environment has any predictive power in explaining the group membership of the respondents. We find that respondents do react to future (predicted) credit access risk. In fact, a one standard deviation increase in future credit access risk is associated with a 4 to 5 percentage points higher probability of being a borrower-saver relative to the saver group, depending on the definition used (baseline or strict). If individuals have private information about their future income risk at ($t + 4$), they might react to this information (as they learn it) before the shock is actually realized.[6] We find support for this hypothesis only under the baseline borrower-saver definition.

To summarize, on average, borrower-savers have slightly lower financial literacy and fewer completed years of formal education, are more likely to be middle risk averse, have higher time discount factors, and have higher expected credit access risk than savers. All else equal, as an individual's credit access risk rises, more financially savvy respondents have a greater likelihood of being borrower-savers. In other words, some consumers seem to be acting strategically given their shocks, and their time and risk preferences.

5 Transitions Into and Out of Borrower-Saver Group

We further exploit the data's panel feature and look at transitions from the borrower-saver group to the saver group, and *vice versa*.[7] The findings in this section are subject to a data caveat: since answers about credit card debt and liquid assets are only available every four years, we cannot

[6] Hendren (2015), using PSID data, finds that individuals have some private information about their likelihood of becoming unemployed and that their consumption falls two periods before an unemployment shock is realized.

[7] Respondents who transition to other groups are dropped from these regressions without loss of generality. The online appendix presents results from multinomial logistic regressions that include all groups.

determine what happens to respondents' co-holding patterns in the years in between the NLSY79 surveys.

Starting with respondents in the borrower-saver group at time $t-4$, we define a transition from this group to the saver group ($P \rightarrow S$) as a dummy variable equal to one at time t if the respondent transitions from borrower-saver to saver, and equal to zero if the respondent remains a borrower-saver. Analogously but starting with savers at $t-4$, a transition from saver to borrower-saver ($S \rightarrow P$) is a dummy variable equal to one at time t if the respondent transitions from the saver group to the borrower-saver group, and is zero if the respondent remains a saver. In these regressions, we also used the predicted credit access risk measure previously discussed, but results are qualitatively similar when using the original measure of credit access risk.

Columns (1) and (2) of Table 8 present results for $P \rightarrow S$ transitions for the baseline and the strict borrower-saver definitions, respectively. Debt and time discounting matter the most in these transitions. Credit access risk matters the way we would expect: individuals are less likely to transition from borrower-savers to savers as credit risk rises, but the coefficient is not precisely estimated. Under the strict definition, discount rates play a significantly more important role than any other variable, except homeownership, in predicting these transitions. Respondents with lower discount rates are 10.8 percentage points more likely to transition from the borrower-saver group to the saver group. Moreover, being a homeowner (at $t-4$) increases the transition likelihood by a substantial and statistically significant amount, 18.5 (18.4) percentage points for owners without (with) a mortgage on a property. This finding could be explained by the fact that home-equity loans can also be used to smooth consumption, and these lines of credit are typically more cost-effective than credit card debt—they likely entail lower interest rates and partially reduce income tax obligations. Having past ($t-4$) car loans reduces the likelihood of transition by 6.4 percentage points.

Columns (3) and (4) contain results for transitions from the saver group to the borrower-saver group. Credit access risk, risk aversion, mortgage debt and car loans play a major role in these transitions. We find that, all else equal, a one standard deviation rise in credit access risk increases the likelihood of transition from saver to borrower-saver by about 3.5 percentage points, using the strict puzzle definition. This result is consistent with the precautionary borrowing hypothesis. Respondents with middle levels of risk aversion are about 7.5 percentage points more likely to experience this transition. Those with previous car loans are 5 percentage points more likely to transition from being savers to borrower-savers. On the other hand, homeowners (at $t-4$) without a mortgage are 17 percentage points less likely to change groups.

Fixed Effects

Although the NLSY79 has a great deal of information about respondents, unobserved factors that we cannot control for could still be affecting the results. To address this issue, we run individual fixed effect regressions, controlling for other potentially important, but unobserved individual specific traits to determine the robustness of our findings. In these regressions, the effect of credit access risk is also identified from respondents whose credit access risk changes over time. However, this specification does not allow us to distinguish between S $\rightarrow$ P and P $\rightarrow$ S transitions.

It is noteworthy that the results regarding the importance of the precautionary borrowing hypothesis do not change even after controlling for potentially omitted, time-invariant factors. We find the effect of credit access risk on borrower-saver behavior to be highly significant for both our baseline and strict definitions, see Table 7, panel C. This result again highlights the importance of the precautionary borrowing motive as a key explanation for this behavior, beyond the role of preferences, impulsiveness, and other self-control problems previously emphasized in the literature. If credit access risk rises by one standard deviation, respondents are between 5.5 and 8 percentage points, depending on the puzzle definition used, more likely to transition from savers to borrow-savers, and *vice versa*.

6 The Cost of Revolving Credit Card Debt

In this section, we quantify the potential interest cost of being a borrower-saver under different scenarios. We then examine whether borrower-saver behavior can predict future financial trouble.

In particular, we study whether this behavior predicts bankruptcy and foreclosure outcomes.

6.1 The Interest Cost of Revolving Credit Card Debt

We calculate the potential cost associated with being a borrower-saver by examining information on the actual interest rates paid on credit card debt from the SCF—the NLSY79 does not provide this information. In particular, the SCF reports the rate a household pays on the credit card with the largest balance. We use data from the closest year in the SCF to our NLSY79 sample (2004 for 2004, 2007 for 2008, and 2010 for 2012). Rates increased over the studied period for all respondents: the average annual percentage rate (APR) on credit cards held by U.S. consumers was 11.6 percent in 2004, while it was 13.9 percent in 2010.

We document changes in the distribution of the interest rates paid by consumers over time as follows. First, we create quartiles of the range of interest rates based on the full sample of SCF respondents in 2004 who belonged to the baseline borrower-saver group (0–7.9 percent, 7.91–11.16 percent, 11.17–17 percent, and 17+ percent). Keeping the thresholds the same, we examine how the distribution of respondents in each interest rate quartile evolves over time. Figure 3 illustrates how dramatic the change in the distribution of interest rates has been. In 2004, 26 percent of respondents in the baseline borrower-saver group were in the first quartile paying under 7.9 percent on their credit card debt, while 24 percent were in the fourth quartile paying at least a 17 percent APR. By 2010, only 17 percent of the respondents were in the first quartile and 32 percent were in the fourth. The pattern for the strict borrower-saver definition is even starker. (Note, however, that individuals in the strict puzzle group paid lower interest rates than individuals in the baseline puzzle group.) The increasing cost of credit card debt may help explain why the proportion of borrower-savers declined so significantly between 2004 and 2012: as the costs of holding debt rose, these costs began to outweigh the potential benefits of borrowing on credit cards for precautionary reasons.

Compared to borrower-savers, savers held credit cards that charged significantly higher APRs. In 2004, 22 percent of savers had credit cards with rates below 7.9 percent, whereas 52 percent held credit cards that charged at least a 11.17 percent APR (third and fourth quartiles). The distribution of interest rates changed over time even more dramatically for savers. By 2010, only 11 percent of savers were in the first quartile, while 74 percent were in the third and fourth quartiles. The pattern using the strict puzzle definition is similar. In sum, the differentially higher rates for savers compared to borrower-savers persist over time. Since savers repay their balances at the end of the month, they may not shop around for the best rates to begin with. At the same time, the significantly higher rates might be the reason why these respondents chose to be savers rather than borrower-savers. Unfortunately, the current dataset does not allow us to disentangle the direction of causality.

Turning back to borrower-savers, we illustrate how costly habitually rolling over credit card balances can be using data from the 2004 SCF. We follow Zinman (2007), who calculates the cost of "borrowing high and lending low". First, we classify respondents in the 2004 puzzle group according to the APR on the highest balance credit card, and compute average APRs, average revolving balances, and average annual family income in each quartile—see Table 9. For each individual, we calculate what Zinman calls a wedge (or the minimum of credit card debt and liquid assets). We then multiply this wedge by the difference between the interest rate paid on credit card debt (individual specific) and the prevailing rate on checking/saving accounts (approximated by the M2 money yield). The idea behind this cost calculation is that households should use low-yielding liquid assets to pay down expensive credit card debt, and their ability to do so depends on the relative magnitudes of debt and assets. In other words, this calculation can be seen as the money that could be saved by using liquid assets to repay credit card debt to the maximum extent possible. Zinman (2007) sees this calculation as an upper bound of the cost of carrying debt because it ignores the value of liquidity. Results are summarized in Panel A of Table 9. We report the average wedge, the mean cost, and the 25th, 50th, and 75th percentiles within each interest rate quartile. The average wedge, as the average credit card balance, decreases with the APR, varying from $4,009 to $2,136 when moving from the first to the fourth APR quartile. Not surprisingly, the cost of carrying debt increases with the APR. For example, the average cost is $137 a year in the first APR quartile, while it is $469 in the fourth APR quartile. However, these numbers are all small relative to income and could be rationalized by the precautionary motive. Average revolving credit card balances, and to a lesser extent wedges, rose across all four interest rate quartiles by 2010 (see the online appendix). In addition, a larger share of respondents in the puzzle group were paying higher interest rates in 2010 compared to 2004. As a result, the overall mean (median) cost of carrying credit card balances increased from $332 ($154) to $423 ($191) per year from 2004 to 2010. While the 2010 cost numbers are still small, the overall increase could explain why the puzzle group became smaller over time.

Another way to compute the cost of rolling over credit card balances, is to simply calculate the interest cost of the average revolving balance, assuming that the individual pays only the minimum monthly payment (set at the minimum of $15 or 2 percent of the total balance) and no other payments or charges are made on the card. We compute these costs under two scenarios: (1) the balance is paid off after one year (Panel B); and (2) only minimum payments are made for the life of the balance (Panel C). As before, we find that the lower the APR, the less costly it is to carry over balances; the larger the debt and the longer you wait to repay it, the costlier it is.

Similarly to Zinman's calculation, the cost of revolving credit relative to annual family income is not large when households are able to fully repay their balances within one year. For people in the first APR quartile, the interest cost at the end of a year is only 0.37 percent of 2004 average annual family income (or $368), and for those in the fourth quartile, it is 2 percent (or $1300).[8] On the other hand, if a family pays only the minimum payment until the credit card balance is fully paid off, the cost of rolling over debt is substantial, and grows exponentially with the APR. With a beginning balance of $8,959 and a 4 percent APR (the first quartile), it would take 203 months (or 16 years) to repay the balance and the interest cost would be $1,712, or 1.72 percent of 2004 average annual family income. However, with an initial balance of $5,927 (the average for the fourth quartile) and a 20 percent APR, it takes 728 months (or over 60 years) to fully repay the

[8]To simplify the calculations, we take 2004 average family income as being constant, and do not adjust for future increases or inflation.

balance and the total interest cost is $26,761, or 41 percent of 2004 annual family income.

In sum, if a respondent is in the puzzle group for a short period of time to smooth current shocks or to insure against future credit uncertainty, the interest cost is not large. Revolving credit card balances over longer periods of time can be very costly, but not prohibitive if the APR is low. To the extent that individuals pay very different APRs on their credit card balances, there is a great deal of heterogeneity in the cost of carrying balances. It is likely that a fraction of individuals in the puzzle group are financial savvy individuals who take advantage of low promotional interest rates. However, it is possible some individuals in the puzzle group do not understand the power of compound interest and get into trouble. We further explore this possibility in the next section.

6.2 Are Borrower-Savers More Likely to Face Future Financial Trouble?

Respondents in the NLSY79 are asked if they filed for bankruptcy, and when, several times throughout the survey. Foreclosure questions are asked only in 2010 and 2012 (for the 2009–2012 reference period). We construct dummy variables to indicate whether a respondent filed for bankruptcy or went through foreclosure any time during the 2009–2012 period. During these years, 3.3 percent of our sample respondents filed for personal bankruptcy, while 5.2 percent of respondents who were homeowners went through foreclosure. Bankruptcy rates for the 2005–2008 period, based on 2004 data, are slightly lower at 2.7 percent. There are important differences in bankruptcy and foreclosure rates between borrower-savers and savers (4.4 versus 0.6 percent for bankruptcy, and 5.7 versus 2 percent for foreclosure), but they fall under the strict borrower-saver definition (2.9 versus 0.4 percent for bankruptcy, and 3.2 versus 1.1 percent for foreclosure).

Comparing borrower-savers to savers, we estimate (weighted) linear probability regressions for each outcome separately, controlling for whether the respondent was in the puzzle group in 2008, in addition to other typical controls in bankruptcy/foreclosure regressions. Foreclosure regressions are restricted to the sample of homeowners as of the 2008 survey. We consider both the baseline and the strict borrower-saver definitions. The regression results are summarized in Table 10.

Under our baseline definition, we find that being a borrower-saver in 2008 increases the probability of filing for bankruptcy by 3.1 percentage points (relative to savers), keeping all else constant. When focusing on the strict definition, the coefficient is lower at 1.7 percent but remains statistically significant. These are substantial effects, given that the unconditional probability of filing for bankruptcy in the sample of borrower-savers and savers is 2.7 percent for the baseline definition and 1.45 percent for the strict definition.

Being a borrower-saver in 2008 also correlates with experiencing foreclosure: these individuals are 2.4 percentage points more likely to report foreclosure than savers. However, under the strict definition, we find no statistical differences between savers and borrower-savers. The fact that the coefficients are smaller (and statistically insignificant) for the strict puzzle definition indicates that it is borrower-savers with little savings relative to debt (those who are more similar to borrowers) who mostly go through foreclosure.

In sum, it seems that some 2008 borrower-savers experienced significant financial trouble during the Great Recession. The fact that this effect is similar for those undergoing bankruptcy and foreclosure casts some doubt on the strategic bankruptcy hypothesis. However, we cannot completely rule out this explanation because of the differential effect for bankruptcy and foreclosure when using the strict puzzle definition (we find an effect for bankruptcy but not for foreclosure). In fact, we find that it is those respondents who understand compound interest that are driving the positive coefficient for the puzzle dummy in the bankruptcy regressions (results not tabulated for brevity), while there is no differential effect for foreclosure. We interpret this result as further evidence that some people may chose to undergo bankruptcy for strategic reasons.

However, further analysis points away from the strategic bankruptcy hypothesis (see Table 11). Borrower-saver behavior in 2004 does not seem to matter for the likelihood of filing for bankruptcy sometime between 2009 and 2012, nor does it predict bankruptcy during the 2005–2008 period, nor foreclosure in the 2009–2012 period. Moreover, borrower-saver behavior in 2012 does not predict bankruptcy between 2013 and 2014 either. These findings suggest that unanticipated shocks experienced during the Great Recession or side-effects stemming from the Credit Reform Act of 2009 may have resulted in financial pressures for some consumers, who under less adverse circumstances may have been able to stay afloat and avoid bankruptcy. These patterns can also be read as a sign of how finances can quickly go amiss if high-interest debt is combined with persistent poor income realizations (e.g., long-term unemployment).

Although some individuals experience financial trouble, the majority of borrower-savers manages to simultaneously carry revolving credit card debt and keep liquid assets on hand without experiencing major financial difficulties.

7 Conclusion

Using data from the NLSY79, this paper revisits the so-called credit card debt puzzle—why consumers simultaneously choose to hold (potentially high-interest) credit card debt and low-interest liquid assets that could be used to pay down this debt.

Compared to the respondents in the neutral and borrower categories, the borrower-savers in the puzzle group are less present biased and more educated, have higher AFQT and financial literacy scores, and significantly more financial resources. Puzzle respondents appear less favorably when compared to the saver group. Relative to savers, borrower-savers have higher discount rates and are more likely to have middle levels of risk aversion, have slightly lower levels of financial literacy and completed education, and hold significantly higher levels of all types of debt.

Credit access risk plays an important role in predicting borrower-saver behavior and transitions into and out of this group holding income volatility, time preferences, risk aversion, demographics, education, financial literacy, and self-assessed financial knowledge constant. Moreover, using the panel dimension of our data, and holding time-invariant, respondent-specific characteristics fixed, we find that increases in perceived credit access risk can explain transitions from the saver to borrower-saver, and vice versa. This finding further corroborates that the precautionary borrowing motive plays a role in explaining this behavior, beyond previously documented reasons such as impulsiveness and other self-control issues.

Our results also indicate that the new financial environment that arose from the Great Recession significantly changed the cost of holding credit card debt for precautionary reasons. We document that 2004 borrower-savers were no more likely to experience bankruptcy between 2005 and 2008 than 2004 savers. But for 2008 borrower-savers, this behavior had clear financial costs: they were significantly more likely than 2008 savers to declare bankruptcy or to go through a property foreclosure some time between 2009 and 2012. Conditions may have normalized somewhat as 2012 borrower-savers were no more likely to declare bankruptcy during the 2013–2014 period than savers.

Our work provides evidence that the group of borrower-savers is highly heterogeneous. Some savvy individuals, likely acting strategically, engage in this behavior as insurance, understand the costs associated with rolling over credit card debt, and are unharmed by it—credit cards can be very useful financial instruments. However, other individuals are not. Preventing consumers from co-holding debt and assets may be beneficial in some cases, but will not be easy since this behavior is highly dependent on preferences towards risk, time discounting, and, importantly, people's perceptions of future credit access risk. Interventions could focus on teaching individuals to manage negative shocks via alternative, and potentially less costly mechanisms.

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Table 1: Group Distribution: NLSY79 versus SCF

Year	Borrower-Saver %	Borrower %	Neutral %	Saver %	Respondents Number
	NLSY79, All				
2004	48.4	4.6	11.4	35.6	3,447
2008	46.0	5.0	12.1	36.8	3,512
2012	40.5	4.5	13.8	41.3	3,570
	SCF, All				
2004	49.3	1.8	7.2	41.6	3,012
2007	50.1	1.0	7.1	41.7	2,874
2010	42.5	0.8	7.4	49.3	4,260
	SCF, Ages 39–47 matching NLSY79				
2004	53.7	1.9	5.5	38.9	806
2007	52.6	0.5	7.6	39.3	813
2010	46.0	0.6	6.5	47	1,172

Notes: All percentages are weighted using survey weights. Groups are defined using the *baseline* definition: (1) borrower-saver: credit card debt and savings > 0; (2) borrower: credit card debt > 0, savings $= 0$; (3) neutral: credit card debt and savings $= 0$; (4) saver: credit card debt $= 0$, savings > 0. NLSY79: National Longitudinal Survey of Youth, Cohort of 1979. SCF: Survey of Consumer Finances.

Table 2: Group Distribution, NLSY79: Alternative Definitions

Year	Borrower-Saver %	Borrower %	Neutral %	Saver %	Respondents Number
	Baseline: Credit Card Debt and Savings > 0				
2004	48.4	4.6	11.4	35.6	3,447
2008	46.0	5.0	12.1	36.8	3,512
2012	40.5	4.5	13.8	41.3	3,570
	Credit Card Debt and Savings ≥*$500*				
2004	40.5	13.1	11.4	35.1	3,447
2008	39.2	12.7	12.1	36.0	3,512
2012	34.3	12.6	13.8	39.3	3,570
	Strict: Credit Card Debt ≥*$500* Savings ≥ one month annual income				
2004	20.1	45.4	11.2	23.2	3,433
2008	18.1	46.8	12.0	23.1	3,503
2012	16.2	43.9	13.6	26.3	3,560

Notes: All percentages are weighted using survey weights.
Definitions: Baseline: (1) borrower-saver: credit card debt and savings $>$ 0; (2) borrower: credit card debt $>$ 0, savings $=$ 0; (3) neutral: credit card debt and savings $=$ 0; (4) saver: credit card debt $=$ 0; savings $>$ 0. Credit Card Debt and Savings ≥$500: (1) borrower-saver: credit card debt and savings $\geq$ $\$500$; (2) borrower: credit card debt > 0, savings $< \$500$ (3) neutral: credit card debt and savings $= 0$; (4) saver: credit card debt $< \$500$, savings $\geq$ $\$500$. Strict: (1) borrower-saver: credit card debt $\geq$ $\$500$ and savings ≥one month income; (2) borrower: credit card debt > 0, savings $<$ one month income (3) neutral: credit card debt and savings $= 0$; (4) saver: credit card debt $< \$500$, savings $\geq$ one month income.

Table 3: Summary Statistics in the NLSY79 by Group in 2004

	Baseline					Strict	
	Total	Borrower-Saver	Saver	Borrower	Neutral	Borrower-Saver	Saver
AFQT Score	55.18	59.27	59.04	44.62	29.98	60.95	64.70
	(28.04)	(25.34)	(28.86)	(23.72)	(23.44)	(24.49)	(26.90)
Highest Grade Completed	13.77	14.00	14.16	12.78	11.94	14.32	14.68
	(2.57)	(2.41)	(2.73)	(2.05)	(2.00)	(2.42)	(2.68)
Financial Literacy, 0–5	3.45	3.52	3.63	3.04	2.74	3.60	3.83
	(1.16)	(1.11)	(1.15)	(1.17)	(1.14)	(1.10)	(1.05)
Financial Knowledge, 1–7	4.89	4.89	5.02	4.78	4.57	5.02	5.20
	(1.42)	(1.32)	(1.39)	(1.56)	(1.79)	(1.28)	(1.23)
Present Bias	0.49	0.48	0.46	0.56	0.60	0.46	0.41
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)
High Discount Rate	0.52	0.54	0.48	0.52	0.53	0.50	0.45
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Middle Risk Aversion	0.31	0.32	0.32	0.30	0.26	0.32	0.36
	(0.46)	(0.47)	(0.46)	(0.46)	(0.44)	(0.47)	(0.48)
Family Income (Thousands)	85.20	89.27	97.72	55.82	39.86	100.58	111.32
	(63.07)	(56.04)	(73.08)	(30.21)	(39.56)	(63.51)	(76.98)
Net Worth (Thousands)	345.07	322.57	492.00	129.54	67.54	468.56	627.13
	(607.76)	(526.79)	(755.62)	(329.70)	(265.00)	672.52)	(804.45)
Assets > Liabilities	0.82	0.87	0.88	0.67	0.48	0.93	0.97
	(0.39)	(0.34)	(0.33)	(0.47)	(0.50)	(0.26)	(0.18)
Has CC or CC Debt	0.72	1.00	0.53	1.00	0.04	1.00	0.72
	(0.45)	(0.00)	(0.50)	(0.00)	(0.19)	(0.00)	(0.45)
Has a Max-Out Credit Card	0.08	0.11	0.02	0.34	0.03	0.06	0.01
	(0.27)	(0.32)	(0.13)	(0.48)	(0.17)	(0.23)	(0.09)
Credit Card Debt (Thousands)	3.43	6.48	0.00	6.52	0.00	6.45	0.03
	(5.45)	(6.01)	(0.00)	(6.28)	(0.00)	(5.78)	(0.10)
Liquid Assets (Thousands)	13.84	13.38	20.68	0.00	0.00	25.55	32.43
	(19.18)	(17.08)	(22.45)	(0.00)	(0.00)	(19.02)	(21.11)
Arbitrage (Thousands)	10.41	6.90	20.68	–6.52	0.00	19.10	32.40
	(20.20)	(18.06)	(22.45)	(6.28)	(0.00)	(19.08)	(21.12)
Applied for Credit, Past Five Years	0.55	0.66	0.51	0.55	0.17	0.66	0.54
	(0.50)	(0.47)	(0.50)	(0.50)	(0.38)	(0.47)	(0.50)
Credit Access Risk	0.15	0.15	0.11	0.30	0.25	0.08	0.05
	(0.36)	(0.35)	(0.31)	(0.46)	(0.44)	(0.27)	(0.22)
Job Shock	0.07	0.06	0.07	0.05	0.15	0.05	0.06
	(0.28)	(0.25)	(0.30)	(0.21)	(0.36)	(0.24)	(0.25)
Observations	3,447	1,579	1,196	172	506	652	748

Notes: mean weighted coefficients; sd in parentheses; amounts are in 2012 dollars.

Table 4: Transition Matrices in the NLSY79

	2008, Baseline Definition				2008, Strict Definition			
2004	Puzzle	Borrower	Neutral	Saver	Puzzle	Borrower	Neutral	Saver
Puzzle	70.2	5.7	3.2	20.9	43.9	36.1	1.9	18.1
Borrower	51.3	15.2	18.9	14.6	13.3	66.4	8.7	11.6
Neutral	10.4	6.2	56.5	27.0	2.4	34.8	56.5	6.3
Saver	24.5	2.6	8.0	64.9	12.9	25.2	3.8	58.1

	2012, Baseline Definition				2012, Strict Definition			
2008	Puzzle	Borrower	Neutral	Saver	Puzzle	Borrower	Neutral	Saver
Puzzle	65.6	4.6	4.5	25.3	40.8	32.7	4.0	22.5
Borrower	33.7	21.9	18.4	26.1	12.2	64.5	9.9	13.5
Neutral	5.4	5.4	61.7	27.5	0.6	29.9	61.4	8.1
Saver	21.9	1.3	8.6	68.2	13.3	18.1	3.7	64.9

	2012, Baseline Definition				2012, Strict Definition			
2004	Puzzle	Borrower	Neutral	Saver	Puzzle	Borrower	Neutral	Saver
Puzzle	59.4	4.8	6.0	29.7	36.0	35.1	5.1	23.9
Borrower	42.1	12.3	24.3	21.4	12.8	61.3	11.6	14.2
Neutral	8.5	4.2	56.8	30.5	1.2	33.2	56.7	8.9
Saver	25.2	3.0	8.6	63.2	12.9	24.0	3.5	59.6

	All Periods in Same Group as 2004							
	Baseline Definition				Strict Definition			
	Puzzle	Borrower	Neutral	Saver	Puzzle	Borrower	Neutral	Saver
2004	48.5	7.0	47.5	48.3	21.2	47.7	47.8	43.7

Notes: All reported numbers are in percentages and weighted using survey weights.
Baseline: (1) borrower-saver (puzzle): credit card debt and savings > 0; (2) borrower: credit card debt > 0, savings $= 0$; (3) neutral: credit card debt and savings $= 0$; (4) saver: credit card debt $= 0$, savings > 0.
Strict: (1) borrower-saver (puzzle): credit card debt $\geq$ $\$500$ and savings $\geq$ one month income; (2) borrower: credit card debt > 0, savings $<$ one month income (3) neutral: credit card debt and savings $= 0$; (4) saver: credit card debt $< \$500$, savings $\geq$ one month income.

Table 5: Characteristics Affecting Group Membership: Borrower-Savers versus Savers

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline				Strict	
	Original		Predicted		Original	Predicted
Credit Access Risk	0.029***	0.022***	0.080***	0.109***	0.030**	0.088***
	(0.006)	(0.006)	(0.008)	(0.013)	(0.012)	(0.018)
Job Shock	–0.007	–0.006	–0.018***	–0.019***	–0.000	–0.010
	(0.005)	(0.005)	(0.006)	(0.005)	(0.009)	(0.009)
Change Unemp. Rate, County	0.000	0.001	0.007	0.010	–0.000	0.006
	(0.010)	(0.010)	(0.011)	(0.012)	(0.015)	(0.016)
HPI Growth Rate, County	–0.017**	–0.014*	–0.019**	–0.018*	–0.014	–0.017
	(0.008)	(0.008)	(0.010)	(0.009)	(0.012)	(0.014)
Present Bias	0.016	0.009	0.002	–0.007	0.032*	0.018
	(0.015)	(0.014)	(0.011)	(0.011)	(0.019)	(0.016)
High Discount Rate	0.061***	0.054***	0.043***	0.031***	0.048**	0.027*
	(0.015)	(0.014)	(0.011)	(0.011)	(0.019)	(0.016)
Middle Risk Aversion	0.039**	0.031**	0.044***	0.035***	0.009	0.011
	(0.016)	(0.015)	(0.012)	(0.012)	(0.020)	(0.017)
AFQT Score	0.027***	0.026***	0.026***	0.024***	–0.001	–0.003
	(0.009)	(0.009)	(0.007)	(0.007)	(0.012)	(0.010)
College or More	–0.048***	–0.039**	–0.025*	–0.011	–0.044*	–0.021
	(0.019)	(0.018)	(0.014)	(0.014)	(0.023)	(0.019)
Financial Literacy	–0.040**	–0.041***	–0.033***	–0.035***	–0.045**	–0.042**
	(0.016)	(0.015)	(0.012)	(0.012)	(0.022)	(0.018)
Financial Self-Knowledge	–0.000	0.010	0.042***	0.056***	0.022	0.058***
	(0.015)	(0.015)	(0.013)	(0.013)	(0.021)	(0.020)
Net Worth		–0.072***		–0.056***	–0.048***	–0.034***
		(0.007)		(0.006)	(0.008)	(0.007)
Homeowner, Mortgage		0.185***		0.297***	0.091***	0.181***
		(0.019)		(0.021)	(0.032)	(0.033)
Homeowner, No Mortgage		0.016		0.158***	–0.066*	0.046
		(0.024)		(0.026)	(0.036)	(0.041)
Has Car Loan		0.141***		0.127***	0.137***	0.123***
		(0.012)		(0.011)	(0.017)	(0.016)
Has Student Debt		0.116***		0.006	0.182***	0.095**
		(0.024)		(0.026)	(0.042)	(0.042)
Year=2008	–0.069***	–0.059***	–0.084***	–0.082***	–0.084***	–0.104***
	(0.022)	(0.021)	(0.025)	(0.024)	(0.031)	(0.035)
Year=2012	–0.097***	–0.099***	–0.127***	–0.138***	–0.164***	–0.200***
	(0.032)	(0.031)	(0.028)	(0.028)	(0.043)	(0.041)
Observations	8,073	8,073	8,073	8,073	3,987	3,987
Adj. R squared	0.03	0.10	0.04	0.11	0.09	0.10

Notes: Linear probability regressions. The dependent variable is a dummy variable equal to one if the respondent is a borrower-saver, and zero if a saver. All regressions control for demographics (age, race, gender, marital status, and the number of children), and state and time and fixed effects. Robust standard errors (in parentheses) are clustered at the individual level in columns (1), (2), and (5), and bootstrapped with 1000 replications, clustered at the individual level in columns (3), (4), and (6). The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY79.

Table 6: Predicting Credit Access Risk

	(1)	(2)	(3)
Present Bias	0.017*	0.021**	
	(0.009)	(0.009)	
High Discount Rate	0.026***	0.024***	
	(0.009)	(0.009)	
Middle Risk Aversion	–0.004	–0.004	
	(0.009)	(0.009)	
College or More	–0.031***	–0.026**	
	(0.011)	(0.011)	
Financial Literacy	–0.005	–0.009	
	(0.010)	(0.010)	
Financial Self-Knowledge	–0.050***	–0.051***	
	(0.011)	(0.010)	
Job Shock	0.020***	0.018***	0.008
	(0.007)	(0.007)	(0.007)
Change in Unemployment Rate, County	–0.010	–0.011	–0.009
	(0.007)	(0.007)	(0.007)
HPI Growth Rate, County	0.004	–0.000	0.005
	(0.006)	(0.006)	(0.006)
Net Wealth	–0.017***	–0.016***	–0.002
	(0.004)	(0.003)	(0.006)
Applied for Credit, Past Five Years		0.099***	0.064***
		(0.008)	(0.009)
Four Year Growth in Population per Branch, County		0.105**	0.084*
		(0.046)	(0.049)
Observations	8,073	8,073	8,073
Adj. R squared	0.09	0.11	0.38
AR F-stat of Excluded Instruments	-	83.84	28.14
Individual Fixed Effects:	No	No	Yes

Notes: The dependent variable is a dummy variable equal to one if the respondent was denied credit in the last 5 years, or was discouraged from applying because she thought she would be denied credit, and zero otherwise. All regressions also control for age, race, gender, marital status, presence of children, AFQT scores, dummies for homeownership with mortgage, homeownership without mortgage, having a car loan, having student debt as well as state and time fixed effects. Robust standard errors (in parentheses) clustered at the individual level. ***(**)[*] significant at the 1(5)[10] percent level. *Source:* NLSY79.

Table 7: Borrower-Savers versus Savers: Further Results

	(1)	(2)	(3)	(4)
	Baseline			Strict
Panel A: The Role of Financial Literacy				
Predicted Credit Access Risk	0.028***	0.076***	0.078***	0.057***
	(0.010)	(0.014)	(0.014)	(0.022)
Job Shock	–0.017***	–0.018***	–0.018***	–0.010
	(0.005)	(0.005)	(0.005)	(0.009)
Financial Literacy	–0.034***	–0.036***	–0.039***	–0.032*
	(0.013)	(0.012)	(0.012)	(0.019)
Credit Access Risk × Fin. Literacy	0.096***	0.060***	0.058***	0.052***
	(0.011)	(0.011)	(0.011)	(0.018)
Observations	8,073	8,073	8,073	3,987
R squared	0.05	0.11	0.12	0.12
Financial Controls:	No	Yes	Yes	Yes
State Fixed Effects:	No	No	Yes	Yes
Panel B: Forward Credit Risk and Future Job Shock				
F4: Predicted Credit Access Risk	0.062***	0.038***	0.038***	0.052***
	(0.010)	(0.012)	(0.011)	(0.017)
F4: Job Shock	0.018**	0.018**	0.019**	–0.004
	(0.008)	(0.008)	(0.008)	(0.014)
Observations	4,553	4,553	4,553	2,353
R squared	0.04	0.10	0.12	0.12
Financial Controls:	Yes	Yes	Yes	Yes
State Fixed Effects:	Yes	Yes	Yes	Yes
Panel C: Individual Fixed Effects				
Predicted Credit Access Risk	0.063***	0.084***	0.081***	0.055**
	(0.015)	(0.016)	(0.016)	(0.025)
Job Shock	–0.015*	–0.016**	–0.015*	0.003
	(0.009)	(0.008)	(0.009)	(0.016)
Observations	8,073	8,073	8,073	3,987
Within R squared	0.02	0.02	0.03	0.03
Financial Controls:	No	Yes	Yes	Yes
State Fixed Effects:	No	No	Yes	Yes

Notes: The dependent variable is a dummy variable equal to one if the respondent is a borrower-saver and zero if a saver. F4 is a four-period forward operator. All regressions include controls as in Table 5. Bootstrapped standard errors with 1000 repetitions (in parentheses) clustered at the individual level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY79.

Table 8: Transitions from Borrower-Saver to Saver, and from Saver to Borrower-Saver

	(1)	(2)	(3)	(4)
	$P \rightarrow S$		$S \rightarrow P$	
	Baseline	Strict	Baseline	Strict
Change in Predicted Credit Access Risk	–0.014	–0.017	0.032***	0.036***
	(0.010)	(0.021)	(0.012)	(0.013)
Change in Job Shock	–0.001	–0.003	–0.006	0.007
	(0.011)	(0.027)	(0.011)	(0.018)
Present Bias	0.011	0.018	–0.003	–0.000
	(0.018)	(0.039)	(0.021)	(0.025)
High Discount Rate	–0.038**	–0.108***	0.042**	0.026
	(0.018)	(0.040)	(0.020)	(0.023)
Middle Risk Aversion	–0.008	–0.027	0.056**	0.075***
	(0.019)	(0.040)	(0.022)	(0.026)
Financial Literacy	0.011	–0.005	–0.009	–0.029
	(0.020)	(0.043)	(0.025)	(0.030)
Financial Self-Knowledge	–0.021	–0.033	–0.021	0.023
	(0.019)	(0.044)	(0.024)	(0.028)
L4: Net Worth	0.007	0.015	–0.013***	–0.001
	(0.006)	(0.010)	(0.005)	(0.005)
L4: Homeowner, with Mortgage	–0.006	0.184***	–0.027	–0.084
	(0.032)	(0.065)	(0.034)	(0.052)
L4: Homeowner, No Mortgage	0.014	0.185**	–0.111***	–0.173***
	(0.046)	(0.088)	(0.035)	(0.056)
L4: Has Car Loan	–0.056***	–0.064*	0.071***	0.050**
	(0.018)	(0.037)	(0.021)	(0.025)
L4: Has Student Debt	–0.094***	–0.046	0.177***	0.072
	(0.029)	(0.091)	(0.055)	(0.077)
Year=2012	0.020	0.083	0.021	0.040
	(0.044)	(0.089)	(0.045)	(0.056)
Observations	2,503	722	2,014	1,092
R squared	0.05	0.12	0.09	0.10

Notes: The dependent variable is a dummy variable equal to one if the transition from borrower-saver to saver occurred, $\boldsymbol{P} \rightarrow \boldsymbol{S}$ (or from saver to borrower-saver $\boldsymbol{S} \rightarrow \boldsymbol{P}$), and zero if the respondent remained in the same group. All regressions also control for formal knowledge (years of completed education) and AFQT scores; demographics (age, race, gender, marital status, and the number of children); county controls for local economic conditions; and state fixed effects. Bootstrapped standard errors with 1000 repetitions (in parentheses) are clustered at the individual level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY79.

Table 9: The Interest Cost of Revolving Credit Card Debt

	2004 Interest Rates Quartiles			
	1	2	3	4
Average Percentage Rate, %	4	10	14	20
Beginning Balance, US$	8,959	7,385	5,999	5,927
Annual Family income, US$	99,412	84,714	87,988	65,002
	A. Zinman (2007) Cost Calculation			
Average wedge = min(CC debt, liquid assets)	4,009	3,341	3,095	2,136
Cost per year:				
Average	137	307	426	469
Percentile 25	–6	57	79	92
Median	58	176	178	206
Percentile 75	179	446	466	506
	B. Balance Paid in Full After One Year			
Balance after 12 months, US$	7,325	6,415	5,426	5,694
Interest Paid in 12 months, US$	368	773	896	1,300
Interest as Percentage of Annual Income, %	0.37	0.91	1.02	2.00
	C. Only Minimum Payments are Made			
Total Number of Months to Repay	203	260	324	728
Total Interest Paid, US$	1,714	4,963	7,732	26,761
Interest as Percentage of Annual Income, %	1.72	5.86	8.71	41.17

Notes: The 2004 interest rate quartiles are computed using the full sample of borrower-savers in the Survey of Consumer Finances (SCF) that year. For panel A, we follow the methodology in Zinman (2007): Cost=min(credit card debt, liquid assets)$\times$ (interest on credit card – interest rate on liquid assets). For panel C, we assume that only the monthly minimum payment is made (set at the maximum of 2 percent of the total balance or $15) until the entire balance is paid off. *Source:* SCF.

Table 10: Bankruptcy and Foreclosure. Borrower-Saver versus Savers, 2008 Classification

	(1)	(2)	(3)	(4)
	Bankruptcy, 2009–12		**Foreclosure, 2009–12**	
	Baseline	Strict	Baseline	Strict
Borrower-Saver 2008	0.031***	0.017**	0.024***	0.014
	(0.006)	(0.007)	(0.009)	(0.009)
Present Bias	0.010	0.012	0.004	–0.012
	(0.008)	(0.011)	(0.009)	(0.009)
High Discount Rate	0.022***	0.019***	0.030***	0.005
	(0.005)	(0.006)	(0.009)	(0.010)
Middle Risk Aversion	0.005	–0.002	0.015	0.013
	(0.006)	(0.008)	(0.011)	(0.009)
College or More	–0.004	0.001	–0.016**	–0.023**
	(0.007)	(0.008)	(0.007)	(0.010)
Financial Literacy	0.006	0.003	0.019	0.008
	(0.008)	(0.009)	(0.013)	(0.013)
Financial Knowledge	–0.004	–0.011	–0.006	0.009
	(0.009)	(0.009)	(0.010)	(0.010)
Log Debt 2008	0.001	0.001	0.002***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Log Assets 2008	0.001	0.004	0.001	0.002
	(0.003)	(0.004)	(0.007)	(0.008)
Assets > Debt, 2008	–0.080***	–0.086**	–0.101***	–0.062
	(0.021)	(0.037)	(0.026)	(0.038)
Self Employed 2008	0.025**	0.018*	0.044***	0.034**
	(0.011)	(0.010)	(0.012)	(0.013)
Bankruptcy Pre-2009	–0.055***	–0.029***	0.035*	–0.030**
	(0.009)	(0.010)	(0.020)	(0.015)
Health Shock	0.042**	0.027	0.031	–0.021**
	(0.020)	(0.027)	(0.024)	(0.010)
Divorce Shock	0.021	0.074**	0.111**	0.042
	(0.020)	(0.034)	(0.048)	(0.054)
Observations	2,437	1,178	2,069	1,067
R squared	0.07	0.10	0.11	0.11

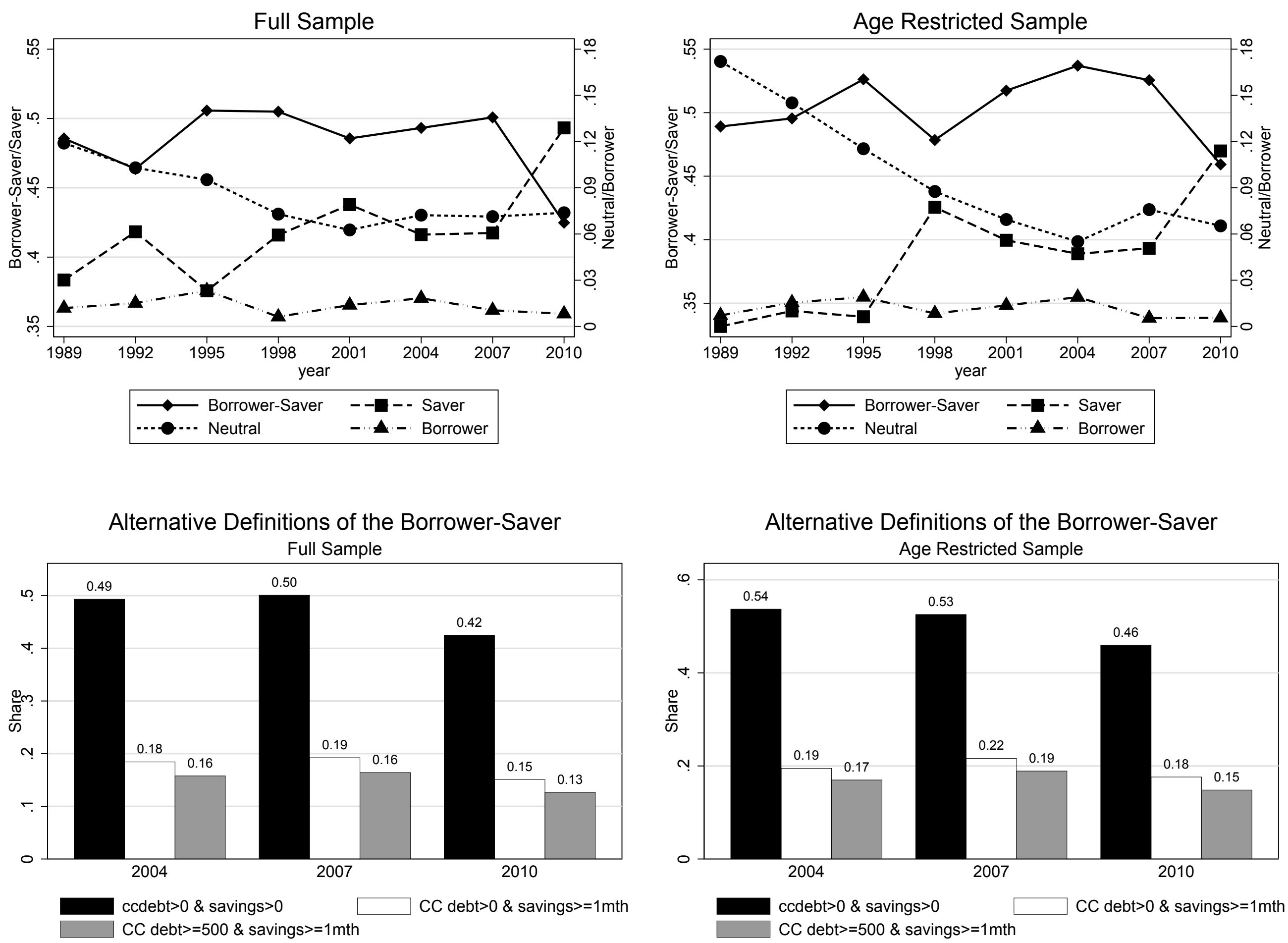
Notes: Linear probability regressions. The dependent variables are dummies equal to one if the respondent filed for bankruptcy or went through foreclosure during the specified periods. All regressions control for demographics (age, race, gender, marital status, presence of kids), AFQT scores, and state fixed effects. Standard errors (in parentheses) clustered at the state level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY79.

Table 11: Borrower-Saver Behavior and Bankruptcy. Different Periods.

	(1)	(2)	(3)	(4)	(5)	(6)
	Bankruptcy, 05–08		**Bankruptcy, 09–12**		**Bankruptcy, 13–14**	
	Borrower-Saver, 04		**Borrower-Saver, 08**		**Borrower-Saver, 12**	
	Baseline	Strict	Baseline	Strict	Baseline	Strict
Borrower-Saver	0.009	0.004	0.031***	0.017**	–0.001	0.002
	(0.161)	(0.443)	(0.006)	(0.007)	(0.766)	(0.664)
Observations	2,433	1,234	2,437	1,178	2,306	1,193
Adj. R squared	0.06	0.08	0.07	0.10	0.02	0.01

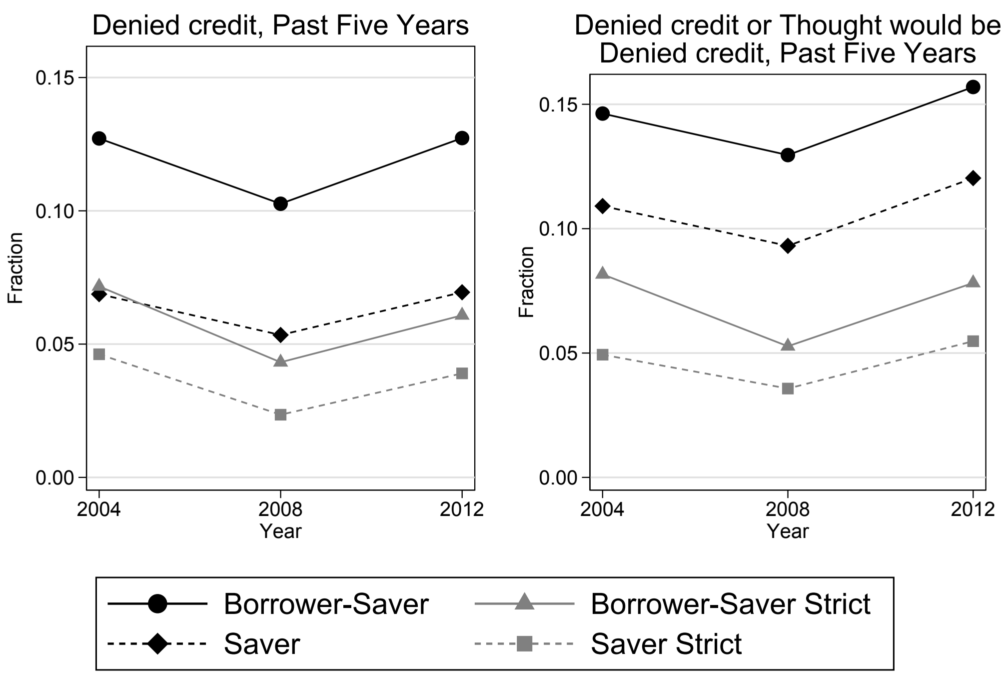
Notes: The dependent variable is equal to one if the respondent filed for bankruptcy during the specified periods. Controls as in Table 10, adjusted to the relevant reference period. Standard errors (in parentheses) clustered at the state level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY79.

Figure 1: Distribution of Respondents in the SCF



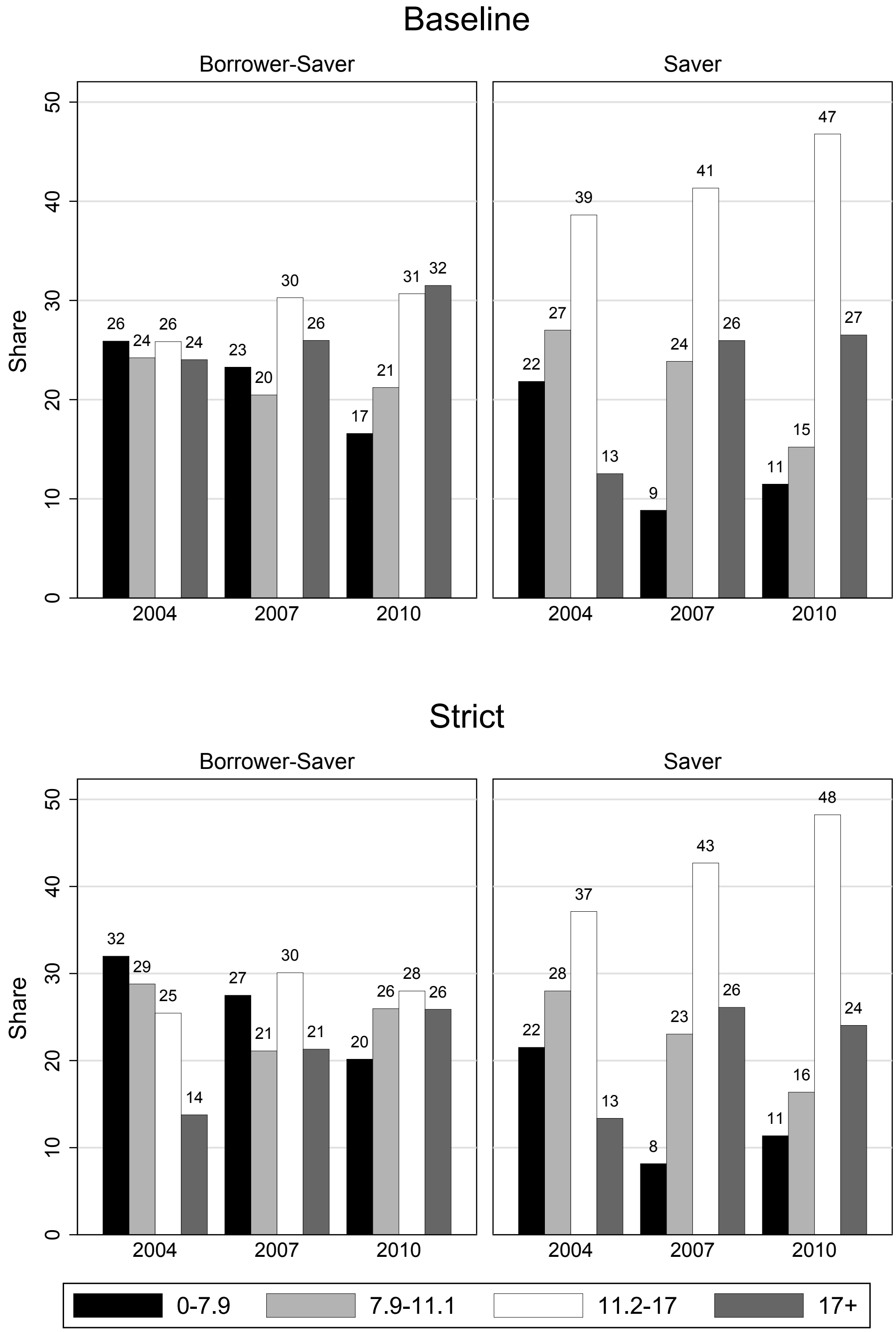
Notes: The age restricted sample includes respondents born between 1956 and 1965, consistent with the birth years of the NLSY79 cohort. *Source*: SCF.

Figure 2: Liquidity Constraints over Time



Notes: The figure depicts the fraction of respondents classified as being liquidity constrained by group. *Source:* NLSY79.

Figure 3: Interest Rates Paid on the Credit Card with the Highest Balance



Notes: The four colors indicate the four quartiles of annual percentage rates (APR) charged on the respondent's credit card with the highest balance. Quartiles are computed on the 2004 sample of puzzle respondents according to the baseline definition of the puzzle. *Source*: SCF.

Online Appendices for "The Credit Card Debt Puzzle: The Role of Preferences, Credit Access Risk, and Financial Literacy"

A Variable Definitions and Summary Statistics

Credit card data in the NLSY79 is available in 2004, 2008, and 2012 only, and our analysis focuses on this period. Our sample consists of approximately 2,700 respondents per year when including all nonmissing controls and restricting the analysis to the random sample. For example, in 2004 there are 7,501 respondents remaining in the survey. Of these, 7,084 respondents report information on credit card debt, liquid assets and family income. Of those, 4,445 belong to the random sample, and 2,688 have nonmissing controls for all the variables of interest. Respondents are 39–47 years-old in 2004.

Financial Literacy and Financial Knowledge

Financial Literacy scores are constructed by combining the number of correct answers to the following questions:

```
(1) "Do you think that the following statement is true or false?
Buying a single company stock usually provides a safer return than
a stock mutual fund."

(2) "Suppose you had $100 in a savings account and the interest
rate was 2 percent per year.  After five years, how much do you
think you would have in the account if you left the money to grow:
more than $102, exactly $102, or less than $102?"

(3) "Imagine that the interest rate on your savings account was
1 percent per year and inflation was 2 percent per year.  After
1 year, would you be able to buy more than, exactly the same as,
or less than today with the money in this account?"

(4) "If interest rates rise, what will typically happen to bond
prices?"

(5) "Do you think that the following statement is true or false?
A 15-year mortgage typically requires higher monthly payments than
a 30-year mortgage, but the total interest paid over the life of
the loan will be less."
```

The self-reported measures of being good with money and financial knowledge are derived from the following two questions:

(1) "How strongly do you agree or disagree with the following statements? Please give your answer on a scale of 1 to 7, where 1 means "strongly disagree" 7 means "strongly agree," and 4 means "neither agree nor disagree": I am good at dealing with day-to-day financial matters, such as checking accounts, credit and debit cards, and tracking expenses."

(2) "On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall financial knowledge."

Net Asset Position

Self-reported net asset position is constructed from a question that reads:

"Suppose you [and] [Spouse/partner's name] were to sell all of your major possessions (including your home), turn all of your investments and other assets into cash, and pay all of your debts. Would you have something left over, break even, or be in debt?"

Risk Aversion

The NLSY79 contains a series of questions on how willing respondents are to take jobs with different income prospects. The questions are asked in 1993, 2002, 2004, 2006 and 2010, and read as follows:

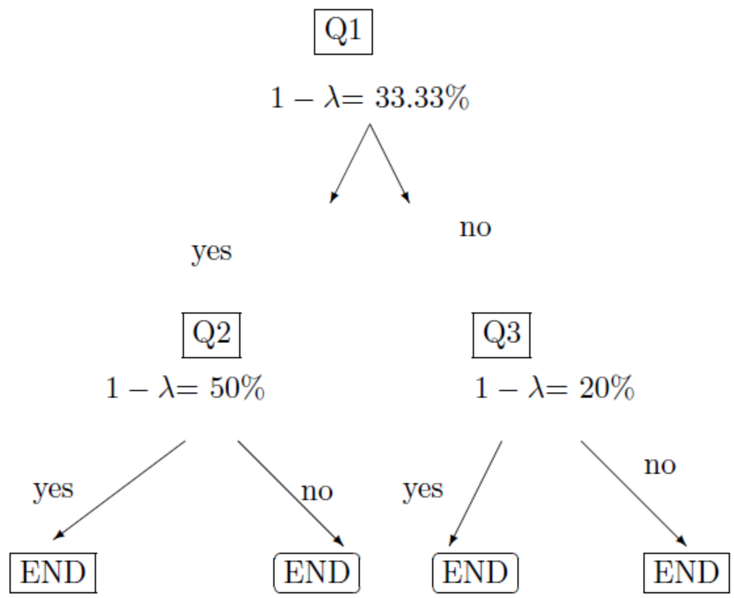
"Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by (*amount*). Would you take the new job?"

The initial cut (denoted $1-\lambda$) is a third. Subsequent questions adjust to higher/lower downside risk, half or a fifth (see Figure A.1). From expected utility theory, if a respondent answers "yes" to a particular question, then:

$$\frac{1}{2}U(2c) + \frac{1}{2}U(\lambda c) \geq U(c).$$

Assuming equality and a constant relative risk aversion utility function, $U(c) = \frac{1}{1-\sigma}c^{1-\sigma}$, it follows that $\lambda = (2 - 2^{1-\sigma})^{\frac{1}{1-\sigma}}$. By changing the cut-off point $(1-\lambda)$, one can bracket the respondent's willingness to take risk measured by the coefficient of relative risk aversion as shown in Table A.1. We could calculate the conditional mean of σ in each group following the methodology described in Barsky et al. (1997), and also correct for transitory errors as in Kimball, Sahm, and Shapiro (2008), given that these questions have been asked in multiple survey years. Previous researchers

Figure A.1: Question Mapping



have argued that a cardinal measure is preferable to using a simpler ordinal measure but our results are qualitatively similar when using a simpler ordinal measure. In our baseline specification, we use a dummy variable for "middle risk aversion" equal to one if the respondent is in groups 2 and 3, and is zero otherwise—this choice is guided by Druedahl and Jorgensen (2018), who find that a large puzzle group can be generated only if households are neither too risk tolerant nor too risk averse. We use 1993, the earliest year the question was asked, to minimize the effect of current background risk. Thirty percent of the respondents are in groups 2 and 3.

Discount Factors and Present Bias

The 2006 wave of the NLSY79 contains the following two questions:

> (1) "Suppose you have won a prize of $1000, which you can claim immediately. However, you can choose to wait one month to claim the prize. If you do wait, you will receive more than $1000. What is the smallest amount of money in addition to the $1000 you would have to receive one month from now to convince you to wait rather than claim the prize now" ($amount_{month}$)

Table A.1: Risk Aversion Mapping from the Survey Questions

		Risk Aversion	
Group	Answers	Lower Bound	Upper Bound
1	Yes/Yes	0	1
2	Yes/No	1	2
3	No/Yes	2	3.7
4	No/No	3.7	∞

(2) "Let me ask the same question but with a one year wait instead of one month. What is the smallest amount of money in addition to the $1000 you would have to receive one year from now to convince you to wait rather than claim the prize now?" ($amount_{year}$)

Following Courtemanche, Heutel, and McAlvanah (2015), we construct discount factors and measures of present bias and long-run patience from the responses given. Specifically, we can calculate yearly and monthly discount factors as follows:

$$DF_{year} = \frac{1000}{1000 + amount_{year}},$$

$$DF_{month} = \frac{1000}{1000 + amount_{month}}.$$

Time-consistent preferences would imply $DF_{year} = (DF_{month})^{12}$, which is rarely the case in the data. Instead, assuming hyperbolic discounting, respondents discount an amount t periods in the future by $\beta\delta^t$, where β capture a respondent's present bias, and δ signifies long-run patience, δ. Using the year and month amounts from the previous questions, we can write:

$$\beta\delta = \frac{1000}{1000 + amount_{year}},$$

$$\beta\delta^{\frac{1}{12}} = \frac{1000}{1000 + amount_{month}}.$$

Solving for β and δ yields:

$$\beta = \frac{1000}{\delta(1000 + amount_{year})}.$$

$$\delta = \left(\frac{1000 + amount_{month}}{1000 + amount_{year}}\right)^{\frac{12}{11}}.$$

Higher levels of $amount_{year}$ imply greater impatience and lower levels of δ. Values of $\beta < 1$ imply present bias. To explore the differences in discount rates (in a general sense) between respondents in the different groups, we initially construct two dummies, "high discount rate" and "present bias". The high discount rate is equal to one if a respondent is below the median level of long-run patience, δ, and is zero otherwise. Present bias is a dummy variable equal to one if β is below its median level and is zero otherwise (although anybody with $\beta < 1$ should technically be classified as having present bias, results are not dependant on the exact definition of this dummy). When answering these questions, respondents give a very wide range of responses including values over $1,000. In keeping with previous studies, we winsorize responses above the 95 percentile.

Income Uncertainty

We use answers to the question *"What is the main reason you happened to leave this job?"* to create a *job shock* variable equal to the total number of times since the previous interview that a respondent lost his/her job for unexpected reasons (such as being discharged or fired, laid off, job eliminated, business closings, business bankruptcies, and/or failure, quits for disabilities or health reasons).

We tested the robustness of our results to other measures of income uncertainty including: the total number of times family income fell by more than 20 percent over the last 6 years; the absolute value of the residuals from backward-looking income regressions that remove the deterministic component of income; and forward income uncertainty computed as the standard deviation of the difference between realized and expected income. We also constructed measures of permanent and transitory income volatility since it is easier to insure against transitory income shocks than permanent income shocks, but for each shock the results were the same: credit access risk matters, not income volatility.

B Figures and Tables with Additional Results

Figures B.1 and B.2 provide information on the distribution of liquid assets, credit card debt and arbitrage (the difference between the two) and their evolution over time.

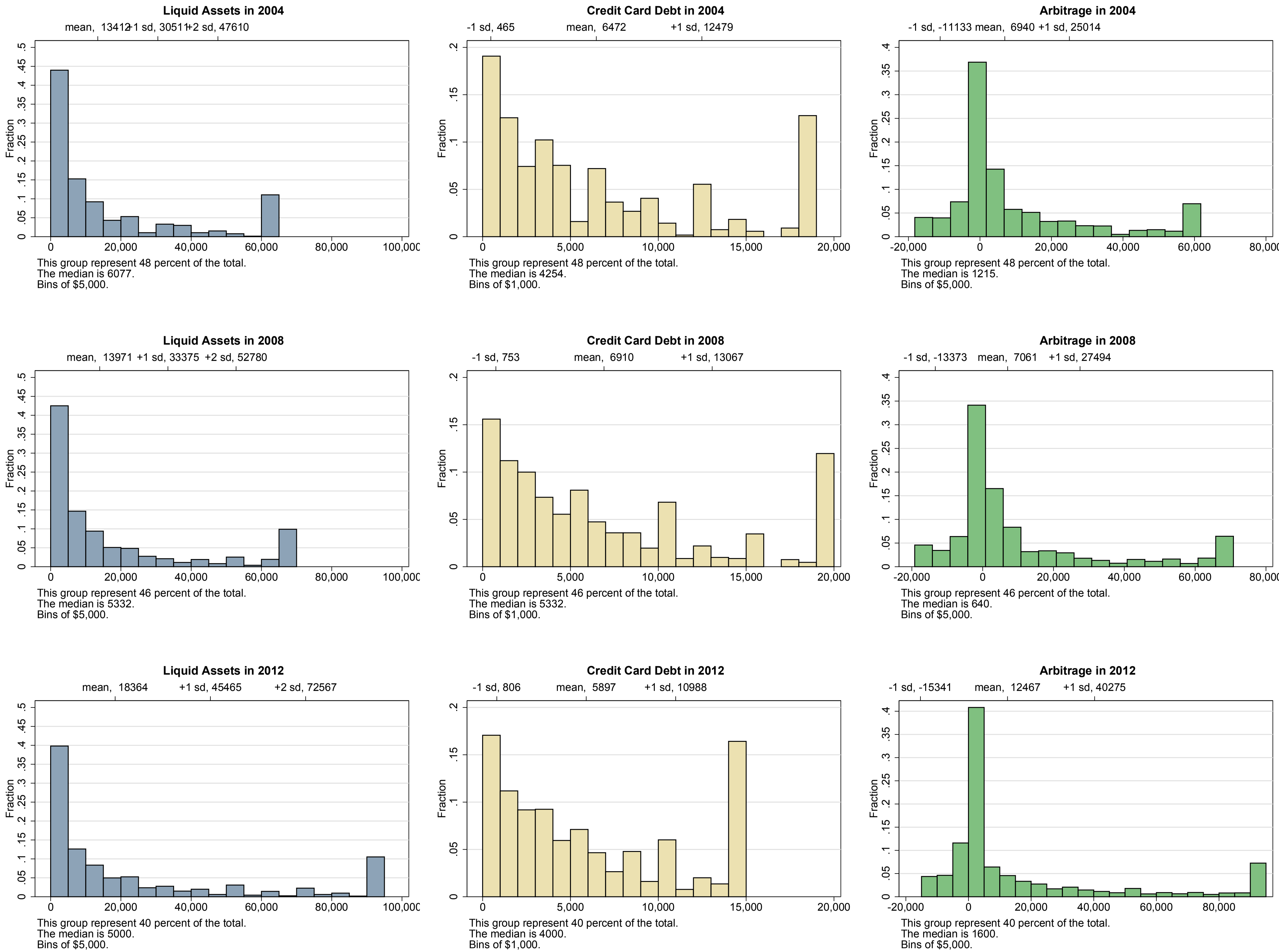
Tables B.1–B.2 present results using the alternative baseline definition of the borrower-saver (at least $500 in both credit card debt and liquid assets).

Tables B.3–B.5 present results from multinomial logit regressions focusing on the strict puzzle definition and the predicted measure of credit access risk for brevity. These results are consistent with the main results in the paper using a simpler linear probability specification.

Tables B.6 presents summary statistics on bankruptcy and foreclosure, and Table B.7 shows that using a probit specification instead of a linear regression model in the bankruptcy and foreclosure regressions does not alter our conclusions.

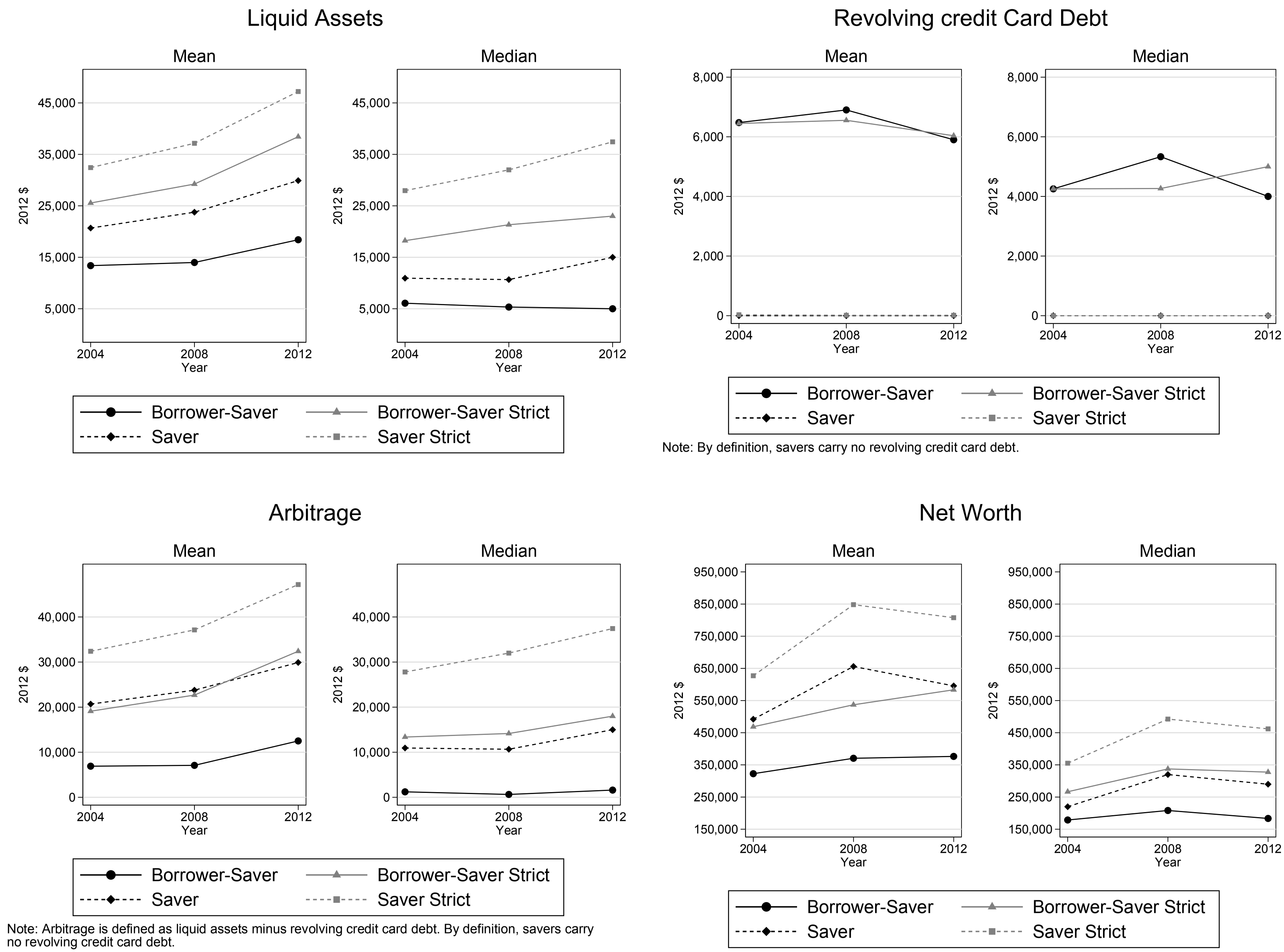
Using SCF data, Table B.8 summarizes the differences in APRs charged on the credit card with the highest balance comparing savers to borrower-savers (based on regression results). Table B.9 reports the interest cost of revolving credit card debt using 2010 data to contrast with the 2004 interest cost numbers reported in the main text.

Figure B.1: Distribution of Liquid Assets, Credit Card Debt, and Arbitrage for the Borrower-Saver Group



Notes: Authors' calculations using the NLSY79. Arbitrage is defined as the difference between liquid assets and credit card debt.

Figure B.2: Liquid Assets, Credit Card Debt, Arbitrage, and Net Worth Over Time by Group



Notes: Authors' calculations using the NLSY79. Arbitrage is defined as the difference between liquid assets and credit card debt.

Table B.1: Characteristics Affecting Group Membership: Borrower-Saver vs. Saver. Linear Probability Regressions, Alternative Baseline Definition

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline ($500-$500)				Strict	
	Original		Predicted		Original	Predicted
Credit Access Risk	0.035***	0.019***	0.086***	0.087***	0.036***	0.080***
	(0.006)	(0.006)	(0.008)	(0.013)	(0.011)	(0.017)
Job Shock	–0.002	–0.003	–0.013**	–0.013**	0.001	–0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Change in Unemployment	0.005	0.007	0.014	0.015	–0.001	0.008
Rate, County	(0.011)	(0.011)	(0.012)	(0.012)	(0.015)	(0.016)
HPI Growth Rate, County	–0.019**	–0.016*	–0.022**	–0.019*	–0.016	–0.013
	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.014)
Present Bias	0.021	0.013	0.006	–0.001	0.036*	0.019
	(0.016)	(0.015)	(0.012)	(0.012)	(0.020)	(0.016)
High Discount Rate	0.053***	0.044***	0.033***	0.025**	0.058***	0.029*
	(0.016)	(0.015)	(0.012)	(0.012)	(0.020)	(0.016)
Middle Risk Aversion	0.031*	0.027*	0.035***	0.030**	0.013	0.012
	(0.017)	(0.016)	(0.013)	(0.012)	(0.021)	(0.016)
AFQT Score	0.024**	0.024***	0.023***	0.022***	–0.004	–0.003
	(0.010)	(0.009)	(0.008)	(0.007)	(0.013)	(0.010)
College or More	–0.048**	–0.025	–0.020	–0.000	–0.047**	–0.007
	(0.019)	(0.018)	(0.014)	(0.015)	(0.024)	(0.021)
Financial Literacy	–0.046***	–0.036**	–0.039***	–0.032**	–0.047**	–0.035**
	(0.017)	(0.016)	(0.013)	(0.013)	(0.023)	(0.018)
Financial Self-Knowledge	0.004	0.022	0.051***	0.061***	0.006	0.063***
	(0.017)	(0.016)	(0.013)	(0.014)	(0.022)	(0.019)
Net Worth		–0.178***		–0.165***		–0.136***
		(0.017)		(0.015)		(0.019)
Net Worth, Squared		0.033***		0.033***		0.027***
		(0.005)		(0.004)		(0.005)
Homeowner, with Mortgage		0.198***		0.294***		0.212***
		(0.022)		(0.023)		(0.037)
Homeowner, No Mortgage		0.013		0.134***		0.084*
		(0.027)		(0.030)		(0.043)
Has Car Loan		0.132***		0.121***		0.120***
		(0.013)		(0.012)		(0.016)
Has Student Debt		0.094***		0.002		0.079*
		(0.027)		(0.028)		(0.045)
Year=2008	–0.084***	–0.075***	–0.101***	–0.093***	–0.100***	–0.102***
	(0.024)	(0.023)	(0.027)	(0.026)	(0.032)	(0.035)
Year=2012	–0.097***	–0.110***	–0.129***	–0.141***	–0.169***	–0.203***
	(0.034)	(0.032)	(0.031)	(0.031)	(0.045)	(0.042)
Observations	7,221	7,221	7,221	7,221	3,987	3,987
R squared	0.04	0.12	0.05	0.12	0.05	0.12
State Fixed Effects:	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy variable equal to one if the respondent is in the borrower-saver group, and zero if a saver. All regressions control for demographics (age, race, gender, marital status, and the number of children), and time and state fixed effects unless indicated. For results using the original measure of credit access risk, robust standard errors clustered at individual level are reported in parentheses. For results using the predicted credit access risk measured, bootstrapped standard errors with 1000 replications, clustered at individual level, are reported in parentheses. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY 1979.

Table B.2: Borrower-Saver versus Saver: Further Results, Alternative Baseline Definition

	(1)	(2)	(3)	(4)
	Baseline ($500-$500)			Strict
Panel A: The Role of Financial Literacy				
Predicted Credit Access Risk	0.038***	0.058***	0.059***	0.054***
	(0.011)	(0.014)	(0.014)	(0.021)
Job Shock	–0.012**	–0.012**	–0.013**	–0.009
	(0.006)	(0.006)	(0.006)	(0.008)
Financial Literacy	–0.044***	–0.044***	–0.045***	–0.037**
	(0.013)	(0.013)	(0.013)	(0.017)
Credit Risk × Fin. Literacy	0.085***	0.058***	0.056***	0.049***
	(0.012)	(0.012)	(0.012)	(0.017)
Observations	7,221	7,221	7,221	3,987
R squared	0.04	0.10	0.12	0.12
Financial Controls:	No	Yes	Yes	Yes
State Fixed Effects:	No	No	Yes	Yes
Panel B: Forward Credit Risk and Future Job Shock				
F4: Predicted Credit Access Risk	0.080***	0.049***	0.049***	0.054***
	(0.011)	(0.012)	(0.012)	(0.017)
F4: Job Shock	–0.005	–0.004	–0.004	–0.016
	(0.010)	(0.009)	(0.010)	(0.014)
Observations	3,978	3,978	3,978	2,299
R squared	0.04	0.10	0.12	0.13
Financial Controls:	Yes	Yes	Yes	Yes
State Fixed Effects:	Yes	Yes	Yes	Yes
Panel C: Individual Fixed Effects				
Predicted Credit Access Risk	0.044***	0.063***	0.061***	0.055**
	(0.015)	(0.016)	(0.016)	(0.025)
Job Shock	–0.004	–0.005	–0.004	0.003
	(0.010)	(0.010)	(0.010)	(0.016)
Observations	7,221	7,221	7,221	3,987
Within R squared	0.02	0.03	0.03	0.03
Financial Controls:	No	Yes	Yes	Yes
State Fixed Effects:	No	No	Yes	Yes
Individual Fixed Effects:	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy variable equal to one if the respondent is in the borrower-saver group and zero if a saver. F4 is a four-period forward operator. All regressions include controls as in Table **??**. Bootstrapped standard errors with 1000 repetitions (in parentheses) clustered at the individual level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY 1979.

Table B.3: Multinomial Logit. Characteristics of the Borrower-Saver Compared to Others. Strict Puzzle

	(1) Borrower	(2) Neutral	(3) Saver
Predicted Credit Risk	–0.154*	–1.133***	–0.351***
	(0.063)	(0.096)	(0.072)
Job Shock	0.048	0.255***	0.043
	(0.036)	(0.045)	(0.041)
Change in Unemployment Rate, County	–0.021	–0.196*	–0.085
	(0.053)	(0.081)	(0.061)
HPI Growth Rate, County	0.010	–0.037	0.035
	(0.047)	(0.066)	(0.058)
Present Bias	0.092	0.324***	–0.069
	(0.063)	(0.090)	(0.072)
High Discount Rate	0.096	0.231**	–0.160*
	(0.060)	(0.087)	(0.065)
Middle Risk Aversion	–0.106	–0.091	–0.025
	(0.061)	(0.095)	(0.070)
Female	0.021	–0.097	–0.074
	(0.060)	(0.086)	(0.070)
Hispanic	–0.067	0.135	–0.185
	(0.133)	(0.164)	(0.166)
Black	0.375**	1.106***	0.358*
	(0.131)	(0.151)	(0.156)
Year=2008	0.438***	0.492**	0.437**
	(0.130)	(0.190)	(0.156)
Year=2012	0.624***	0.637**	0.722***
	(0.158)	(0.224)	(0.174)
Married	–0.157*	–0.934***	–0.128
	(0.079)	(0.115)	(0.089)
Has kids	0.377***	1.139***	–0.027
	(0.078)	(0.116)	(0.088)
AFQT Score	–0.113**	–0.742***	0.052
	(0.040)	(0.061)	(0.045)
College or More	–0.241**	–0.807***	0.064
	(0.079)	(0.155)	(0.084)
Financial Literacy	–0.103	–0.247**	0.172*
	(0.068)	(0.096)	(0.077)
Financial Self-Knowledge	–0.335***	–0.737***	–0.197*
	(0.068)	(0.100)	(0.079)
Net Wealth	–0.613***	–2.087***	0.084**
	(0.075)	(0.464)	(0.030)
Homeowner, with Mortgage	–0.825***	–2.802***	–0.731***
	(0.123)	(0.170)	(0.141)
Homeowner, No Mortgage	–0.986***	–2.352***	–0.032
	(0.156)	(0.212)	(0.172)
Has Car Loan	–0.052	–0.828***	–0.601***
	(0.063)	(0.093)	(0.072)
Has Student Debt	0.384**	1.344***	–0.407*
	(0.138)	(0.209)	(0.191)
Observations	9,951	Pseudo R squared	0.18

Notes: The table presents average marginal effects from multinomial logit regressions with individuals in the borrower-saver group as the comparison group. Bootstrapped standard errors with 1000 repetitions (in parentheses) are clustered at the individual level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY 1979.

Table B.4: Multinomial Logit. Transitions from the Borrower-Saver (Puzzle) Group to Other Groups. Strict Puzzle

	(1) Puzzle to Saver	(2) Puzzle to Borrower	(3) Puzzle to Neutral
Change in Predicted Credit Risk	–0.126	0.178	–0.245
	(0.120)	(0.102)	(0.266)
Change in Job Shock	–0.033	0.160	0.258
	(0.385)	(0.086)	(0.653)
Change in Unemployment Rate, County	–0.233	0.051	0.034
	(0.180)	(0.159)	(0.409)
HPI Growth Rate, County	0.033	0.113	–0.031
	(0.130)	(0.111)	(0.341)
Age	–0.064	–0.033	–0.033
	(0.038)	(0.034)	(0.092)
Present Bias	–0.024	–0.034	0.298
	(0.169)	(0.147)	(0.425)
High Discount Rate	–0.424*	0.014	–0.372
	(0.179)	(0.155)	(0.430)
Middle Risk Aversion	–0.105	–0.135	–1.111
	(0.179)	(0.152)	(1.936)
Married	–0.174	0.022	–0.966
	(0.211)	(0.192)	(0.528)
Has kids	–0.174	–0.083	0.285
	(0.235)	(0.206)	(0.608)
AFQT Score	–0.044	–0.347***	–0.857*
	(0.125)	(0.106)	(0.322)
College or More	–0.241	–0.043	–0.241
	(0.214)	(0.171)	(0.941)
Financial Literacy	0.061	–0.125	–0.084
	(0.186)	(0.155)	(0.506)
Financial Self-Knowledge	–0.092	–0.238	–0.245
	(0.216)	(0.170)	(0.497)
L4: Net Worth	0.071	–0.094	–0.649
	(0.077)	(0.097)	(0.529)
L4: Homeowner, with Mortgage	0.673	0.159	–1.168
	(0.407)	(0.279)	(0.611)
L4: Homeowner, No Mortgage	0.794	–0.458	–0.668
	(0.477)	(0.377)	(1.092)
L4: Has Car Loan	–0.336*	–0.126	–0.109
	(0.171)	(0.146)	(0.431)
L4: Has Student Debt	0.019	0.242	–0.189
	(0.428)	(0.313)	(6.402)
Year=2012	0.061	–0.099	1.171
	(0.344)	(0.303)	(1.052)
Observations	1,126	Pseudo R squared	0.061

Notes: The table presents average marginal effects from multinomial logit regressions with individuals transitioning from the borrower-saver (puzzle) group to other groups(puzzle to puzzle being the baseline of comparison). Bootstrapped standard errors with 1000 repetitions (in parentheses) are clustered at the individual level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY 1979.

Table B.5: Multinomial Logit. Transitions from the Saver Group to Other Groups. Strict Puzzle

	(1) Saver to Puzzle	(2) Saver to Borrower	(3) Saver to Neutral
Change in Predicted Credit Risk	0.390**	0.455***	0.085
	(0.130)	(0.108)	(0.209)
Change in Job Shock	0.027	–0.028	–2.354***
	(0.090)	(0.067)	(0.140)
Change in Unemployment Rate, County	0.173	0.138	0.113
	(0.177)	(0.152)	(0.325)
HPI Growth Rate, County	0.193	0.201	–0.088
	(0.141)	(0.111)	(0.187)
Age	–0.032	0.033	0.037
	(0.040)	(0.035)	(0.074)
Present Bias	0.027	0.140	0.135
	(0.183)	(0.151)	(0.339)
High Discount Rate	0.114	0.154	0.050
	(0.179)	(0.151)	(0.350)
Middle Risk Aversion	0.407*	–0.105	–0.172
	(0.197)	(0.159)	(0.410)
Married	0.471	–0.042	–1.825***
	(0.257)	(0.191)	(0.443)
Has kids	–0.256	0.352	1.118*
	(0.229)	(0.192)	(0.498)
AFQT Score	–0.222	–0.400***	–1.203***
	(0.119)	(0.100)	(0.225)
College or More	–0.194	0.013	–0.142
	(0.205)	(0.172)	(0.542)
Financial Literacy	–0.208	0.020	0.331
	(0.200)	(0.165)	(0.356)
Financial Self-Knowledge	0.261	–0.153	–0.274
	(0.214)	(0.164)	(0.395)
L4: Net Worth	0.082	–0.136	–0.029
	(0.101)	(0.114)	(0.327)
L4: Homeowner, with Mortgage	–0.079	0.287	–0.675
	(0.336)	(0.282)	(0.471)
L4: Homeowner, No Mortgage	–0.754	–0.255	–1.096*
	(0.408)	(0.329)	(0.507)
L4: Has Car Loan	0.370*	–0.005	–0.794
	(0.179)	(0.153)	(0.428)
L4: Has Student Debt	0.116	0.373	0.828
	(1.033)	(0.449)	(3.321)
Year=2012	0.117	–0.617*	–0.044
	(0.380)	(0.309)	(0.745)
Observations	1,377	Pseudo R squared	0.107

Notes: The table presents average marginal effects from multinomial logit regressions with individuals transitioning from the saver group to other groups(saver to saver being the baseline of comparison). Bootstrapped standard errors with 1000 repetitions (in parentheses) are clustered at the individual level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level. *Source:* NLSY 1979.

Table B.6: Bankruptcy and Foreclosure Rates

	2008 Classification				2004 Classification	
	Bankruptcy, 2009–2012		**Foreclosure, 2009–2012**		**Bankruptcy, 2005–2008**	
	Baseline	Strict	Baseline	Strict	Baseline	Strict
Borrower	8.7	4.5	22.6	7.9	6.6	4.8
Neutral	5.4	5.1	10.5	11.1	2.3	2.3
Borrower-Saver	4.4	2.9	5.7	3.2	3.1	0.9
Saver	0.6	0.4	2.0	1.1	1.9	0.6
Total	3.3	3.2	5.2	5.2	2.7	2.7
Observations	2,927	2,921	2,286	2,282	2,880	2,872

Notes: Mean coefficients

Source: NLSY 1979.

Table B.7: Bankruptcy and Foreclosure. Borrower-Saver versus Saver, 2008 Classification. Probit Regressions

	(1)	(2)	(3)	(4)
	Bankruptcy, 2009–12		**Foreclosure, 2009–12**	
	Baseline	Strict	Baseline	Strict
Borrower-Saver, 2008	0.032***	0.018***	0.018**	0.013
	(0.006)	(0.006)	(0.007)	(0.009)
Present Bias	0.013	0.014*	0.005	–0.012
	(0.008)	(0.008)	(0.008)	(0.008)
High Discount Rate	0.023***	0.025***	0.029***	0.005
	(0.007)	(0.009)	(0.009)	(0.007)
Middle Risk Aversion	0.002	–0.004	0.014	0.005
	(0.006)	(0.007)	(0.010)	(0.006)
AFQT Score	–0.002	–0.001	–0.004	–0.008
	(0.005)	(0.005)	(0.007)	(0.005)
College or More	–0.002	0.001	–0.014**	–0.022***
	(0.007)	(0.006)	(0.006)	(0.008)
Financial Literacy	0.003	0.001	0.010	0.005
	(0.007)	(0.007)	(0.011)	(0.010)
Financial Knowledge	0.001	0.000	–0.003	0.015
	(0.008)	(0.007)	(0.008)	(0.013)
Log Debt 2008	0.006	0.007*	0.019**	0.016*
	(0.006)	(0.004)	(0.008)	(0.010)
Log Assets 2008	–0.005	–0.006*	–0.008	–0.001
	(0.005)	(0.003)	(0.007)	(0.007)
Assets $>$ Debt, 2008	–0.045***	–0.031***	–0.041***	–0.018
	(0.011)	(0.010)	(0.010)	(0.012)
Self Employed 2008	0.018***	0.013**	0.037***	0.022***
	(0.007)	(0.007)	(0.009)	(0.008)
Health Shock	0.032***	0.017	0.024	–0.041***
	(0.012)	(0.010)	(0.015)	(0.015)
Divorce Shock	0.019	0.025**	0.032*	0.010
	(0.013)	(0.012)	(0.016)	(0.015)
Observations	2,152	1,064	2,074	1,073
Pseudo-R squared	0.21	0.37	0.23	0.32
χ^2	185.59	210.40	881.85	380.76
p-value	0.00	0.00	0.00	0.00

Notes: The dependent variables are dummies equal to one if the respondent filed for bankruptcy or went through foreclosure during the specified periods. All regressions control for demographics (age, race, gender, marital status, presence of kids). Standard errors (in parentheses) clustered at the state level. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level.
Source: NLSY 1979.

Table B.8: The Interest Rates Charged on the Credit Card with the Highest Balance

	(1)	(2)	(3)	(4)
	Baseline		Strict	
Borrower-Saver × year=2004	0.740***	0.286	–0.926**	–0.962**
	(0.287)	(0.299)	(0.403)	(0.411)
Borrower-Saver × year=2007	1.377***	0.934***	0.257	0.248
	(0.297)	(0.307)	(0.431)	(0.442)
Borrower-Saver × year=2010	2.705***	2.245***	1.461***	1.351***
	(0.273)	(0.286)	(0.390)	(0.401)
Saver × year=2007	2.246***	2.221***	2.231***	2.289***
	(0.296)	(0.304)	(0.327)	(0.331)
Saver × year=2010	2.792***	2.799***	2.478***	2.548***
	(0.281)	(0.290)	(0.313)	(0.323)
Constant (Saver × year=2004)	11.092***	13.446***	11.162***	12.160***
	(0.200)	(0.760)	(0.229)	(1.030)
Observations	7,502	7,502	4,069	4,069
R squared	0.02	0.05	0.05	0.07
Demographics:	No	Yes	No	Yes

Notes: The dependent variable is a dummy variable equal to one if the respondent is in the borrower-saver group, and zero if a saver. Demographic controls include dummies for age, race, gender, marital status; completed years of schooling and the number of children and adults in the household. Robust standard errors are reported in parentheses. The symbols ***(**)[*] indicate significance at the 1(5)[10] percent level.
Source: Survey of Consumer Finances

Table B.9: The Interest Cost of Revolving Credit Card Debt, 2010

	2004 Interest Rates Quartiles			
	1	2	3	4
Average Percentage Rate, %	4	10	14	22
Beginning Balance in 2010, US$	10,460	8,469	8,706	8,064
Annual Family income in 2010, US$	99,254	90,844	84,726	72,894
	A. Zinman (2007) Cost Calculation			
Average wedge = min(CC debt, liquid assets)	4,806	3,890	2,864	2,419
Cost per year:				
Average	196	374	411	587
Percentile 25	6	57	90	68
Median	59	182	226	253
Percentile 75	216	491	493	618
	B. Balance is Paid in Full After One Year			
Balance after 12 months, US$	8,579	7,322	7,860	7,875
Interest Paid in 12 months, US$	463	843	1,282	1,928
Interest as Percentage of Annual Income, %	0.47	0.93	1.51	2.64
	C. Only Minimum Payments are Made			
Total Number of Years to Repay	17.6	22.6	30+	30+
Total Interest Paid, US$	2,014	5,738	11,516	40,209
Interest as Percentage of Annual Income, %	2.0	6.3	13.6	55.2

Notes: Calculations are based on data from the using 2010 average values, splitting the sample of respondents in the puzzle group according to interest rate quartiles based on 2004 data. For panel A, we follow the methodology in Zinman (2007): Cost=min(credit card debt, liquid assets)$\times$ (interest on credit card – interest rate on liquid assets). For panel C, we assume that only the monthly minimum payment is made (set at the maximum of 2 percent of the total balance or $15) until the entire balance is paid off.
Source: Survey of Consumer Finances.

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