EMPIRICAL ANALYSES ON THE DEMAND OF UNSECURED CREDIT

by
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Introduction[1]

“Send me a bill that stops credit card companies from taking advantage of consumers, and do it by month’s end” – demanded President Barack Obama the Congress on the 9th of May, 2009. In the middle of the subprime mortgage crisis, the speech of the president of the United States has several interesting implications. First, he no longer speaks only about a mortgage bill. It is now clear that the current turmoil has broad implications to the whole consumer credit industry through various channels. The demand for unsecured consumer credit has expanded as a result of job losses and salary cuts. At the same time, the supply for credit has shrunk as banks want to mitigate losses due to previously accumulated risky assets, and this tension led to higher prices on the credit market. Second, President Obama points towards credit card providers “ripping off” U.S. households through shrouded product attributes communicated in “fine prints that hide the truth” so households would “need a magnifying glass and a reference book to read a credit card application”. The president thus states that customer protection acts need to be strengthened, as households are hurt by the tricks and traps of credit cards as well as by the tighter credit rationing in the midst of the crisis.

Obama’s speech gives a strong retrospective motivation for the current research. It suggests that U.S. households can not follow their long term interest while exposed to unsecured lending, and this is a likely component of the depth and length of the current subprime crisis. In the economics literature, there is a long debate whether borrowing decisions can be described by neoclassical (profit maximizing) rules or whether behavioral considerations (such as time-inconsistency, self-control or mistakes) are necessary building blocks of a model that aims to explain the choices of households. Some selected milestones of this literature are the papers of Ausubel (1991), Bertaut & Haliassos (2005) and Zinman (2009), focusing specifically on credit cards. Joining this debate, this thesis provides empirical evidence on the neoclassical versus behavioral drivers of unsecured household indebtedness. This thesis consists of three largely independent chapters: two about credit cards and one about unsecured personal loans. The two credit card related chapters carry out empirical analysis of the pre-crisis U.S. mar-

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ket, while the third analyzes a unique banking dataset from a developed European country, hence, its implications can be also relevant for the U.S.

Chapter 1 demonstrates that while among others, Dynan, Skinner & Zeldes (2004) show that the rich should save more and should have lower debt burden, in the case of credit cards the relationship is empirically non-monotonic: credit card borrowing (measured by proportion of debt holders or by the debt-to-income ratio) is the highest in the case of households with medium permanent income. Notable empirical aspects of this chapter are the correct treatment of income imputation in the used survey data (2007 wave of Survey of Consumer Finances) and the usage of alternative definitions of permanent income (income, present and future consumption or education). The chapter then reviews the related literature, which is at the intersection of two broad topics: existing research on how income drives savings and previous research on credit cards. By presenting supporting empirical evidence, the chapter argues that the neoclassical explanations (*e.g.,* liquidity constraints or precautionary savings) account for about half of the peak in the credit card debt-to-income ratio of the middle-class, so these should be extended with behavioral explanations (*e.g.,* with "animal spirits" models of temptation and self control or with investment mistakes) to fully understand the empirical fact.

Chapter 2 contributes to the emerging literature of the transactional use of credit cards. The chapter formalizes the advantages of credit cards as payment tools and investigates empirically the behavior of transactional credit card users. First, a simple neoclassical model of convenience use is presented in which households use credit card if the marginal benefit from the usage is higher than the marginal cost. In terms of the benefits, the credit card user may receive an immediate cash back and he/she may delay or even avoid the costly liquidation of his/her interest bearing investments. In terms of the costs, if the household revolves with its credit card balances, a marginal interest rate has to be paid. Afterwards, the model is extended to incorporate uncertainty and present biased preferences, and it is shown that this latter extension leads to the divergence of *ex ante* and *ex post* behavior. Using the 2004-2007 waves of the Consumer Expenditure Survey and the 2007 wave of the Survey of Consumer Finances, the second part of this chapter presents an empirical analysis that supports the previous transactional use model. To disentangle the current model's predictions from the implications of the life cycle model, only those households are analyzed that have sufficiently large financial assets (these households are called individual investors). First, it is shown that consumption in general is a main driver of credit card balances and of debt, but unexpected consumption shocks (*e.g.,* a health expenditure shock) have an even larger impact. Second, a novel finding of the chapter is that stock owner investors hold higher credit card debt. While these findings are fully in line with the neoclassical version of the model, several other empirical examples point towards potential biases and mistakes in the transactional use decision. The fact that investors charge their credit cards in the holiday seasons less often but they revolve more frequently with their accumulated balances, is analogous with the existence of sophisticated present-biased preferences. Also, investors with more credit cards revolve more often, which indicate that they may forget the payback. Finally, previous gains on the stock market lead to more frequent credit card use, which points towards the irrational projection of high past stock returns to the future.

Contributing to the literature of advertising, Chapter 3 uses a unique data set of an anonymous European bank to analyze the impact of personal loan advertising on loan demand. The data set consists of a highly accurate measure of advertising exposure (Gross Rating Points) gathered on a weekly basis through three media, namely television, internet and newspapers and a highly accurate measure of consumer demand for personal loan. In the reviewed literature, such detailed financial services advertising data is not available on these media types. Using the appropriate time series models, the chapter reports that television commercials have higher impact on loan applications than internet or newspaper advertising. Furthermore, certain customer segments, namely rich or young individuals react to TV advertising more than poorer or older individuals, respectively. Motivated by these empirical facts, the chapter develops a life cycle consumption model with three potential channels through which advertising alters borrowing. First, advertising may provide information about the existence of the brand. Second, commercials may provide information about the interest rates. Finally, advertising may act as a taste shifter. The empirical facts are in line with the latter persuasive view of advertising, and among other plausible explanations, the facts point towards the importance of internal self-control mechanisms.

In sum, this thesis has found in all chapters some evidence in favor of both neoclassical and behavioral mechanisms to be important in the determination of unsecured credit demand. Consequently, both schools have to be integrated to fully explain economic business cycles, such as the subprime mortgage crisis. Also, governmental regulation and customer protection on the borrowing market is essential, just as highlighted by the worries of President Obama. Presumably, the empirical results and conceptual frameworks used in the three chapters contribute to the exciting and very timely research of household indebtedness.

Chapter 1

Do the Rich Borrow Less?

1.1 Introduction

Consider two middle-class individuals living in the U.S., who are identical in their socio-demographic and financial characteristics and both have \$100,000 liquid assets in a bank. In 2002, both persons purchase a new house, for \$100,000. One of them uses liquid assets to purchase the house, and keeps his previous level of consumption stable after the purchase. The other person applies successfully for a 30 year balloon payment mortgage with low monthly payments. Using his liquid assets he lifts the level of his yearly consumption by \$20,000 in the next 5 years, for instance through buying a nice car, building a patio and installing on it a grill oven equipped with the latest technology. Comparing the two individuals in 2007, can one state that the second one financed his house with the mortgage? Rather he used mortgage indirectly to finance his non-housing incremental consumption during the 5 years. Meanwhile assuming that the value of houses dropped in 2008 to \$60,000 and the mortgage payments went up as a result of higher margins charged by the bank, one can see that the second person is hit more by these changes and probably had more gloomy subsequent family dinners.

This simplified example is intended to highlight two important points about the 2008-2009 subprime mortgage crisis. First, while it is called *mortgage crisis*, its depth and length suggests that unsustainable housing and non-housing consumption patterns equally accelerate the turmoil. Based on the 2006 Consumer Expenditure Survey, only 33.8% of total household expenditures are related to housing. As the households make simultaneous decisions about savings and consumption in various expenditure groups, it is a rational behavior to maximize debt in the cheapest alternative, which is mortgage, and indirectly fund from this loan other expenditures. Second, while everyone speaks about the *subprime crisis*, recent news about spillovers of delinquencies to the prime segment and high indebtedness of this segment suggest that the depth and length of the turmoil is determined by the behavior of multiple income segments. Hence, a comprehensive analysis of consumption-saving decisions has a high potential contribution to the understanding of the current crisis, especially if it is related to multiple consumer segments and multiple expenditure categories.

This chapter focuses on credit card debt burden, which satisfies both these criteria above. The chapter intends to answer a simple question: how does income drive credit card debt? Compared with other specific purpose loans (*e.g.,* mortgage, vehicle or education loans), credit card debt is driven by a mixture of various smaller expenses. Cards are frequently used, and their use is more independent of the economics of special goods and services (*e.g.,* housing or education). As a result, if properly defined, credit card debt can be treated as a good proxy to represent the total life cycle borrowing need that is associated with household consumption-saving decisions.

The relationship between income, saving and consumption is well researched. It can be easily derived that in the benchmark model of the life cycle / permanent income hypothesis (LCPIH henceforth) if one controls with income growth rate (driven for instance by age), discount rate and interest rate differences, the saving rate has to be constant and independent of income. Meanwhile Dynan et al. (2004) show empirical evidence that controlling with age the saving rate is actually *increasing* with permanent income – *i.e., the rich save more*. According to the authors, heterogeneity in interest rate or in discount rate does not contribute to this fact, which can be well explained by a set of extensions of the LCPIH, including bequest motives or precautionary saving. If one looks at credit demand as simply the negative side of saving, these findings have to work for credit demand as well: if permanent income is increasing, then the "borrowing rate" either has to be constant (LCPIH) or has to decrease (Dynan et al. (2004)). The following analysis will show that this is not the case. To preview the results, it will be demonstrated that the middle-class has the highest credit card debt burden measured both by the proportion of debt holders and by the debt-to-income ratio. Empirical credit card literature frequently overlooks this phenomenon by focusing on the dollar level of debt instead of debt-to-income ratio or by analyzing current income instead of permanent income. The high indebtedness of the middle-class is not explained by other socio-demographic characteristics *e.g.,* by age, family size or house ownership. This statement is true with the correct econometric treatment of missing income data, which is typically not performed in the empirical literature. As the low indebtedness of the rich is consistent with the "rich save more" theory of Dynan et al. (2004), the striking feature of the results is that middle-income households are more indebted than the poor. Quantitatively, the middle-class holds non-zero credit card debt with 23% higher probability than the poor, leading to a higher debt-to-income ratio by half month permanent income in average.

Motivated by the non-monotonicity, the related literature is reviewed, first focusing on neoclassical models. Importantly, it is shown that the role of liquidity constraints is smaller than expected: according to a conservative estimate, relaxing credit rationing would increase the probability to be indebted by maximum 7% in the case of the poor. This difference is not satisfactory to rationalize why the middle-class borrows more. This finding is strengthened by fact that the debt-to-income ratio difference between the poor and the middle-class is even larger for the two thirds of households that have low credit default risk[1], while the theory of credit rationing would suggest a more even debt distribution. Furthermore, a multivariate Tobit model also justifies the small impact of liquidity constraints on the hump-shaped curvature of credit card debt-to-income ratio. Intuitively, in the pre-crisis U.S. credit card market, vast majority of those who wanted to have a credit card got accepted by a bank sooner or later, even if rejected several times before. Also, it is shown that the impact of risk-based-pricing – *i.e.,* the fact that the poor are charged with higher interest rates as a result of their higher bankruptcy risk, is existing but small. This analysis suggests that the explanation of credit card indebtedness is primarily demand driven. Precautionary savings or non-fungible consumption prove to be important determinants of demand, but it will be shown that the LCPIH model together with its neoclassical extensions is likely to explain only about *half* of the peaking credit card debt of middle income households. This motivates the need to incorporate behavioral models into the analysis (*e.g.,* animal spirits, investment mistakes or social preferences) to explain the empirical fact. Providing empirical evidence about the existence of these latter theories, the chapter suggests that future research needs to embrace both schools to understand credit card related decisions.

The structure of this chapter is the following: Section 1.2 discusses the data used. Section 1.3 presents the econometric analysis that shows middle-income households have the highest credit card indebtedness. Section 1.4 reviews the potential neoclassical reasons behind this empirical fact. Section 1.5 adds potential behavioral mechanisms to understand the observed indebtedness patterns better, and finally, Section 1.6 concludes.

1.2 The Data and the Treatment of Missing Income

The primary data source of the chapter is the triennial Survey of Consumer Finance (SCF), which is a cross section of about 5,000 households with very detailed information on savings and credit. The latest available wave, 2007 is used in this chapter. According to Bucks, Kennickell, Mach & Moore (2009), the survey data is largely unaffected by the decline of economic activity in 2008 caused

[1] *E.g.,* who were not rejected by any loan applications or were not late recently with credit payments, see the exact definition in Section 4.1.

by the subprime crisis, so this wave also represents the likely peak in household's debt burden in the 2000s decade. Similarly to Dynan et al. (2004), the analysis excludes households below $1,000 yearly income and the sample is restricted to household heads aged between 30 and 59 years.[2] Due to these exclusions, the discussion is not affected by the economics of the young (mainly students) and the old (mainly retired). These exclusions lead to 2,600 households, where the heads of households are typically employed or self-employed, but for a small portion they are students or unemployed.

The explanatory variable in the focus of the current research is permanent income. Fortunately, in the SCF households are not only asked their one-year past income but also whether this income is typical, and if not, what is the typical yearly income. This provides an accurate metric for permanent income. The econometric challenge of the dataset is related to income imputation: in the analyzed sample of 2,600 households, 46.6% of households do not have permanent income data. Fortunately, the Federal Reserve team created multiple imputation for the missing data,[3] which makes it possible to perform the econometric analysis.

In the chapter the SCF data is used both in cross tabulations of certain metrics and drivers of indebtedness by permanent income, and in multivariate econometric models. The cross tabulations are based on all 2,600 households and the SCF-provided population weights are used to calculate mean or percentile values. For the cross tabulations, households are frequently divided into three groups by the household head's age (657 household heads are in their thirties, 940 in their forties while 1,003 in their fifties), following the related literature. Households are also grouped into five equal sized income quintiles within each age groups (referred as Quintile 1 to 5). Appendix A.1 contains the thresholds used to identify the income quintiles and the number of observations in the income groups.

The cross tabulation is enriched with t-tests and Chi-squared tests, depending on whether the analysis variable is continuous or binary. These tests always compare Quintile 1 values with the other quintiles, as this is adequate to evaluate whether the values increase monotonically as income grows or whether there is a hump shaped relationship between the metrics and household income. Further-

[2]Dynan et al. (2004) analyze also the savings of the old to some limited extent. This is understandable as households with heads more than 60 years old hold 46% of total net worth. However, this ratio is only 24% of total credit card debt, so the current exclusion of these households is not as restrictive.

[3]In the survey the yearly actual household income is imputed, but if the household does not report its permanent income, the household's yearly income and its imputation is used in this chapter as the best potential proxy. Note that the proportion of missing actual income data is higher (52.6%) than the proportion of missing permanent income data, as some households do not report their actual income but answer the question about their typical yearly income.

more, several Tobit models will be presented to show the multivariate relationship between the analysis variables. For the statistical tests as well as for the Tobit models, the correct missing income treatment technique is used. This is an important step as based on Montalto & Sung (1996), dropping observations with missing income leads to inefficient and potentially biased estimates, while using a single imputed value for missing income leads to invalid inferences and invalid tests of significance. For instance, the main result of this chapter is that the middle-class has higher debt-to-income ratio: in a Tobit model the zero-one dummy representing Quintile 3 households is statistically significant. On one hand, by dropping the observations with missing income, half of the data would be lost, so significance tests would become weaker, and as high income households report their income less often, the parameter estimates would be biased. On the other hand, by keeping observations with missing income but using one (averaged) imputation for missing income, the statistical tests would become stronger due to the underestimation of the standard errors. So the statistical significance of the main result of this chapter – *i.e.,* the higher indebtedness of the middle-class could be driven by the incorrect treatment of missing income data. Consequently, the "repeated-imputation inference" recommended by the SCF team is implemented in this chapter.

According to Montalto & Sung (1996), not to interfere with the income imputation, the original sample weights are *not* used. But high income households are overweighted in the SCF sample, to be able to correctly measure the financial wealth held by this population. While from the bottom four income quintiles approximately 400 households are sampled per wave, from the top quintile more than 1,000 households are interviewed. To remove this sampling effect, from the highest income quintile only a 40% sample of households is drawn randomly (observations with higher population weights were drawn proportionally more likely), to have equally sized quintiles without the weights.[4] This reduces the sample size to 1,999 households. With this modification, no biases are caused by the omitted weights. For each five imputations (so called *implicates*) for income, five t-tests, Chi-squared tests or Tobit models are run, and the Q_{ij} income quintiles can be different for the same i household depending on the imputed income value. The algorithm and the Stata codes of aggregating the results to calculate the correct standard errors can be found in the Codebook for 2007 Survey of Consumer Finances.[5]

The secondary data source of the empirical analysis is the Consumer Expen-

[4]Montalto & Sung (1996) solve otherwise the problem of overweighted high income households: they cap simply income at $100,000. For the current analysis, this cap would lead to the exclusion of Quintile 5 and a portion of Quintile 4 households which is not a viable solution facing the research question of the current chapter.

[5]http://www.federalreserve.gov/PUBS/oss/oss2/2007/codebk2007.txt

diture Survey (CEX, 2004-2007 waves), as it contains accurate information about the total consumption of U.S. households. The CEX is a rotating panel of about 5,000 households per wave with more limited information on consumer finances compared with the SCF. Only those households were selected from the sample that did not attrite during the 12-month interview period, in order to observe their yearly consumption and debt, which latter was asked only during the first and the last interviews. As consumption is used as a measure of permanent income in the analysis, to keep the sample similar for both surveys, from the CEX only those households are selected that have at least $1,000 yearly consumption and where the household head is between 30 and 59 years old. These exclusions lead to a sample size of 9,381 households.

1.3 The Empirical Analysis

The main claim of this chapter is that credit card borrowing in the U.S. is the highest in the case of the middle income households. Obviously this statement depends on the definitions of both income and credit card borrowing, but the chapter uses multiple metrics that make the statement robust to the change of definitions. It is a known fact that middle income households have high credit card debt. Bucks, Kennickell & Moore (2006) state for instance that "the carrying of credit card balances is notably lower among the highest and lowest income groups", based on a recent wave of the nationwide Survey of Consumer Finances. Meanwhile the related empirical literature did not reach a consensus about how income drives credit card borrowing. This is because these empirical works typically focus symmetrically on multiple socio-demographic factors (such as age, wealth, income, household size and marital status, sometimes even attitudinal and liquidity related variables) and report income as one of many key drivers of credit card debt without detailed explanation of the mechanism behind the observed relationship.

Let us first review the related empirical literature. Some papers estimate credit card debt in one step. Kinsey (1981) predicts the number of credit cards as a rough metric of indebtedness and finds that this depends positively on the logarithm of income. Jiang (2006) uses a Tobit model to predict credit card debt (and payback rates separately) and finds that income is negatively related to indebtedness if forced log-linearly into the model. Meanwhile the author is aware of the hump-shaped income-debt relationship and highlights that a squared term of the logarithm of income also enters into the model as a significant predictor. As her main interest in the paper is to identify age and cohort effects to credit demand, she does not discuss in detail the possible reasons that can lead to the non-monotonic income-debt functional form, but she mentions liquidity constraint as a possible explanation.

Most of the studies predict credit card debt in multiple steps (two or three). Bertaut & Haliassos (2001) estimate the probability of having a bank-type credit card in the first stage and the probability of having credit card debt[6] as a second stage using a bivariate probit model, and find that the first probability depends positively and the second probability negatively on the logarithm of income. As their paper is both theoretical and empirical, the authors give a very specific explanation of this phenomenon (mental accounting) that is discussed in the behavioral section of this chapter. Kim & DeVaney (2001) uses the 1998 Survey of Consumer Finances to estimate a two stage model. In the first stage a probit model is used to predict which households revolve with their credit card and the authors find that high income households revolve less often. In the second stage they estimate the revolving balances with the Heckman two-stage procedure and find that income is positively correlated with the amount of balances. Hence, similarly to Bertaut & Haliassos (2001), the paper of Kim & DeVaney (2001) implicitly contains the possibility for the hump shaped income-debt relationship, but these latter authors only report the model results and do not comment further their findings about income. Similar results are presented by Yilmazer & DeVaney (2005) and by Min & Kim (2003) for the 1998 and the 2001 waves of the Survey of Consumer Finances, respectively, but the authors unfortunately do not draw inferences from these interesting results about income. Min & Kim (2003) point out that a simple Tobit model leads to dramatically different marginal effects in terms of income compared with the two-step estimation, but fails to recognize that this can easily happen because of the omitted squared income term from the Tobit model. Still using two step estimation, Castronova & Hagstrom (2004) estimate credit limit as a first decision of the household, and borrowing rate from the credit limit as the second decision using a nested Tobit model. Importantly the authors include the logarithm of income both linearly and in a squared term and find that both terms are significant drivers of credit limit, creating the hump-shaped functional form. Meanwhile similarly to the majority of literature, the authors do not intend to explain the economics behind this interesting finding.

Some authors look at credit card borrowing as a three-stage problem. Baek & Hong (2001) estimate a double-hurdle model with holding a credit card and having any debt on the credit card as the two hurdles, and overlay this with a truncated regression to estimate the amount borrowed. They find that income positively alters both the probability to hold a credit card and the credit card debt dollar amounts. Finally, Reynolds, Hogarth & Taylor (2006) focus on the same three decisions, but use the double hurdle model in a different setup: first they estimate the probability to have a credit card, and they use the fitted values of this probability in a double

[6]Instead of looking at actual credit card debt, the authors use the answer to the question whether the household does not usually pay off balance on bank-type credit card as the explained variable.

hurdle model that jointly estimates the probability of having credit card debt and the amount of credit card debt. Importantly, the authors correctly worry about the potential non-linearities in the relationship between income and debt and use *five income quintiles* in their model instead of the typical log-linear form. Interestingly, using two distant waves of the Survey of Consumer Finances, they find that the probability to have credit card debt depends on income in a non-monotonic way in both waves and the same is observed with the borrowed amount, but only in the case of one of the waves. Focusing on age as the main explanatory variable of interest, that paper also fails to discuss the role of income in more detail.

To sum up, the hump-shaped relationship between income and credit card debt is *frequently observed* in empirical papers that intend to find the drivers of borrowing. Unfortunately, typically these papers do not find the economics of this result interesting and do not dig deeper to find potential explanations. It is not difficult to find at least three possible explanations for this attitude. First, it is no consensus on how credit card debt should be measured. The reviewed papers measure often the dollar amount of debt, but also the proportion of debt holders and even the credit limit utilization rate are scrutinized. However, in the consumption-savings literature the *saving rate* itself is frequently in focus, and to the analogy of this, the analysis of credit card *debt-to-income ratio* would be welcome. Second, difficulties exist in the measurement of household income. As mentioned in Section 2, in the Survey of Consumer Finances multiple imputation techniques have to be used to tackle this missing data problem. However, *none* of the papers listed above treat correctly the imputed income and as a result, they have inconsistent estimates for income related parameters.[7] While possibly harmful in this chapter, the negligence of this step in the literature is an understandable compromise as in the majority of reviewed papers income is only one out of many independent variables that enter the econometric models, and missing data in other variables is scarce.[8] Another reason behind the lack of interest about this empirical fact is the general non-conformity with respect to non-monotonicity. A linear relationship is easy to explain, and the empirical literature intends to break down the borrowing decision into multiple steps (having a card, deciding on credit limit, yes-no decision about borrowing and amount of borrowing) so that a single decision has the preferred linear dependency on income. But as seen in the review, these single

[7]Typical wrong solutions are to average the implicates or select one of the five implicates of imputed income.

[8]Interestingly, the recent paper of Ozawa, Kim & Joo (2006) that focuses specifically on how income drives net wealth of the U.S. households based on the same SCF survey also fails to treat the missing income data correctly. On the other hand, the recent paper of Calem, Gordy & Mester (2006) uses the correct treatment of missing data in the SCF, though income is only a control variable in their model which focuses on switching cost and adverse selection in the credit card market.

components of credit card usage also often depend on income in a hump-shaped way.

The current chapter therefore intends to fill the gap in the literature: besides focusing on debt-to-income ratio as opposed to the dollar amount of loan and treating correctly the missing income data, it leaves no stones unturned to explain the potential mechanisms behind the non-monotonic relationship.

1.3.1 The Descriptive Evidence

This section presents the descriptive evidence about the empirical fact in focus: credit card borrowing is the highest in the case of middle income households. First, several tables focus on savings behavior. Table 1.1 shows that "the rich save more" finding of Dynan et al. (2004) holds for the analyzed survey data.[9] While Dynan et al. (2004) analyzes the average savings rate instead of the proportion of households being a saver, the evidence in Table 1.1 – *i.e.,* households save 3-4 times as much in the top quintile as in the bottom one and this proportion is monotonously increasing, is analogous to their finding about the saving rates. Restating this evidence is important as the paper of Dynan et al. (2004) uses SCF data from 1983-1989, so the 20 year period passed since that time is long enough to potentially contain a trend reversal.

Table 1.1: Percentage of households with positive savings over the last year

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	39%	45%	49%
Quintile 1	16%	22%	27%
Quintile 2	30%*	39%*	38%*
Quintile 3	34%*	47%*	45%*
Quintile 4	53%*	53%*	65%*
Quintile 5	63%*	64%*	71%*

Chi-squared tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

Table 1.2 shows that not only are there more savers in the higher income quintiles, but also the number of those who have negative savings decreases with permanent income. In the SCF, it is asked how the households cover the gap between their expenses and their income, and Table 1.3 shows that typically the higher the

[9]Households are asked specifically whether the yearly spending (excluding purchases of houses, vehicles or other investments) exceeds, is equal or falls below their yearly income.

permanent income, the lower the proportion of households using loans. Those who do not use loans to cover the gap, typically use their previous year's saving.

Table 1.2: Percentage of households with negative savings over the last year

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	17%	17%	15%
Quintile 1	24%	27%	27%
Quintile 2	17%	17%	20%
Quintile 3	22%	15%	16%
Quintile 4	14%	17%*	8%*
Quintile 5	10%*	10%*	6%*

Chi-squared tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

Table 1.3: Percentage of households with negative savings over the last year covering their expenses with loans

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	9%	9%	7%
Quintile 1	10%	14%	14%
Quintile 2	11%	9%	11%
Quintile 3	14%	8%	7%
Quintile 4	6%	9%	2%*
Quintile 5	5%*	3%*	3%*

Chi-squared tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

As the previous three tables are based on attitudinal questions and cover only the last year's saving behavior, one might be curious whether the cumulative wealth patterns are similar. Table 1.4 contains net worth-to-income ratios, in which the numerator is the total net worth defined by the SCF staff (total liquid and illiquid assets minus total debt, see more details in Bucks et al. (2009)) and the denominator is the *yearly* average income of the household. Note that the ratio is increasing with income significantly, except the oldest segment, in which case the large volatility of net worth leads to non-significant t-tests, but the average worth-to-income ratio in higher income quintiles is higher, except Quintile 2.

Table 1.4: Total net worth-to-income ratio

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	1.87	3.39	5.86
Quintile 1	0.84	1.74	5.9
Quintile 2	1.45	2.82*	4.43
Quintile 3	1.32*	3.23*	5.15
Quintile 4	2.54*	3.9*	6.22
Quintile 5	3.29*	5.4*	7.68

T-tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

This table shows that the "rich save more" statement holds in the case of cumulative savings balances as well. Note that this finding is robust to the replacement of net worth with total financial assets or with liquid assets, which results are not reported.

All previous tables indicate that the higher the permanent income is, the less households need to borrow to cover their expenses. Does this mean that high income means less credit card debt burden? Table 1.5 shows the relationship between income and having a credit card revolving balance. Fortunately, in the SCF households report the unpaid revolving balance on credit cards that excludes balances paid back during the grace period. Furthermore, in the SCF it is asked how often households pay back their credit balance fully: always or almost always, sometimes or hardly ever. Out of these responses, only those credit card balances are considered which are paid back sometimes or hardly ever paid back. In this way it is possible to distinguish between "serious" credit card debt and balances that might arise due to the convenience use of credit card.[10] This way, out of the average of $4,135 credit card balance per household, only 83% or $3,427 is analyzed further in this chapter. One striking feature of Table 1.5 is that a much higher proportion of households have credit card debt than the proportion of households who finance their higher consumption by loans based on Table 1.3. This is partly understandable as Table 1.3 is a flow analysis (presenting one-year dynamics), while Table 1.5 is stock analysis focusing on all credit card debt accumulated over the last years. However, one third of households holding credit card debt is significant in the presence of other (frequently cheaper) borrowing opportunities. The second important point of Table 1.5 is the *hump shaped income-debt relationship*.

[10] Convenience use refers to the fact that cards are used to exploit cash-back and other promotions or to benefit from security, speed of payment or from other non-monetary advantages, see Johnson (2004) for a detailed discussion.

In all age groups, the third income quintile has significantly higher proportion of credit card debt holders than the poorer segment, but this ratio decreases as income grows further, and in Quintile 5 the ratio of debt holders is close to the Quintile 1 level, shown by the insignificant Chi-squared statistics as well. Table 1.6 shows that not only the proportion of households owning debt peaks in the middle quintile, but also the debt-to-income ratio follows a similar trend. The ratio is defined as the dollar amount of credit card debt divided by the *monthly* permanent income of the household, and t-tests confirm the peak of indebtedness in the case of the middle-class except the lowest age group.

Table 1.5: Percentage of households with revolving credit card balance

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	37%	35%	37%
Quintile 1	29%	17%	29%
Quintile 2	27%	38%*	42%*
Quintile 3	48%*	48%*	48%*
Quintile 4	45%*	47%*	45%*
Quintile 5	36%	26%*	22%

Chi-squared tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

Table 1.6: Mean credit card debt-to-income ratios

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	0.53	0.61	0.69
Quintile 1	0.54	0.26	0.72
Quintile 2	0.43	0.71*	0.67
Quintile 3	0.59	1.14*	1.19*
Quintile 4	0.66	0.7*	0.53
Quintile 5	0.42	0.25	0.32

T-tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

As Table 1.6 shows the main empirical fact that will be scrutinized in this chapter, some robustness checks of the hump-shaped income-debt relationship can be found in Appendix A.2. Specifically, following Dynan et al. (2004), percentile values are calculated (75% percentiles are shown instead of median values because of the large number of households without any credit card debt) and the debt-to-income rate is also calculated for employees only, showing that the curvature is not caused by the behavior of entrepreneurs[11] or by the behavior of inactive households in different income groups.

Credit cards have some close "substitutes" or outside options in the lending market, meaning other loans that have typically lower interest rate and are used for similar purposes as credit cards. First, households may apply for unsecured installment loans (meaning that the household gets a fixed amount and pays the loan back in fixed monthly installments), for example sales finance for a new TV set. A second option is to open a line of credit (might be secured by home equity or unsecured) to buy goods or services and finally, the household can refinance its existing mortgage with a higher value contract and use the incremental money for undefined purposes.[12] The SCF makes it possible to identify the reasons behind these substitute loans, and this way it is possible to exclude some specific purpose loans such as housing related, education and vehicle related lending, which are close substitutes of mortgage, education loans and secured vehicle loans, respectively. The purpose of the remaining loan amount can be the purchase of some brown goods (consumer electronics) or white goods (major appliances), travel or family expenses, debt consolidation and other undefined purposes. This list fits well the general usage patterns of credit card, and also includes debt consolidation which is a large size business specifically designed to collateralize credit card debt, this way providing lower interest rates. As these substitute loans have typically lower interest rates and larger size, the credit card trends identified above are not fully valid without the analysis of these substitutes. Column (1) of Table 1.7 shows that the proportion of households with this type of loan is flat over income. Column (2) of Table 1.7 shows the debt-to-income ratios related to these substitutes of credit card, and while statistically significant differences do not exist, middle-income households seem to hold slightly higher debt.[13]

To sum up the empirical facts in this section, this chapter finds that the rich save more based on the 2007 wave of the SCF, and in parallel, the rich are less frequently in need of borrowing to cover their negative savings. However, the

[11] Dynan et al. (2004) uses similar robustness check for entrepreneurs in their savings rate analysis, while Kennickell & Lusardi (2004) shows that entrepreneurs accumulate precautionary savings differently. Castronova & Hagstrom (2004) argues that entrepreneurs have different credit card usage patterns.

[12] Note that some loan types are neglected in the empirical presentation as a result of their smaller size, such as margin loans or loans against the pension scheme.

[13] These graphs contain the impact of home ownership: higher income leads to higher percentage of home ownership and home owners can refinance their mortgage to smooth their consumption. See Hurst & Stafford (2004) about the role of home equity refinancing as a stimulus to liquidity constrained households. Meanwhile the tables show similar trends with the exclusion of loans secured to home equity, which results are not reported in detail.

Table 1.7: Percentage of households holding other general purpose loans and mean debt-to-income ratios of other general purpose loans

	(1) % of households holding other general purpose loans	(2) Mean debt-to-income ratios of other general purpose loans
Total	0.15	0.55
Quintile 1	0.12	0.45
Quintile 2	0.16	0.62
Quintile 3	0.14	0.63
Quintile 4	0.17	0.59
Quintile 5	0.14	0.46

Chi-squared tests in Column (1) and T-tests in Column (2) to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

middle class seems to hold the highest credit card debt. One might argue that this could be explained by the fact that low income households use other types of loans more frequently and the overall indebtedness of the poor is higher. However, looking at close substitutes of credit card debt, one can see that even if debt in these outside options are combined with credit card debt, the high indebtedness of the middle-class does not change. This contradicts the fact that the rich would borrow less. As income is largely correlated with other socio-demographic factors, the next section runs a formal model to check whether this statement is robust to the inclusion of other household characteristics.

1.3.2 Tobit Model on the SCF Data

Several potential explanations might lead to the results on credit card debt in the previous section. Permanent income is correlated with other socio-demographics, and while age was already separately highlighted, other important characteristics, such as family size, gender or education may be main drivers of credit demand. Furthermore, households might have different liquid or illiquid assets and also, house ownership is a key driver of consumption and of the availability of credit. Hence, this section intends to rule out the trivial explanations of the hump shaped relationship between credit card debt and income. If an other socio-demographic factor is responsible for this empirical fact, the peak should disappear in the case of controlling with that given factor. The following econometric model is run for this investigation:

$$L_i^* = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \sum_{j=2}^{5} \gamma_j Q_{ij} + \varepsilon_i$$

$$L_i = L_i^* \; if \; L_i^* > 0; \; L_i = 0 \; otherwise \tag{1.1}$$

where L_i is the i-th household's credit card debt-to-income ratio, which is left censored at zero, therefore parameters are estimated using the Tobit model, due to the assumption of i.i.d. normally distributed error terms in the measurement of the latent variable L^*. X_{ik} is a set of household characteristics, including two age dummies if the household head's age is between 40-49 or between 50-59 years, dummies for male, black, hispanic and married household head, a dummy representing house ownership, the number of kids in the family, dummies for high school and university education and finally, one-one dummy if the financial assets (including savings accounts or securities) and non-financial assets (including vehicles, housing or business assets) are higher than a full year's permanent income of the household. Q_{ij} represents four income quintile dummies, with the omission of the lowest quintile, to avoid multicollinearity.

Note that here borrowing is estimated in one step, similarly to papers of Jiang (2006) and Kinsey (1981). As seen in the empirical literature review, it is also feasible to break down the borrowing decision to multiple stages, but both the empirical literature reviewed at the beginning of Section 3 and the current data analysis (see Table 1.5 on the probability of borrowing or Table 1.16 in Section 4.2 about credit limits) suggest that the sub-decisions also depend on income in a non-monotonic way, therefore the breakdown is in fact not necessary for the purposes of the current chapter.[14]

The results can be seen in Table 1.8. The main interest is on the γ_j parameters that show the impact of income quintiles. Keeping other household socio-demographics constant, income explains credit card indebtedness in a non-monotonic way: in the middle quintile the debt-to-income ratio is significantly higher than in the lowest (omitted) income quintile, while it decreases afterwards. In addition to the income quintiles, house ownership and high school education increases credit card debt while the dummy showing high financial assets (higher than a yearly income) decreases credit demand significantly, which findings match the intuition.

Calculating the marginal effects, the impact of income is large. Recall that the population mean of debt-to-income ratio is 0.61. Relative to the lowest income group, being in income Quintile 3 shifts up the debt-to-income ratio by 0.50, while being in income Quintile 2 or 4 raises it by 0.24 and 0.27, respectively. This means

[14]Specifically, the papers of Jiang (2006) and Castronova & Hagstrom (2004) provide further examples for the non-monotonic income-debt relationship in the sub-decisions.

Table 1.8: Tobit model to estimate credit the card debt-to-income ratio using SCF-reported permanent income

Variable	Parameter	Standard error
Intercept	-3.305	(0.403)*
Quintile 2	0.742	(0.358)*
Quintile 3	1.447	(0.381)*
Quintile 4	0.825	(0.399)*
Quintile 5	-0.591	(0.455)
Age 40-49	0.260	(0.249)
Age 50-59	0.432	(0.275)
Black	0.090	(0.319)
Hispanic	-0.179	(0.342)
High School	0.477	(0.233)*
University	0.650	(0.362)
Male	-0.459	(0.355)
Married	0.347	(0.330)
Number of kids	-0.056	(0.088)
House owner	1.418	(0.264)*
High financial assets	-1.233	(0.264)*
High non-financial assets	0.262	(0.248)

T-tests are shown with (*) if they are significant at the 95 % significance level.

that a large portion in the credit card debt variation is correlated with income variation. To sum up, the hump shaped income vs. credit card debt relationship holds after a careful econometric analysis, and this empirical fact creates a need to review the related economic theories.

1.3.3 Alternative Definitions of Income

Having an accurate measurement for permanent income (also called as lifetime income) is important to argue the theoretical implications of the life cycle hypothesis. If the observed income contains transitory elements, higher income can lead to higher savings and accordingly, to lower credit demand. For a detailed explanation of this statement see the related part of the consumption chapter of Romer (1996) (pages 312-316). Intuitively, if the transitory income is a large portion of the observed income, then the household has lower income growth expectation compared with a household with identical observed income but lower transitory income. As high observed income is typically associated with high transitory income (*e.g.,* bonuses) and low observed income with low (negative) transitory income (*e.g.,* unemployment), the varying income expectations lead to upward sloping savings and to downward sloping borrowing need as income rises.

Focusing on the permanent income of households is not only important theoretically, but also the policy implications of the chapter's findings become different. If an income group is identified to be highly indebted based on transitory income, it suggests a short term vulnerability, as in a few years the households' income reverts to its permanent level so they move away from the highly indebted income group. However, if the poor, the rich or the middle-class have high debt based on permanent income, that effect may last long so governmental and market policies need to be aligned with that to mitigate the negative effects.

While this chapter intended to use the best proxy for permanent income in the previous cross tabulations and modeling, it is worthwhile to discuss how reliable this proxy is. As mentioned, in the SCF households are not only asked about their past year income but also whether this income is typical, and if not, what is the typical yearly income. Out of the 2,600 households in the analysis, 28.4% said that their permanent income is different from their yearly actual income. 33.7% of households either report only their permanent income but not their actual income, or report their actual income and state that this equals to their typical income. So altogether 62.1% of households provide a self-reported permanent income data. The remaining 37.9% of households did not report any income statistics (neither actual nor permanent income), for them income imputation was implemented by the SCF team. Imputed income is also believed to be an accurate estimate of permanent income, as it is based by the stochastic estimation of income so it excludes by definition large idiosyncratic income shocks. As a result, the used proxy for permanent income should be largely independent from transitory components.

Having a closer look at those households who report both their transitory and permanent income, it is also possible to check whether the theoretical prediction of the life cycle model in the presence of transitory income holds. Table 1.9 shows the debt-to-income ratios of these household both based on transitory income and on permanent income. According to the theory, if the transitory component of income is high (Column (1)) then the poor should have higher demand for borrowing. As opposed to this, using the self-reported permanent income in Column (2), the transitory income component is small. As expected, in Column (2) compared with Column (1) the negative correlation between income and debt induced by transitory income disappears, leading to the high indebtedness of the middle-class which is also observed in the total population. Consequently, Table 1.9 indicates well that the permanent income definition used in Section 3.2 proves to be reliable.

Table 1.9: Credit card debt-to-income ratios based on transitory and permanent income for households who report a difference between the two

	(1) Debt-to-income ratio based on transitory income	(2) Debt-to-income ratio based on permanent income
Total	0.73	0.55
Quintile 1	0.87	0.36
Quintile 2	0.95	0.45
Quintile 3	0.71	0.96*
Quintile 4	0.74	0.59
Quintile 5	0.38*	0.31

T-tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level. As all 738 households in this table reported their income, standard errors are not corrected.

Nevertheless, one might argue that the permanent income proxy captures well only the income received in a 5-10 years period, but does not reflect perfectly the *lifetime* income due to future long term uncertainties. So similarly to Dynan et al. (2004), the current analysis can be strengthened by some alternative measures of permanent income. First, education is a usual proxy for lifetime permanent income. To show the impact of education on credit card debt, Equation 1.1 is rerun without the Q_{ij} dummies, and without three other variables that can be correlated with transitory wealth and transitory income (financial assets, non-financial assets and house ownership dummies). By omitting income from the estimation, one does not have to worry about income imputation, therefore the Tobit model is run for all the 2,600 households identified in Section 2 using the survey population weights and the "pweight" option of Stata. Table 1.10 shows that controlling with the remaining household characteristics, the education of the household head explains credit card debt-to-income ratio in a non-monotonic way. Less than high school education households (omitted variable) have slightly (but non-significantly) higher debt-to-income ratio than households with university education, while high school education leads to significantly higher debt-to-income ratio (only at the 90% significance level). Note that only marital status is a more important socio-demographic driver of credit card debt than high school education.

Table 1.10: Tobit model to estimate credit card debt-to-income ratio using education as permanent income

Variable	Parameter	Standard error
Intercept	-1.878	(0.389)*
Age 40-49	0.054	(0.233)
Age 50-59	0.228	(0.266)
Black	-0.032	(0.253)
Hispanic	-0.144	(0.342)
High School	0.340	(0.206)
University	-0.131	(0.358)
Male	-0.386	(0.377)
Married	0.628	(0.311)*
Number of kids	-0.059	(0.083)

T-tests are shown with (*) if they are significant at the 95 % significance level.

An alternative permanent income definition in the paper of Dynan et al. (2004) is consumption. Unfortunately the Survey of Consumer Finances contains only a rough approximation of household consumption: food expenditures. Being a necessity, food consumption does not create the same ranking as total consumption. As a result, this chapter uses the Consumer Expenditure Survey sample defined in the Data Description section.[15] Fortunately, the CEX contains information on

[15] In this sample the relationship between food expenditures and total expenditure can be easily checked. The correlation between the two variables is only 52.3% and ranking both expenditures in 3 groups, only 55.2% of households fall into the same rank in terms of both food expenditures and total expenditures, showing that for a large portion of households, narrowing the definition of expenditures to food consumption leads to a dramatically different population ranking.

credit card debt and socio-demograpics used in the previous analysis.[16] Permanent income is now defined as the monthly average expenditure of a household based on the 12 month observation period.[17] Credit card debt is the sum of balances at the end of the 12-month interviews on all credit cards of the household, including store cards and gas cards as well. Unfortunately, the CEX does not specifically ask the households to report their revolving credit card balances. But as it contains information about financial charges (interest) paid for credit card debt, those households who have credit card balances but do not pay financial charges on them, are assumed to hold zero credit card debt in the analysis (these are the convenience users). Note that the average credit card debt-to-income ratio is smaller (0.46) in the sample than in case of SCF analysis in the previous section (0.61). This difference is due to the different definition of permanent income and debt in the two surveys and due to the potential underreporting of indebtedness by the CEX compared with the SCF. As the current chapter focuses on relative differences between income groups, this disparity in the levels does not undermine the results.

Equation 1.1 is rerun for the new sample by using the new definition for the target variable L_i. Similarly to Dynan et al. (2004), CEX weights are not used as those are not clearly justifiable in the case of using observations from a period other than a calendar quarter. Having full information about consumption, no handling of missing data is required. The results can be seen in Table 1.11. Note, that due to the larger sample size (9,381), more parameters are significant. The Q_{ij} consumption dummies show significantly the hump-shaped consumption-debt relationship. Other explanatory variables have typically the same sign as in the SCF model (with the exception of being black or married), demonstrating the robustness of the finding and the well comparable definitions of credit card debt. The parameters of Q_{ij} dummies are all statistically different from zero. Note that the peak of credit card debt is in Quintile 4 instead of the previous SCF analysis, where the peak was present in Quintile 3. F-test statistics (4.45) confirm that Quintile 5 debt-to-income ratio is significantly smaller than that in Quintile 4, showing the hump-shaped relationship between consumption and debt.

A potential bias in this consumption exercise may arise in case of idiosyncratic consumption shocks. Previously in this section it was shown that if income contains a large transitory component then the poor borrow more. To the analogy of this, if consumption is decomposed to a permanent consumption and a to con-

[16]Non-financial assets matching the SCF definition are difficult to construct in the CEX survey. As house ownership is present in both surveys and non-financial assets did not explain significantly credit card debt in the SCF Tobit model, this variable is excluded from the CEX analysis.

[17]Note that as the CEX sample covers four years between 2004 and 2007, so the dollar consumption expenditures and credit card debt metrics are corrected with the aggregate Consumer Price Index to be able to treat them as one homogenous sample.

Table 1.11: Tobit model to estimate credit card debt-to-income ratio using consumption consumption as permanent income

Variable	Parameter	Standard error
Intercept	-3.847	(0.253) *
Quintile 2	0.801	(0.159) *
Quintile 3	1.262	(0.163) *
Quintile 4	1.630	(0.172) *
Quintile 5	1.343	(0.183) *
Age 40-49	-0.008	(0.105)
Age 50-59	0.012	(0.110)
Black	-0.639	(0.162) *
Hispanic	-0.122	(0.153)
High School	1.072	(0.202) *
University	0.791	(0.215) *
Male	-0.061	(0.091)
Married	-0.254	(0.109) *
Number of kids	-0.117	(0.035) *
House owner	0.321	(0.124) *
High financial assets	-0.744	(0.162) *

T-tests are shown with (*) if they are significant at the 95 % significance level.

sumption shock, and this latter is large, then the rich borrow more. Intuitively, if the washing machine gets broken in a family and needs to be replaced, this creates an immediate rise in consumption and if funded by credit card then the indebtedness of the family also rises. So the observed positive slope between Quintile 1 and Quintile 4 may be partially caused by consumption shocks. To argue that this is not the case, a final definition of permanent income is used, again based on the Consumer Expenditure Survey: the *future* consumption of a household. A consumption shock in the future can not alter automatically the level of debt in the past, so this trick makes it possible to shed light even more accurately to the relationship between lifetime income and credit card debt. Fortunately the CEX asks the level of credit card debt both at the beginning and at the end of the 12-month period during which the expenditure data is collected. While Table 1.11 previously was based on credit card debt at the end of the 12-month period, in Table 1.12 the debt-to-income ratio is calculated using the level of borrowing at the beginning of the period. All the other features of the Tobit model remain the same as in the previous exercise that used present consumption. Table 1.12 shows that the hump shaped income-debt relationship holds using future consumption as a proxy for lifetime income. Just as before, indebtedness is the highest in Quintile 4, however, the F-test statistics to compare the parameters of Quintile 4 and Quintile 5 becomes weaker (2.04 representing 0.15 P-value).

To sum up, the main empirical finding of the chapter is robust to the use of a different dataset and also, to alternative permanent income definitions. Importantly, the use of present and future consumption shifts the distribution of debt towards the rich. As the rich save more, so they should borrow less, this section have been strengthened further the fact that credit card usage behavior of households is unusual, so the further investigation of this phenomenon is meaningful.

1.4 Neoclassical Explanations of the Income-Debt Relationship

As mentioned in the introduction, the typical starting point of any consumption-savings analysis, the life cyle / permanent income hypothesis (LCPIH) alone cannot explain why middle income households have the highest indebtedness. This section elaborates this statement, first by the detailed discussion of the LCPIH model's implications, then adding neoclassical extensions to it that might explain the empirical fact – *i.e.,* middle-income households have the highest indebtedness. Note that the related literature is large (it is the theory of consumption), so the analysis cannot be complete in a single paper, but the major relevant theories will be covered. The analysis contains the main arguments of Dynan et al. (2004) and other papers that present mechanisms that lead to the rich save more and borrow less (see also Carroll (1997)). However, because of the hump-shaped

Table 1.12: Tobit model to estimate credit card debt-to-income ratio using future consumption as permanent income

Variable	Parameter	Standard error
Variable	Parameter	Standard error
Intercept	-4.861	(0.302) *
Quintile 2	0.935	(0.187) *
Quintile 3	1.488	(0.192) *
Quintile 4	1.906	(0.201) *
Quintile 5	1.684	(0.214) *
Age 40-49	-0.053	(0.121)
Age 50-59	-0.048	(0.128)
Black	-0.653	(0.190) *
Hispanic	-0.315	(0.179)
High School	1.062	(0.238) *
University	0.794	(0.252) *
Male	-0.016	(0.105)
Married	-0.367	(0.126) *
Number of kids	-0.106	(0.040) *
House owner	0.482	(0.146) *
High financial assets	-0.685	(0.186) *

T-tests are shown with (*) if they are significant at the 95 % significance level.

income-debt functional form, also those theories are reviewed that suggest that the poor borrow less, such as liquidity constraints.

To preview the results, household heterogeneity in discount rates and in interest rates, liquidity constraints, precautionary savings and non-fungible consumption are all important drivers of credit card indebtedness and explain partially why the middle-class borrows the most. However, these extensions altogether explain only about the half of the peaking credit card debt in the case of middle income households, so neoclassical theories are not adequate to understand fully this empirical fact.

The consecutive sections show how a certain model drives savings and debt theoretically, and whether there is heterogeneity in the drivers of the specific model across income groups. In several cases, the exact causal relationship between a savings driver and credit card debt is presented only in a multivariate model in Section 4.6. This way it is possible to avoid running too many statistical models that keeps the chapter more compact.

1.4.1 Heterogeneity in the LCPIH Model Parameters

The determinants of credit demand in the LCPIH model (see Romer (1996) for a formal model description or see Rha, Montalto & Hanna (2006) and their references about the recent "rational" extensions of the life cycle model) are discount rate, income growth rate, the length of lifespan and interest rate. This section reviews whether heterogeneity in these four characteristics exists as it may lead to heterogeneity in credit demand. Note that this section is closely related to Section 3.3 which introduced socio-demographics as the drivers of borrowing. Those household characteristics such as age, education or house ownership are strong determinants of discount rate, interest rates charged or income growth rate, so the previous findings about the importance of these variables in borrowing are consistent with the life cycle model. However, this section intends to add some further non-trivial implications of the LCPIH model, which are not clearly observable solely based on the socio-demographic status of the household.

First, *ceteris paribus,* if the discount rate is higher then a household evaluates present consumption higher compared with future consumption and consumes more in the present accordingly. The higher consumption is accompanied with higher loan demand as well. The difficulty in the measurement of discount rates is well summarized in the paper of Loewenstein & O'Donoghue (2002) on time discounting and time preference and can be well demonstrated by the following quotation:

> "While the DM [discounted utility] model assumes that intertemporal preferences can be characterized by a single discount rate, the large

empirical literature devoted to measuring discount rates has failed to establish any stable estimate. There is extraordinary variation across studies, and sometimes even within studies." (p. 393).

Fortunately, the SCF survey contains a question that can be used as a household level measure of the discount rate. The SCF asks the households' planning time horizon of saving and spending, which ranges from a few months (value of 1) to more than 10 years (value of 5). This question approximates well the subjective discount rate of the household, as those who plan only for a few months are putting low weight on future consumption, and have a high discount rate. While the response to this question is categorical, the values from one to five indicate a gradual shift towards longer planning horizon, therefore this metric is treated as continuous in the following analysis. Column (1) of Table 1.13 shows that the planning horizon of consumption-saving decisions is longer in the case of rich households, and this difference is statistically significant based on t-tests. This means that low income households are more impatient and as a result, should consume a larger portion of their income and borrow more often.

Table 1.13: The life cycle drivers of savings by permanent income

	(1) Planning horizon	(2) Income Exp High	(3) Income Exp Low	(4) Lifespan expectation	(5) Interest Rate
Total	3.1	23%	42%	81.3	12.9%
Quintile 1	2.47	20%	37%	79.6	14.8%
Quintile 2	2.75*	20%	40%	80.7	13.2%*
Quintile 3	3.19*	20%	41%	81.3	12.3%*
Quintile 4	3.43*	21%	49%*	81.5*	12.2%*
Quintile 5	3.69*	32%*	42%	83.4*	13.1%*

T-tests for Column (1), (4) and (5) and Chi-square tests for the other columns to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

Second, *ceteris paribus*, if income growth rate is higher for a household, then the life cycle model predicts that this household borrows more often, as it covers its present consumption from the future incremental income. Brown, Garino, Taylor & Price (2005) show that the financial expectations (that they call alternatively "optimism") *per se* are important in the determination of unsecured debt, rather than the accuracy of households' predictions and the actual future financial situation. Columns (2) and (3) of Table 1.13 test for heterogeneity in the income growth rate across income groups. The SCF question asks whether a household expects its total income to go up more than the prices, less than the prices, or about the same as the prices. Column (2) contains the proportion of households who expect an income growth higher than inflation, while Column (3) contains those who expect a lower income growth than inflation. These indicators of the income growth expectation are fairly flat in the lowest three income quintiles, while the proportion of those who expect a low income growth is significantly higher in Quintile 4, and the proportion of those who expect a high income growth is significantly higher in Quintile 5. So there is no clear trend in the interaction between income growth rate and permanent income, based on these attitudinal questions.

Third, one further parameter to consider is the subjective expectation of one's time of death. *Ceteris paribus,* longer time to live leads to higher savings and lower credit demand. Column (4) of Table 1.13 shows that there is a positive interaction between income and the subjective lifespan expectation (probably explained by the better health condition due to being able to pay for better health services), so the rich may save more because they expect to live longer, leading to a downward sloping credit card debt as income grows.

Whether the heterogeneity in the previously mentioned three savings drivers in fact alters credit card indebtedness will be tested in Section 4.6 in a multivariate model. However, the fourth and last scrutinized driver of the LCPIH model, interest rate is hereby analyzed more carefully because of some endogeneity issues listed below.

Ceteris paribus, if the interest rate of borrowing is higher, households should borrow less, based on the standard lifecyle consumption model. Column (5) of Table 1.13 shows that the average interest rate in Quintile 1 is significantly higher than in the other income groups,[18] and surprisingly the interest rate is the lowest in the case of middle income households. If loan demand is interest rate elastic, this trend may lead to high demand in the case of middle income households, which is exactly the empirical fact that this chapter intends to explain. Is interest rate heterogeneity a key driver of the hump-shaped loan demand with respect to income? The remainder of this section shows that unfortunately this is not the case.

Interest elasticity of loan demand has been in the focus of research since the 1990's, but surprisingly the main question is not the magnitude of it but whether interest rates matter at all in the household's decision making. Ausubel (1991) first drew attention to the fact that credit card margins in the U.S. are high and he explained this with customers' insensitivity to interest rate changes. Whether credit card debt is interest elastic is non-trivial to answer because of the endogeneity problem of interest rate. Karlan & Zinman (2008) state for instance that:

[18] Only credit card owners are included in the calculation of averages.

"The standard identification problem in estimating loan demand elasticities is that the loan contract terms of interest may be correlated with unobserved investment opportunities, financing alternatives, or supply decisions that are not actually functions of the interest rate or maturity per se." The primary supply-side phenomenon is the so-called "risk-based pricing": the provision of higher interest rates for those with higher probability of not paying back the loan. As these "high risk" households typically need more loan, risk-based pricing immediately creates a positive supply driven correlation between interest rate and loan demand, which works against the negative correlation induced by the standard demand theory. Furthermore, households with large balances suffer from higher switching cost (Calem & Mester (1995) and Calem et al. (2006)) as they are declined more often when applying for a new card with lower interest rates and better conditions. This is due to fact that the lender is unable to distinguish those consumers who want to transfer only their existing balances from those who want to borrow more against the new limits and have high default risk. This means that switching costs induced by the banks create another source for positive interaction between interest rates and loan demand, but again the causality is reverse compared with the standard demand theory.

While the previous two mechanisms are relevant mainly for the "high risk" card holders, potential interest inelasticity may exist in the case of the low risk segment as well. First, Ausubel (1991) argues that interest inelasticity of demand has some "irrational" roots as well: a significant portion of (mainly "low risk") card holders think that they will not use credit cards and therefore accept higher interest rates at the time of application, but later on they will decide to pay with the credit card. Second, Calem & Mester (1995) argue that low risk borrowers are typically granted with favorable credit limits by their current issuers so they face high switching cost if they want to have similar credit limits at another issuer.

To sum up, both "high risk" and "low risk" credit card users face various supply and demand driven mechanisms that may lead to interest inelasticity or reverse causality between interest rate and credit demand. However, in case of risky clients the importance of these mechanisms is higher.

In the empirical literature, these endogeneity problems lead to a wide range of estimates of interest elasticity of demand. Some papers find that it is empirically large. Gross & Souleles (2001) report a long run interest elasticity of credit card balances of -1.3, based on a U.S. panel data set of several hundred thousand credit card accounts received from multiple credit card issuers. Several authors analyze microfinance in developing countries and find significant negative elasticities (between -0.7 and -1.0 in the paper of Dehejia & Morduch (2007) or -0.3 by Karlan & Zinman (2008)). While these papers use individual level data to estimate the elasticities, a result of similar magnitude arises from the analysis of bank level data (call reports) by Stavins (1996), who estimates an elasticity of -1.5. However, all these empirical papers estimate demand elasticity *in a given financial organization*, so that if someone simply transfers his credit card balance to a new bank, that is treated as a change in demand. However, from the point of view of the household, moving balances from one bank to the other is not creating new demand for loan.

Instead of using bank level data, another option is to rely on household surveys in the estimation of interest elasticities of demand. However, in the case of a nationwide survey, such as the SCF, it is not possible to perform randomized tests to create exogenous variation in interest rates, as it is done in case of some papers using bank level data. As a result, due to the mentioned endogeneity problem, estimates from household surveys have to be interpreted carefully, and show large variation.

Some survey-based papers estimate the impact of interest rates on loan demand without specifically treating the endogeneity problem. First, Min & Kim (2003) use the SCF to show that interest rate negatively alters credit card borrowing, but they seem to overweight high income households by not using the population weights of the survey. Second, Jiang (2006) finds based on the Ohio Economic Survey that credit card balances are smaller if interest rates increase, but the payback rate of balances is higher, so the joint impact of interest rates on credit card debt is dubious. Third, Kim & DeVaney (2001) find *positive* parameter estimate for interest rates in a model that predicts credit card debt based on SCF data, and the authors interpret this counterintuitive result as the impact of potential correlations between interest rates and credit limits or correlations between interest rates and the level of actual borrowing, which latter is the switching cost argument of Calem & Mester (1995). An interesting approach is taken by Ekici (2006) who shows based on the SCF data that high interest rate expectations lower the level of borrowing. His results are consistent with standard demand theory, but unfortunately his findings about future interest rate expectations (which can be interpreted as the expectation of the prime rate) can not be generalized to actual credit card interest rates.

Still based on survey data (SCF), Castronova & Hagstrom (2004) uses the technique of instrumental variables to tackle the endogeneity problem of interest rates, and so they find a significant negative causal effect of interest rate on credit card limits. They also show that the credit card utilization rates are independent of interest rate, and so their estimates are consistent with a negative interest elasticity of credit demand. However, their choice for instruments used is questionable: while the riskiness of a household is correlated with the interest rate, it is also correlated with credit demand, therefore should be a weak instrument.

Lacking a consensus in the literature about the impact of interest rates on loan demand, this chapter calculates a new estimate for the elasticity based on the 2007 wave of the SCF. Instead of using the proposed instrumental variables method, but still worrying about the endogeneity of interest rates, this chapter uses the method inspired by Karlan & Zinman (2008) who estimate and validate their models *by risk grades* to avoid the endogeneity caused by the riskiness of the household. Based on the 2007 SCF, two groups of households are identified. The first group consists of those credit card holders who have high probability of default. This "high risk" group is defined as the union of (1) households that sometimes got behind or missed payments related to all the various loan or mortgage payments they made during the last year; (2) households with any of the family members filed ever for bankruptcy; (3) households being declined with any loan during the last 5 years, including those who received only smaller loan amount than requested; (4) households that refrained from applying for a loan during the last 5 years because of potential turn down. The second group of card holders are called "low risk" and for these households none of the conditions (1)–(4) hold. The analysis is restricted to credit card owners only as the interest rate information required to calculate interest elasticities is available only for the credit card holders. Out of the total 2,018 credit card holders in the previously used SCF 2007 sample, there are 675 "high risk" households with an average of 14.0% interest rate on their cards with the highest balance and with an average of 1.32 credit card debt-to-income ratio. On the other hand, there are 1,343 "low risk" households with a lower average of interest rate (12.1%) as well as a lower credit card debt-to-income ratio (0.52). These descriptive statistics immediately point out the impact of the endogeneity problem: "high risk" households are charged high interest rates, and in parallel they hold higher debt, though they should hold less debt based on standard demand theory. This fact is due to risk-based pricing and high switching cost for high risk, high balance households. To calculate interest elasticity of loan demand, one can easily see that the pooling of "low risk" and "high risk" households leads to biased estimates. However, in the case of "low risk" households, the estimation of elasticities is possible as the impact of various endogeneity problems is much smaller. Using data from credit bureaus and advanced predictive analytics, banks are able to recognize the low risk of these households and as a result, do not charge them high interest neither at the application nor later on. Furthermore, the inelastic behavior suggested by Ausubel (1991) can be also ruled out: based on Section 3, those households that identify themselves as transactors (do not pay interest on their balances) are excluded completely from the definition of credit card debt holders in this chapter.

Consequently, for the "low risk" households only, it is possible to rerun the Tobit model to estimate credit card debt-to-income ratio (Equation 1.1) with the same explanatory variables as in Section 3 but including interest rate on the right hand side. The parameter of interest rate in this regression is significant and negative (see Appendix A.3 for the estimation result). Based on the calculation of marginal effects, keeping other socio-demographic and financial characteristics of the household constant, 1% increase in the interest rate charged on the card with the highest balance leads to -0.028 decrease in credit card debt-to-income ratio. The derived interest rate elasticity of credit demand is -0.67, which number is in the range of estimated elasticities reviewed in the literature, however, it is smaller than many elasticities that do not filter out balance movements between banks. Note that the same Tobit model is also executed for the "high risk" customer group (results not reported), in which case the parameter estimate of interest rate is positive and insignificant, justifying the existence of endogeneity problems.

Having an estimate for the elasticity, it is possible to infer whether interest rate heterogeneity explains the hump-shaped income-debt curve in focus. Based on Column (4) of Table 1.13, in Quintile 3 interest rates are 2.5% lower in average than in Quintile 1, and 0.8% lower than in Quintile 5. Multiplying these differences with the marginal effect of interest rate change, one can conclude that Quintile 3 households should have 0.07 higher debt-to-income ratio than Quintile 1 households, while 0.02 higher debt-to-income ratio than Quintile 5 households.[19] In Section 3 it was shown that the the peak in Quintile 3 means a 0.5 higher debt-to-income ratio compared both with the lowest and with the highest income groups. This means that interest rate heterogeneity and interest elasticity leads to the explanation of about one tenth of this increment, leaving the major part of it unexplained.

1.4.2 Liquidity Constraints

Probably the most straightforward explanation of why low income households would borrow less is the existence of liquidity constraints (or credit rationing). According to Weinberg (2006), credit supply has increased in the last decades, as there are more funds available due to increasing competition and funds from other countries, so it is easier and quicker to evaluate eligibility and use risk based pricing to satisfy the needs of customers. As Reynolds et al. (2006) note, the decision to grant credit has changed over the past 20 years from a "yes or no" decision to a "yes, but at what price" decision. However, it is possible that this expansion of supply still leaves unaffected a good portion of low income households. Both from a theoretical and an empirical point of view, Browning & Lusardi (1996) find liquidity constraints one of the major extensions of standard consumption-saving models and lists the main theoretical contributors of this literature. An important theoretical argument is that in the presence of future uncertainties of income, not only the current liquidity constraints decrease current consumption but also the

[19] Note that these estimations are possibly upward biased because the derived elasticity is valid only for "low risk" households, and it is only assumed that "high risk" households have similarly interest elastic demand, which is unobservable in the data because of the endogeneity problems listed.

possibility of future liquidity constraints.

In the empirical literature, Crook & Hochguertel (2007) show in a cross-country comparison that credit rationing is significant but varies over countries based on their institutional differences. Their analysis about the U.S. shows that the middle-income households suffer less from credit rationing relative to low or high income households. Zeldes (1989) shows that liquidity constraints alter the intertemporal Euler equations based on a panel data study (Panel Study of Income Dynamics). Jappelli (1990) argues based on multiple cross section studies that as many as 20% of households can be liquidity constrained in the U.S. concerning all debts (including mortgage or vehicle loans), and income has a negative impact on the probability of being credit rationed. Duca & Rosenthal (1993) find that this proportion is even higher in the case of young households and can reach 30%. This latter paper estimates credit demand in the presence of liquidity constraints for the young using the Survey of Consumer Finances.

As an important reference, Crook (2001) performs a complete supply-demand analysis for the overall population using the SCF survey and uses a bivariate probit model (to estimate jointly the demand for positive debt and not being credit constrained) followed by a two stage least squares selection model to estimate the dollar amount of the desired demand for debt. Importantly, in the paper of Crook (2001) current income is found to be positively related to the desired stock of debt, and current income squared is negatively related to it. This means that the author finds that demand for debt depends on income in a non-monotonic way, *even after correcting for liquidity constraints*, so the low debt in the case of the poor is not solely driven by credit rationing.

This reviewed literature finds credit rationing an important driver of household debt holdings, and it is widely accepted that low income is associated with higher banking rejection rates. Meanwhile this does not necessarily mean that low income households have higher demand than the rest of the population, just as shown in the selection corrected demand estimation of Crook (2001).

Unfortunately the previous literature is not satisfactory to draw accurate inference on whether the hump-shaped relationship between income and credit card debt can fully be explained by liquidity constraints. On one hand, the empirical papers use typically 10-20 year old data, and the recent expansion of credit eligibility is not captured by them. One the other hand, all the referred articles focus on *total debt* including mortgage and car loans rather than *credit card debt* only. This is mainly due to the fact that the most frequently analyzed survey, the SCF contains limited information on credit card rejection and eligibility.

In Section 3, nine papers were listed that estimate *credit card indebtedness* of U.S. households and a natural question is how those papers treat the problem of potential liquidity constraints. Out of the nine papers, five does not include any proxy for being liquidity constrained, and while these papers mention that the estimations of indebtedness contain the joint effect of demand and supply, implicitly they assume that banking rejections do not dramatically alter the debt holdings, and therefore do not need special treatment. The remaining four papers (Baek & Hong (2001), Bertaut & Haliassos (2001), Min & Kim (2003) and Reynolds et al. (2006)) contain a proxy for credit rationing in the first stage of their multiple stage debt estimation and find it a significant driver decreasing debt holding. Importantly, the last three of these papers contain the potential non-monotonic relationship between income and debt *even after controlling with liquidity constraints*. Hence, none of the nine papers contains evidence towards liquidity constraints being able to create the frequently reported hump-shaped income-debt relationship. But unfortunately, none of these credit demand oriented papers focus on income as the key explanatory variable.

Therefore the rest of this section uses information from the SCF to show that liquidity constraints in 2007 did not alter credit card debt holdings in such a way that it would explain the non-monotonic income-debt relationship.

First, in the case of those households that had a loan application rejected by a bank at least once during the last five years (including those who were approved smaller amount than required), the SCF asks what is the reason behind the rejection. Only 7.0% of households report that their rejection was caused by unsatisfactory income. Furthermore, in the bottom quintile this ratio is only 8.5%, minimally higher than the population average, suggesting that banking declines should not change dramatically the distribution of debt holding across income.

Second, one may recall that the previous section analyzing the interest elasticity of credit demand defined "low risk" and "high risk" households, based on four definitions that are related to high credit default risk, such as banking rejection or previous bankruptcy. Liquidity constraints – *i.e.,* the banks' yes-no decision to credit card applications should be driven by this default risk. As a result, if the lower end of the hump-shaped income-debt curvature is driven by liquidity constraints, then for the low risk households - who face less credit rationing - one would expect a more even distribution of credit card debt across income. Table 1.14 shows the *opposite* finding: the middle-income holds significantly more credit card debt than the poor in the "low risk" customer segment (the difference in the debt-to-income ratio between Quintile 3 and Quintile 1 is 0.73), while this gap is smaller (0.40) and statistically insignificant in the case of the "high risk" group, even if the debt-to-income ratio of this segment is almost twice as much as that of the "low risk" segment. Rerunning the multivariate Tobit model specified in Equation 1.1 that controls with household characteristics, the middle-income dummy remains statistically significant in the case of the "low risk" segment, and the marginal effect of this dummy much larger (0.84) than in the "high risk" segment (0.34). Intuitively, this analysis shows that the peaking debt of the middle-class is not determined by the supply-side of the credit card market, as in that case the "low risk" but low income households should borrow similarly to the middle-class as opposed to their riskier counterparts.

Table 1.14: Credit card debt-to-income ratios for "low risk" and "high risk" households

	(1) "Low risk" households	(2) "High risk" households
Total	0.42	0.82
Quintile 1	0.14	0.69
Quintile 2	0.49	0.69
Quintile 3	0.87*	1.09
Quintile 4	0.42	1.02
Quintile 5	0.24	0.58

T-tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

Table 1.15 uses some selected questions from the SCF and a slightly more complex reasoning to quantify the exact percentage of households that are credit rationed in the different income groups. Row A restates the previous results, – *i.e.,* the hump shaped income-debt relationship (already documented by age categories in Table 1.5). The main question that the table intends to answer is whether the difference between Quintile 1 and Quintile 3 in the proportion of households with no credit card debt can be fully explained by liquidity constraints. Otherwise stated, are rejection rates 23% more in the case of the poor compared with the middle class? Row B shows that in the case of low income Quintiles, a large portion of those who do not have credit card revolving debt, did not even have a credit card at the time of the 2007 interview. 61% of low income households without a credit card versus 17% in the medium income quintile immediately drives the intuitive appeal for serious liquidity constraints. But Row C shows that only about one third of these households actually applied for any loan in the last 5 years, so the differences are both supply and demand driven. Out of these households who applied for any loans, Row D shows the proportion of households which were rejected at least once in the last 5 years related to any kind of loans. This 14% proportion of total Quintile 1 households is a high overestimation (but also an upper cap) of the real impact of credit card rejections. Fortunately, the SCF asks also which credit product the household was referring to when speaking about rejection. Row E contains the proportion of households which had a rejected credit card application. One can observe that in the bottom two quintiles 1 out of 20 households is likely not to have a credit card as a result of being rejected, while this proportion is negligible in the other quintiles. Note that Row E might be a slight downward estimation of the real impact as those households not counted in Row E which were rejected with a credit card application but after were rejected again related to another loan (mortgage, car loan, etc.). Having Row D as an upper ceiling and Row E as a more accurate but biased measure for credit card liquidity constraints, one can conclude that it is relatively low. Based on Row E, there can not be more than 4% difference between Quintile 1 and Quintile 3 in the impact of banking rejection on card ownership and on revolving debt.

But a second important argument arises: is it possible that the demand for credit card is altered by liquidity constraints? Are households applying less often because they *expect to be rejected*? This mechanism is hereby called the indirect liquidity constraint. As in Quintile 1 40% of households have no credit card and did not apply for any loans at all for the last 5 years (Row F), this argument seems to be more important than the actual banking rejections. Fortunately, the Survey of Consumer Finances contains a question that helps to understand this aspect: whether the household did not apply for a loan in the last 5 years because it expected to be rejected. Row G shows that a larger portion of households in Quintile 1 did not apply for a loan because of this fear (Jappelli (1990) calls these households *discouraged* from applying for a loan). But Row G is a large overestimation of the real impact of the indirect liquidity constraint, as there may be a large number of households who do refrain from loan application once but do not refrain at other times. To filter out this potential bias, those households are selected from Row G who do not actually have any loans. Row H shows that in case of low income households this proportion is still significant (9%), but fades away as income grows. Row H is still an overestimation of the impact of indirect liquidity constraints on credit cards as households might have thought about having a mortgage or other loan while responding to the survey question. For this reason, from Row H only one third of households are allocated to credit card liquidity constraints.[20] Accordingly, not applying for a credit card because of the expectation to be rejected can lead to approximately a 3% change between Quintile 1 and Quintile 3 in credit card ownership or credit card debt holding.

Adding up the direct and indirect effects of liquidity constraints, according to a conservative estimate, a 7% difference could exist between Quintile 1 and Quintile 3 credit card holdership rates. Row B shows that the actual difference is much higher, 44% more households hold credit cards in Quintile 3 than in Quintile 1. Furthermore, the 7% difference in the share of potential liquidity constrained households falls below the 23% difference of households holding credit card debt

[20]This one third portion reflects the differences in credit card rejections and general rejections between Row D and Row E, as well as a generous estimate of the portion of credit applications out of total loan applications.

according to Row A. As a result, while responsible for a small portion of the difference, liquidity constraints cannot explain the full magnitude of the upward sloping credit card debt in the case of lower income households.

Two smaller comments strengthen the analysis above. First, Row I in Table 1.15 contains the proportion of households who do not have credit card but applied during the last year for payday loan (short term borrowing with extremely high interest rates that are supposed to be repaid in full out of the next paycheck of the household). These loans demonstrate well the magnitude of liquidity constraints, as those households who are able to get loans through other channels (credit card, personal loans, secured loans) avoid this expensive solution to finance consumption. One can observe that the proportion of payday loan holders is low, suggesting that there are few households who have to resort to this as being constrained from other lending products.

Second, in 2007, out of the total 5.2 billion credit card offers sent by direct mail (or by junk mail, according to the more popular naming), 2.1 billion was sent to households with a yearly income less than $50,000.[21] This group represents Quintile 1 and Quntile 2 in the current analysis. A large portion of these credit card offers are pre-screened, meaning that the household is automatically accepted in the case of applying for the given card. This statistic shows that financial companies do *not* disfavor low income households and hence, liquidity constraints in recent years have been less substantive.

Table 1.15: Percentage of total households facing liquidity constraint by income quintiles using various proxies

		Quintile				
Row	Definition	1	2	3	4	5
A	Households with no credit card debt	75%	63%	52%	55%	73%
B	- From A: Households with no credit card	61%	39%	17%	8%	4%
C	- - From B: Applied for loan	21%	24%	11%	7%	3%
D	- - - From C: Rejected at least once	14%	13%	6%	2%	0%
E	- - - - From D: Rejected credit card application	5%	5%	1%	0%	0%
F	- - From B: Did not apply for loan	40%	15%	6%	1%	1%
G	- - - From F: Refrained at least once	14%	4%	2%	0%	0%
H	- - - - From G: Does not have any loan	9%	2%	0%	0%	0%
I	- From A: Borrowed payday loan	3%	3%	2%	0%	0%

[21] mailmonitor.synovate.com

The previous discussion argued the impact of liquidity constraints on the proportion of credit card debt holders. Recalling Table 1.6, not only the proportion of households with debt but also the credit card debt-to-income ratios show the hump-shaped form with respect to income. Table 1.16 shows the age-income breakdown of limit-to-income ratios, which is defined as the total credit limit on credit cards divided by the monthly permanent income. One can observe that middle-income households have typically the highest credit limit compared with their income, except the youngest age group where the maximum is in Quintile 4. Based on this table, one might argue that while liquidity constraints do not prevent poor households from holding a credit card as often, but the limits assigned are lower than required by this segment.

Table 1.16: Average limit-to-income ratios (credit limit per monthly income) by income quintiles and age

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	2.51	3.16	4.03
Quintile 1	1.31	2.23	3.3
Quintile 2	2.34	2.87	4.34
Quintile 3	2.51*	4.14*	5.01*
Quintile 4	3.38*	3.76*	4
Quintile 5	3.04*	2.8	3.46

T-tests to compare means in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

To show that this is not the case, the approach of Gross & Souleles (2001) is used, who find that a significant portion of bankcard accounts have a utilization rate, defined as the balance divided by the credit limit, above 90 percent, leaving less than 10 percent of the credit line free. The authors argue that for these accounts liquidity constraints are arguably binding. Table 1.17 shows the breakdown of these households by age and income based on the 2007 SCF. Note that the overall portion of these households is low (6%) showing that the vast majority of card holder households are not being credit rationed in terms of their credit card debt, using the 90% utilization definition.[22] Interestingly, in the lower two age groups, the proportion of rationed households shows the peak in Quintile 3, while in case of the highest age category, middle quintile households perform similar patterns to the poorer households. This empirical evidence shows that for card holders,

[22]Gross & Souleles (2001) correctly notes that because of precautionary reasons, household might want to hold free utilization to be able to insure against future uncertainties, so households with lower utilization might also be liquidity constrained.

liquidity constraints do not explain the highest debt holdings for middle-income households, and assuming higher credit limits, middle-income households would have *even higher* credit card debt. Note also that the credit limits are in average about five times as high as the revolving debt-to-income ratios in Table 1.6, strengthening the argument of the low importance of credit rationing.

Table 1.17: Percentage of households with higher than 90% credit card utilization rate

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	6%	6%	5%
Quintile 1	7%	4%	6%
Quintile 2	3%	7%	6%
Quintile 3	12%	11%*	5%
Quintile 4	8%	4%	4%
Quintile 5	2%	4%	2%

Chi-squared tests to compare means in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

To sum up this section, the existence of liquidity constraint alone does not seem to explain empirically either the peak of credit card debt holders or the peak of credit card debt-to-income ratio in the case of medium income households. Section 4.6 will include credit card limit-to-income ratio as the best available proxy for credit rationing into a multivariate model to estimate credit card indebtedness, thus strengthening this finding.

1.4.3 Precautionary Savings

According to the LCPIH, the primary value of savings is to cover future consumption. The previous sections showed that this assumption is not adequate to explain the income-debt patterns, even in the presence of liquidity constraints. However, savings have an other important interpretation: security for future uncertainties.

According to Leland (1968), the "precautionary demand for saving usually is described as the extra saving caused by future income being random rather than determinate". The author shows that plausible assumptions about the utility function (having positive third derivative) and income uncertainly together lead to positive amount of precautionary savings. Since the work of Leland (1968), this extension of the standard savings model has been a milestone of the consumption literature.

Do precautionary savings – *i.e.,* precautionary wealth[23] vary across income? Do the rich hold less liquid assets relative to their income to cover larger uncertainties in the future compared with the poor? If yes, this mechanism may generate higher consumption and higher demand for loan in the case of the rich compared with the poor. Note that the analysis of total liquid assets or wealth is inadequate to answer this question, as it contains total savings due to various savings motives. As a result, from the fact that the rich save more (see Section 3.1) one cannot infer that precautionary savings follow the same trend, and hence, the analysis hereby is relevant.

A first important question is whether precautionary savings are empirically large. Kennickell & Lusardi (2004) and Browning & Lusardi (1996) review the latest literature about precautionary savings and find that the range of empirical estimates is wide: some papers report no significant precautionary wealth at all while some others measure it to be as high as 50% of total wealth. Kennickell & Lusardi (2004) argue that this lack of consensus is due to measurement problems of precautionary savings, and the authors argue that their estimate (8% of total wealth or 20% of financial wealth) using a direct measure of precautionary wealth is more accurate. Nevertheless, the majority of the literature agrees on precautionary savings being empirically important.

As a first measure of precautionary motives, the 2007 SCF asked what the families' most important reasons are for saving, and one response approximates very well the precautionary savings motive.[24] Table 1.18 shows that in the case of the youngest households, the proportion of those with precautionary savings motive increases significantly as income grows. However, this pattern is not visible in older age groups. Note that the hump-shaped income-debt curve in Table 1.6 is mostly visible in the case of those households which are older than 40 years old, therefore Table 1.18 does not contribute to the understanding of that non-linearity.

As a second measure of precautionary motives, the 2007 SCF asked about how much households need to have in savings for emergencies and other unexpected things that may come up, which is a very accurate subjective measure. Based on this question (and the 1995 SCF wave) Kennickell & Lusardi (2004) show that the dollar amount of precautionary savings increases with income. However, they do not focus on *savings rate*, which is consistent with the other metrics used in this current chapter. So precautionary savings-to-income rate is calculated hereby in which the numerator is the dollar amount of savings identified in the

[23]In this chapter the terminology of Carroll & Kimball (2007) is used: "Precautionary *saving* is a response of current spending to future risk, conditional on current circumstances. Precautionary *savings* [or precautionary wealth] is the additional wealth owned at a given point in time as the result of past precautionary behavior."

[24]This specific response is defined by SCF as "Emergencies; rainy days; other unexpected needs; for security and independence"

Table 1.18: Percentage of households reporting precautionary motives being an important reason for their savings

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	0.32	0.28	0.27
Quintile 1	0.22	0.27	0.26
Quintile 2	0.3	0.32	0.3
Quintile 3	0.36*	0.32	0.28
Quintile 4	0.35*	0.18	0.27
Quintile 5	0.35*	0.31	0.26

Chi-square tests to compare proportions in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

question above and the denominator is the monthly average permanent income of the household.[25] The usual age-income breakdown of the precautionary savings-to-income can be found in Table 1.19. One can see that the poorest segment has slightly higher precautionary savings rates, and the rate differences between Quintile 1 and the other quintiles are sometimes even statistically significant. This means that the poor have to have more liquid assets relative to their income to prepare for emergencies, and as a result, keeping other drivers of the consumption-savings decision constant, the poor should have lower consumption and lower loan demand – *i.e.,* lower credit card debt-to-income ratio. So, this mechanism may contribute to the understanding of the hump-shaped debt-to-income ratio, specifically to the lower end of the distribution.

However, the previous two subjective questions about precautionary motives may not be adequate to accurately measure the actual behavior of households. Therefore the next part of this section investigates whether *some drivers* of precautionary savings are correlated with income. Kennickell & Lusardi (2004) identify eight such drivers, out of those three major ones are scrutinized here, namely "risk" or uncertainty, preferences towards risk and other forms of insurance against risk.

The majority of the related literature primarily focuses on uncertainty, and Kennickell & Lusardi (2004) correctly argue that uncertainty is not limited to income only, but households may face consumption risk, longevity risk, health risk,

[25]Note that the rate is capped at 12, meaning that households reporting larger emergency savings than their yearly household income are treated as outliers. These outliers typically occur in the case of those households which do not report their yearly income, and hence, permanent income arises from income imputation. This suggest that the SCF staff does not use the information in this precautionary savings metric in the income imputation algorithm.

Table 1.19: Precautionary savings-to-income rates by income and age

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	1.55	1.83	1.96
Quintile 1	1.88	2.28	2.51
Quintile 2	1.32	1.6	1.99
Quintile 3	1.41	2.05	1.72*
Quintile 4	1.44	1.49	1.58
Quintile 5	1.69	1.72*	2

T-tests to compare means in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

interest rate or investment risk as well. The first two columns of Table 1.20 contain two proxies for income risk and show the interaction of those with income. Column (1) shows the proportion of households that were unemployed for some time during the 12 months previous to the interview. The proportion of unemployed households decreases as income grows, showing that if the rich are aware of their lower probability to become unemployed, they should allocate less wealth for precautionary reasons and therefore can consume more and apply more often for credit.

Table 1.20: The drivers of precautionary savings by permanent income

	(1) Unemp-loyment	(2) Income risk	(3) Consumption risk	(4) Medical expense	(5) Risk aversion	(6) Can borrow from family
Total	12%	33%	8%	14%	35%	67%
Quintile 1	24%	50%	8%	14%	68%	41%
Quintile 2	13%*	37%*	10%	15%	48%*	56%*
Quintile 3	11%*	28%*	9%	17%	29%*	71%*
Quintile 4	4%*	23%*	7%	13%	20%*	83%*
Quintile 5	5%*	24%*	5%*	8%	8%*	83%*

Chi-square tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

Column (2) of Table 1.20 shows the proportion of households that do not have a good idea about their next year's income, which is also a good attitudinal proxy for income uncertainty. One can see that this proportion significantly decreases as income grows. Again, this column supports that the higher the permanent income is, the lower the future variation of income, leading to lower necessary precautionary holdings.[26]

Moving towards other risks than income uncertainty, consumption risk is an other potential driver of precautionary savings. Kennickell & Lusardi (2004) mention as an example of this the risk that durable goods break down and should be replaced quickly. This example can be generalized to other consumption risks as well, and each household is flagged if it reports to expect large expenses in the next 5-10 years of their life related to the purchase of a car or other large durable goods, home repairs/improvements, major purchase or bills/living expenses.[27] Column (3) of Table 1.20 shows that the proportion of households flagged to have high consumption risk is the highest in Quintile 2, but this metric is decreasing with income afterwards, showing that low income households have higher expected consumption variability – *i.e.,* higher consumption risk.

Dynan et al. (2004) stress the importance of medical expenses in the determination of precautionary savings. They argue that U.S. households have a possible large medical expense near death, which is largely independent of the income of the household. Households facing the same fixed cost ($150,000) with the same probability (10%) towards the end of their life, the authors show through simulation that low income households obviously have to save more to prepare for this health risk. Column (4) of Table 1.20 shows based on the 2007 SCF the proportion of households who report that they expect to face large medical expenses in the next 5-10 years of their life. While this proportion does not vary significantly over income quintiles, the argument of Dynan et al. (2004) – *i.e.,* the poor have to save more to cover the large nominal future medical expenses, is still a potential source of heterogeneity in consumption-savings decision over income.

A further important driver of precautionary savings is the preference towards risk. Even facing high income risk, a household might evaluate potential consumption drops similarly to consumption increases through a utility function with third derivative close to zero; so the household might not save to insure itself for uncertainties. Fortunately, the SCF contains an attitudinal question to measure the risk taking behavior of the household, and those households can be flagged that are "not willing to take any financial risks". Column (5) of Table 1.20 shows that

[26]Without reporting those results, low income households are proven to have higher future income risk using an other metric as well: the standard deviation of $D_i = \ln(CI_i) - \ln(PI_i)$ within each income quintile, where CI stands for current income and PI refers to permanent income for each household i.

[27]These categories are a subjective selection from a list of 23 expense categories. Large expected medical expense is discussed later, while large expected expenses related to education, home purchase, family support or other smaller categories are neglected, primarily because those reflect the choice of the household instead of future risk in consumption.

the proportion of these risk averse households is the highest in the income Quintile 1, and it decreases gradually and significantly as income grows. This finding is in line with the observed precautionary savings patterns and higher savings-to-income ratio may be explained by the more limited willingness to take risks of the poor households.

The final scrutinized driver of precautionary savings from the extensive list of Kennickell & Lusardi (2004) is the "other form of insurance against risk". Here one can think of governmental initiatives such as social security programs or help from family and friends in the case of financial need. Income uncertainty is mitigated in the U.S. by social security programs. Dynan et al. (2004) find that higher income in the U.S. is accompanied with lower income replacement rates; and the authors show through simulation that this should lead to higher savings rate for the rich. However, Column (2) of Table 1.20 provides evidence towards the poor having higher income risk, showing that the higher probability of getting unemployed based on Column (1) and other potential disadvantages in case of the poor overweighs the effects of higher replacement rates offered to this segment. Government health insurance programs (such as Medicaid) provide insurance against the previously mentioned potentially large health expenses, and Dynan et al. (2004) (and the papers they cite) find that participation in these programs is an important motivation to dissave. As more low income households participate in these programs, health insurance may generate a positive interaction between income and savings, so a negative interaction between income and borrowing. In terms of support from the family, the SCF asks the following question: "In an emergency could you get financial assistance of $3,000 or more from any friends or relatives who do not live with you?". Column (6) of Table 1.20 shows the proportion of "yes" answers to this question, and one can see that this is significantly increasing as income grows, showing less insurance against risks for poor households.

Note that looser liquidity constraints can be interpreted as insurance against risk as more constrained households have to accumulate more savings to cover uncertainties. Browning & Lusardi (1996) point out that the impact of binding liquidity constraints and of precautionary savings motives are very difficult to differentiate empirically. As a result, this section and the previous section about liquidity constraints are closely related.

To sum up this section, it is visible that several drivers of precautionary savings are correlated with income. The rich face less income and consumption risk, are less risk averse and can borrow more from the family, and as a result, the rich have to hold less precautionary savings compared with their income, such as shown in Table 1.19. Theoretically this means that *ceteris paribus*, the rich can consume more and can hold higher credit card balances. So similarly to liquidity constraints, the theory of precautionary savings is a good candidate to explain the upward sloping curvature of credit card debt-to-income ratio between income

Quintile 1 and Quintile 3. Section 4.6 will show that indeed, precautionary savings matter in credit demand, using a multivariate Tobit model.

1.4.4 Non-Fungible Consumption

In the analysis so far consumption has been interpreted as a unique good, a simplification typically used in the standard consumption-savings literature. However, several notable extensions of the standard model divide consumption into non-fungible components, and this section argues that the existence of these components has impact on credit demand.

First, Weinberg (2006) argues that one of the likely causes of the expansion of borrowing in the last fifty years is the an increase in consumers' relative demand for housing and durable goods, as these goods are more typically purchased on credit. Fernandez-Villaverde & Krueger (2004) analyze in more detail the importance of *durables* in consumption-savings decisions. In their theoretical work, durables provide both a consumption stream for the future and a collateral for borrowing, leading to endogenous liquidity constraints for the households. The authors argue that a model with durables can explain for instance why young households consume more durables and why middle age households consume more (both durables and non-durables) compared with the young and the old.

Second, Telyukova (2008) differentiates cash-only goods – *i.e.,* goods that can typically be purchased only with cash from credit goods in which case credit cards and other borrowing facilities are also used. Cash-only goods are rents, mortgages, utilities, repairs, household operations, property taxes, insurance, public transportation, health insurance, and also food, alcohol and tobacco, but Telyukova (2008) is aware of the fact that the definition is not perfect. While based on this distinction Telyukova (2008) sets up a macro model, her work clearly points out the importance of various consumption components in the determination of credit demand.

Finally, the existence of a subsistence amount of consumption might be an important driver of consumption-savings decisions. Certain goods may be must-to-have for the household (one can think of food) and consumption of these goods does not even enter into the utility function. If a household consumes a fixed subsistence amount, which is identical for the present and the future periods as well, the the standard LCPIH model is only valid for the income and consumption which is incremental to the subsistence amount. The existence of a subsistence consumption that is identical for all households increase the debt-to-income ratio for poor households due to two mechanisms. On one hand, households with lower income than the cost of the subsistence consumption and no assets carried over from earlier periods have to borrow to cover their basic needs. This may be a phenomenon with those below the poverty line, mainly Quintile 1 households.

On the other hand, assuming identical total income growth rates within all income quintiles,[28] subsistence consumption leads to higher income growth in the case of the poor after removing the part of income that is allocated to compensate for the costs of it.[29]

Thus the existence of consumption components may explain some portion of the interaction between income and borrowing. For instance, if the rich hold more durables, this provides a higher consumption stream and better liquidity position for them, so they need to use their credit cards less often. Similar implications arise in the presence of significant subsistence amount: the poor should borrow more. On the other hand, if the rich consume relatively less goods which can be financed only with cash, the rich should use their credit cards more frequently.

Figure 1.1(a) - 1.1(b) shows that indeed, there is an interaction between permanent income and the share of consumption components. These Engel curves are based on the 2004-2007 Consumer Expenditure Survey. Figure 1.1(a) shows the categories in which the rich spend more (luxuries), for instance vehicle purchase, entertainment or education. Figure 1.1(b) shows the remaining consumption categories in which the rich spend less (necessities *e.g.,* housing or food at home) or there is no clear relationship between income and consumption share (transportation or health expenditures). These consumption patterns are in line with all listed theories in this section: there is heterogeneity in the share of durables (*e.g.,* vehicle purchase or furnishing & appliances), the Engel curves suggest the presence of subsistence consumption (share of food at home and housing decreases with income), and categories where credit cards are more frequently used (*e.g.,* furnishing & appliances, apparel or audiovisual equipment) represent different shares in the consumption of the rich and the poor.

To see how important this heterogeneity in consumption shares is in the demand for credit card debt, the Tobit model of Section 3.2 is extended in the following way:

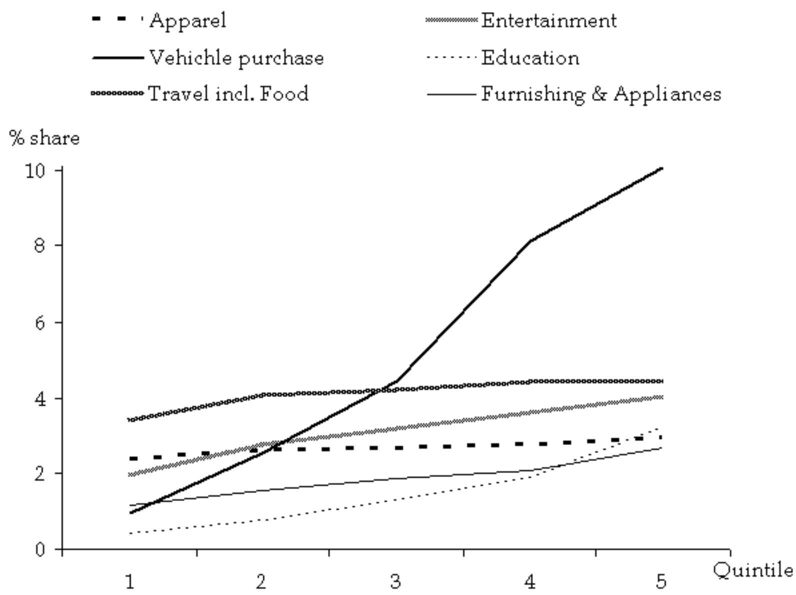
$$L_i^* = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \sum_{j=2}^{5} \gamma_j Q_{ij} + \sum_{m=1}^{12} \delta_m W_{im} + \varepsilon_i$$

$$L_i = L_i^* \; if \; L_i^* > 0; \; L_i = 0 \; otherwise \tag{1.2}$$

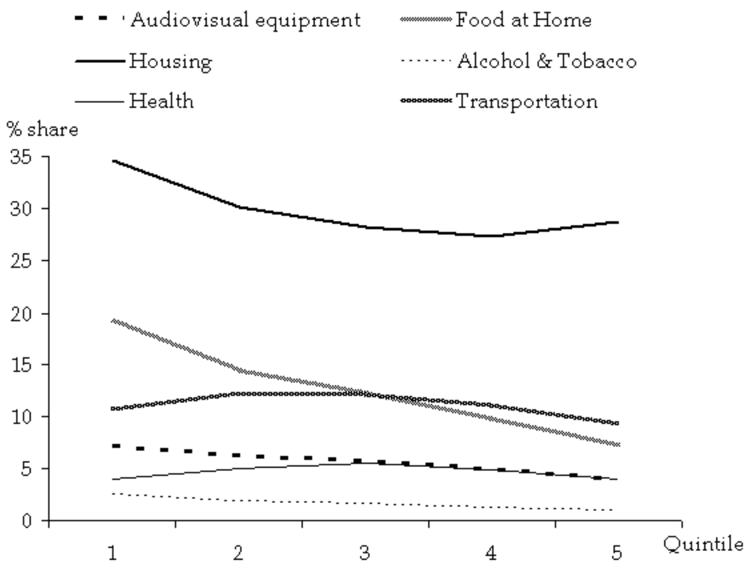
which is identical to Equation 1.1 except the addition of W_{im} explanatory variables representing the expenditure share of category m, where the 12 categories

[28] Based on Table 1.13 in Section 4.1 it is not possible to reject that *expected* income growth rates are different in the five income quintiles.

[29] For example, if two households have \$10,000 and \$20,000 present income, respectively, income growth rate is 100% and the cost of the subsistence consumption is \$5,000, then the income growth rate after removing the costs from the present and future income is \$15,000/\$5,000-1=200% and \$35,000/\$15,000-1=133%, respectively.



(a) Luxuries



(b) Necessities and dubious categories

Figure 1.1: Engel curves

are those shown in Figure 1.1(a) - 1.1(b). Note that to avoid multicollinearity, the miscellaneous category is excluded (not shown in the figures either). As the expenditure shares are available only in the Consumer Expenditure Survey, the 12 month average of total household consumption is used as the proxy for permanent income, just as in Section 3.3. So the results of the extended regression are comparable with Table 1.11. The estimated parameters are shown in Table 1.21, with the δ_m parameters showing the impact of expenditure shares. As expected, the expenditure shares of the households alter the credit card debt-to-income ratio. Those with high food consumption at home have significantly lower credit card debt, while those who spend more on audiovisual equipment, alcohol & tobacco, health, transportation or entertainment, have significantly higher credit card debt. As based on Figure 1.1(a) - 1.1(b), audiovisual equipment and alcohol & tobacco categories are necessities, the positive parameters of these expenditure shares lead to the rich borrowing less. On the other hand, the negative parameter of food at home (which is a necessity) and the positive parameter of entertainment (which is a luxury) lead to the rich borrowing more. Finally, the two remaining categories (health and transportation) represent higher consumption shares in case of middle-income households. As a result, the positive parameters of these category shares increase borrowing in the middle income quintiles. Due to this constellation of the parameters, the different expenditure shares across income groups potentially explain the hump-shaped income-debt relationship.

To see how much these expenditure shares actually matter, first it is worthwhile to have a look at the estimated parameters of Q_{ij} income quintiles. One can see that the estimates are statistically significant, showing that debt-to-income ratio is higher in Quintile 2-5 than in the omitted category Quintile 1, even after controlling with the expenditure shares. This finding is identical with that of Table 1.11, just as the fact that the highest debt-to-income ratio can be found in Quintile 4. So the inclusion of expenditure shares does not change the shape of the income-debt functional form. However, the marginal effects of the income dummies are different. Based on the Tobit model in Section 3.3 without the expenditure shares, the marginal effect of Quintile 4 (which represents the peak in debt-to-income ratio) was 0.49, showing that Quintile 4 households have 0.49 higher debt-to-income ratio, controlling with major socio-demographics. This metric decreases by 28% to 0.35 if the expenditure shares are included into the Tobit model based on Equation 1.3. This means that varying expenditure shares in different income ranges are an important explanation of why middle income (Quintile 4) households have the highest credit card debt.

As a qualitative evaluation of these results, one might conclude that neither the theory of subsistence consumption nor that of durables are the sole explanation behind these findings. The first suggests that the share of necessities alters credit demand positively. However the share of the largest necessity, housing does not

Table 1.21: Tobit model to estimate credit card debt-to-income ratio using SCF-reported permanent income

Variable	Parameter	Standard error
Intercept	-5.187	(.571)*
Quintile 2	.514	(.164)*
Quintile 3	.855	(.177)*
Quintile 4	1.256	(.199)*
Quintile 5	1.058	(.228)*
Age 40-49	-.032	(.104)
Age 50-59	-.019	(.111)
Black	-.570	(.166)*
Hispanic	.098	(.154)
High School	.780	(.202)*
University	.586	(.218)*
Male	-.011	(.091)
Married	-.179	(.111)
Number of kids	-.037	(.037)
House owner	.219	(.125)
High financial assets	-.774	(.161)*
Consumption shares (δ_m)		
Apparel	2.491	(2.138)
Furnishing & Appliances	1.645	(1.693)
Audiovisual Equipment	14.696	(1.676)*
Vehicle Purchase	.446	(.607)
Travel incl. Food	-1.206	(1.503)
Alcohol & Tobacco	4.927	(1.857)*
Food at Home	-7.005	(1.079)*
Health	6.063	(1.044)*
Housing	.571	(.593)
Transportation	7.225	(.984)*
Education	-.240	(1.188)
Entertainment	11.336	(1.775)*

T-tests are shown with (*) if they are significant at the 95 % significance level.

alter the debt-to-income ratio, while the share of food at home, which is most often associated with subsistence consumption, negatively alters credit demand. On the other hand, the theory of durables would suggest that the high share of durable consumption leads to low credit demand. While almost all expenditure categories with significant positive parameters are non-durables, both the exception of audio-visual equipment (which is a durable but has the highest impact on credit demand) and the negative parameter of food at home (which is a non-durable) weakens the explanation of the results solely with the theory of durables. Consequently, it is highly probable that the fact whether credit card can be used or not to purchase items in a given category, is also an important driver of credit card debt, showing future research possibilities in this direction.

Finally, it is important to mention that while this section provides sensible findings to understand the indebtedness of the households, the causality between expenditure shares and debt has to be interpreted carefully. Category spending is determined by the preferences of households, such as impatience or risk taking behavior, so it is possible that expenditure shares simply reflect some important unobserved preferences that also drive total consumption and credit demand. Consequently, the 28% decrease in the marginal effect of Quintile 4 is a likely overestimation of the real impact of expenditure shares on credit demand.

1.4.5 Other Neoclassical Considerations

While the list of neoclassical extensions of the standard lifecyle model is long, this section presents three other models that may be of interest in the understanding of credit card demand.

Firstly, Dynan et al. (2004) point out that an operative bequest motive together with a mean reverting income process across generations may lead to higher savings for higher income households. Simply stated, rich households are likely to expect their children to be worse off financially, so the marginal utility of leaving a bequest becomes higher compared with poor households who expect their children to be better off. However, the literature frequently finds this bequest motive unimportant, just as the paper of Gan, Gong, Hurd & McFadden (2004). Furthermore, Column (1) of Table 1.22 tests whether the importance of the bequest motive[30] varies over income groups, and finds no statistically significant correlation between them, suggesting that the bequest motive is not a key driver of savings and debt heterogeneity with respect to income.

The two remaining neoclassical extensions are related to the so-called borrowing high and lending low (BHHL) puzzle of credit cards – *i.e.,* a significant portion of households hold simultaneously high liquid assets and high credit card

[30] Households are asked in the SCF whether they find it important to leave inheritance.

Table 1.22: Other neoclassical drivers of savings by permanent income

	(1) Inheritance important	(2) BHHL debt-to-income	(3) Past Bankruptcy	(4) Transaction-to-income
Total	54%	0.09	15%	0.1
Quintile 1	57%	0.07	25%	0.06
Quintile 2	53%	0.06	24%	0.08
Quintile 3	51%	0.11	15%*	0.1*
Quintile 4	52%	0.14*	13%*	0.13*
Quintile 5	55%	0.07	6%*	0.16*

T-tests for Column (2) and (4) and Chi-square tests for the other columns to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

balances (Zinman (2007*a*)). Column (2) of Table 1.22 shows BHHL credit card debt-to-income, which is the debt-to-income ratio of households multiplied with a zero-one indicator variable which is 1 if the household has higher liquid asset-to-income ratio (already analyzed in Table 1.4) than its credit card debt-to-income ratio – *i.e.,* the household would be able to pay back all of its credit card debt from liquid assets at the time of the interview. Since the interest rate paid on credit card debt is much higher than the interest received on liquid assets (this leads to the label of "borrowing high and lending low"), the existence of this puzzle shows a potential arbitrage opportunity for the households. However, two major neoclassical explanations of this puzzle are discussed here. First, households might borrow on credit cards to be able to go bankrupt, which is the strategic default theory of Lehnert & Maki (2002), who provide various justifications of the existence of this mechanism in the U.S. Weinberg (2006) also points out that recent credit trends are boosted by the looser bankruptcy laws and smaller stigma associated with bankruptcies. Second, Zinman (2007*a*) argues that the reason behind this puzzle arises from the transactional demand for money, and the small pecuniary cost of not paying back credit card debt with liquid assets (typically less than $10 per month) is overweighed by the implicit value of liquidity. In his recent paper Zinman (2009) provides further evidence that credit card usage and debt is largely determined by the transactional demand for money, which can be either satisfied by using a credit card or a debit card.

Columns (3) and (4) of Table 1.22 show that both these mechanisms might be correlated with income. Column (3) is the proportion of those households that declared bankruptcy in the past out of those who were provided any type of loan during the past 5 years. This proportion significantly decreases as income grows. Unfortunately it is very difficult to judge whether these bankruptcies are strategic by nature, as the larger proportion of bankruptcies is expected to arise because of cash flow considerations as a result of inadequate precautionary savings to cover potential risks.[31] But having a smaller fraction of households filing for bankruptcy for strategic reasons could explain why Quintile 5 households hold lower BHHL debt than households in Quintile 4. Column (4) shows the monthly credit card transaction value divided by the monthly permanent income, which is a measure of the transactional use of credit card.[32] One can see that the rich use significantly more their credit card for transactions, which may lead to the positive interaction between income and BHHL balance between Quintile 1 and Quintile 4. So these two neoclassical models are in line with the observed hump-shaped BHHL debt-to-income ratio in Column (2).

However, the sample average of the BHHL ratio (0.09) is only about 15% of the sample average of the credit card debt-to-income ratio (0.61). Furthermore, the BHHL ratio difference for instance between Quintile 1 and Quintile 3 (0.04) is only a minor fraction of the difference in total credit card debt-to-income ratio (recall that the marginal effect of being in Quintile 3 compared with Quintile 1 was 0.5 in Section 3.2), showing that the strategic default or the transactional demand for money may only moderately contribute to the hump shaped income-debt relationship. Furthermore, the results of the multivariate model in Section 4.6 provide further arguments against these neoclassical extensions being important.

1.4.6 Tobit Model on the SCF Data

So far this section has reviewed how certain potential drivers of credit demand are correlated with income. Also, it has been argued how these drivers should alter credit demand *in theory* according to neoclassical models. However, with the exception of liquidity constraints, interest rates and non-fungible consumption,[33] the *actual* relationship between the neoclassical drivers and credit card debt has remained uncovered. This section extends the Tobit model in Section 3.2 run on

[31] According to a recent paper of Guiso, Sapienza & Zingales (2009), in case of mortgages during the subprime crisis the portion of strategic defaults was 26% of total bankruptcies. As this current chapter covers the period before the crisis, and as the potential benefits of defaulting with credit cards are much smaller compared with mortgages, the share of strategic defaults in the case of credit card debt has to be much smaller.

[32] Note that this ratio still excludes the transactions of those households who use credit cards but pay back always or almost always their credit card balances (pure "free riders").

[33] In the case of the relationship between credit card debt and interest rate and liquidity constraints, endogeneity problems led to special discussion, while the impact of non-fungible consumption to credit card debt could be analyzed based on a separate dataset (CEX) which cannot be combined with the SCF.

SCF data, and Equation 1.1 is rerun with the inclusion of the neoclassical savings drivers analyzed in Section 4 into the matrix of X_{ik} explanatory variables. Using this approach, it can be shown which model contributes to the understanding of the U.S. credit card debt patterns in 2007.

Table 1.23 shows the parameter estimates of the Tobit model. Note that the majority of estimates of the added variables, including all four significant added variables, have the expected sign based on the theoretical models listed before. First, heterogeneity in the life cycle model parameters matter in credit demand: the longer is the planning horizon of saving and spending of a household, the higher is the credit demand. This means that households with low discount rate save more and borrow less. Second, the impact of liquidity constraints is tested with the inclusion of the credit card limit-to-income ratio into the Tobit model. Other liquidity metrics discussed in Section 4.2 are highly endogenous (such as being rejected with a credit card application), so those are excluded from the final reported analysis, but the inclusion of these variables does not alter the main findings. The positive significant parameter of the limit-to-income ratio is consistent with the theory of binding liquidity constraints. If a household is credit rationed and is offered with lower than necessary credit limit, the household is unable to hold as much debt as it demands. Third, precautionary savings matter in credit card debt demand. If a household needs to allocate a higher portion of its income to prepare for future risks (so has a higher precautionary savings-to-income ratio) then the household can consume today less and hence, accumulates a lower credit card debt relative to its income. Finally, preference towards risk is an important driver of credit demand. If a household is risk averse, even small future uncertainties lead to lower present consumption and lower credit demand, again according to the theory of precautionary savings.

So a good portion of the listed theories seem to partially explain the credit card debt held by the households. As the level of liquidity constraints, precautionary savings or by preference heterogeneity varies across income, does this mean that these neoclassical models explain the hump-shaped income-debt relationship discovered in Section 3? Table 1.23 shows that the parameter estimates of income Quintiles 3 and 4 are still significant even after controlling with a rich set of variables that capture heterogeneity in neoclassical credit demand drivers. Calculating the marginal effect of Quintile 3 dummy, one can infer that *ceteris paribus*, households in the middle income group have 0.40 higher credit card debt-to-income ratio than households in the poorest income group. This marginal effect is 80% of the total marginal effect calculated in Section 3, showing that a large majority of the hump-shaped income-debt curvature remains unexplained by neoclassical models. The income dummies remain significant even if the so-called BHHL balance is excluded from the credit card debt-to-income ratio based on the arguments in Section 4.5. Also, if the four endogenous credit rationing metrics are included

Table 1.23: Tobit model to estimate credit card debt-to-income ratio using SCF-reported permanent income

Type	Variable	Parameter	Standard error
	Intercept	-2.822	(0.758)*
Income segments	Quintile 2	0.455	(0.332)
	Quintile 3	1.212	(0.352)*
	Quintile 4	0.793	(0.372)*
	Quintile 5	0.088	(0.427)
Demographic controls	Age 40-49	0.162	(0.211)
	Age 50-59	0.173	(0.237)
	Black	0.631	(0.276)*
	Hispanic	0.119	(0.293)
	High School	0.073	(0.198)
	University	0.031	(0.309)
	Male	-0.217	(0.304)
	Married	0.310	(0.280)
	Number of kids	-0.007	(0.076)
	House owner	0.722	(0.232)*
	High financial assets	-1.577	(0.221)*
	High non-financial assets	-0.054	(0.216)
LCPIH model	Planning time horizon for saving and spending	-0.178	(0.068)*
	Income expectation higher than inflation	-0.242	(0.238)
	Income expectation lower than inflation	0.029	(0.195)
	Lifespan expectation	0.003	(0.008)
Liquidity constraint	Credit card limit-to-income ratio	0.278	(0.019)*
Precautionary savings	Precautionary savings-to-income ratio	-0.094	(0.039)*
	Precautionary motive is important	-0.125	(0.185)
	Unemployment during the last 12 months	0.006	(0.286)
	Good idea about next year's income	0.306	(0.191)
	Major consumption expenses in the next 5-10 years	-0.094	(0.325)
	Major medical expenses in the next 5-10 years	0.272	(0.246)
	Risk aversion	-0.480	(0.211)*
	Can borrow from family	-0.015	(0.198)
Bequest motive	Bequest is important	0.190	(0.174)
Money demand	Transactions-to-income ratio	0.325	(0.381)

T-tests are shown with (*) if they are significant at the 95 % significance level.

in the model (such as the past bankruptcy or banking rejection, defined in detail in Section 4.1 as the determinants of "high risk" households), the marginal effect of the Quintile 3 dummy changes only to 0.38 from 0.40, leaving the quantitative findings of the model identical.

The high indebtedness of the middle-income households is valid by the combination of the results of this Tobit-model with the previous discussions about those debt drivers that were not be included into this model, such as interest rate or consumption components. Adding all impacts, the reviewed neoclassical models seem to explain approximately *half* of the variability of debt across income, while the other half remains unexplained.

1.5 Behavioral Explanations of the Income-Debt Relationship

The neoclassical consumption-saving model is restrictive even in the presence of the added building blocks in the previous sections. It assumes that households behave as *homo economicus* and maximize their lifetime profit through all their decisions. According to Rabin (1998), psychology can teach researchers important facts about how humans differ from traditional economic assumptions. Behavioral economics has been working on the border of economics and psychology and produced numerous important extensions that led to a departure from the "long-run perspective". Among these, Browning & Lusardi (1996) list self-control problems (for instance time inconsistent preferences), mistakes due to the complexity of the dynamic life cycle optimization problem and the failing assumption of fungibility of consumption (for instance mental accounting). Rabin (1998) adds to the previous list non-standard preferences and argues that the mistakes (or biases) made in household decisions are partly due to future uncertainties. DellaVigna (2007) groups behavioral models into three major groups: non-standard preferences, non-standard beliefs and non-standard decision making processes.

These deviations from the standard economic model, the mistakes and irrational behavior are frequently observed in credit card usage decisions as well, see Ausubel (1991) for an early discussion. This is not surprising as this current chapter argues that credit card debt maps well the household's consumption-savings decisions and therefore absorbs the behavior predicted by both the standard and behavioral economics models. Bertaut & Haliassos (2005) provide a review of behavioral models that are relevant for credit cards and find time-inconsistent preferences and mental accounting as two important approaches.

In this section these approaches are reviewed together with some other popular non-standard topics in the light of the research question – *i.e.*, whether the behavioral extensions are able to explain better the empirical fact that middle-income households have higher than average credit card debt.

1.5.1 Animal Spirits

A large family of non-standard models is hereby labeled as the models with "animal sprits", following Loewenstein & O'Donoghue (2004). The main assumption of these models is that the "person's behavior is the outcome of an interaction between two systems: a deliberative system that assesses options with a broad, goal-based perspective, and an affective system that encompasses emotions and motivational drives". A related field of research is neuroeconomics, which is a recently developed initiative to leverage the knowledge of neuroscience and economics to understand human behavior better. Neuroscience highlights that different types of environmental stimuli affect different brain areas and neural systems. Both Camerer, Loewenstein & Prelec (2005) and Sanfey, Loewenstein, McClure & Cohen (2006) list various examples of this fact, such as tracking neural activities to pain, monetary reward, risk or uncertainty. The idea of people having specialized mental systems (affective and deliberative) could have dramatic consequences for economics. The assumption that people have a unitary set of preferences, which they seek to satisfy, can not always capture the complexities of human behavior and the processes in the brain. Hence, the existence of two sets of preferences, and two utility functions seems to be a reasonable assumption, and leads to the complete revision of the existing utility theory. Further evidence shows that a higher level neural system exists (mentalizing module) that is involved only in the decision making process. However, the exact interaction of these systems is still uncovered, which has led to the use of economic models that might approximate the decision making process.

Loewenstein & O'Donoghue (2004) show that the models with animal spirits with appropriate assumptions are identical to models with hyperbolic (or $\beta\delta$) preferences, such as that of Laibson, Repetto & Tobacman (2003). Other important applications of animal spirits lead to the understanding of risk preferences and social preferences.

How can animal spirits contribute to the explanation of the empirical fact of this chapter? Two major explanations arise from this theory. First, it points out that emotions have a role in decisions, through the affective system. Theoretically, emotions can enter into the additive discounted utility function as a downward modifier of discount factor of future utilities. Empirically, there are several papers showing that psychological features or emotions matter in financial decisions (see Bertrand, Karlan, Mullainathan, Shafir & Zinman (2005) about personal loans or Agarwal & Ambrose (2008) about mortgages). Hence, a potential explanation of middle-income households having more debt can be that these households face more emotions or, alternatively stated, more *temptations* in their consumption-savings decisions or credit card usage decisions. Second, animal spirit models predict that the final decision of individuals is based on the "battle" between the deliberative and affective mind. Hence, even if households in all income categories face the same emotions and temptations, income still can be related to the "battle" between the two selves and this way to the final decision whether the deliberative or the affective optimum will be selected. This mechanism can be alternatively called *self control*, as from the long-term perspective, the deliberative optimum should be selected, and any deviation from the deliberative optimum is treated as a self control issue in the literature. These two aspects of models with animal spirits are reviewed in the following two sections.

1.5.2 Animal Spirits & Temptation

Two pieces of empirical evidence are presented to support the first mechanism – *i.e.*, the middle-income households might face more temptations. First, recall Table 1.16 in Section 4.2 that shows the age-income breakdown of credit card limit-to-income ratios. It was observed that middle-income households have typically the highest credit limit compared with their income. One can interpret credit limit as liquidity constraint, but in Section 4 it was shown that liquidity constraints do not explain a large part of the hump shape observed in credit card demand. Therefore one can interpret credit limits as the result of the marketing effort of the financial service companies providing the card. A frequent practice of the banks is to CLIP consumers (credit limit increase process), either automatically or with the consent of the customer. Both based on the personal experience of the author of this thesis and based on industry evidence, banks target middle-income households with the CLIP programs the most heavily, due to their modest default probabilities compared with the poor and due to their high response rates compared with the rich. Gross & Souleles (2001) show that the increase of credit limit leads to rising borrowing in the case of both high and low utilization households, which finding is consistent with the assumption of limit being a temptation for consumption.[34] One can observe in the current SCF data that the average credit limit is approximately 5 times as high as the actual borrowing, showing the potentially high importance of bank's marketing activities. Assuming that high limits mean high temptations for households to use credit cards and revolve with credit card debt, animal spirits can lead to higher indebtedness of middle-income households.

The second empirical evidence towards middle-income households facing more emotions is related to the direct mail (or junk mail) activities of the banks. In 2007, U.S. households were targeted by credit card offers close to 50 times per year through direct mail.[35] This statistic is available by income groups as well: house-

[34]However, the authors associate these findings with possible precautionary motives, but their data is not satisfactory to prove this assumption.

[35]http://mailmonitor.synovate.com/

holds with less than $50,000 yearly income receive 35.1 mails per year, those between $50,000 and $100,000 yearly income receive 62.7 junk mails, while the richest segment with six digit (or more) yearly income get 46.1 direct mails. These numbers immediately show that the middle income households are more exposed to direct marketing as a result of the banks' targeting strategies that are based on risk and marketing forecast models. However, these aggregate statistics may be misleading, as one household can be mailed several times, and the statistics include all households in the denominator, even those that are outside the scope of the current chapter (younger than 30 or older than 60 years old). Fortunately, the SCF provides household level information about whether a household makes its borrowing decision based on direct mails, which is a good proxy for receiving direct mails. Appendix A.4 shows a result of a probit model that estimates whether the household uses direct mails to make borrowing decisions. Based on the results, one can see that *ceteris paribus*, middle-income households use direct mails more often in their borrowing decisions, as a result, are likely to be targeted with junk mails more often. A separate model which is identical with the Tobit model Equation 1.1 that estimates credit card debt-to-income ratio was rerun with the inclusion of the direct mail dummy defined in this section (results are not reported). Surprisingly, the direct mail dummy becomes the most significant positive driver of credit card debt. This means that the direct mail targeting strategies of banks contribute to the hump-shaped income-debt relationship, being a temptation that increases the preference towards present consumption.

1.5.3 Animal Spirits & Self-Control

Even if the temptation is identical in different income quintiles, animal spirits can lead to surprising implications about the impact of income. Self control is an important building block of behavioral models, whether it is an observed action or an internal unobserved debate in the brain. This section covers two major theories with observable self-control tools, then discusses the implications of internal self-control mechanisms with some illustrative statistics pointing towards its existence.

The first model to review is that of Bertaut & Haliassos (2001) as the authors provide a direct explanation of the hump-shaped income-credit relationship in their paper. Belonging to the family of mental accounting, multiple selves form the household: one can think about different household members or the same member behaving differently facing multiple decisions. The "shopper" self is the owner of a credit card and uses a single rule of thumb for consumption: it always fills the credit card up to a pre-determined utilization rate.[36] The "accountant" self

[36]Note that the assumption of the shoppers' behavior matches the intuition of Section 5.2: credit limit itself can be interpreted as temptation.

is a long-term utility maximizer who can select the limits on the credit card (including zero limits – *i.e.* not to have a credit card) and selects the monthly repayments on the credit card. Having this setup, the credit card is a self-control tool as households with a "shopper" that consumes too much given its rule of thumb decision can be prevented by the "accountant" from high consumption through lower paybacks of previous balances, through lowering credit limit or, in the extreme, through canceling the credit card ownership. The accountant-shopper model has a striking consequence for the impact of income on credit demand. On one hand, high income households are more able to control credit card spending and are less likely to revolve with credit card debt. On the other hand, these households are more likely to hold a card and more likely to have higher credit limits as they are more confident about their ability to perform self control. This mechanism leads to sign reversals in credit demand: as income grows, the probability of holding a credit card goes up but the probability of revolving with the credit card decreases. The resulting impact is the hump-shaped functional form between credit card debt and income. Bertaut & Haliassos (2001) use the 1995 and 1998 waves of the Survey of Consumer Finances to justify their findings, and next to income, they find that other household characteristics that are related to confidence about the ability to control credit card spending similarly perform the sign reversals predicted by the theoretical model. In the current chapter, Row B of Table 1.15 already demonstrated that as income grows, the proportion of households without a credit card falls sharply, so the 2007 SCF data is still consistent with the findings of Bertaut & Haliassos (2001). Furthermore, the experiment of Prelec & Simester (2001) shows that the option to pay with credit card, or even looking at the picture of a credit card raises the willingness-to-pay for a large value item such as a ticket to a basketball game, which shows the strong intuitive appeal of the credit card being a self-control tool, strengthening further the argument of Bertaut & Haliassos (2001). Note that while the accountant-shopper model potentially explains the peak of credit card debt in the case of middle-income households, it is difficult to directly quantify the impact of this mechanism. Similarly to other behavioral models discussed later, more detailed questions about credit card usage are needed to identify the exact contribution of this mechanism to credit card indebtedness.

The other notable observable self-control action of U.S. households is the investment into illiquid wealth. If household preferences are time-inconsistent (which is a special case of animal spirits), in each time period the household consumes too much, but is willing to take proactive actions to avoid high consumption in future periods. Laibson et al. (2003) argue that investment in illiquid assets or pension schemes is an optimal behavior for many households even if this leads to short term liquidity needs and higher credit card debt. However, for low income households, these investment opportunities are scarce, leading to a so-called "hyperbolic saving trap". This model explains a famous credit card puzzle *i.e.,* why so many households hold credit card debt and illiquid assets simultaneously, and also potentially explains why poor households have low credit card debt-to-income ratio. The 2007 SCF contains some evidence in favor of the argument of Laibson et al. (2003): Table 1.24 shows the median liquid and illiquid wealth-to-income ratios of U.S. households as a function of income.[37] One can see that as income grows, households accumulate more illiquid wealth (except the top quintile), and illiquid wealth represents 4.9 times the yearly income for the median household. But Column (1) shows that liquid wealth that represents -1.3 times the monthly income for the median household, is the lowest in the case of middle income households. Contrasting these two patterns the argument of Laibson et al. (2003) may hold empirically: middle income households face less constraints in terms of housing and pension so invest more in illiquid wealth than the poor to prevent high future consumption, but this is accompanied with higher short term indebtedness reflected in Column (1).

Table 1.24: Liquid and illiquid asset holdings by permanent income

	(1) Median liquid assets-to-income ratio	(2) Median illiquid asset-to-income ratio
Total	-1.32	4.88
Quintile 1	-0.38	2.78
Quintile 2	-1.26	4.32
Quintile 3	-2.49	5.66
Quintile 4	-1.89	5.73
Quintile 5	-0.6	5.2

Note that monthly income is used to calculate the liquid assets-to-income ratio, while yearly income is used to calculate the illiquid assets-to-income ratio.

As a potential shortage, instead of a direct empirical justification for their theory, Laibson et al. (2003) use macroeconomic simulations to derive their results, and due to the lack of appropriate surveys, it is still uncovered how much hyperbolic preferences drive investments in housing or in pension. Without knowing how important empirically the role of illiquid assets is as a self-control tool, it is difficult to assign any portion of credit card debt to be driven by this mechanism. However, this is a fruitful research area as the list of empirical evidence

[37]Wealth refers to assets minus debt, where the debt related to illiquid assets such as housing or vehicles is added to illiquid wealth, and other debt is added to liquid wealth. As opposed to credit card debt-to-income ratio, in the case of liquid and illiquid wealth the median and mean values differ significantly, so to represent the population properly, the median values are shown.

about time-inconsistent decision making is rapidly increasing: for instance Shui & Ausubel (2005) show through a field experiment that the choice of credit card terms reflects time inconsistency; while Meier & Sprenger (2008) show that based on a choice experiment, the proportion of present biased households is 25%, and these households have higher credit card indebtedness.

Unfortunately, a large portion of self control is unobservable for researchers, as it is the result of the interaction of decision making units within the brain. According to the paper of Benhabib & Bisin (2005), the internal self control mechanism is intended to *override* the affective decision and stick with the deliberative decision. The override process activates if the utility loss that would arise by consuming the affective optimum is greater than the so-called attention cost, observed by the long-term deliberative self. Using standard assumptions about utilities, this utility loss can depend on income in a positive way. This can lead to the override process to be executed more frequently in the case of high income, leading to a negative interaction between income and temptation. Let us consider a simple example. A less wealthy individual is facing a decision whether to buy a city bike or a motorcycle to travel to work. The deliberative optimum would be to buy the city bike (same speed, cheaper, more environmentally friendly) but the affective optimum is to buy the motorcycle (better social status). As the utility loss in the case of selecting the motorcycle from the deliberative self's point of view is not large in absolute terms, the final decision will be to buy the motorcycle. A more wealthy individual faces the question whether to buy a sedan or a SUV to travel to work. Similarly, the more expensive SUV is the affective optimum. But as the utility loss is large in case of purchasing the SUV (in absolute terms, compared with the utility loss in case of purchasing the motorcycle versus bike), the override process will force the individual to stick with the deliberative optimum and the final decision will be to buy the sedan.

Internal self-control models can lead to positive interaction between income and temptation, using for instance assumptions from the model of Bernheim & Rangel (2004) who focus on addition. In that model temptation (environmental cues) drives customers entering to the so-called *hot mode* when they always consume the addictive substance, meanwhile the customer can make self control steps (like rehabilitation) to alter the probability to fall into the hot mode. This model suggests that large emotional shocks are difficult to resist, which is an opposite mechanism compared with the previous override model. The assumption of making the final decisions based on utility differences (used by Benhabib & Bisin (2005)) can be combined with this model of addiction: if the utility differences observed by the affective self are too large (higher than the attention cost) by not consuming the affective optimum, then the consumer decides to choose the affective optimum. Again, with standard assumptions about utilities, income can be a positive driver of the utility differences, and hence higher income leads to a more frequent fall into the hot mode, leading to a positive interaction between income and temptation. Recalling the previous example, the low income household can force itself to choose the city bike as the joy by purchasing the motorcycle is not large enough, while the high income household will purchase the SUV, as it falls into a hot mode, as large utility losses would arise (observed by the affective self) by selecting the sedan.

Hence, internal self-control mechanisms can explain both positive and negative interaction between temptation and income, and as a result, even if temptation and observed usage of self-control tools (such as house or credit card ownership) is identical in different income groups, heterogeneity in decision making can lead to a hump-shaped income-consumption (and income-debt) relationship.

One empirical caveat of animal spirit models is the difficulty of measuring how self control mechanisms and decision making work in people's brain. Nevertheless, several suggestive empirical findings are hereby presented to show the potential importance of internal debates of multiple selves and internal self control mechanisms. Column (1) of Table 1.25 shows the portion of households that hold credit card debt and also have negative attitudes toward holding debt.[38] These households face potential internal conflict between their long-term deliberative decision (not to use card) and their affective decision (use credit card and consume more in the present). One can see that the proportion of conflicted households is much higher in the case of middle-income households.

Table 1.25: Conflicting behavior as a potential result of internal debates

Income	(1) Debt holders with negative attitude towards debt	(2) Credit card debt-to-income ratio of transactors
Total	18%	0.09
Quintile 1	16%	0.02
Quintile 2	18%	0.06*
Quintile 3	28%*	0.16*
Quintile 4	19%*	0.12*
Quintile 5	7%	0.07*

T-tests for Column (2) and Chi-square tests for Column (1) to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

[38] Negative attitude is defined as negative answer to whether it is a good idea to use borrowing to cover the expenses of a vacation trip or to cover living expenses when income is cut or to finance the purchase of a fur coat or jewelry. These questions were selected from a longer list to match well the usage patterns of credit card.

Column (2) of Table 1.25 shows the average credit card debt-to-income ratios of households that identify themselves as never or almost never being revolvers (so-called "transactors" based on the industry jargon). These households are not counted as debt holders in the previous debt analysis, as their debt might be a result of convenience use. However it can be observed that medium income is associated with higher debt-to-income ratio. Again, stating not to be a revolver but revolving with credit card balance can be a sign of an internal "battle" between the two selves, and one can conclude that middle income households suffer from this battle more heavily. Note that the fact that the total share of households in Column (2) is non-zero led Ausubel (1991) in his seminal paper to conclude that households are irrational in their credit card decisions.

As a final empirical evidence in favor of existing self control actions, recall that in Section 4 it was shown that risk aversion, which is widespread among the poor, negatively alters the credit card indebtedness, even after controlling with various metrics of precautionary savings. Intuitively, risk aversion should be correlated with the execution frequency of the internal self control actions, this way explaining why the risk averse have lower credit card debt, and as a result, why the poor are less indebted.

1.5.4 Investment Mistakes

A related area of research is that of investment mistakes, popularized by the recent work of Campbell (2006) within the field of household finance. The author defines investment mistakes as "discrepancies between observed and ideal behavior" and argues that poor and low education households do not take advantage of such "low-hanging fruits" as the participation in the stock markets, optimal portfolio selection / diversification or the refinancing of unbeneficial mortgage contracts. To mitigate the effects of these mistakes, Campbell (2006) calls for an expansion of financial education, just as Lusardi & Tufano (2009) do, who show that debt literacy is lower in the case of the poor and the elderly (among other groups) and that the level of debt literacy negatively alters the cost of debt and the probability of being in financial distress. Agarwal, Driscoll, Gabaix & Laibson (2007) argue that a key driver of mistakes and biases in the credit markets is age,[39] and middle-aged households have the optimal blend of analytic capital and experience – *i.e.,* the highest cognitive capital so they are the most cost-efficient by paying low late fees, overlimit fees or cash advance fees, and by using optimally the cards with various functionalities (low APR on balance transfers versus low APR on new purchases). Also, Stango & Zinman (2008) show that a specific mistake related to the problem-solving capabilities of households, the exponential growth bias – the

[39]The authors highlight the importance of selection effect and cohort effect as well, and analyze various credit products such as credit cards, mortgages or car loans.

tendency to linearize functions containing exponential terms when assessing them intuitively – is more frequent in the case of low income and low education households. So the empirical literature reaches a consensus on poor and uneducated households performing more mistakes in their finances.

As it was already discussed in this chapter, low income households do not only have low credit card debt-to-income ratios but also a high portion of poorer households does not even hold a credit card. Is the nonparticipation in the market of credit cards a mistake similarly to the nonparticipation in the stock market or paying high cost for credit services? If so, this theory could contribute to the low indebtedness of poorer households.

Recalling Table 1.8 from Section 3.2, it is possible to find some evidence to support the existence investment mistakes. In the Tobit regression, households with high school or university education have a significantly higher credit card debt-to-income ratio than households without a high school degree, controlling with other socio-demographic characteristics, as both the high school dummy alone and the high school and university dummies jointly are significant at the 95% significance level. This finding supports the importance of debt literacy in indebtedness, so the poor may refrain from borrowing for similar reasons as households with low education. Note that the same argument does not hold for age, as it is not a significant driver of credit card indebtedness. This is consistent with the lack of consensus in the reviewed literature about the role of age in experiencing investment mistakes.

The implications of potentially large investment mistakes in the case of the poor are similar to binding liquidity constraints: not the excess borrowing of the middle income households but the lower than optimal indebtedness of low income households is driving the hump-shaped credit card debt.

1.5.5 Social Preferences

Social preference models as the final set of models considered in this chapter fall to the family of behavioral extensions of non-standard preferences. However, Loewenstein & O'Donoghue (2004) argue that social preferences are another application of the models with animal spirits. Frank (2005) dates back this theory to Duesenberry's relative income hypothesis and argues that this model has crucial policy implications and therefore the current economic community needs to accept and adopt this theory more. Frank (2005) also differentiates positional goods (such as housing) from non-positional goods (such as leisure) and argues that only the consumption of other's positional goods should enter into one's utility function. Social preferences are part of many economic models, probably the most well known application is its inclusion into the CAPM model by Gali (1994).

The fact that social preferences enter into households' consumption-savings decisions is well demonstrated by the paper of Ravina (2005), who shows that new credit card purchases (which is interpreted as a good proxy for consumption) depend significantly on one's past credit card purchases (she calls this internal habit persistence) and on the credit card purchases by other households in the same city (she calls this external habit persistence). However, no known paper shows empirical analysis of the impact of social preferences as a function of income.

The rich consumption data of the Consumer Expenditure Survey makes it possible to show a simple empirical evidence towards the importance of social preferences in credit demand. Let us extend the usual Tobit model to estimate credit card debt-to-income ratio in the following way:

$$L_i^* = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \sum_{j=2}^{5} \gamma_j Q_{ij} + \sum_{j=1}^{5} \omega_j Q_{ij} S_i + \varepsilon_i$$

$$L_i = L_i^* \ if \ L_i^* > 0; \ L_i = 0 \ otherwise \tag{1.3}$$

where the added term compared with the original Tobit model (Equation 1.1) is the interaction between the income dummies Q_{ij} and the share of luxuries S_i, which latter is the sum of expenditure shares in categories shown in Figure 1.1(a) in Section 4.4. On average, households spend 13.7% of their income on luxuries such as vehicles, entertainment or travel. In Section 4.4 it was already shown that expenditure categories drive credit demand differently due to various neoclassical considerations, for instance due to the fact that credit cards can be used to buy certain goods and services, while other ones can be paid only in cash. A joint F-test with the value of 10.6 for $\sum_{j=1}^{5} \omega_j = 0$ shows that S_i is a significant positive driver of credit demand, suggesting that luxuries are purchased more frequently by paying with credit card compared with necessities.

However, looking at the newly introduced interaction terms one can see in Table 1.26 that the impact of S_i varies over income, and in Quintile 1 and 2 it is positive, while in higher income categories it is negative. F-tests with the value of 11.3 and 5.6 show that the null hypotheses of $\omega_1 = \omega_2$ and $\omega_2 = \omega_3$ can be rejected at the 95% significance level, respectively. This result is hard to rationalize with the neoclassical explanations listed in Section 4.4, but are consistent with the theory of social preferences. High income households purchase more luxuries if they can do that without accumulating excessive credit card debt. A joint F-test of $\omega_3 + \omega_4 + \omega_5 = 0$ with the value of 4.3 shows that high income households (Quintile 3 or higher) with high spending on luxuries have significantly *lower* credit card-to-income ratio. On the other hand, low income households intend to "keep up with the Joneses" and consume luxuries even if their financial assets and income are unsatisfactory to cover them. Poorer households have to borrow to be able to purchase luxuries, leading to large positive parameters for the share of luxuries in the low income groups.

Table 1.26: Tobit model to estimate credit card debt-to-income ratio extended with interactions between income and the share of luxury consumption

Variable	Parameter	Standard error
Intercept	-4.425	(0.281) *
Q_{i2}	1.190	(0.226) *
Q_{i3}	2.032	(0.234) *
Q_{i4}	2.491	(0.249) *
Q_{i5}	1.983	(0.271)
Age 40-49	0.302	(0.250)
Age 50-59	0.493	(0.276)
Black	-0.608	(0.162) *
Hispanic	-0.127	(0.153)
High School	1.058	(0.202) *
University	0.754	(0.215) *
Male	-0.056	(0.091)
Married	-0.249	(0.109)
Number of kids	-0.122	(0.035) *
House owner	0.319	(0.124) *
High financial assets	-0.766	(0.162) *
$Q_{i1} \times S_i$	8.643	(1.583) *
$Q_{i2} \times S_i$	2.118	(1.124)
$Q_{i3} \times S_i$	-1.354	(0.941)
$Q_{i4} \times S_i$	-1.444	(0.743)
$Q_{i5} \times S_i$	-0.128	(0.718)

T-tests are shown with (*) if they are significant at the 95 % significance level.

1.6 Conclusion

This chapter has found that medium income households have above-average credit card debt holding. Consequently, the “rich borrow less” implication of previous savings research is true only for the very rich. Importantly, the analysis is based on permanent income, so the high indebtedness of the middle class is a long term phenomenon leading to the high financial vulnerability of this segment. The chapter argues that the standard life cycle model can not explain this empirical fact, even with the inclusion of the major neoclassical modifications, such as liquidity constraints or precautionary savings, as by these theories approximately half of the peak of indebtedness of the middle-class remains unexplained. The chapter lists certain components from the behavioral economics toolkit, notably models of animal spirit, investment mistakes or social preferences, that help to understand this phenomenon better and empirical justification for them are provided.

Next to the economic importance of the research question – *i.e.,* which extension of the lifecyle model explains the findings the best, one can see several policy implications as well. As Reynolds et al. (2006) state, payments to creditors may crowd out savings (*e.g.,* for retirement or for home equity) and reduce flexibility in family budgets. These negative effects have to be understood and mitigated by governments, and it has to be clearly understood which customer segments are affected the most by the indebtedness. Furthermore, important practical implications arise in the middle of the subprime crisis. On the one hand, if the middle-class suffers from a debt burden, the reactive bail out programmes should be tailored to fit the needs of both this segment and the subprime. On the other hand, proactive actions have to be developed not only for the subprime but also for prime customers, for instance in education about the riskiness of the lending market.

Future research in this area is essential. On one hand, even more accurate information is needed about households' credit card decisions, as the current nationwide surveys make it cumbersome to answer such simple questions as what portion of households suffer from liquidity constraints. On the other hand, surveys with more attitudinal questions are needed to capture the reasons behind using or not using credit cards, to be able to evaluate which behavioral extension drives decision making the best. While this chapter has covered several major theories and showed that a household's behavior may be consistent with many of those, the exact contribution of each theory has remained uncovered. As the theories have various policy implications, investments in this area are likely to pay off. For instance, if solely neoclassical reasons would drive credit card usage, the "laissez-faire" strategy is the first best in the markets. If households use credit cards for self control purposes, banks and regulators have to help them in this goal, probably by introducing innovative services such as fixing the credit card limit one month in advance without the option to change it later. If similarly to pension schemes, investment mistakes lead to the poor's nonparticipation in the credit card market, financial education is a must. However, this chapter has shown that middle-income households face more temptation and are able to resist this less successfully, so if this mechanism is driving credit card indebtedness the most, customer protection has to be strengthened.

Chapter 2

The Transactional Credit Card Use of Individual Investors

2.1 Introduction

It is a good deal to use credit cards, at least according to the marketing materials of U.S. financial service providers. In 2007, U.S. households were reminded on average close to 50 times per year about the cash backs, rebates, zero APR or balance transfer offers by direct mail,[1] and probably were reluctant to open any such envelop and were suspicious about the potential benefits listed. But consider a simple calculation. In 2007 the average U.S. credit card user purchased goods and services for an average of $1,329 per month using credit cards, based on the Survey of Consumer Finances. If the card was issued by one of the top cash back and benefit providers, the user could earn a yearly $300 benefit or 1.88% yield with the card,[2] mainly through the cash back promotions. Additionally, if the household ran out of cash and had to sell its Google stocks to finance the consumption expenditures, the fact that by using the credit card one could delay the liquidation of this investment each month by 30 days in average, led to an additional $400 yearly benefit.[3] This $700 gain is large and it indicates that even if a household did not have the best cash back terms or did not make such a lucky investment, the benefits of credit card use are non-negligible. It therefore seems to be rational that a lot of U.S. families decide to use credit cards.

The current example monetized some important benefits of the so-called transactional use of credit card, while there are other important gains as well such as security or speed of payment. The main research question of this chapter is how

[1]http://mailmonitor.synovate.com/

[2]http://www.askmrcreditcard.com/cashbackcreditcardcalculator.html

[3]In 2007, Google, Inc. stocks experienced a 44.2% price increase between January 5 and December 28.

this transactional use of credit cards drives credit card balances and revolving behavior?[4] Some researchers assume that the transactional use only increases credit card balances, and all these balances are paid back at the end of the grace period by definition (Johnson (2004)). However, alternative views exist that allow the transactional credit card use also to generate revolving debt. On one hand, some neoclassical papers capture well the transactional use of credit card. For instance, Brito & Hartley (1995) apply to credit cards the inventory based approach of cash of Baumol (1952), but their model can not be generalized to capture all recent features of credit cards, such as the cash-back or the existence of grace period. Zinman (2009) correctly shows that households use a simple cost-benefit analysis to decide whether to use credit cards or debit cards, however, he uses no economic model to formalize this process and he treats out of scope the analysis of financial assets other than demand deposits.[5] On the other hand, the behavioral view of credit cards (starting with Ausubel (1991)) puts in focus customer irrationality *e.g.,* time-inconsistent decision making or other mistakes to explain why the transactional use would lead to revolving debt, as “there are consumers who do not intend to borrow but continuously do so”.

The first contribution of the current chapter is to present a simple model of transactional use that both fits better the features of the credit card of the 21[st] century (cash-back, grace period) and also incorporates the opportunity cost of money. First, by using the credit card an individual may receive an immediate cash back or other benefit. Second, if the household has no cash balances available at the time of the payment then the credit card use delays the costly liquidation of interest bearing investments. The marginal benefits from this item depend on the expected rate of return on the investments and also on the level of marginal transaction costs (called also as the broker’s fee henceforth). Third, if the individual has no cash balances at the time of the payment but expects to save cash before the end of the grace period (by having lower consumption than income during the grace period), he may lower or even avoid the sale of its investments. The cost associated with credit card use occurs only if the household revolves with its credit card balances. In this case a marginal interest rate has to be paid for the outstanding balances.

[4]While this chapter focuses only on credit cards, the discussion can be extended to other unsecured credit facilities as well, which have similar asymmetry between the cost of short term and long term usage, therefore might be used for transactional purpose. For example installment loans for durable consumption have often “buy now pay later” functionality or have other teasers.

[5]Zinman (2007*a*) proposes for future research the extension of his debit analysis to other financial assets, but he also identifies some caveats such as “Broader definitions could turn up more substantial and disconcerting costs” and “The ability to liquidate other assets (e.g., CDs, stocks, bonds, home equity) in order to reduce borrowing costs may be constrained by illiquidity and transaction costs.”

After the basic model setup, it is argued that under some reasonable assumptions on the model parameters, the benefit of the usage is almost always higher than the cost, so it is a good deal to use credit cards, and frequently it is also worthwhile to revolve after the grace period. In a deterministic setup, the household always know his *ex post* revolving behavior, but if some model parameters, such as the interest rate or the savings rate are uncertain, the household only knows *ex ante* the probability of revolving, but the *ex post* behavior gets determined only after the realization of the uncertain variables. Thus, uncertainly explains how the transactional use leads to large variation in *ex post* behavior, which is in line with some empirical findings of the literature, such as the fact that based on the Survey of Consumer Finances, also those households hold significant revolving credit card debt who report to always or almost always paying back revolving balances (see Ausubel (1991)). This variation in revolving behavior can be mitigated or accelerated by a correlation between the uncertain variables in time, so the chapter also reviews the potential reasons behind this correlation.

Afterwards, the model is extended to incorporate present biased preferences with naive and sophisticated households, repeating partially the analysis of the papers of DellaVigna & Malmendier (2004) and Heidhues & Koszegi (2008), which latter focuses on credit cards as a special case of general non-linear time-inconsistent contracts. Naive time-inconsistent preferences may lead to the divergence of *ex ante* and *ex post* revolving behavior, so those credit card users who think that they will pay back the balances during the grace period, but because of present bias they will not do so, may be worse off by using their credit card.

The second part of the chapter presents a detailed empirical analysis of the 2004-2007 waves of the Consumer Expenditure Survey (CEX) and the 2007 wave of the Survey of Consumer Finances (SCF) to find evidence in favor of the previously introduced transactional use model. To disentangle the current model's predictions from the implications of the life cycle model, only those households are analyzed that have sufficiently large financial assets. These households are called individual investors or simply investors henceforth. Several Tobit type models are set up to predict the new balance, revolving balance or financial charges of households as the left hand side variables, and the drivers of the transactional use model as the right hand side variables.

First, through some stylized facts and using Tobit type models it is shown that consumption in general is a main driver of credit card balances and debt. This is in line with the simple theoretical model: if the marginal benefits of credit card use are higher than the marginal costs, it is worthwhile to use credit cards *as much as possible*, so the balances become proportional to consumption. As in the case of investors the revolving balances are also driven by the transactional use, the indebtedness has to be also proportional to consumption. As an interesting checkpoint, the effect of a consumption increase compensated with an identical income rise is tested, and it is shown that credit card indebtedness increases in this case, so credit card use is not purely driven by the fact that households run out of cash balances.

The second empirical finding is that a health shock representing an unexpected consumption shock has larger impact both on balances and on indebtedness relative to the remainder of consumption. This is explained by two features of the model. On the one hand, households may adjust their cash balances after a permanent consumption increase, so are less likely to run out of cash. On the other hand, in the case of a transitory consumption shock, it is more likely that the household will be able to save during the grace period enough cash to pay back at least a portion of credit card balances, as opposed to a permanent consumption shock. Note, that both the first and the second empirical findings are based on the analysis of the CEX, and hold for credit card balances and charges in a cross section model, with or without socio-demographic controls. In the case of credit card balances a difference in difference estimation also strengthens these results.[6]

Third, still related to consumption, the impact of the holiday season, as an expected consumption shock is analyzed. For this purpose, from the CEX those consumption categories are flagged that have a seasonal consumption peak in December, such as apparel or entertainment. It is shown that high consumption in these categories in December has a slightly lower impact on credit card balances but a slightly higher impact on credit card indebtedness compared with an other random month. This result is consistent with the existence of sophisticated time-inconsistent agents in the economy. Higher consumption in December and marketing campaigns of credit card issuers would suggest the frequent use of credit cards. But December is the time of yearly personal holidays, so it is possible that households forget more frequently the payback of loans, which behavior can be represented with present-biased preferences in the transactional use model. Sophisticated agents know in advance that they would revolve more frequently, so they refrain from credit card use more often during the holiday seasons compared with the rest of the year.

Fourth, probably the most unexpected finding of the chapter is that stock owner investors accumulate more new balances and hold higher debt on their credit card compared with those investors that hold other assets, such as savings account balances or bonds. Previous literature, such as Becker & Shabani (2009), already analyzed the relationship between loans and stock market participation: for households with high debt holdings (mortgage, car loan or even credit card debt) the "loan retirement" is a high return investment with low risk, so it is expected that indebted households engage less often in stock investments. While

[6]Unfortunately, the CEX does not make it possible to perform the difference analysis in case of credit card charges.

this may be true for mortgages, the current chapter present an *opposite*, positive correlation between credit card debt and stock market participation. This result holds both in the CEX cross section and difference analysis, and also in the SCF analysis. Both the CEX difference in difference estimation and the inclusion of risk preference, time preference and other questions about financial attitudes into the SCF model suggest that this finding is a causality and not only a correlation. The marginal effect of the stock market participation is large, for instance in the case of the SCF it represents about one quarter of the average revolving balances of households. While this may seem dubious at first sight, this finding is fully consistent with the transactional use model: on the one hand, stock owners have higher marginal broker's fee compared with some other assets such as savings accounts, on the other hand, the expected rate of return on stocks is higher compared with other less risky assets, so it is worthwhile to use credit cards to delay the liquidation of stock investments due to multiple reasons. Some further empirical analysis (for instance the analysis of bonds in the SCF) suggests that the high expected rate of return itself is the most important driver of transactional use.

Fifth, still related to common stocks, the relationship between past individual stock returns and credit card indebtedness is investigated. The primary motivation behind this analysis is to find some individual level predictor for future rate of return expectations, which is a key driver of credit card's transactional use. In the CEX difference in difference case, it is possible to construct 12 month stock returns, and surprisingly both who had a positive or a negative stock return accumulate more new credit card balances relative to those who had a return close to zero. The impact of positive returns can be justified either with the momentum effect[7] or with the fact that both past and future stock returns are the function of preferences towards risk, while the irrational projection of past performance to the future may also be considered. The weaker positive impact of negative returns may also simply reflect risk preferences, as those who select riskier portfolios in the hope of high future returns, may be more often in the red. Under-diversification may enlarge the volatility of stock returns and the probability of experiencing short term losses accompanied with high future return expectations. Finally, rational or irrational mean reversion of stock prices (popularized by Odean (1998)) also predicts that stock market losers have higher future expectations, so it is more profitable for them to use credit card to delay the liquidation of stock investments. To get more insights, past stock returns are included in the SCF Tobit type models as well: here these returns represent long term returns from the beginning of stock market participation. The negative long term returns do not drive credit card statis-

[7]The momentum effect is an empirical phenomenon according to which stocks with high returns over the past three to twelve months tend to outperform the market in the future for a similarly long period, see for instance the review of Campbell (2000)

tics anymore, indicating that all three listed potential explanations are feasible, as all these lead to negative correlation between past and future returns only in the short term. On the other hand, long term positive historical returns significantly drive new balances in the SCF. As this result holds even by controlling with risk preferences, the most likely explanation of this empirical finding is the irrational projection of past stock return to future return expectations.

Sixth, it is shown in the SCF analysis that the number of credit cards held by investors is positively correlated with both credit card new balances and revolving balances, and in the latter case its impact is larger. This is true in the presence of credit limit, interest rate and risk controls, so the correlation is not likely to be supply driven. This result can be justified by the fact that households with more cards have access to higher immediate benefits, but may forget the payback of credit card balances during the grace period more often. This mistake can be interpreted through the lens of naive present-biased preferences in the transactional credit card use model.

Last, some of the previous results are further strengthened by the inclusion of interactions into the Tobit type models. Specifically, based on the SCF, those stock owners that have access to low interest rate credit cards revolve more often than other stock owners or other households with low interest cards, showing a neat justification of the transactional use mechanism. Furthermore, in the CEX model there is a positive interaction between the impact of the health shock and stock ownership, again consistent with the findings of the model. Finally, in the SCF analysis of stock market returns, it is shown that those who under-diversify their stock portfolio are more likely to project past stock returns to the future – *i.e.,* they use credit cards more often. This last correlation makes perfect sense as different investment mistakes are likely to occur with the same households that have potentially lower financial literacy.

Altogether, the presented set of empirical results can be separated into two groups. First, many of these results are consistent with the neoclassical setup of the transactional use model of credit cards. Second, some results point toward the fact that households are biased and make mistakes in their transactional decisions. This way the current chapter is situated between the neoclassical and the behavioral view of credit card use.

The structure of this chapter is as follows: Section 2.2 presents a parsimonious model of transactional credit card use. Section 2.3 introduces the data. Section 2.4 presents the econometric analysis that shows the impact of the drivers of transactional use on credit card balances and debt. Finally, Section 2.5 concludes.

2.2 A Parsimonious Model of Transactional Use

Since the inventory based approach of cash by Baumol (1952), households are believed to hold cash balances to minimize the cost of paying for consumption. However, the credit card of the 21^{st} century became a major competitor of cash, debit and other payment tools as it provides various unique advantages (high cash back rate, promotions, "floating" – *i.e.,* zero interest paid in the grace period, etc.). So the analysis of credit card as a payment tool (instead of a life cycle borrowing tool only) has had it renaissance recently.

In the literature, Zinman (2009) interprets transactional use in a neoclassical way, according to which households consist of profit maximizing *homo economicus* agents which use credit card for payments only if the benefit from the card usage exceeds its cost. He estimates a discrete choice model on whether a household uses debit versus credit, and finds that three factors (card ownership, being a credit card revolver or high utilization rate on the credit card) increase the probability to use debit, as these increase the price of the marginal credit card charge. Zinman (2009) states that this is an evidence for the neoclassical customer behavior, but he does not provide a more detailed economic model of transactional use.

In an earlier related paper Brito & Hartley (1995) treat money and credit card as two costly options to pay for consumption. In the case of using credit cards, households have to pay interest on the revolving balances, while in the case of using money balances, households lose the opportunity cost of money – *i.e.,* the interest that could be earned in the case of investing money into interest yielding securities. Brito & Hartley (1995) show that if investments can be arranged only at discrete intervals but credit card can be used continuously, then even if the interest rate of a credit card is much higher than the opportunity cost of money, credit card will be used to cover a fraction of consumption. However, their work does not appreciate fully certain important features of modern credit cards, such as a grace period or a cash back promotion.

2.2.1 The Basic Setup

This section presents a simple model of credit card transactional use. Let us consider a three period economy. Period 1 is the *billing cycle*: one full month when the credit card is used to finance a part of consumption expenditures. Period 2 is called the *grace period*. In the case of credit cards this lasts typically 15-20 days after the billing cycle period during which no interest is paid for the credit card balances accumulated in Period 1 if those are paid back on time fully.[8] Recent

[8]The 2009 Credit Card Act prohibits card companies from charging interest on debt that is paid on time during the grace period. Before this Act if any small portion of credit card balances was

innovations include an even longer grace period, as long as 50 days. Period 3 is called the *invoice period*, which is the month after the grace period, when the households receive the credit card invoice with the interest charges applied to their unpaid balances.

Each household faces two decisions. In Period 1, it has to decide whether or not to use credit card to finance a portion of its consumption, and what is the optimal share of credit card financing. In Period 2, the household has to decide whether or not to pay back the credit card balances, and what is the optimal payback ratio. If a household uses credit card financing in Period 1 and does not pay it back fully in Period 2, the remaining balance has to be paid back fully in Period 3, together with the incurred interest charges.

Several factors determine these decisions, which factors are all assumed to be exogenous. Section 2.4 will provide more detailed justification of this exogeneity assumption. The household has to pay for c_1 consumption, out of which λ portion can be covered both by cash or credit card. The remaining $1 - \lambda$ proportion can be covered only by cash.[9] The household in this exercise is a transactional user – *i.e.,* he has sufficient financial assets to be able to decide not to use credit card at all in Period 1. First, the households may use y_1 Period 1 income and its initial cash or checking account reserves (w_0) to pay for a portion of consumption. This payment is costless. Second, it is possible to use credit card, up to λc_1 expenditure amount. Finally, the household finances the remainder of its expenditure by deploying its homogeneous interest yielding financial asset (otherwise called hereby as investments, one may think of savings accounts, stocks or bonds, etc.), but this can be done only by paying a marginal pecuniary cost called broker's fee, which is denoted by θ and is assumed to be identical and deterministic in all three time periods. Just as the term of broker's fee, the definition of that is also borrowed from Baumol (1952):

> The term "broker's fee" is not meant to be taken literally. It covers all non-interest costs of borrowing or making a cash withdrawal. These include opportunity losses which result from having to dispose of assets just at the moment the cash is needed, losses involved in the poor resale price which results from an asset becoming "second-hand" when purchased by a nonprofessional dealer, administrative costs, and psychic costs (the trouble involved in making a withdrawal) as well as payment to a middleman. So conceived it seems likely that the "broker's fee" will, in fact, vary considerably with the magnitude

not paid back during the grace period, the household incurred interest charges for the full balance. This change in legislation has some impact on the mechanism of the model presented.

[9]The differentiation between cash-only goods and credit goods is an important step to understand credit card use as described in detail for instance by Telyukova (2008).

of the funds involved.

Motivated by the worries in the last sentence of the quotation, θ is assumed to be proportional to the amount of financial assets used to pay for Period 1 consumption.[10] The other important characteristic of the financial asset is that it provides a non-zero rate of return, denoted by π_2 and π_3 in the second and the third time periods, respectively. Low risk assets (like a governmental bond or a certificate of deposit) typically provide low rate of return, while according to the standard portfolio theory, high uncertainty is associated with higher rate of return, such as in the case of stocks and mutual funds. The liquidation of the financial assets leads to the loss of this π opportunity cost, which together with the θ transaction cost, makes the other two forms of financing (credit card and cash) more attractive.

Credit cards have a further important benefit over other payment methods. If the individual accumulates l credit card balances, then bl immediate benefits can be accumulated which contains cash back, air miles and other promotions. The inclusion of these benefits is an essential part of the current model, as for instance Stavins (1996) shows that these benefits (extended warranties, rebates or travel related discounts) are more significant drivers of credit card demand than interest rate itself. Also, the numerical example in the introduction demonstrated that these benefits may indeed be large, so narrowing the analysis to the other drivers is a too restrictive approach.

In the second and third periods the household faces c_2 and c_3 consumption expenditures and y_2 and y_3 income flows. The financing of consumption c_2 and c_3 is done after the Period 2 repayment decision, and is assumed to be two further independent problems that future selves face. The modeling of these problems is out of our scope, which assumption will be shown not to be restrictive. Note, that the household makes no investment decisions during the three periods – *i.e.,* the initial w_0 cash and the income flows are not transformed into interest bearing financial assets. This latter assumption is motivated by the short time period encompassed by the model.

At the end of Period 2 the household has a second decision point: either it pays back the loan l or does not pay it back fully. For the repayment, the household can use cash (including checking accounts) for free, or the financial asset by paying the θ marginal cost. Those balances that are not paid back in Period 2 (called *revolving balance*), have to be paid back in Period 3, again by using cash or by liquidating investments. As the final important driver of the model, in the case of revolving the household experiences financial charges billed in Period 3, with the

[10]Interesting extension is the introduction of fixed payback cost. This leads to the payback decision to depend on the size of the loan. As the reality may lay between the two extreme approaches, for the sake of simplicity the variable cost version of the model is selected. With the introduction of fixed broker's fee the parsimony of the model is lost.

marginal rate of r. These financial charges have to be settled together with the revolving balances in Period 3.

Households intend to maximize their expected dollar benefits by deciding which payment method to use. As the payment of expenditures with cash is always more profitable than withdraw investments (given by positive θ and/or positive π), the optimization problem can be broken down into two parts. First, the household may use credit card instead of available cash. Second, credit card may be used instead of the withdrawal of financial investments. The remainder of this section reviews these two situations in detail.

The first case occurs if cash (including Period 1 income) is larger than the purchase amount that must to be paid with cash, or $w_0 + y_1 - c_1(1 - \lambda) > 0$. This should be a very usual situation that transactional users face: whether to grab the debit card or the credit card from one's purse. In the presence of a positive marginal cash back rate b, it is always optimal to use credit card instead of cash, as the cash back benefits can be realized without any other costs. So if $b > 0$ then the transactional users pay with credit card in Period 1 for the amount of

$$l_c = min(\lambda c_1, w_0 + y_1 - c_1(1 - \lambda))$$

and pay this amount back fully in Period 2, as revolving with any balance would generate Period 3 marginal cost of r without any further benefits.

The level and sign of the marginal benefit b depend in reality on the household's credit card and debit card contracts. For instance, it may happen that a household gets 1% rebate for credit card purchases, but if the debit card payments lead to 0.5% cash back, then the net benefit of using credit card is only $b = 0.5\%$. It is also important whether the credit card has a yearly fee or a monthly fee, as the household may include those as well into their calculations of credit card benefits. Finally, the settlement of payments with credit card may lead to future money transfer fees, which may be significant in several countries. Fortunately, the current chapter focuses on the U.S., where households can write a check free of charge to pay for their credit balances, so the transaction costs related to the repayment are negligible. Nevertheless, b is not restricted to be positive, representing all costs associated with credit card financing.

The more complex case occurs if households run out of cash, or $w_0 + y_1 - c_1 < 0$. In the case of no access to credit cards, these households need to liquidate their investments. However, credit cards make possible to accumulate balances up to

$$l_i = \min(\lambda c_1, c_1 - w_0 - y_1)$$

instead of breaking up *e.g.,* term deposits or selling stocks. This strategy of using credit cards instead of investments has multiple advantages. First, households can enjoy the monetary cash back benefits. Second, unliquidated investments generate positive π rate of return. Third, through paying by card it is possible to delay the transaction cost θ into the future. Finally, due to the positive return on investments and due to the possibility that the household may save a portion of its income in Periods 2 and 3, the household may hold higher cash balances in the future. This means that less investments has to be liquidated and a portion of the broker's fee can be saved.

Formally, the conditions to use credit card instead of investments can be shown by describing the costs and benefits of financing the previously defined l_i consumption expenditure in Period 1. Figure 2.1 shows these benefits for three groups: for those households who do not use the credit card, for credit card user households who pay back their balances in Period 2 (convenience users or "transactors"), and finally for those credit card user households who pay back the balances only in Period 3 (borrowers or "revolvers").[11]

Figure 2.1: The benefits and cost of credit card's transactional use

	No credit card use	Convenience user	Borrower
Billing cycle	$-\theta$ *(broker's fee)*	b *(benefit)*	b *(benefit)*
Grace period		$-\theta(1-\pi_2-\sigma_2)$ *(broker's fee)* π_2 *(rate of return)*	π_2 *(rate of return)*
Invoice period		$(\pi_2+\sigma_2)\pi_3$ *(rate of return)*	$-\theta(1-\pi_2-\sigma_2-\pi_3-\sigma_3)$ *(broker's fee)* π_3-r *(rate of return less interest)*

Parameters used: immediate benefits such as cash back (b), broker's fee / liquidation cost (θ), rate of return on investments (π), saving rate (σ), credit card interest rate (r) and discount factor (δ).

It can be seen that the immediate marginal benefit of using credit card instead of selling investments in Period 1 is independent on the payback decision, and has the value of

$$\theta + b$$

In terms of the further marginal costs and benefits, firstly the convenience users are reviewed: their future marginal net benefit (denoted by Ω_p) is described by the formula

[11] The differentiation between "borrowers" and "convenience users" follows the related literature, such as Johnson (2004).

$$\Omega_p = \delta\pi_2 - \delta\theta(1 - \sigma_2 - \pi_2) + \delta^2(\sigma_2 + \pi_2)\pi_3$$

where $0 < \delta \leq 1$ is the one-period discount factor of the household and

$$\sigma_t = \frac{\min(0, y_t - c_t)}{l_i}$$

is the percentage of loan amount that can be saved in Period t. The Period 2 and Period 3 costs and benefits are discounted to Period 1 values by using δ and δ^2, respectively. The first component of Ω_p is the marginal rate of return obtained on the unliquidated investments in the case of using the credit card. The second term is the marginal broker's fee if the balance is fully paid back in Period 2. Note, that the broker's fee has to be paid only for $1 - \sigma_2 - \pi_2$ portion of the loan, as the cash savings σ_2 generated in Period 2 as well as the π_2 return on investments can be used free of charge to pay back a portion of the credit card balances. The final component arises from the fact that the household has to liquidate only $1 - \sigma_2 - \pi_2$ portion of its investments, so compared with the case of no credit card use, the unliquidated assets with the share of $\sigma_2 + \pi_2$ generate further return in Period 3.

Second, the Period 2 and Period 3 marginal benefits of the borrowers are reviewed: their future benefit (denoted by Ω_r) is described by the formula

$$\Omega_r = \delta\pi_2 - \delta^2\theta(1 - \sigma_2 - \sigma_3 - \pi_2 - \pi_3 + r) + \delta^2(\pi_3 - r)$$

In this case the only benefit the household experiences in Period 2 is the π_2 rate of return. The second component of the formula is the broker's fee paid in the last period. Revolvers pay less broker's fee compared with transactors, as Period 3 savings and investment returns (σ_3 and π_3) can also be used free of charge to pay for the respective portion of credit card debt. To simplify the discussion, the parameters are assumed to satisfy the condition of $\sigma_1 + \sigma_2 + \pi_1 + \pi_2 \leq 1$, as the broker's fee can not become negative. Finally, in Period 3 the revolver household receives π_3 rate of return for all his unliquidated investments, but has to pay the marginal interest rate charge of r.

It is profitable to revolve with the credit card balances in Period 2 if $\Omega_p < \Omega_r$. This condition can be simplified to

$$[\delta\pi_3 + (1 - \delta)\theta]\,(1 - \sigma_2 - \pi_2) + \delta\theta(\sigma_3 + \pi_3 - r) > \delta r \tag{2.1}$$

Summed up on the left hand side of Inequality 2.1, the benefits of revolving versus transacting are threefold. First, the household gets π_3 returns on all of its investments compared with only $\sigma_2 + \pi_2$ portion. Second, the broker's fee that should be paid in Period 2 can be delayed by one further period, leading to $(1 - \delta)$ gain through the discounting. However, in this case one has to pay the interest charges as well, which increases the broker's fee. Finally, Period 3 investment return and saving reduce further the broker's fee. The marginal cost that may overweight these benefits is the r interest rate on credit cards, showed on the right hand side of Inequality 2.1.

The Period 1 decision is to use the credit card to pay for l_i consumption expenditure if

$$\theta + b + \max(\Omega_p, \Omega_r) > 0 \tag{2.2}$$

Note, that if the household also accumulates l_c credit card balance instead of using its available cash balances (which is always profitable if $b > 0$), then the interest rates paid in the case of revolving with l_i has to be paid also for l_c, so the marginal interest rate of r has to be replaced with $r^* = r(l_i + l_c)/l_i$ in Inequality 1.

The comparative statics of this model is straightforward. The consumption, the share of "credit goods", cash balances and income in Period 1 determine the values of l_i and l_c: while the first two increase (or do not alter) the credit card balances, the second two decrease (or do not alter) those. The level of consumption also changes the benefits of revolving versus paying back l_i: *ceteris paribus,* higher c_1 decreases r^*, so makes revolving more likely and increases slightly the overall benefits of using credit card instead of investments.

Whether l_i or l_c amounts really become credit card balances, depends on the marginal benefits. As previously mentioned, for l_c balances that could be also paid with cash, the only necessary and sufficient condition to be charged on credit cards is $b > 0$. If credit card is used instead of breaking up investments, the constellation of multiple benefits has to be evaluated. A positive transaction cost θ, positive rates of returns on the investments and the positive future savings rates (led by high future income or low future consumption) all increase the marginal benefit of credit card use. The interest rate r is the only parameter that represents a cost item, and only if the household decides to revolve based on Inequality 2.1. Altogether, based on Inequality 2.2, the household is more likely to use its credit card instead of liquidating investments than instead of paying with cash in hand, due to the various further benefits, and limited costs. Even if $b < 0$ (*e.g.,* an expensive credit card without cash back or other promotions), due to the mitigation of the liquidation costs, it may be profitable to use the credit card. Finally, the choice to revolve is led by Inequality 2.1. This depends positively on π_3, σ_3 and δ, but negatively on π_2, σ_2 and r. Here the negative impact of Period 2 saving and rate of return might sound non-trivial. The intuition is that if a large portion of the broker's fee could be saved already in Period 2, the further benefits, such as the value of delaying the broker's fee payment and the future gains on unliquidated investments, become smaller.

To demonstrate the relative impact of the different drivers of the model, two example cases are presented. Table 2.1 contains the first scenario, with realistic parameter values listed in the "Baseline Parameter" column. In this example, the π interest rates are set relatively high, so that the household becomes a revolver, which is a necessary condition to see the overall impact of all parameters. If one thinks about the stock market, a 12% expectation of the yearly rate of return is a reasonable assumption for a good portion of investors. This scenario leads to a 1.92% total benefit of using the credit card. This high benefit reflects the joint effect of the cash back, high rates of return on investments and future cash inflow through savings that can be used to pay back the credit card debt. The level of the parameters in the baseline scenario is then shifted (typically doubled, except time discount factor and interest rate on credit card), and the elasticity of the benefit is calculated. One can see that the rate of return on investment, together with the credit card interest rate are the main driver of the benefits of using credit card, with elasticities higher than 0.4. The immediate benefits and the level of the broker's fee also drive largely the level of the benefits, with elasticities close to 0.3. The impact of future saving rate of the household is still important but less pronounced, while the least important driver of the benefits is the discount factor, given the current selection of the benchmark case. Note, that the same shift in σ and π in Period 2 is better for the customer than in Period 3, matching the predictions of the model.

An important message of this is that credit card as a transaction tool is not only beneficial for convenience users but also for borrowers if the households runs out of cash and the returns on investment are high, or if the household expects to save significant amounts after the grace period that can be used instead of liquidating investments. As a result, the coexistence of investments with revolving credit card debt may be easily justified by this model. The example also demonstrates that if $\pi_3 \geq r$, then it is always profitable to revolve. As a result, high future rate of return expectations lead to large potential indebtedness on credit cards arising from the transactional use. This strategy may be very risky as a financial turmoil (such as the recent subprime mortgage crisis) may lead both to decreasing rate of return accompanied with increasing credit card interest rate, resulting in a large welfare loss of the exposed households.

Table 2.2 contains a scenario which is identical to the previous one except the rate of return on investments, which is now set to a monthly rate of 0.5%, representing a low risk, low return financial investment. One can see that the benefit in this scenario becomes lower (1.32%), but the gain from the delayed liquidation of investments (1.32%-0.5%) still remains larger than the immediate cash back rate (0.5%). In this scenario the households always use credit cards but they pay back the balances at the end of the grace period. Compared with Table 2.1, the elasticities of the benefit vary slightly: one may note that the impact of the time discount factor gets larger and the importance of the parameters from Period

Table 2.1: Benefits Gained with Credit Card Financing – High Return Investments

Parameter	Baseline Parameter	Shifted Parameter	New Benefit	Elasticity of Benefit
b	0.5%	1%	2.42%	0.26
θ	1%	2%	2.44%	0.27
δ	90%	60%	1.89%	0.05
π_2	1%	2%	2.83%	0.47
π_3	1%	2%	2.74%	0.43
σ_2	20%	40%	2.20%	0.15
σ_3	20%	40%	2.08%	0.08
r	1%	0.5%	2.33%	-0.43

Note: The baseline benefit is 1.92%. To calculate the new benefits and the elasticities, in each line only the selected one parameter is changed to the "shifted parameter" value, while all other parameters stay on the "baseline parameter" value.

3 is lower. Doubling the rate of return or tripling the savings rate in Period 3 leads to borrowing, but the benefits of revolving are much smaller compared with the previous scenario.

To sum up this section, under some reasonable assumptions about the transactional use model, if a household has high return investments, the most profitable action is to be a credit card revolver, while if the household has low return safe investments, the most profitable action is to be a transactor. As a result, one would expect high credit card new balances and lower, but positive revolving balances in the overall U.S. investor population, with a possible correlation between becoming a revolver and the expected rate of return on investments. The empirical section will build on this implication of the transactional use model.

2.2.2 Uncertainty and Ex Post Behavior

If all parameters of the model in the previous section are deterministic, the model leads to a simple decision rule for each household. The investor decides to be a convenience user or a borrower, depending on Inequality 2.1and Inequality 2.2. In this case the Period 1 *ex ante* revolving and usage behavior is identical to the Period 2 *ex post* revolving and usage behavior.

An interesting extension in this section is to see what happens if some parameters are uncertain. The introduction of uncertainty into credit card models of transactional use is not a novel idea. Brito & Hartley (1995) show that if the households face uncertainties in terms of the future consumption, the optimal strategy is to invest some money and use credit card if the realization of future consumption is high. However, in that work consumption uncertainty is limited to happen only

Table 2.2: Benefits Gained with Credit Card Financing – Low Return Investments

Parameter	Baseline Parameter	Shifted Parameter	New Benefit	Elasticity of Benefit
b	0.5%	1%	1.82%	0.38
θ	1%	2%	1.60%	0.22
δ	90%	60%	1.40%	-0.20
π_2	0.5%	1%	1.77%	0.35
π_3	0.5%	1%	1.47%	0.11
σ_2	20%	40%	1.58%	0.20
σ_3	20%	60%	1.38%	0.02
r	1.0%	0.5%	1.47%	-0.23

Note: The baseline benefit is 1.32%. To calculate the new benefits and the elasticities, in each line only the selected one parameter is changed to the "shifted parameter" value, while all other parameters stay on the "baseline parameter" value.

before the credit card use. Telyukova (2008) analyzes random preference and income shocks in a model of credit card as a liquidity tool, but she assumes (and calibrates the model accordingly) that a portion of the households already hold revolving balances and pay financial charges due to life cycle purposes.

The impact of uncertainty obviously depends on the risk preference of households. For the sake of simplicity, in the transactional use decision households are assumed to be risk neutral – *i.e.,* they simply evaluate the expected dollar benefits when they decide to use or not to use credit cards to finance consumption.

It can be shown that in the present model under some further mild assumptions about the values of the parameters, saving uncertainty in Period 2 can lead to a large variation of the *ex post* revolving behavior, while the role of a potential interest rate uncertainty in Period 2 is less prominent. For this simple calculation, let us stick with the benchmark case in Table 2.1. The calibration of that scenario led to the revolving behavior of the household. Using Inequality 2.1, it is possible to calculate the level of σ_2 and π_2 that makes the household indifferent between paying back the balances or revolving with that, which is $\sigma_2 = 27\%$ and $\pi_2 = 8\%$. This means that households who save higher than 27% of their outstanding credit card balances in Period 2, as well as household that have an 8% monthly return on their investments, switch their behavior from being a borrowing user to become a convenience user. Note, that the same change (7% increase) is required both for the saving rate and for the rate of return, just as shown by the symmetric role of σ_2 and π_2 in Inequality 2.1.

Simple calculations show that the uncertainty of the saving rate may be large. In the CEX, those transactional user "investor" households (defined properly in the empirical section) who hold a positive credit card balance, have in average

\$5,000 balance but save \$35,000 in a year. This means that one monthly saving of this typical household could be used to pay back 60% of the credit card balance in one month. But for the same population, the standard deviation of the monthly consumption is higher than \$5,000, leading frequently to occasions when the household save much more or do not actually save at all. Based on these aggregate statistics, the assumption of σ_2 saving rate to be uniformly distributed in the $[0, 1]$ interval is believed to be a potentially good representation of the reality. Having this large variation in σ_2, one can easily compute that this sample household revolves with 27% chance and pays back the balances with 73% chance (if $\sigma_2 > 27\%$). Consequently, households facing saving uncertainty (driven by consumption and/or income uncertainty) may vary largely their credit card repayment behavior as a function of the realization of the grace period saving rate. *Ex ante,* this sample household knows that he will be a transactor three times as often as a revolver, and based on this expectation it is profitable to use the credit card. *Ex post,* the household may behave as a convenience user or a borrower, depending on the realization of σ_2. This means that uncertainty in the current model contributes to the understanding of why households with high financial assets may switch frequently between being a convenience user or a borrower.

Focusing on the rate of the return, it was argued that for the sample household an 8% monthly return on investments is required to switch from revolving behavior to transactor behavior. Note, that this means 96% yearly return, which is very unusual for a typical stock investment. If the rate of return expectations are in line with past stock market performance, an expectation of 1-2% monthly return is more reasonable. Nevertheless, even if less frequently, it may easily happen that the investor gets much higher (or lower) actual monthly return in Period 2 that leads to the change of *ex post* behavior. For instance, the 2008 subprime mortgage crisis led to a continuous large decline of stock prices, which leads to increasing revolve rate of individual investors holding credit card debt according to the present model.

To sum up this case example until the current point, based on reasonable assumptions on the parameters of the model, saving uncertainty leads to high variation in *ex post* revolving behavior, but a lower variation in the *ex post* total benefits, shown by the lower elasticity of σ_2 in Table 2.1. On the other hand, uncertainty of the rate of return is accompanied with lower variation in *ex post* revolving behavior, but a very high variation in the *ex post* total benefits, shown by the highest elasticity of π_2.

It is also possible that uncertainty coexists both in Period 2 and Period 3 and it is accompanied with correlation between Period 2 and Period 3 saving rates or rates of return on investment. Positive correlation of saving rates may arise from a persistent income or consumption shock. For instance, in the case of illness the length of being on sick leave is sometimes unknown for the individuals. Positive correlation between σ_2 and σ_3 lowers the difference between the benefits of revolving and transacting, so reduces the variation in the *ex post* revolving behavior, but leads to larger variation in the *ex post* benefits of credit card usage. A negative correlation in saving rates may occur if the time of purchase of certain goods or services is uncertain. For instance, in the case of a household that plans to purchase a TV set either during the grace period or during the invoice period, if the purchase does not occur during the grace period, the lower σ_2 parameter will be accompanied with higher σ_3 parameter. This negative correlation makes the *ex post* behavior of investors even less predictable. However, the total benefits of the card use become less volatile compared with the case when σ_2 varies largely but σ_3 remains constant.

Moving to the rate of return, the empirical positive short term correlation between the uncertain rate of returns is called the *momentum effect*, according to which the stocks with high returns over the past three to twelve months tend to outperform the market in the future for a similarly long period, see for instance the review of Campbell (2000). Similarly to the saving rate, this positive correlation between π_2 and π_3 leads to small variation in the *ex post* revolve rate but to higher variation in the *ex post* benefits of credit card use. To the contrary, a negative correlation is also observed empirically. Odean (1998) reviews some important rational reasons for this, out of which probably the most accepted is the asymmetric information of investors, more discussed for instance by Lakonishok & Smidt (1986). According to this theory, investors are believed to own favorable information about a specific stock at the time of the purchase, and have a target sale price level that reflects this information. Short term price changes do not alter this target level, so the expectation of future returns are negatively correlated with actual returns. Odean (1998) finds evidence against this theory, and proposes irrational mean reversion (probably explained by prospect theory) to explain this negative correlation. Similarly to the saving behavior, a negative correlation between π_2 and π_3 leads to higher variation of *ex post* revolving behavior but a lower variation in total *ex post* benefits, compared with the case of uncertain π_2 but deterministic π_3.

Consequently, the current section introduced some important concepts that can lead to large variation in *ex post* revolving behavior and in the *ex post* benefits of credit card users. Households rich in financial assets may engage in credit card usage even if this leads to revolving in some cases, as the overall gain of this activity is positive. This mechanism adds an important point to the existing neoclassical literature as the fact that transactional use can lead to revolving debt is not appreciated enough. For instance Johnson (2004) has a detailed paper on the transactional use of credit cards, and by definition she focuses on those households only that are paying back all their credit card balances within the grace period.

2.2.3 Present-Biased Preferences

Let us enrich further the model of transactional use of credit cards with time-inconsistency, based on the paper of DellaVigna & Malmendier (2004). This model is also a special case of non-linear contracts theoretically scrutinized by Heidhues & Koszegi (2008). They put credit card and subprime mortgages as the real life motivation of their paper, and go further than modeling solely the household decisions and also analyze the market equilibrium of non-linear contracts. This section adds a novel empirical specification related to these works and discusses some specific implications.

Let us assume that between Period 2 and Period 3 households have (β, δ) preferences (see Laibson et al. (2003)): $\beta \leq 1$ is a taste parameter for immediate gratification and $\delta < 1$ is the discount factor. The source of low beta in the transactional use model may incorporate psychological features as well. For instance, individuals may simply forget to pay back the credit card balances at the end of the grace period, which may easily happen *e.g.,* if the household head has to settle the invoices of many family members holding credit cards. The prior belief about the taste parameter β in Period 1 is denoted by $\widehat{\beta} \geq \beta$. Between Period 1 and Period 2 the same δ discount factor is used as earlier.

In the case of time-inconsistency, Inequality 2.1 showing the condition to revolve becomes

$$\left[\pi_3 + \left(\frac{1}{\beta\delta} - 1\right)\theta\right](1 - \sigma_2 - \pi_2) + \theta(\sigma_3 + \pi_3 - r) > r \tag{2.3}$$

Let us denote with $I(\beta)$ the indicator variable which has the value of one if Inequality 2.3 holds, and zero otherwise. Time-inconsistent agents with $\beta < 1$ revolve with credit card more often than their $\beta = 1$ time-consistent counterparts, as the left hand side of Inequality 2.1 increases without a change in the right hand side. Note, that the revolving behavior depends on the true value of β, so is independent on the type of household – *i.e.,* whether it is sophisticated or naive.

The Period 1 decision is to use the credit card if

$$\theta + b + \Omega_p I(\widehat{\beta}) + \Omega_r[1 - I(\widehat{\beta})] > 0 \tag{2.4}$$

In this equation the future benefits of revolving or paying back the loan are identical with that of the time-consistent agent in Section 2.1. This is due to the fact that the Period 1 self makes its choices based on its long term preferences, which are independent from the taste of immediate gratification in Period 2. However, the $I(\cdot)$ indicator variable is evaluated at $\widehat{\beta}$: the agent knows about his future present bias, and makes his choice accordingly.

The future benefit of a time-inconsistent agent with $\widehat{\beta} < 1$ is lower than that of a time-consistent agent, due to the fact that the household revolves in certain

Table 2.3: Time-inconsistent decision making

Agent type	Time-consistent	Sophisticated time-inconsistent	Naive time-inconsistent
$\widehat{\beta}$	1	0.6	1
β	1	0.6	0.6
Ex ante behavior	Pay back	Borrow	Pay back
Ex ante benefit of card usage	0.07%	-0.19%	0.07%
Card usage decision	Yes	No	Yes
Ex post behavior	Pay back	-	Borrow
Ex post benefit	0.07%	0%	-0.19%

Note: $b = -0.75\%$, $\theta = 1\%$, $\delta = 90\%$, $\pi_2 = \pi_3 = 0.5\%$, $\sigma_2 = \sigma_3 = 20\%$, $r = 1\%$

cases, when it would be optimal to pay back the balances from the long-term self's perspective. As a result, the time-inconsistent household uses its credit card less frequently. However, there is a difference between sophisticated and naive agents in this case. Sophisticated agents are fully aware of their present bias ($\widehat{\beta} = \beta$), so they use credit card if it is profitable both *ex ante* and *ex post*. On the other hand, naive agents with identical β to sophisticated agents but with $\widehat{\beta} \geq \beta$ underestimate their present bias and as a result, expect higher benefits from the credit card use that they actually will have. *Ex ante,* naive households may use credit card because they think it will a profitable move, but as they revolve much more often then they expect, their overall *ex post* benefit from the credit card use drops, even may become negative. Consequently, naivete in this model setup can be interpreted as a formal definition of the irrational credit card usage phrased by Ausubel (1991) as "there are consumers who do not intend to borrow but continuously do so". Note that the impact of present bias on credit card usage and debt repayment is already presented by Heidhues & Koszegi (2008), though not in the context of transactional credit card use.

A numerical example in Table 2.3 demonstrates the potentially large welfare consequences of time-inconsistency. In the example similar parameters are used as in Table 2.2 in the previous section representing a low risk, low return investment ($\theta = 1\%$, $\delta = 90\%$, $\sigma_2 = \sigma_3 = 20\%$, $r = 1\%$, $\pi_2 = \pi_3 = 0.5\%$) but instead of a marginal benefit in Period 1, now the household faces a marginal cost of -0.75%. This upfront cost may occur in the case of credit cards without cash back or other immediate benefits but with significant monthly fees or yearly fees. This calibration leads to a modest 0.07% benefit in the case of transacting but to a larger loss of -0.19% in the case of revolving for a time consistent household. Accordingly, Table 2.3 shows that the time consistent agent *ex ante* expects to pay back the loan during the grace period, *ex post* behaves as expected, so uses the credit card to realize the 0.07% benefit. A fully sophisticated time-inconsistent agent with $\widehat{\beta} = \beta = 0.6$ knows *ex ante* that he will not pay back the loan during the grace period, due to its future taste for immediate gratification. Specifically, at the end of the grace period the benefits of delaying the payment of the broker's fee from Period 2 to Period 3 will be larger than the future costs of this delay (credit card interest rate less the rates of return on the investment). Table 2.3 shows that this agent does not use the credit card, as his long term self would experience the -0.19% loss in the case of revolving with the debt.[12] Finally, the naive time-inconsistent agent *ex ante* expects to pay back the loan during the grace period just as his time-consistent counterpart, so he uses the credit card due to the positive benefit expectation. However, his *ex post* behavior is to revolve, leading to an *ex post* loss of -0.19%.

If naivete is a general feature in the transactional use decision of household then banks may generate extra profit from richer credit card users as well. This means that the current behavioral extension has important policy implications. Empirically, unfortunately it is very difficult to infer whether households are present biased or not. Nevertheless, if a preference shock can be observed in the data together with detailed credit card usage statistics, the response to the preference shock may provide useful insights. For instance, let us assume that the researcher can observe increasing credit card usage rate in an economy after a preference shock. Based on the model of transactional use, the rising loan demand, assuming naive present biased decision making, leads to unchanged payback probability. Rising loan demand with sophisticated present biased agents leads to increasing probability to payback the loan. Finally, rising loan demand paired with the assumption of decreasing discount rate leads to decreasing payback probability. Consequently, the comparison of usage rate and payback rate development after a preference shock provides testable implications about the nature of preferences. A similar exercise will be performed in the empirical section, where seasonality serves as a predictable preference shock.

2.2.4 Intertemporal Optimization and Portfolio Choice

Following the related literature (Zinman (2007*a*) and Zinman (2009)), the level of consumption expenditures as well as the portfolio choice (the level of cash and the investments in stocks, bonds, savings accounts, etc.) are taken to be exogenous in the transactional use decision. To make this point clear, it is important to reem-

[12]Similarly to other behavioral models, sophisticated agents are able to use precommitment tools to maximize their welfare: *not to use the credit card* itself is the precommitment tool, probably customers "immerse their credit cards in trays of water and place them in the freezer", based on the anecdotal evidence of self-control given by Ausubel (1991). This self control step is already introduced for instance in the model of DellaVigna & Malmendier (2004) or in Bertaut & Haliassos (2001).

phasize that both the modeling and the empirical part of this chapter focuses on households that are rich in financial assets, so they could pay for their consumption even without having access to credit cards (individual investors). This means that the current exogeneity assumption is only true for those households that do not need to borrow for life cycle purposes.

The consumption flow of investors can be the result of a well maximized intertemporal optimization process. This is analogous to the "transactional demand" term of Zinman (2009), who actually models a slightly different problem (the choice between debit card and credit card instead of the current problem which is about the choice between credit card and an arbitrary financial asset), but also handles the credit card usage decision separately from the "transactional demand" decision. Note, that the assumption of separability is believed to be a good but not perfect description of the economy. Prelec & Simester (2001) for instance show in an experimental study that the availability of different payment options (credit card versus cash) significantly alter the willingness to pay (WTP) for a basketball or baseball ticket, and the difference can be high, up to 100% in favor of the credit cards. This is an evidence towards the fact that the payment method alters the intertemporal optimization, as the potential benefits of using credit are not in line with the large increase in WTP. But this study is based on the behavior of MBA students who might be credit constrained compared with the overall U.S. population, and also the hypothetical purchase situation might prevent the generalization of this result to a wider range of consumption decisions.

The portfolio choice decision of investors is the function of risk preferences and it is well integrated with the intertemporal consumption optimization process. Risk tolerant households hold more risky assets such as mutual funds and stocks, and have higher future consumption flow, while risk averse households put their wealth more likely into savings accounts and experience a lower consumption trajectory. The level of cash held by households is the function of a cost minimization problem: households hold cash balances to pay for the consumption flow for the lowest cost possible, given that they have access to other financing forms as well, such as interest bearing investments, credit cards or other loans. The inventory based approach of Baumol (1952) and its application to credit cards by Brito & Hartley (1995) give more insights into this cost optimization problem. Note, that similarly to these papers, the transactional use model presented in the current chapter directly determines the total cost of financing a consumption stream, so it would be possible to continue the modeling exercise and identify the optimal level of cash held by a household. However, this is not necessary to perform the empirical analysis of the current chapter, so it is left for future research, as more assumptions would be required about the finances of households. Simply stated, the current chapter takes exogenously the level of cash and only focuses on the question whether it is profitable to use credit card or not to finance consumption.

In longer term, the household may fine tune the level of cash balances taking into consideration the cost savings achieved by credit card financing, but this longer term adjustment is left out of scope.

The main intuition is that intertemporal consumption optimization and portfolio choice is likely to be decided as first priority and first in time, given the large implications of these decisions on total consumer welfare. The decision of how to finance the transactions is likely to be of second order, because of the smaller pecuniary cost involved (probably a few hundred dollars per year).

2.3 The Data

For the empirical analysis in the next section, two U.S. household surveys are used. First, four waves of the Consumer Expenditure Survey (2004-2007 CEX) are combined. This is the widest consumption survey data in the U.S., a rotating panel of close to 5,000 observations per wave. Households are required to report in detail their monthly dollar expenditures for a 12 month period, together with major socio-demographic, income and credit details. The main power of the CEX is the monthly rhythm of expenditure collection which allows the researcher to analyze monthly seasonality. Furthermore, the CEX contains detailed expenditure distribution providing data for about 600 expenditure categories (so called UCC classification) in major categories like Food or Entertainment, etc.

From the CEX, only those households are selected that did not vanish from the panel through attrition, as the credit statistics are only asked during the last interview. This restricts the sample to 15,120 households. Furthermore, a small percentage of households have missing values for any financial assets (checking accounts, savings accounts or securities), which is treated as non-response. After excluding these observations, 12,699 households remain in the sample. In the empirical analysis the CEX weights are not used as those are not clearly justifiable in the case of using observations from a period other than a calendar quarter, see for instance Dynan et al. (2004) and their references.

The second data source of the chapter is the triennial Survey of Consumer Finance (SCF), which is a cross section of about 5,000 households with rich data on savings and credit facts and attitudes. The latest available wave, 2007 is used in this chapter, with 4,418 sample observations. A significant portion of the SCF contains missing data on certain variables, but quite often this problem is limited only to household income and its components. As household income itself is one of many equally important explanatory variables used in the current analysis, instead of using more sophisticated imputation techniques, from the five imputations (so called *implicates*) simple arithmetic averages are calculated, and the analyses are performed for these averages. The SCF reported population weights are also averaged over the implicates.

Note, that according to Zinman (2007*b*), households in the Survey of Consumer Finances (SCF) are likely to underreport their credit holdings. In the Consumer Expenditure Survey (CEX) households report *even less* credit card debt that in the SCF. Hence, this underreporting problem is probably also an issue in the CEX. Consequently, all parameters and marginal effects estimated in this chapter may potentially be downward biased. Luckily, this fact is not likely to change neither the significance of the parameter estimates nor the relative relationship between them.

2.4 Empirical Results

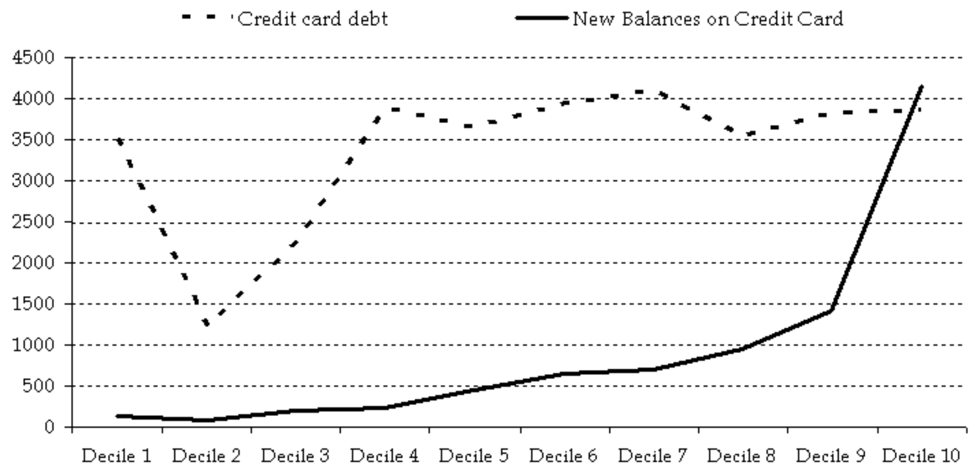
Let us first review two stylized facts about the transactional use of credit cards. First, Figure 2.2 shows the average credit card debt (total balance still owed after the last payments were made, also called as revolving debt) and the new balances (new monthly charges) on credit cards as a function of net worth, based on the SCF data. Decile 1 consists of the negative net worth households, and looking through the lens of the life cycle model, one would expect that a large portion of credit card debt is concentrated in this decile. To the contrary, credit card indebtedness is only low in the second and third deciles (probably reflecting some liquidity constraints or the resistance of low-income households to participate in the credit markets), but reverts back close to \$4,000 in the higher net worth classes. The credit card indebtedness of the richest net worth class that consists mainly of dollar millionaires, also seems to be puzzling. This is a special feature of credit cards: while only 10.4% of total credit card debt is held by Decile 1 households, the same negative net worth class holds 63.8% of other unsecured debt (personal loans, installment loans, etc).[13] On the other hand, Figure 2.2 also shows that new balances start to increase from Decile 3, and becomes extremely large in the case of the richest.

Second, Table 2.4 shows the distribution of average credit card balances[14] and the 12-month overall financial charges (interest paid) based on the CEX database. The horizontal axis of the cross table shows three equally sized groups defined by the dollar amount of the 12-month total consumption expenditure. The vertical axis shows three equally sized groups representing the level of "net asset", defined

[13]One would argue that the revolving debt may not reflect the actual debt burden, if the higher net worth households are provided with lower (even zero) interest rates. However, this point is not valid. The average interest rate weighted by the amount of revolving debt falls into the tight interval of [11.0%,12.7%] in the deciles except of Decile 9 with the value of 9.7%. This small variation without a systematic trend does not change largely the distribution of the interest paid.

[14]This is defined as the average of credit card balances observed at the end of the third month and at the end of the twelfth month of the observed one year period.

Figure 2.2: Average credit card debt and new balances by net worth deciles



N=4,418

as the sum of the 12-month income and of the financial assets at the beginning of the period less the 12-month consumption expenditure. If the net asset is positive, the household had enough assets (financial assets and income) to fund its consumption. Otherwise the household had to sell some illiquid assets or had to borrow, for instance on its credit card. Consequently, the life cycle model predicts that low net asset households borrow on credit cards (for instance the young), while the level of consumption itself is less important in the borrowing decision, as it is driven by the level of income, and the rich households should be merely blown up versions of the poor. To the contrary, Table 2.4 shows that the level of net asset does not drive credit card balances or indebtedness as much as the level of consumption. The highest consumption segment accumulates at least four times as much credit card debt as the low consumption segment, while variation by net asset is almost invisible.

Both large new balances of the higher net worth groups in the SCF and large average balances of the higher consumption groups in the CEX point towards the importance of credit card as a transactional tool to finance a portion of consumption and exploit the associated benefits. Also, the fact that credit card charges (interest paid) show similar pattern than balances, provide the intuitive appeal towards the previously presented model of transactional use, according to which the large benefits and/or some uncertainty in the realization of the benefits may lead to *ex post* borrowing behavior. The next empirical sections provide further justification for this intuition.

Table 2.4: Average credit card balances and financial charges by consumption and net financial assets

	Low Consumption	Medium Consumption	High Consumption
		Balance	
Low Net Asset	612	1,891	4,189
Medium Net Asset	985	2,613	4,813
High Net Asset	749	2,002	3,604
		Charge	
Low Net Asset	51	143	342
Medium Net Asset	78	209	330
High Net Asset	64	184	277

N=12,669. Consumption thresholds ($29,265 and $53,639) and net asset thresholds ($2,534 and $29,766) are defined to split the sample into three-three equally sized groups.

2.4.1 The CEX Cross Section Analysis

This section intends to analyze households without life cycle borrowing need, to be able to focus purely on the transactional credit card use. Let us define the group of "individual investors" as those households that satisfy all the following conditions:

- Have higher financial assets (checking or savings accounts as well as securities) than the sum of their outstanding credit card balances and the dollar amount of their 2-month consumption.
- Have higher income than consumption during the 12-month observation period (so are savers by definition).
- Did not purchase any housing property during the 12-month period (the potential purchase is not included into the consumption expenditures so may lead to a large drop in financial wealth).
- Have at least $1,000 12-month income.

The first three assumptions are designed to filter out households that are very unlikely to face a situation, during the 12 month period, in which they are unable to finance their consumption expenditure from their income or from their liquid asset holdings. Note, that these households have high enough assets to be able to pay back their credit card debt and still hold some precautionary balances. The last point excludes a small portion of very low income households. 2,384 households satisfy these conditions, which represents 18.8% of the total population. While this portion is relatively small due to the tight definition of transactional credit card users, the credit card behavior of this population may be partially extrapolated to those households who use the credit cards both for life cycle and transactional purposes.

In the empirical analysis, consumption, financial assets and income serve as explanatory variables together with a set of households characteristics, specifically the average age of the household head and spouse, age squared, dummies for high school and university education, for African-American and Hispanic origin and gender of the household head, dummies for region (Northeast, South and West), and settlement type (whether the household lives in city or in a Metropolitan State Area), number of earners and dependents in the family and a dummy for household ownership. Table 2.5 contains summary statistics for these variables both for the analyzed individual investors as well as for the remaining households. Not surprisingly, the average investor household is more wealthy, consumes more, is a house owner more frequently and consists of slightly older but more educated individuals. Surprisingly, the investors hold very similar credit card average balances and pay similar interest charges as the remaining population.

To see whether the investor group behaves according to the implications of the transactional credit card use model, the following Tobit type model is estimated:

$$L_i^* = \beta_0 + \beta_1 C_i + \beta_2 Y_i + \beta_3 F_i + \sum_{k=1}^{K} \gamma_k X_{ik} + \varepsilon_i$$
$$L_i = L_i^* \ if \ L_i^* > 0; \ L_i = 0 \ otherwise$$

where L_i stands for credit card balances and interest paid, C_i is the 12-month consumption expenditure, Y_i is the 12-month income, F_i is the dollar amount of financial assets at the beginning of the 12-month period and X_{ik} represents the set of household controls defined earlier. As the monetary variables are measured in dollars, here robust standard errors are calculated to correct for the potential heteroscedasticity of the error term.[15]

Columns (1) - (4) of Table 2.6 restate the finding of the stylized facts – *i.e.,* consumption is correlated with credit card balances and charges more than available financial assets, just as shown by the large significant parameter of consumption.[16] In Column (1) and (2), that represents the Tobit type model without the household controls, both $\beta_1 = \beta_2$ and $\beta_1 = \beta_3$ can be rejected with F-tests at the 5% significance level. These results hold in Column (3) and (4) as well, when the household controls are added. Simply stated, even a compensated consumption

[15]The empirical analysis is implemented in Stata 10 and the "robust" option of the "tobit" model is used.

[16]Note, that due to the cross section data structure, the term "correlation" should be used instead of "causality", following related literature, such as Zinman (2009). Nevertheless, the inclusion of important control variables later on as well as the difference-in-difference estimation will justify the casual relationship.

Table 2.5: Summary Statistics (mean values) for Individual Investors and Other Households

	Individual Investors	Other Households
Number of households	2,384	10,285
Consumption	\$59,432	\$47,076
Income	\$94,769	\$52,973
Checking account balance	\$16,008	\$3,045
Savings account balance and bonds	\$45,786	\$6,147
Stocks and mutual funds	\$119,478	\$19,494
Socio-demographic controls		
Male	56%	45%
Age	53.9	50.0
High School	40%	56%
University	55%	29%
Black	4%	12%
Hispanic	4%	13%
City	95%	93%
Metropolitan state area	91%	87%
Northeast	20%	17%
South	28%	36%
West	24%	23%
Number of earners	1.2	1.0
Number of dependents	1.2	1.6
House owner	90%	70%
Credit card statistics		
Average balance	\$1,991	\$2,407
12-month financial charges	\$183	\$183

Interpretation of the percentage values: for instance, 56% of households classified as Individual Investors have a male household head.

increase (with income or asset increase) raises indebtedness. The transactional credit card use model provides several reasons for this behavior: households use their credit card as frequently as possible (so proportionally to consumption) to gain immediate benefits like cash back or to delay or even avoid the liquidation of investments.

Furthermore, one may observe that compared with the credit card charges, the balances are more sensitive to consumption changes relative to income changes. The β_1/β_3 ratio drops from 4 to -1 in Column (3) to 2.5 to -1 in Column (4). This finding again matches the implications of the theoretical model. When facing a consumption increase, the cash rich population (earning very high income or holding high checking account balances) uses credit card more often if they can get positive b marginal benefits by doing so, while this population should not revolve (there are no further benefits of revolving), and neither should react to marginal income or asset changes (they hold large cash balances to tackle with that).

So far no proxies were used in terms of the expected rate of return on investments, however, in Section 3 this was shown to be one of the most important drivers of transactional use. A further shortcoming of the previous reduced form analysis is that it is very difficult to disentangle the transitory versus permanent components of income and consumption, while those two have different empirical implications. For instance, a transitory consumption shock should induce immediate credit card usage, while a permanent increase in the level of consumption gives opportunity to the investor to balance its portfolio towards cash and so reduce the benefits of credit card use. Fortunately, the CEX gives opportunity to enrich the previous models with several more specific explanatory variables. Let us reformulate the Tobit type model to

$$L_i^* = \beta_0 + \beta_1 C_i + \beta_2 Y_i + \beta_3 F_i + \beta_4 D_i^{St} + \beta_5 D_i^{Sav} + \beta_6 D_i^{H} +$$
$$+\beta_7 D_i^{X5} + \beta_8 D_i^{R5} + \sum_{k=1}^{K} \gamma_k X_{ik} + \varepsilon_i$$
$$L_i = L_i^* \ if \ L_i^* > 0; \ L_i = 0 \ otherwise$$

where the added variables D_i^{St} and D_i^{Sav} are indicator variables with the value of one if the household has positive savings account balance or stock holding, respectively. Note, that in the CEX stocks and other risky securities such as mutual funds are not distinguished, simply referred to as "stocks" in this section for the sake of simplicity. As an unexpected consumption shock, a health shock dummy D_i^H is generated, with the value of one if health expenditure is higher than \$2,500 in any of the 12 observed months. Finally, as an expected consumption shock, the D_i^{X5}

Table 2.6: Correlations Between Credit Card Balance/Charge and Drivers of the Transactional Use.

	Balance	Charge	Balance	Charge	Balance	Charge
	(1)	(2)	(3)	(4)	(5)	(6)
C_i	.058 (.008)*	.015 (.003)*	.041 (.008)*	.012 (.003)*	.026 (.008)*	.008 (.003)*
F_i	-.002 (.0004)*	-.0009 (.0002)*	-.001 (.0004)*	-.0007 (.0002)*	-.001 (.0004)*	-.0008 (.0002)*
Y_i	-.008 (.004)*	-.004 (.002)*	-.010 (.004)*	-.005 (.002)*	-.008 (.004)	-.004 (.002)*
D_i^{St}					1475.898 (326.668)*	545.679 (113.410)*
D_i^{Sav}					192.989 (529.826)	111.323 (153.398)
D_i^{H}					1549.246 (799.738)	288.400 (177.425)
D_i^{X5}					709.004 (332.898)*	277.085 (117.742)*
D_i^{R5}					1300.777 (388.536)*	232.402 (128.859)
High School			2095.289 (711.673)*	404.372 (239.214)	1655.744 (687.838)*	231.850 (238.667)
University			1842.278 (741.613)*	311.092 (251.086)	1141.475 (721.610)	62.884 (250.575)
Male			-444.420 (305.464)	-130.016 (106.253)	-430.288 (301.901)	-128.085 (105.542)
Age			289.580 (71.253)*	87.273 (25.392)*	248.180 (70.616)*	72.513 (25.012)*
Age squared			-2.994 (.689)*	-.883 (.240)*	-2.631 (.682)*	-.749 (.237)*
Black			1173.594 (689.180)	582.835 (308.230)	1509.993 (678.087)*	707.307 (311.741)*
Hispanic			1186.438 (622.495)	22.354 (252.942)	1327.666 (624.331)*	85.516 (257.974)
City			489.988 (993.465)	489.544 (363.359)	440.525 (986.386)	499.589 (364.934)
Metropolitan state area			643.730 (838.814)	-21.613 (298.727)	549.343 (832.121)	-57.963 (299.283)
Northeast			467.042 (459.548)	-365.001 (167.478)*	568.343 (458.034)	-323.598 (167.649)
South			244.619 (437.429)	-341.182 (162.609)*	325.285 (424.964)	-318.848 (161.439)*
West			440.084 (447.033)	-39.303 (149.300)	444.870 (437.812)	-34.440 (149.166)
Number of dependents			250.760 (154.560)	52.527 (46.779)	150.898 (149.663)	30.784 (45.412)
Number of earners			782.596 (307.464)*	222.433 (100.382)*	614.889 (300.501)*	174.150 (98.603)
House owneship			154.928 (458.241)	-300.775 (192.927)	-126.868 (455.510)	-396.711 (196.290)*

N=2,384. Robust standard errors are in parentheses. T-tests are shown with (*) if they are significant at the 95% significance level.

dummy is generated, which has the value of one if the sum of consumption in December is higher than \$500 in the following five consumption categories: apparel, major appliances, entertainment, audiovisual equipments and finally, household furnishing. The basis of the selection is that these categories have the highest seasonal peak in December based on the CEX. As a control variable, D_i^{R5} is one if the household's consumption expenditure in the same five categories is higher than \$500 in a randomly selected month other than December.

Columns (5) and (6) of Table 2.6 contain the results of this enhanced model specification. The most important result of this chapter is that *ceteris paribus,* stock ownership increases both credit card balances and credit card indebtedness, just as shown by the parameter of D_i^{St}. The parameter of savings is positive but insignificant, and with an F-test $D_i^{St} = D_i^{Sav}$ is rejected at the 5% significance level both in the case of credit card balances and charges (the F-tests have the value of 4.6 and 5.8, respectively). The large positive impact of stock ownership is a direct consequence of the transactional credit card use model. First, stock owners have higher explicit transactional costs than savings or checking account holders. Second, and more important, stock owners have high future expectation on the rate of return on their investments, so may be reluctant to sell the stocks to pay for consumption or credit card balances at the end of the grace period.

The positive significant parameter of D_i^H shows that this unexpected consumption shock increases both credit card balances and credit card debt. This is true by including the level of consumption (C_i), which already contains the health shock, so the impact of the dummy is not tautologous. The increase of balances may be the simple consequence of running out of cash in the case of a health shock as well as the impact of previous revolving balances generated by a potential previous health shock. The larger financial charge payments may be the result of multiple mechanisms. First, it may happen that an *ex ante* convenience user faces the health shock during the grace period, so he can not use its grace period savings to pay for previously accumulated credit card balances. Second, even if the health shock hits the consumer during the billing cycle, the household may revolve if the benefit of that move is higher than its cost. Finally, in the case of a transitory health shock it is more likely that the household will be able to save during the grace period enough cash to pay back at least a portion of credit card balances as opposed to a permanent consumption shock.

The final added variable is related to seasonality. The seasonal fluctuation of consumption and credit card debt is a well know empirical fact. In terms of consumption, there is some research of seasonality, see for instance the work of Miron (1986). However, there is not much research on the seasonality of credit card debt (or any other debt). Appendix B contains some facts and figures about this topic, motivating further investigation in this area.

In the model of transactional credit card use, seasonality is interpreted as an expected consumption shock. In the highlighted five consumption categories, such as apparel, U.S. households spend a lot before Christmas, for themselves as well as for other family members and friends. Specifically, 50% of households reach the \$500 threshold expenditure in December in the five categories, while this portion is only 33% for an other random month. However, as the Christmas period arrives every year, this higher consumption is not a surprise, so a rational household should prepare for it in advance. Consequently, high consumption in the seasonal five categories should have similar impact than high consumption in an other random month. In Table 2.6, both the D_i^{X5} and D_i^{R5} dummies have significant positive impact on credit card balances and debt. This result matches expectations, as many of the selected products and services can be purchased for instance in convenience stores where credit card payments are more general. However, an interesting finding is that relatively to the random month, the December expenditure dummy drives *less* the credit card balances, but has a stronger impact on charges. Simply stated, households use less often their credit card to finance their December consumption of apparel, major appliances, etc. but revolve with this debt more frequently. This is surprising as credit card companies schedule their promotions typically before Christmas, so the opposite relationship would be more plausible. Fortunately, the transactional use model of this chapter provides justification for this phenomenon. The preferred explanation is the potential existence of sophisticated time-inconsistent households. Large advertising campaigns before Christmas and low price post-Christmas clearances direct households toward present consumption during the holiday season. The potential present bias in intertemporal consumption may be associated with a present bias in the transactional decisions as well. Additionally, as the grace period includes the holiday season, the individuals spending their well deserved yearly holidays may pay less attention to the credit card repayments, or use more credit cards in December, leading to a higher attention cost of the repayment that raises the probability to revolve. This attention cost also can be interpreted as immediate gratification, leading to low β preference parameter. If the time-inconsistent households are sophisticated, they may refrain from the credit card use during the holiday seasons, as they correctly expect to be *ex post* revolvers more often. The self-control efforts of not using the credit card together with the higher revolve rates in case of usage explain exactly the observed data pattern. Unfortunately, more information would be necessary to unambiguously justify this reasoning, as it may be possible to construct alternative explanations.

A final evidence in favor of the transactional model is the investigation of the interactions between the identified model drivers. It was shown that the stock ownership and the health shock dummies increases credit card use, and the December consumption dummy is associated with lower usage rate but higher revolve rate.

The Tobit type model containing these dummies was extended with three interaction terms between these three dummies (results not reported in detail). In the case of credit card charges, the interaction term between stock ownership and the health shock became positive and significant, though only at the 10% significance level. The t-test value is 1.9, which is close to the threshold of the required 5% significance level and consequently it is evaluated as a weaker, but still interpretable relationship in the case of an interaction term. This correlation arises from Inequality 2.1 that shows the condition to revolve with credit card debt: a health shock during the grace period decreases σ_2 saving rate, while stock ownership raises π_3 expected rate of return. One can see that these two terms are negatively interacted in Inequality 2.1, so the positive parameter for the product of the two dummies is justified by the simple model. Also in the case of the credit card charges, the interaction term between stock ownership and the December consumption dummies is negative and significant at the 5% significance level (t-test is -2.0). Intuitively, the stock owners who have large consumption in December, accumulate lower credit card debt. This finding can also be related to self-control considerations. Stock owners know that they have higher tendency towards revolving with credit card debt, and a potential present-bias in their transaction decision leads to larger welfare loss compared with households without stocks. As a result, sophisticated stock owner households restrict their card usage during the holiday seasons, leading to both lower balances and lower financial charges paid. Note, that in the model that estimates charges, the interaction term between the health shock and the December consumption dummy is small and insignificant, while all the three interaction terms in the balance model have similar sign than in the charge model, but are statistically insignificant.

Through the calculation of marginal effects it is possible to summarize the most important findings of this section. Stock ownership is associated with 17.3% of credit card balance changes and 31.3% of charge changes. The higher impact of stock ownership on financial charges matches the model predictions, in which the revolving decision is the most sensitive to the π_3 rate of return. Consequently, this cross section analysis indicates that stock ownership is responsible for almost a *third* of financial charges paid by the relatively rich households that use credit cards mainly for transactional purposes. The marginal effect of health shock is much smaller (explains 2.6% of balances and 2.8% of financial charges). Nevertheless, health shock is only one of many potential unexpected consumption shocks, so the overall impact of consumption uncertainty on credit card indebtedness may be large. High consumption in the selected five expenditure categories in December explains 8.9% of credit card balances, which is smaller than the impact of high consumption in an other month. Finally, the December dummy explains 15.8% of credit card financial charges, which number is economically large and almost twice as much as the impact of high consumption in an other month. As previously discussed, time-inconsistent decision making is believed to explain a portion of this large marginal effect.

2.4.2 Difference Analysis of Credit Card Balances in the CEX

The findings of the previous section suffer some potential shortcomings. For instance, it may be that some unobserved preferences drive the credit card usage and the stock ownership in parallel. As in the CEX credit card balances are observed both after the third and the twelfth month – *i.e.,* at the end of first and the last quarter of the 12-month observation period, it is possible to estimate balance differences to strengthen the previous results. Unfortunately, this exercise can be only performed for balances, as yearly financial charges are reported only at the end of the 12-month period.

Similarly to the cross-section analysis, balance differences are estimated with a Tobit type model

$$\Delta L_i^* = \beta_0 + \beta_1 \Delta C_i + \beta_2 \Delta Y_i + \beta_4 \Delta D_i^{St} + \beta_5 \Delta D_i^{Sav} + \beta_6 \Delta D_i^{H} +$$

$$+ \beta_7 \Delta D_i^{X5} + \beta_8 \Delta D_i^{Y5} + \beta_9 \Delta D_i^{Xmas} + \beta_{10} \Delta E_i + \beta_{11} \Delta F_i + \varepsilon_i$$

$$L_i = L_i^* \; if \; L_i^* > 0; \; L_i = 0 \; otherwise$$

Though the interpretation of the variables is similar to the cross section analysis, the definitions change slightly. ΔC_i is the difference between the total consumption in the twelfth month and the third month. ΔY_i is the difference between income reported after the the twelfth month and the third month. The reported income has a yearly retrospective time frame, so the two observed amounts are overlapping. As the number of new entrants to the stock or saving market is small during a year, ΔD_i^{St} has the value of 1 if the household is a net buyer of stocks during the one-year period (the value of purchased stocks is higher than the value of sold stocks), while ΔD_i^{Sav} is one if the savings balance at the end of the 12-month period is higher than 1.1 times the balance at the beginning of the period.[17] According to these rules 10.7% of the population has new stock investments, while 18.8% has new investments on savings accounts. ΔD_i^{H}, the health shock dummy difference variable has the value of 1 if the household has at least \$1,000 higher health expenditure in the twelfth month as in the third month, has the value of -1 if the household has at least \$1,000 less health expenditure in the twelfth month

[17] While in the case of stocks the purchases and sales of securities are reported, in the case of saving accounts only two balances are observed at the beginning and at the end of the 12-month period. The multiplier 1.1 is used to avoid to classify those households that earned a modest one digit rate of return on their investment as new savers.

as in the third month, and zero otherwise. Compared with the cross-section analysis, the threshold used to identify a change in the shock became lower in order to achieve significant number of observations. ΔD_i^{Y5} variable is similarly generated as the health shock variable, but taking into account the consumption of the five selected categories (apparel, major appliances, etc.) and using the difference threshold of \$250. ΔD_i^{Xmas} variable represents the difference between the two dummies indicating whether the twelfth month or the third month falls in December. ΔD_i^{X5} interaction term is one if $\Delta D_i^{Y5} = 1$ and $\Delta D_i^{Xmas} = 1$, has the value of -1 if $\Delta D_i^{Y5} = -1$ and $\Delta D_i^{Xmas} = -1$, and is zero otherwise. This interaction term shows whether a significant consumption increase in the five categories coincides with December. As the large majority of socio-demographic controls are fairly stable over time, only two controls are included into the model: ΔE_i represents the change in the number of earners, while ΔF_i the change in the number of dependents between the twelfth and the third month.

Column (1) of Table 2.7 shows the estimation results of the model with robust standard errors. The estimated parameter of ΔC_i is significant at the 5% significance level, while the impact of income change is negligible, supporting again the important role of the level of consumption in the transactional use model. The estimated parameter of the new stock purchase is significant and large, and with an F-test, that has the value of 4.71, the equality of the parameter of the stock and the saving investments can be rejected at the 5% significance level. Simply stated, those who shift their investment portfolio towards stocks become more active in the credit card market as well. The ΔD_i^H health shock dummy in difference has large and significant impact on credit card balance differences, even if it is already contained in ΔC_i. Unfortunately, the consumption in the seasonal expenditure categories is very noisy, so it was not possible to replicate the significant cross-section results. However, the larger positive sign of the parameter of ΔD_i^{Y5} and the very small but negative sign of the estimated parameter of ΔD_i^{X5} are in line with the findings of the cross-section analysis.

The rich data set of the CEX gives opportunity to perform a further important analysis. As the yearly change in the market value of stocks is reported together with the dollar value of stock purchases and stock sales over the year, it is possible to derive a 12-month market capitalization gain variable. According to the model of transactional credit card use, the higher the expected rate of return on investments, the higher the incentive to use credit cards to delay the liquidation of investments. While the expected returns are unfortunately unobservable, it is possible to check the impact of the historical returns on credit card balances. For this purpose, two indicator variables are derived: D_i^{Gain} is one if the 12-month historical return on stock (and mutual fund) investments is higher than 5%, and zero otherwise (37% of stock owners in the investor sample), while D_i^{Loss} is one if the same investments experience 20% loss over the same period (this criterium

Table 2.7: Difference Analysis of Credit Card Balances

	(1)	(2)
ΔC_i	.069 (.024)*	.089 (.031)*
ΔY_i	.007 (.006)	.013 (.008)
ΔD_i^{St}	1685.507 (697.693)*	1304.219 (884.992)
ΔD_i^{Sav}	-164.539 (560.086)	-1283.498 (806.569)
ΔD_i^{H}	2773.274 (1198.352)*	4659.109 (1929.823)*
ΔD_i^{Y5}	292.408 (345.646)	366.941 (496.129)
ΔD_i^{X5}	-28.518 (1079.082)	-211.384 (1635.397)
ΔD_i^{Xmas}	1054.781 (586.435)	1081.177 (922.982)
ΔE_i	-2230.916 (748.753)*	-2411.965 (1043.468)*
ΔF_i	-1118.573 (275.071)*	-970.826 (395.912)*
D_i^{Gain}		1898.533 (716.851)*
D_i^{Loss}		2190.374 (1284.476)
N	2384	1200

Robust standard errors are in parentheses. T-tests are shown with (*) if they are significant at the 95% significance level.

characterize 7% of the stock owner sample). Column (2) of Table 2.7 is a similar Tobit type model to the one presented in Column (1), but now the explanatory variables include the two indicators about past stock returns and the model is only run for the stock owner subsample (N=1,200). The results may be slightly surprising at first sight: not only the market value gain but also the market value *loss* dummy leads to higher credit card balances. Fortunately, the estimated parameter of the gain metric is significant, while the parameter of the loss metric is not different from zero at the 5% significance level. Nevertheless, the large positive size of the estimated parameter of D_i^{Loss} (which is larger indeed than that of D_i^{Gain}) together with a t-test close to the critical value require some further justification.

According to the transactional model of credit card use, higher future expectations of the rate of return is required to accumulate higher credit card balances. Higher return expectation for those who gained historically on the market may arise from the momentum effect – *i.e.,* the empirically observed positive correlation between short term stock prices. Also, standard asset pricing theory predicts that the level of risk aversion determines the portfolio choice and the expected rate of return, and the more risk taking households with higher return expectations also gain higher historical rate of return in average. The level of risk taking also may explain the weak positive impact of the D_i^{Loss} dummy: those who decide to hold a more risky portfolio, end up more frequently in the red. So those 7% of households who lost a fifth of their stock investments in a year may belong to the risk seeking population that has high future rate expectations, so uses more frequently its credit card. However, it also may be that the lack of diversification, which is an important investment mistake identified by Campbell (2006), lays behind the bad stock market performance of these 7% of households. Other than the level of risk that households face, Section 3.1 introduced rational and irrational theories behind the negative correlation between uncertain stock prices (for instance the existence of target sales price or prospect theory), which could also justify why the drop of market capitalization can be followed with higher rate of return expectations. The analysis of the SCF data intends to go one step further to exploit this question.

To sum up this section, there is strong empirical evidence in favor of the facts that stock ownership, consumption shocks, high rate of return expectations and the level of consumption in general has a large positive impact on the credit card usage of individual investors. However, the December exercise and the analysis of stock market losses indicate that the inherently rational transactional use decision may also suffer from irregularities explained by non-standard theories.

2.4.3 The SCF Cross Section Analysis

Similarly to the CEX analysis, this section defines first the group of "individual investors" who are unlikely to use credit card for life cycle purposes. The conditions that this group needs to satisfy are:

- Have higher financial assets (checking or savings accounts as well as securities) than the sum of their outstanding credit card balances and the dollar amount of their self reported precautionary savings amount.

- If during the last 12-month the household had negative savings then they did not apply for any kind of loans to make up the difference between income and spending. All households with non-negative savings are included.

- The households hold at least one credit card.

- The households have at least \$1,000 12-month income.

An advantage of the SCF is that it asks specifically the level of necessary precautionary money balances of the households. So even with no consumption data, it is possible to infer which households have satisfactory investments to pay back their credit card debt (if any) and still hold enough money to fund consumption emergencies. The second point exploits a specific question about last year's savings that can be used to exclude a further set of life cycle borrowers. The sample is restricted only to credit card holders, as vast majority (more than 90%) of households satisfying the first condition hold at least one credit card, and this way some credit card specific variables can be also used in the analysis. The last point excludes a small portion of very low income households, similarly to the CEX sample. Using the population weight of the SCF, it can be seen that this investor definition filters out 36.4% of households, who hold only 19.3% of credit card debt (revolving balances left after last payments) but generate 68.4% of new balances (new purchases made in the last billing cycle), which statistics intuitively are aligned with the definition of a transactional credit card user. Table 2.8 contains the summary statistics of investors and non-investors. Comparing the SCF with the CEX, one may notice that the investor criteria hereby identify a larger portion of the population; the SCF investor group has higher income and financial assets, but very similar credit card balances. The data asymmetries arise from the more accurate wealth data collected in the SCF, especially in the top wealth decile. The comparison of investors and non-investors in terms of socio-demographics leads to same conclusions as in the CEX analysis.

After the careful definition of investors, this section estimates credit card new balances and revolving balances with a Tobit type model similarly to the CEX data analysis. The model specification is:

$$L_i^* = \beta_0 + \beta_1 C_i + \beta_2 Y_i + \beta_3 F_i + \beta_4 NF_i + \beta_5 D_i^{St} + \beta_6 D_i^{Bond} +$$

Table 2.8: Summary Statistics (mean values) for Individual Investors and Other Households

	Individual Investors	Other Households
Weighted # of households	42 million	74 million
Precautinary Savings	$28,367	$20,868
Income	$143,054	$52,124
Checking account balance	$9,548	$2,092
Savings account balance	$49,286	$3,452
Bonds	$26,995	$680
Stocks	$104,364	$2,729
Non money market mutual funds	$92,620	$2,683
Socio-demographic controls		
Male	78%	69%
Age	53.2	48.5
High School	49%	39%
University	20%	7%
Black	7%	15%
Hispanic	5%	12%
Married	66%	55%
Number of kids	0.7	0.9
House owner	83%	61%
Credit card statistics		
New balance	$1,685	$445
Revolving balance	$1,753	$4,177

Interpretation of the percentage values: for instance, 78% of households classified as Individual Investors have a male household head.

$$+\beta_7 D_i^{Mut} + \beta_8 D_i^{Sav} + \sum_{k=1}^{K} \gamma_k X_{ik} + \varepsilon_i$$

$$L_i = L_i^* \; if \; L_i^* > 0; \; L_i = 0 \; otherwise$$

where C_i, Y_i and F_i refer to consumption, income and financial assets, respectively. Income and financial assets are similarly measured as in the CEX database, but the SCF unfortunately lacks an accurate metric of total consumption, so the amount of precautionary savings (used also to indentify investors) is used as a rough estimation. As the SCF collects rich data on non-liquid assets (such as housing or vehicles), the dollar value of all these assets is also included in the model (denoted by NF_i). D_i^{St}, D_i^{Bond} D_i^{Mut} and D_i^{Sav} refer to the indicator variables with the value of one if the household owns stocks, bonds, mutual funds (excluding money market mutual funds) or has positive savings account balances (including money market mutual funds), respectively. This means that the Survey of Consumer Finances distinguishes between more financial asset types than the CEX, leading to a more informative inference. X_{ik} is a set of household controls, including almost identical socio-demographic characteristics to the CEX analysis.

Columns (1) and (2) of Table 2.9 show how credit card new balances and revolving balances depend on assets, controlled with socio-demographics. These results are comparable with Columns (3) and (4) of Table 2.6 that used CEX data. One major difference is that due to the lack of a good proxy for consumption in the SCF data, the negative impact of income and assets on credit card statistics switches to a positive relationship. This is due to the fact that consumption itself depends positively on income, financial and non-financial assets, so the estimated parameters include the highly positive effect of consumption. More importantly, stock ownership is a significant positive driver of both new balances and revolving credit card debt, which reinstates the results of the CEX analysis. This finding is in line with the transactional model of credit card use, as stock owners expect the highest rate of return on their investments so they pay purchases frequently with credit cards and sometimes even revolve with their balances. The ownership of mutual funds, which represents the other major risky asset type, also has a positive significant impact on new balances, but this impact is not significant in the revolving balance model. As the mutual fund rate of return expectation is typically lower compared with stocks, this empirical fact also fits the predictions of the theoretical model. Bond ownership and the existence of positive balances on savings accounts do not alter the level of credit card balances or debt, as these are low risk financial products providing low interest. The insignificance of the estimated parameter of the bond indicator suggests that the transaction cost (which should be larger for bonds than for savings accounts, as these latter frequently provide checking options) is not such an important driver of the transactional use of credit cards as the expected rate of return.

Table 2.9: Correlations Between New Credit Card Balance / Revolving Balance and Drivers of Transactional Use Based on the SCF

	New	Revolving	New	Revolving	Revolving	New	Revolving
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
C_i (Precautionary savings)	.0007 (.0003)*	-.0009 (.002)	.0004 (.0003)	-.003 (.004)	-.003 (.004)	.0007 (.0003)*	-.0003 (.002)
Y_i	.0009 (.0003)*	.0003 (.0003)	.0008 (.0002)*	.0003 (.0003)	.0003 (.0003)	.0005 (.0002)*	.00004 (.0005)
F_i	.0002 (.00005)*	-.0009 (.0003)*	.0002 (.00005)*	-.0008 (.0003)*	-.0007 (.0003)*	.0001 (.00004)*	-.001 (.0006)
NF_i	.0001 (.00003)*	.00002 (.00005)	.0001 (.00003)*	2.26e-06 (.00005)	1.91e-06 (.00005)	.0001 (.00003)*	-.00006 (.0001)
D_i^{St}	804.540 (181.824)*	1609.415 (661.951)*	568.118 (174.882)*	1317.860 (617.010)*	709.789 (670.810)		
D_i^{Bond}	-9.927 (186.393)	875.070 (644.830)	-18.610 (176.712)	219.484 (607.311)	258.278 (603.623)	-220.336 (310.692)	1051.604 (1361.107)
D_i^{Mut}	663.460 (199.416)*	402.382 (766.196)	493.961 (190.315)*	280.457 (700.824)	217.526 (703.812)	284.654 (325.873)	-1283.257 (1555.554)
D_i^{Sav}	304.041 (191.751)	-979.403 (760.008)	126.059 (186.238)	-756.240 (740.212)	-663.395 (742.625)	-246.257 (365.919)	-2235.500 (1975.421)
Number of credit cards			135.012 (34.100)*	546.722 (100.435)*	521.574 (99.123)*	245.954 (54.639)*	973.079 (199.334)*
Credit card interest rate			70.637 (14.726)*	-238.337 (52.833)*	-128.893 (63.967)*	89.062 (27.748)*	-412.542 (126.390)*
Limit on credit cards			.007 (.004)	.008 (.004)	.007 (.004)	.005 (.003)	.004 (.004)
Planning time horizon			142.020 (58.795)*	-326.100 (211.021)	-330.568 (209.363)	369.344 (127.194)*	-1231.375 (568.939)*
Takes above average risk			637.384 (234.711)*	153.313 (819.442)	95.275 (817.092)	679.493 (540.866)	305.296 (2320.038)
Takes average risk			150.380 (177.212)	-362.273 (623.608)	-418.831 (622.418)	-256.804 (483.496)	-763.119 (2023.182)
D_i^r: interest $< 6\%$					1243.898 (1338.543)		
$D_i^r \cdot D_i^{St}$					4233.270 (1894.330)*		
D_i^{Gain}						1498.886 (425.760)*	2024.715 (1771.328)
N_i						44.414 (13.661)*	60.907 (100.047)
$D_i^{Gain} \cdot N_i$						-39.532 (17.893)*	-220.013 (128.138)
D_i^{Loss}						196.987 (396.012)	-1138.183 (1701.648)
e(N)	2141	2141	2141	2141	2141	1139	1139

Robust standard errors are in parentheses. T-tests are shown with (*) if they are significant at the 95% significance level.

The primary goal of the replication of the results already observed in the CEX data is to use the rich financial attitude information contained in the SCF to gain deeper insights. The positive impact of stock ownership to credit card indebtedness may not be a causal relationship, if both these financial decisions are driven by the same preferences or socio-demographic factors. Bilias & Haliassos (2004) show that stock ownership is mainly driven by income, wealth and age, which characteristics are already contained in the previous Tobit type models. However, Bilias & Haliassos (2004) also point out that the level of risk aversion is a vital determinant of stock ownership. So it may be that the risk seeking behavior drives stock ownership and credit card use in parallel, causing the observed correlation between these two financial decisions. As a result, two self reported risk preference indicators (whether the household is willing to take average or above average risk to gain benefits) are added to the X_{ik} variable set of the Tobit type model. Furthermore, it may be that stock owners are offered with lower interest rates and targeted with a large number of direct mail offers because of their low expected default risk. To control with the supply side effect, the number of credit cards, credit limits and interest rates as well as three risk indicators (whether the household was bankrupt previously, whether it is late with a payment on any of its loans or whether the household had a declined loan application in the last 5 years) are added to the list of explanatory variables. It may be also that the level of financial education is an unobserved variable that leads to more frequent credit card use but also to higher willingness to participate in the stock market. The SCF asks whether it is is a good idea to pay with credit cards the purchase of jewelries, vacation expenses or living expenses when income is cut. These three dummies represent positive attitude towards credit cards, hence, if stock market participation only coincides with larger preference towards credit cards, the inclusion of these preferences as explanatory variables should weaken the impact of the D_i^{St} indicator. As a final added variable, the SCF asks the time horizon of planning saving and spending of the household, which ranges from a few months (value of 1) to more than 10 years (value of 5). This question approximates well the subjective discount rate of the household, as those who plan only for a few months are putting low weight on future consumption, and have a high discount rate.

Column (3) shows the extended Tobit type model results in the case of new balances while Column (4) in the case of revolving balances. Fortunately, the added variables do not alter the significance of the D_i^{St} indicator. Though the marginal effect of D_i^{St} decrease by 29% in the case of new balances (from \$522 to \$371) and by 22% in the case of revolving balances (from \$559 to \$433), stock market participation remains a key driver of credit card balances and indebtedness.

Interestingly, some of the added financial "control" variables have their own individual importance in the decision about the way of transactions, listed hereby. For instance, while also related to banking supply, the number of credit cards is believed to be correlated with the level of immediate benefits b in the transactional credit card model. The investor households have in average 4.5 credit cards, which is high and quite difficult to justify with other reasons, such as precautionary reasons, etc. U.S. households typically activate a new card if it has a low interest or if it provides a appealing cash back / air miles promotion. Column (3) shows that the number of credit cards significantly increases the new balances, even if credit limits and interest rates are also included in the Tobit type model. Recalling the simple credit card model, large immediate benefits also trigger credit card use for those households who do have cash balances, so this result matches expectations. However, the significant positive impact on revolving balances in Column (4) is surprising, furthermore, the marginal effects of the number of cards (\$180) is more than double than in the case of new balances (\$88).

Two potential explanations of this phenomemon arise. First, those with several credit cards may transfer their balances from one card to the other, to revolve with debt at the lowest possible cost. However, some further statistics do not support the large importance of balance transfers. For instance, those with a lot of credit cards do not have actually lower interest rates so the high number of credit cards does not reflect the effort of shopping for low interest rates. Also, it is possible to run the Tobit type model only for those investors who have high, at least 15% yearly interest rate on their credit card with the best condition (40% of the total investor population). The results show (not reported in detail) that also in this segment the high number of credit cards correlates with high indebtedness (marginal effect is \$112), pointing toward the fact that balance transfer can not explain fully this empirical fact.

The second potential reason behind the large impact of the number of cards is that those who use multiple cards to accumulate more marginal benefits, simply *forget* to pay back the money by the end of the grace period on any of these accounts. This mechanism is even more likely if one thinks about a household with spouse and children who all use credit cards, and sometime leave the household head uninformed about their past spendings. The fact that the households forget to pay back the credit card debt is analogous with naive time-inconsistent preferences: during the billing cycle the households spend on multiple cards without knowing that they may forget to pay back the balance on any of those cards. Consequently, the large impact of the number of cards on credit card indebtedness may point towards the deviation from the fully rational decision process in terms of the choice of a transactional tool.

A further control variable of interest is the time horizon for financial planning: Columns (3) and (4) show that the longer planning horizon leads to higher new balances but slightly lower credit card debt. This result fits the implications of the theoretical model: higher discount rate leads to unfrequent revolving behavior, but to frequent credit card usage if the rate of return on unliquidated investments is high.

If a household takes above average risk then it accumulates significantly higher new credit card balances, but these balances do not become revolving debt. This result is in line with the assumption that risk tolerance drives future return expectations. The fact that revolving balances are not altered by risk tolerance is explained by the fact that stock ownership (already included into the Tobit type model) absorbs a large portion of heterogeneity in risk preferences.

Finally, one may observe that the impact of interest rate is positive on new balances but negative on revolving balances. While the negative price elasticity of revolving debt matches the transactional model and standard economic theory, the positive estimated parameter in the case of new balances may be surprising. A potential explanation of this is that those who have low interest rate and revolve with credit card debt, are not able to "float" new balances, as revolvers have to pay interest for any new purchase. Alternatively, a supply side driven correlation between the interest rates and the magnitude of cash back (or other immediate benefits) may exist.

Column (5) of Table 2.9 contains an important test of the transactional use model. If stock holders really hold credit cards to delay the liquidation of stock investments, then they are the most likely to do so in the presence of low interest rates. Column (5) shows the result of the Tobit type model with two additional variables: D_i^r (zero-one dummy with the value of one if the credit card interest rate is less than 6%) and the interaction between D_i^r and D_i^{St}. Interestingly, the interaction term is economically large and significant, while D_i^{St} indicator in the presence of this interaction becomes insignificant. This means that those stock owners revolve more with credit card debt who have access to cards with low interest rate, justifying the theoretical model in which the revolving decision large depends on the relationship between r and π_3.

The final two columns of Table 2.9 checks the impact of historical stock returns on new credit card balances and debt, similarly to the CEX analysis. Unfortunately in the SCF it is not possible to observe the 12-month historical return, only an overall return since the beginning of stock market participation. If stock owners report that they experienced at least 20% rate of return on their stock investments (this is not a yearly rate but an overall rate), then D_i^{Gain} dummy has the value of one (36% of stock owners), while D_i^{Loss} indicator is one if the household has an overall loss on stock investments (18% of stock owners). The inclusion of these two indicators into the Tobit type model where the sample is restricted to the stock owners leads to a large significant estimated parameter for D_i^{Gain} in the case of new balances. In the case of the other parameters (the gain dummy for revolving balances and the loss dummy in both models) the model leads to statistically insignificant estimates. The marginal effect of D_i^{Gain} is \$818, which represents a large portion (31%) of the average new balances of stock holder investors ($2,778).

To interpret this result, let us contrast the SCF findings with the CEX analysis. Stock market losses lead to slightly higher credit card balances in the short term (based on the CEX analysis), but not in the long term (current SCF result). This difference matches the predictions of the three theories listed after the CEX analysis that explain a negative correlation between historical stock return and future return expectations. First, households are able to hold private information about a company only in the short term, so the setup of a target sales price that is suggested by Lakonishok & Smidt (1986) to explain the negative correlation between past returns and future expectations is more likely to hold in the short term. Second, prospect theory with stock purchase price as the reference point, proposed by Odean (1998) to explain this negative correlation, also fades away over multiple years. Finally, those who invest in high risk portfolios or under-diversify, but experience high long term losses on the stock market, may adjust their portfolio to pursue lower return with smaller risk exposure, or may decrease their high future return expectations without changing their portfolio. Unfortunately, through the current analysis it is not possible to rank better these competing theories, which in practice may also coexist.

The positive impact of stock market gains on credit card balances is a robust result that holds both in the CEX and in the SCF sample. As the momentum effect of stock prices is a short term phenomenon, this theory can not explain the positive correlation. Consequently, a likely explanation may be that risk tolerant households have high historical returns and also high future return expectations, so they use credit card for transactions more frequently. One counterargument against this is that self-reported risk preference is already included into the Tobit type model. Furthermore, if the Tobit type model is rerun without the two dummies representing self-reported risk preference, the marginal effect D_i^{Gain} is $868, only about 5% higher than the original value.

Lakonishok & Smidt (1986) argues that the extrapolation of past positive returns to the future is a potential irrational phenomenon in the stock market.[18] The magnitude and the significance of the D_i^{Gain} indicator both in the case of the SCF and the CEX data suggest that this potential investment mistake is an important force to understand the results. The final extension of the Tobit type model is intended to show a further evidence towards this argument. Under-diversification is a well-accepted investment mistake, see Campbell (2006), and this can be captured well in the SCF data by observing the number of different shares held by stock owners (N_i). Columns (6) and (7) of Table 2.9 contains the already ana-

[18] According to Lakonishok & Smidt (1986), "if investors believe that price changes are positively correlated, they may be attracted to stocks with rising prices and may avoid stocks with falling prices".

lyzed D_i^{Gain} and D_i^{Loss} dummies, N_i, and the interaction between N_i and D_i^{Gain}. One can see that there is a negative correlation between the number of shares held by a household and the indicator of the large historical stock market gain. This can be interpreted as a correlation of two investment mistakes: low N_i means under-diversification, and those who under-diversify, are likely to extrapolate more their past positive stock market benefits, which may be an other investment mistake. Note that this correlation is observable both in the case of new and revolving balances, however, in the case of revolving balances the t-test falls slightly below the 5% significance level threshold. Nevertheless, the parameter of D_i^{Gain} remains large and significant by the inclusion of this interaction as well, pointing to the inference that coexisting investment mistakes are a likely, but not exhaustive explanation of the impact of past stock returns on credit card balances.

2.5 Conclusion

This chapter analyzed the behavior of transactional users of credit card in the U.S. Several empirical results are reported, most importantly that stock owners have higher credit card indebtedness, high consumption in general leads to high credit card debt and transitory consumption shocks lead to even larger new and revolving balances on cards. These findings indicate that households apply a simple cost benefit analysis when they decide whether or not to use credit cards, taking into consideration the level of transaction costs, future interests on investments or future potential savings. However, some other facts reported, such as the behavior of households in the holiday seasons, the positive impact of the number of credit cards held on credit card debt and the fact that past stock returns have large impact on credit card balances indicate that the selection of the way to transact is likely to be disturbed by biases and mistakes, leading to potentially suboptimal decisions.

As a first implication, this analysis suggests that the widespread definition of transactional use (no interest paid on balances) is overly simplistic. Hence, it is proposed to extend transactional use to the behavior of paying interest on balances sometimes but making profits in the long run by using credit cards instead of other payment methods. Johnson (2004) estimates the share of balance carried by transactional users to 5-10%, but she narrows down the definition of transactional use to convenience users, who do not pay any interest at all. If the definition is extended to those who revolve occasionally but still make long term profits with paying by credit cards, this share should be more significant. This chapter for instance concluded that individual investors who are likely to revolve mainly due to transactional purposes, hold 19% of revolving debt, both based on the SCF and the CEX surveys. Among other consequences, the riskiness of the U.S. credit card portfolio certainly depends negatively on the share of debt held by transactional users, so this research provides some more optimistic view of credit card indebtedness in the middle of the subprime mortgage crisis.

As a second implication, this chapter contributes to the understanding of the demographic profile of credit card debt holders. For instance, based on the recent literature (Dynan et al. (2004)) the rich save more and as a result, should hold lower level of debt. However in practice, rich still hold high credit card balances and pay interest on that. This paradox can be resolved with the presented model, as the transactional use leads to more financial benefits for the rich, so the importance of it should increase as income grows. Analyzing the cash back and other benefits provided by credit cards is also essential to justify the existence of such high-end credit cards as the American Express Centurion, which had $2,500 yearly fee and $5,000 initiation fee in 2007.[19]

As this research found some evidence against rational decision making in the credit card markets, in terms of optimal policy and regulation, sometimes government intervention is suggested. Hence, the current empirical results fit well the previous literature, as it is widely accepted since decades that for instance naivete and self control problems are essential on the credit market to explain the overall profitability of the industry.[20] As an important novelty in this field, this chapter stresses that differentiating between the life cycle use and the transactional use is essential and the proper analysis of the second one is crucial to explain overall credit card trends.

[19] Source: http://en.wikipedia.org/wiki/Centurion_Card

[20] Note that this extra profit is likely to be associated with extra risk, such as the subprime crisis shows, or the early analysis of this risk-return tradeoff in the credit card market by Nash & Sinkey Jr. (1997) using securitization data.

Chapter 3

Borrowing and Advertising

3.1 Introduction

"There are times when money should be the last thing on your mind". These are the first words of the TV spots of a major U.S. payday loan provider, depicting a worried husband purchasing a crib with his expectant wife or showing an African American father opening his daughter's college acceptance letter.[1] These spots suggest that the lack of money should not alter the level of investment in one's future, such as education or being able to raise children, and also that credit constrained households should approach banks with confidence and borrow in these situations. On one hand, these advertisements provide useful information for those who are just in the process of searching for the right financial service provider to get a loan. On the other hand, these spots might create additional loan demand in the case of households who are in a difficult financial situation but did not consider taking out a loan. Whether advertising creates excess demand in the unsecured lending market is a crucial question, as for instance in the U.S., the financial services industry is the second largest consumer of advertising (after the auto industry but before the phone industry) with $9.1 billion expenditures in 2007.[2]

In this chapter a unique dataset received from an anonymous European bank is used to understand the relationship between advertising and household's borrowing decisions. The dataset contains an accurate measure of advertising exposure through three media, namely television, Internet and newspapers[3] and an accurate measure of consumer demand of personal loan at the European bank.

[1]Source: www.providentfinancial.com

[2]Source: TNS Media Intelligence. http://www.tns-mi.com/news/03252008.htm

[3]In the media jargon all these media types are part of the "traditional" or so-called "above the line" (ATL) media, which is characterized by indirect mass communication between the company and the consumer.

In the first part of this chapter, two empirical calculations will be presented. First, the chapter shows that the marginal effect of advertising is higher in the case of TV commercials than in the case of Internet or newspaper advertising. Second, household level data makes it possible to identify household heterogeneity in loan demand. An interesting empirical question is whether the impact of advertising varies over customer segments. It is shown that statistically significant differences indeed do exist in the impact of media. Specifically, rich or young households react more to the TV commercials of the personal loan product than poor or old households, respectively.

To explain these two empirical facts, in the second part of this chapter a structural modeling exercise is performed. Personal loan is a special product as its demand is determined by the total household consumption and by intertemporal optimization. Hence, a simple life cycle consumption model is presented with three impacts of advertising: advertising as information about the brand, advertising as information about the interest rates and finally, advertising changing customer's tastes. The first two mechanisms belong to the the informative view of advertising (advertising provides information about the brand or product/service features), while the last mechanism is called the persuasive view of advertising in the literature (see Bagwell (2005) for more details). The advertising elasticity of demand is determined as a joint effect of these three impacts. Therefore the efficiency of different media and the interactions between socio-demographics and advertisement need to act through some of these channels.

Through the lens of the presented structural model, the empirical facts reported in this chapter are in line with the persuasive view of advertising. First, it is widely accepted that due to the usage of visualization, humor or music, *etc.,* TV commercials alter customer preferences in a larger extent compared with other media, see *e.g.* the meta-analysis of marketing advertising papers by Vakratsas & Ambler (1999) or Abernethy & Franke (1996). This observation directly leads to the observed high efficiency of TV to drive personal loan demand. Alternative explanations of this large impact, such as the provision of different information or longer recall of TV spots, will be ruled out in the discussion below.

Second, the observed heterogeneity in the impact of advertising between customer segments also points towards the persuasive view of advertising. On the one hand, further data analysis proves that alternative explanations, such as the different media usage patterns of segments, media content, the role of previous experience with the service or financial education, do not explain fully why the rich and the young would react more to TV commercials. On the other hand, the life cycle model of consumption provides multiple sensible explanations of this heterogeneity. For instance, internal self control mechanisms, such as the application of the addiction model of Bernheim & Rangel (2004) to life cycle consumption, provide a parsimonious way to explain this empirical irregularity.

Alternatively, the rational extensions of the life cycle model, such as the introduction of transitory income shocks or a subsistence level of consumption also lead to heterogeneity in the impact of advertising with respect to income and age, but not in a way which is fully supported by the currently analyzed empirical dataset.

Previous research has found already some evidence towards loan advertising changing households' preferences (Agarwal & Ambrose (2008) and Bertrand et al. (2005)). However, these papers utilize data on the direct mail activities of the banks. To the best knowledge of the author, for personal loans no similar evidence on the persuasive view was published using television, Internet or newspapers advertisement data. As these are more impersonal media channels, the findings of direct marketing can not be generalized for them, so the empirical contribution of this chapter is relevant.

The structure of this chapter is the following: Section 3.2 shows how the current analysis adds to advertising literature. Section 3.3 discusses the data and shows which are the life cycle drivers of personal loan. Section 3.4 presents the time series analysis of the impact of advertising on aggregate loan demand. Section 3.5 examines the impact of advertising in separate customer groups and reports that young and rich react more to TV advertising. Section 3.6 shows the structural model that explains personal loan demand in the presence of advertising, and finally, Section 3.7 concludes.

3.2 Related Literature

There has been a long debate in the literature on how advertisements change consumption decisions, see Bagwell (2005) for an extensive review. The three main views are the *persuasive view*,[4] according to which advertising shifts the tastes of households, the *informative view* (see Stigler (1961) and Nelson (1974)), in which case firms provide direct or indirect (signalling) information through advertising and finally, the *complementary view* of Stigler & Becker (1977), who interpret advertising as a commodity complementary to the consumption of the goods advertised. These views have diverse welfare implications for the consumers. The persuasive view is believed to create excess demand and high prices, while the informative view increases welfare in the presence of significant search costs.

Hence, empirical work is important to distinguish between the different effects of advertising to implement optimal policies. However, the various roles of advertising may coexist, and the complexity of markets *e.g.,* the interactions between firms, products and households make them difficult to disentangle.[5] As a result of

[4]Bagwell (2005) traces back this approach to the early papers of Braithwaite (1928) and Robinson (1933).

[5]Majority of theoretical contributions are looking at the role of advertising as a result of these

these difficulties, typically only the two end of the spectrum – *i.e.,* the informative view and the persuasive view is differentiated empirically and the complementary view is less frequently discussed.

This current chapter contributes to the literature of advertising at least at three points. First, it is an empirical analysis that investigates whether the informative view or the persuasive view describes better the impact of advertising on demand. Historically, the first approach for this comparison is the content analysis of advertisements. For instance, Resnik & Stern (1977) shows that approximately half of television advertising does not contain any information that should help households to make a well informed decision. They argue that firms would not post these uninformative advertisements if households did not respond to them. Hence, the existence of these spots is evidence towards the persuasive view, *per se*. Mullainathan & Shleifer (2005) demonstrate with mutual fund magazine advertisements over the course of the internet bubble that advertisers fit the message into the audience's already held beliefs, which shows again the importance of the persuasive view. A second generation of empirical papers that intend to differentiate between the informative and persuasive views directly analyzes the demand for a brand or a product being advertised. The focus on a single product enables the measurement of advertising and the response to it very accurately, and this is frequently done since the pioneer analysis about the impact of promotions on coffee sales using scanner data by Guadagni & Little (1983)). These empirical papers show dominating evidence in favor of the *informative view*.

The majority of these papers are reduced form – *i.e.,* intend solely to prove the causal effect of advertising to demand and infer about the nature of the relationship without specifying *how* exactly commercials alter consumer choices. Another part of the literature provides structural form models. For instance, Ackerberg (2003) creates a dynamic learning model to differentiate between the informative and persuasive effect of advertising, stating that the previous experience with a product determines the role of advertising. These structural models of advertising are designed to explain brand choice or product choice in complex market structures assuming sophisticated household decision making processes.

However, personal loan is a financial service related to households' total consumption and to their intertemporal choices, so previous structural models may not capture fully its specialities. While the life cycle consumption models can be used to understand the demand for personal loan, it is not yet clear based on the literature how advertising fits into the life cycle model.[6] As the second touch

complex joint decisions of firms and households. Some important contributions are that of Grossman & Shapiro (1984), Gabaix & Laibson (2006) and Mullainathan, Schwartzstein & Shleifer (2008).

[6]Whether aggregate advertising has a positive impact on aggregate demand is an empirical question in focus since decades at the macroeconomic level (see Ashley, Granger & Schmalensee

point with the literature, the current chapter fills this gap and integrates a simple life cycle consumption model with three various roles of advertising to provide a testable structural model. Additionally, as highlighted by Bagwell (2005), advertising theories should be enriched with building blocks taken from behavioral economics and neuroscience studies. Motivated by this field of research, among other extensions, the current chapter integrates internal self control mechanisms with the life cycle consumption model to be able to explain better the empirical irregularities.

Unfortunately the main area of advertising research is the fast moving consumer goods sector, with several specialities that cannot be generalized to other goods or services. Financial services advertising literature is more limited. Some marketing papers report empirical differences in the impact of commercials via different media from the banking sector (see Greenyer (2004)); some others present the varying impact of advertising in different demographic groups (specifically, gender differences are analyzed in Lawson, Borgman & Brotherton (2007) and Maltby, Chudry & Wedande (2004)). Another exciting field of research is mutual funds advertising (see Sirri & Tufano (1998), Cronqvist (2005)). In terms of lending, a recent paper of Agarwal & Ambrose (2008) focuses on the mortgage market and uses data on direct mail solicitations to evaluate the role of persuasive versus informative advertising. The paper finds evidence towards taste changes, as customers facing the direct mail offer are less sensitive to financial variables underlying the relative price of debt contracts. In terms of personal loan, which is in focus in this chapter, an important reference is Bertrand et al. (2005), who analyze the psychological features of a South-American personal loan direct mail offer, and find that these features have important effect on loan demand, according to the persuasive view of advertising. Meanwhile both Agarwal & Ambrose (2008) and Bertrand et al. (2005) focus on direct mail advertising,[7] so as the third touch point with the literature, the current chapter provides novel evidence on the impact of financial service advertising using data about rarely analyzed media types.

3.3 Data Description and Life Cycle Drivers of Loan Applications

A personal loan, the borrowing product analyzed in this chapter, is a closed end loan of relatively large size mainly used for borrowing purposes – *i.e.,* customers are planning to pay back the loan over a longer time frame, as opposed to credit

(1980)) without consensus. Similarly to the current chapter, this macroeconomic research is based on the link between advertising and the life cycle model of consumption.

[7]Direct mail belongs to the so-called “below the line” (BTL) or “untraditional” media types, which are characterized by direct communication between the company and the customer.

card, which might serve both as a borrowing and as a transactional (or convenience) tool. Hence, the pure effect of being in borrowing need can be identified from personal loan data, which is important to be able to explain the loan demand with a simple life cycle consumption model. The anonymous dataset consists of individual level socio-demographic information which is available for every personal loan applicant at the given retail bank. This makes it possible to identify credit demand directly without the bias of the bank's accept-reject decision, as opposed to analyzing only the accepted customers. From this data set of applications the economically inactive groups are excluded, as the behavior of students or pensioners may differ from the employees', and this heterogeneity can not be captured with a parsimonious economic model. Available individual characteristics include age, income, marital status and gender. Weekly credit advertising of the bank is also available with respect to the most important media types including television broadcasting, newspapers and Internet. Advertising is measured by Gross Rating Point (GRP), which represents the percentage of the population reached by the advertisement. GRP is an internationally accepted measurement of advertising exposure and most importantly, it is comparable across different media types.

In addition to the retail banking data, nationwide statistical data is also available on the given European country from the Luxembourg Income Study (LIS).[8] From the LIS, it is possible to create nationally representative socio-demographic segments. A segment is defined by four dimensions: marital status (non-married households are combined), gender, income (10 income deciles) and age (9 age quantiles). All these characteristics are that of the household head. For these 356 segments (4 combinations do not exist), one can see the number of households in each segment, and compare that with the number of applications at the bank, and so calculate market share in each socio-demographic segment. Fortunately, the time frames of the two datasets are largely overlapping. Dividing the number of applications in the bank by the total number of individuals in the European country, it is possible to calculate market penetrations, showing how many individuals out of 100 applied at the given bank for personal loan during the time period covered.

The markets penetrations by segments are described in Figure3.1. Some patterns are aligned with the expectations, such as the hump shaped age-loan relationship or male customers applying more frequently for personal loans. Interestingly, income and marital status do not explain loan demand in the traditional way. Having non-monotonic income-loan relationship raises the need to present further arguments that could explain this pattern. These unusual loan demand pat-

[8]Luxembourg Income Study (LIS) Micro database, 2000; harmonization of original surveys conducted by the Luxembourg Income Study, Asbl. Louxembourg, periodic updating.

terns provide motivation to analyze the impact of advertising on loan demand. The next sections will show that indeed, advertising of the personal loan can contribute to the explanation of some of these patterns.

Figure 3.1: Market penetrations (# of loan applications per population size) by life cycle drivers

The data is not shown due to confidentiality reasons. Please contact the author for further details.

3.4 Advertising and Loan Applications

This section investigates how advertising alters the number of loan applications in the given bank. Figure 3.2 shows the number of personal loan applications (denoted by Y_t) and the media activity of the anonymous bank for each of the observed weeks. Media activity is measured by the weekly sum of purchased Gross Rating Points (GRP), which represents the percentage of the population reached by the advertisement, and therefore is comparable across media types. Just looking at Figure 3.2, there is a clear relationship between advertising and the number of applications. The peaks in advertising are typically followed by peaks in loan demand, either during the same week and/or the following week.

Figure 3.2: Time series of advertising GRP and number of personal loan applications

The data is not shown due to confidentiality reasons. Please contact the author for further details.

By merging the internal banking data with European household survey data, which is done for instance in Section 3 to show some stylized facts, it would be possible to use a discrete choice models to estimate the probability of given households to apply at the bank. The application of such a discrete choice model would lead to the straightforward interpretation of the role of advertising and socio-demographic factors, including their interaction. However, the merging creates certain biases caused by the different data structures and time frames of the two databases. Furthermore, in the following section the empirical analysis will be extended to panel data, and running a panel probit instead of the simple fixed effect panel model is a further complication. As a result, the final choice was to avoid this merge and use the banking data solely together with time series and panel data analysis to derive the results. This way the results do not depend on merging assumptions, calibrations and on the settings and distributional assumptions of more complex econometric models.

To formally start the time series analysis, first the time series properties of the loan application process have to be investigated. The 2.5 year long loan application time series may be integrated from economic point of view, therefore the non-stationarity of the Y_t series is tested using the sequential procedure of Ayat & Burridge (2000). The Dickey-Fuller (DF) test that is executed in the first step contains both the drift (μ) and the trend (αt) terms:

$$\Delta Y_t = \mu + \gamma Y_{t-1} + \alpha t + \varepsilon_t$$

where Δ is the first difference operator. The estimated parameters (not reported) show that both α and γ are significant at the 5% significance level.[9] Since the null hypothesis of $\gamma = 0$ can be rejected, the second step of the sequential procedure of Ayat & Burridge (2000) is to test the null hypothesis of $\alpha = 0$. As this can be also rejected, the Y_t *process is stationary around a linear trend*.

The time-series analysis of advertising exposure is much simpler as advertising is expensive and planned by the bank's marketing department. Therefore economically there is no reason why it would be integrated. One might observe the reversion of the time series to zero frequently, which suggests that the time series cannot have a large trend. For the total advertising exposure as well as for the three media types separately, the Dickey-Fuller tests in the light of the sequential procedure of Ayat & Burridge (2000) also confirm that *the media exposure time series are stationary without a trend* (results are not reported here). As a result, there is no need for cointegration analysis to determine the relationship between advertising and loan applications and standard econometric techniques will be used.

The econometric model to formally show the impact of advertising on loan applications has the form of

$$Y_t = \beta_0 + \beta_1 TV_t + \beta_2 N_t + \beta_3 I_t + \beta_4 TV_{t-1} + \beta_5 N_{t-1} + \beta_6 I_{t-1} + \beta_7 t + \sum_{j=1}^{12} \gamma_j M_j + u_t$$

$$u_t = \rho u_{t-1} + \varepsilon_t \tag{3.1}$$

where Y_t is the number of applications, t refers to the time trend, M_j is a set of seasonal dummies, TV_t, N_t and I_t are denoting the GRP per week in television, newspapers and Internet, respectively. It is possible that not only the current week's advertising but also the lagged advertising drives loan demand. To accommodate the potential lagged effect, one week lags of the three media exposures are included into the model.[10]

[9] Note that the strong significance of γ and the weaker significance of α is robust to the inclusion of lagged terms of ΔY_t (Augmented Dickey-Fuller test).

[10] More than 1 week lags are also tested but not reported here, as those are not changing loan demand.

As the Dickey-Fuller test shows that the loan application process is stationary with a time trend, a linear trend is included into the model. This solution is identical with the detrending of the Y_t series. Note that it is irrelevant for the model estimation whether this trend is a market trend or a trend that only characterizes the bank in focus.

Seasonality is tackled with the inclusion of 4-week seasonal dummies. As a year consists of 52 weeks, thirteen 4-week periods can be constructed and one of these dummies is excluded to avoid multicollinearity. The preference for using 4-week periods instead of calendar months is due to the weekly data structure of advertising and application data.

The error term u_t is assumed to be autocorrelated and hence, Y_t is specified as a moving average process. The reason behind this assumption is that while advertising is expected to explain a good portion of variation in Y_t, there are other unobserved bank specific drivers of loan demand that are persistent in time. These drivers include for instance unobserved marketing activities of the bank (*e.g.,* direct mails sent out, promotions, sponsoring), unobserved brand awareness towards the bank or changes in technology of the bank (*e.g.,* opening new branches, launching new banking communication channels). The preference for introducing autocorrelated errors instead of lagged dependent variable is explained by three main arguments.[11] First, the DF test of integration shows that the time series is not integrated, so the introduction of first differences of the time series would lead to biases in the estimation. Second, the primary empirical goal of this section is to identify the current and lagged effect of advertising on loan applications. However, the introduction of lagged dependent variables would make it cumbersome to disentangle the impact of advertising on the present and on the lagged loan applications. Finally and most importantly, there is little economic meaning to introduce the lagged number of applications in the model. Each week there is a completely new group of customers applying for loans, so an observation (an application in a given week) does not generate another observation in the next time period, unlike in many other time series.[12] Meanwhile, the omission of both the lagged dependent variable and of the autocorrelated error structure leads to a misspecified model, detected by the Durbin-Watson test ($d = 1.32$).

As the last step of the model specification, reverse causality can be ruled out: it is not possible that the loan applications drive the advertising spending of the bank. This is due to the long term horizon of advertising planning of the bank: marketing expenditures are planned yearly and it takes several months to introduce

[11]As a robustness check, loan application differences have been regressed on advertising innovations and the results are qualitatively identical to the findings of the model without differences.

[12]Consider for instance the case of Consumer Price Index. If the price of an item does not change between two measurement points, it will enter identically into the next time period's index, leading to potential integration of the CPI time series.

a new TV campaign or to modify existing advertising strategy. This prevents any short term feedback between the applications and the media expenditures, that would be required to generate reverse causality.

Table 3.1 contains the parameter estimates of the model using generalized least squares estimation technique of the "prais" procedure of Stata 10. As indicated by the Durbin-Watson test, the autocorrelation of the error terms is significantly different from zero and has the value of 0.42. The results show that television and newspapers seem to be similarly strong drivers of demand, while the Internet has smaller impact. However, Table 3.1 shows that lagged television GRP is also a key driver of loan applications, and it has almost identical impact as the current television advertising. Aggregating the contribution of all the media ($\sum_{i=1}^{6} \beta_i \bar{A}_i$ where $\bar{A}_i$ refers to the average advertising GRP based on Equation 3.1) it can be concluded that advertising accounts for more than ten percent of the total applications, so it is a key driver of loan demand. Note that this metric is an underestimation of the real impact of advertising, as it is likely that the seasonality and the growth of advertising contributes to the seasonality and to the growth of loan applications, respectively. Meanwhile in the formal econometric analysis of the causal effect of commercials on loan demand does not makes it possible to directly measure that impact.

Table 3.1: The impact of personal loan advertising on loan applications (Y_t) based on GLS estimation
The data is not shown due to confidentiality reasons. Please contact the author for further details.

Given these results of the model, the long term marginal effect of advertising can be easily calculated using the parameter estimates of the current and lagged week's media GRP. The marginal effect of television ($\beta_1 + \beta_4$) is higher than the marginal effect of newspapers ($\beta_2 + \beta_5$) and both marginal effects are larger than that of Internet ($\beta_3 + \beta_6$). Pairwise F-tests to compare the marginal effect of different media show that the null hypothesis of TV being more efficient than newspapers can not be rejected, while the null hypothesis of TV being more efficient than Internet is rejected. Meanwhile the difference between the marginal effect of TV and newspaper is clearly visible.

As all media activity is measured in gross rating points, these marginal effects are comparable, showing that households are the most sensitive to TV spots *conditional on being reached* and the least sensitive to the Internet. One important note strengthens this inference. While one GRP for Internet or Television stands for one time exposure to advertising per customer, in the case of newspapers the customers may face multiple exposures. This is due to the fact that the newspapers category contains magazines as well that individuals sometimes read over several days, as opposed to daily newspapers, TV spots or Internet web sites in which cases advertising on a new day counts as a new GRP. This leads to the fact that speaking about only one time exposure, the parameters of newspapers are *overestimated*, as they contain the impact of multiple exposures for a portion of individuals. This means that the marginal effect of newspapers is closer to that of Internet, with respect to one time exposure only. This note strengthens the main inference of this section – *i.e.,* TV commercials are more efficient than reaching customers through the other two media.

This result may simply reflect the fact that TV commercials are recalled for a longer time. This explanation is also supported by the estimated parameters reported in Table 3.1: the higher efficiency of TV arises from the significant large impact of the lagged TV GRP metric, while the lagged advertising in the case of the other media does not alter loan demand. To investigate, whether this is the right interpretation, fortunately the anonymous bank provides further advertising data about the bank in general *e.g.* branding and responsible lending. This advertising (henceforth called "general advertisement" as opposed to "personal loan advertisement") is available through TV and newspapers only. While this information will be particularly important in the next section, currently it can be used to extend the time series model specified by Equation 3.1. The results of this extension can be found in Table 3.2, where GTV_t and GN_t time series denote the "general advertising" GRP per week via television and newspapers, respectively. One can see that there is a weaker, but positive causal relationship between the general advertising and the number of incoming personal loan applications. This is not surprising: if a household is in liquidity need and sees a general brand building ad of the bank, this provides information that the bank is a strong player on the market and personal loans are possibly part of its product offering. One can also see that the current period "general advertising" through TV (GTV_t) is positive and significant at the 10% significance level (which differs from the standard 5% level, but is still acceptable given the small sample size), while the lag of the same variable (GTV_{t-1}) has a negligible size. This result contradicts the argument that television would induce longer recall, as this memory effect should work also in the case of "general advertisements".

Table 3.2: The impact of "general" and "personal loan" advertisements on loan applications (Y_t) based on GLS estimation
The data is not shown due to confidentiality reasons. Please contact the author for further details.

As the importance of longer recall of TV messages is empirically not justified, furthermore, TV, Internet and newspaper commercials contain the same level of information about the brand and both contain very limited information about the competitive interest rate, the higher efficiency of TV commercials is more in line with the persuasive view of advertising. According to this view, a likely mechanism behind the higher efficiency is that TV commercials contain more emotional cues leading to preference changes and higher consumption. Section 6 will elaborate the theoretical background of this last statement.

3.5 Does the Effect of Advertising Differ by Household?

The fact that advertising raises the number of loan applications is not a surprising result, with the exception of the varying efficiency of different media. Meanwhile the availability of customer level data makes it possible to test for interactions between socio-demographic factors and commercials – *i.e.,* whether certain customer groups are more sensitive to advertising than others. To keep the evidence for the interaction simple, instead of using continuous variables or categorical characteristics with multiple values, in this chapter binary customer groups are defined by four dimensions: young versus old, rich versus poor, unmarried (Single, Divorced, Widow(er), etc. combined) versus married and finally, female versus male.

Before an econometric model is estimated, let us see some descriptive evidence of the interaction between commercials and these customer groups. Advertising GRP is a continuous variable, but for the descriptive evidence it is also transformed to a binary indicator. For each medium, 25% of the weeks are flagged as high exposure weeks, where the given media GRP is in the top quartile of the GRP distribution. Based on the estimation of Equation 3.1, current and lagged TV GRP both significantly influence loan demand with similar estimated parameters, which fact motivates the simple addition of these two values. After defining these categories, a simple 2×2 cross table is generated with a customer group (*e.g.,* young versus old) and a media exposure dummy (*e.g.,* exposed to high TV advertising versus not exposed) as the two dimensions. The χ^2 tests of independence in these frequency tables show whether the advertising exposure creates different distribution in terms of the selected socio-demographic factors.

The second test that is presented in this section as a descriptive evidence is inspired by the "short-term advertising strength" (STAS) measure that was introduced by Jones (1995) into the marketing literature. In its original version, for each brand STAS is computed as the percentage of purchases among consumers exposed to advertising divided by the percentage of purchases among consumers not exposed to advertising for the brand. To the analogy of STAS, in the current chapter a simple metric of advertising can be defined (hereby called as "relative advertising strength"): the share of customers belonging to a given demographic segment in the case of high advertising exposure divided by the share of individuals who belong to the same segment in the case of low (even zero) advertising exposure. For instance, if out of the total 20 customers that apply at the bank during the weeks with high TV exposure 12 people are young, while during the other weeks with low TV advertising 50 young and 50 old customers apply, then the relative advertising strength is $\frac{12/20}{50/100} \cdot 100 = 120$. A ratio greater than 100 means that the given customer segment (young in the example) react more to advertising (to TV commercials in the example). The χ^2 test of independence P-values as well as the relative advertising strengths are shown in Table 3.3. Young households apply more often when TV advertising is high. Rich individuals react similarly to advertising as the young.

Table 3.3: The impact of "personal loan advertisements" in different socio-demographic segments measured by χ^2 test of independence and relative advertising strength (RAS)
The data is not shown due to confidentiality reasons. Please contact the author for further details.

The fact that rich and young households are more sensitive to TV commercials compared with the poor and the old is unexpected due to multiple reasons. First, in the marketing campaign of the European bank the same information is communicated via various media, as a result, through the lens of the informative view of advertising, the impact of various commercials should be identical. Specifically, the advertisements contain strong information about the brand name but very limited information about the interest rate via all media, that only consists of some regulatory compulsory statements with very small letters.

Second, the content of the advertisements is not tailored to attract any special socio-demographic segments, according to the information received from the anonymous lender. The anonymous bank rather focuses on humor than on targeting a special customer group. The review of the marketing materials of the bank leads to the conclusion that via all media the bank focuses on a general situation that can happen virtually with any socio-demographic group.

Third, also related to the informative view, a possible explanation of higher media efficiency in a given customer segment is that the given media reaches more individuals in that segment. As the Gross Rating Point advertising exposure metric is available only for the overall population, it is possible that it varies over customer segments. So the following analysis examines the media usage habits of the rich and the young, as it should explain why TV is more efficient in these segments. Table 3.4 shows nationwide media usage statistics. One can observe that TV and newspapers are more popular media in case of the old. Hence, the impact of TV should be *lower* in case of the young. Unfortunately the same statistic is not available for income breakdown, but due to a positive correlation between age and income one would expect the same pattern – *i.e.,* the impact of TV commercials should be *lower* for rich households. Anecdotal evidence also suggests that high income households are typically more educated, thus read more newspapers and watch less television.

Table 3.4: National media usage statistics.
The data is not shown due to confidentiality reasons. Please contact the author for further details.

Fourth, a further potential argument towards the existence of this empirical fact is that *in terms of financial services*, households might get information in a different way. Even if they watch less television, young or rich households might get *banking* information from television, while old and poor households might read newspapers and visit bank branches more often to obtain this information. To refute this argument, a further calculation is presented. As it was previously mentioned, the anonymous bank provides advertising data about the bank in general, called as "general advertisements". The time series analysis in Section 4 showed that there is a weaker, but positive correlation between the general advertising and the number of incoming personal loan applications. So a 2×2 frequency table between the "general advertisements" and the socio-demographic segments should lead to the same inference as Table 3.3. Table 3.5 shows that this is not the case. Not to interfere with the effect of personal loan commercials, Table 3.5 contains analysis on only those weeks when all three personal loan media exposure dummies defined previously are zero. Similarly to Table 3.3, high and low media exposure dummies are defined. Table 3.5 shows that the impact of "general advertising" via TV is the opposite to the impact of "personal loan" TV commercials. Young or rich households apply *less frequently* if exposed to TV advertising. This pattern matches expectations in terms of nationwide media usage trends. So it is not true that young and rich individuals obtain financial information more frequently from TV compared with the poor and the old. Consequently, Table 3.3 remains to be an unresolved empirical puzzle, so other economic mechanisms have to be at work behind this empirical fact.

Table 3.5: Impact of advertising of the bank's "general advertisements" in different socio-demographic segments measured by χ^2 test of independence and relative advertising strength (RAS)
The data is not shown due to confidentiality reasons. Please contact the author for further details.

While it has been shown above that certain socio-demographic factors interact with advertising in terms of driving loan demand, it is not yet clear whether these interactions are independent or related to each other. For instance, if an individual is married, it is likely that he is older and has higher income than a single individual. Similarly, income and age are correlated over the customer life cycle. Therefore the remainder of this section presents the results of a multivariate econometric model that justifies the previous statement, namely that the rich and the young react more to TV commercials.

For this purpose a panel data set is constructed. Based on the four socio-demographic dimensions defined previously – *i.e.,* age, income, marital status and gender, 16 customer groups can be identified. In terms of notation, let us denote the 16 socio-demographic groups with $g = 0, 1, ..., 15$.[13] The number of loan applications in group g at time $t = 1, 2, ..., T$ is denoted by Y_{gt}. This means that Y_{gt} forms a panel dataset so that $\sum_{g=0}^{15} \sum_{t=1}^{T} Y_{gt} = N$, where N is the total number of applications. The socio-demographic segments are characterized by four binary indicator variables: $\{X_{gk}\}_{k=1}^{4} \equiv \{old, male, married, rich\}$. In the model the media variables defined in Equation 3.1 are reused, specifically the current and one-week lagged media GRP for television, Internet and newspapers. $\{A_{jt}\}_{j=1}^{6} \equiv \{TV_t, TV_{t-1}, I_t, I_{t-1}, N_t, N_{t-1}\}$ is the simplified notation of the advertising time series. Unlike in the descriptive statistics, the advertising GRP series are included here as untransformed continuous variables, resulting in no information loss.

Using this notation, the following analysis shows that for some j and k, there exists an interaction between the advertising series A_{jt} and the socio-demographic factors X_{gk} in the determination of Y_{gt} loan applications. As shown in Section 4, the portfolio level loan application process is a fairly sophisticated time series process that is characterized by a time trend, seasonality and an autoregressive bank specific loan demand absorbed in the error terms. These time series properties are inherited by the derived panel data set as well, which makes the direct estimation of Y_{gt} cumbersome. This problem can be avoided by using the following trick: instead of using the number of applications in a group, the weekly share of applications of the given group is measured and estimated as the left hand side variable:

$$s_{gt} \equiv \frac{Y_{gt}}{\sum_{g=0}^{15} Y_{gt}}$$

With this trick, the time trend and seasonality in the number of total applications does not alter the group shares. The full econometric model specification is the following:

[13] The index starts from zero because of technical reasons, as $g = 0$ is used as a reference group later in this section.

$$s_{gt} = \frac{\exp(\delta_{gt})}{\sum_{g=0}^{15} \exp(\delta_{gt})}$$

where

$$\delta_{gt} = \alpha_g + \sum_{k=1}^{4} \beta_k X_{gk} t + \sum_{k=1}^{4} \sum_{j=1}^{6} \gamma_{kj} X_{gk} A_{jt} + \varepsilon_{gt}$$

This specification resembles the multinomial logit model, and the motivation behind this is threefold. First, it assures that the sum of the group shares in each time period t is one. Second, this specification leads to the fact that if the group share of a given group increases then the group shares of all other groups proportionally decrease. Finally, this functional form is adequate to tackle the contemporaneous correlation of the error terms. However, this functional form is not derived from utility theory so the interpretation of it is different from the classical multinomial logit model.

The parameter α_g is a group specific constant representing a fixed market share for a specific group g over time. While the group shares are independent from the trend in loan applications, it is possible that some segments experience growth in shares over time. For instance, at the end of the observation period more wealthy individuals may apply for loans, or more females may become engaged with the finances of families compared with the beginning of the observation period. To allow market shares to change over time, β_k parameters are introduced.

The main interest is to estimate interactions between advertising and socio-demographic factors, which are captured by the γ_{kj} parameters. The interpretation of γ_{kj} is the following: *ceteris paribus,* increasing advertising exposure in media j by a unity leads to γ_{kj} change in δ_{gt}, which determines the group share of those groups that belong to the k-th socio-demographic factor – *i.e.,* $X_{gk} = 1$.

Under the null hypothesis $\gamma_{kj} = 0$, more advertising through the given media j does not change the group share of groups with socio-demographic factors k, controlling with linear time trend in group shares. Rejecting the null hypothesis means that advertising alters the group share and this is not due to a spurious regression – *i.e.,* by the fact that both the group share and advertising has a trend, but these two trends are unrelated. Also note that not being able to reject any of the null hypotheses of $\gamma_{kj} = 0$ does not mean that advertising is an inefficient driver of loan applications. Rather it means that advertising drives loan demand in such a way that it does not changes groups shares of different socio-demographic segments, so there is no interaction between advertising and socio-demographics.

To estimate this highly non-linear model, a transformation is necessary.[14] First,

[14]The following transformation is motivated by the paper of Berry, Levinsohn & Pakes (1995)

let's denote the group with $\{X_{gk}\}_{k=1}^{4} = \{0,0,0,0\}$ with group index $g = 0$. This group is the young, female, unmarried and poor segment which will be used as the benchmark. For $g = 1, 2, ..., 15$, taking the logarithm of the group shares and subtracting from them the logarithm of the benchmark group share leads to a surprisingly simple functional form:

$$\ln(s_{gt}) - \ln(s_{0t}) = \alpha_g - \alpha_0 + \sum_{k=1}^{4} \beta_k X_{gk} t + \sum_{k=1}^{4} \sum_{j=1}^{6} \gamma_{kj} X_{gk} A_{jt} + \varepsilon_{gt} - \varepsilon_{0t}$$

The simple result is due to the fact that $X_{gk} = 0$ for all k. This transformation leads to 15 observations per time period, and this transformed model can be estimated linearly. For this purpose, first the structure of the error terms $\varepsilon_{gt} - \varepsilon_{0t}$ has to be discussed. Because of the selected functional form, contemporaneous correlation of the error terms is not an issue, as all positive error terms automatically increase the group share of the given group and automatically decreases the group share of all other groups. This is the main advantage of using the logit-like specification instead of estimating group shares linearly or log-linearly. As Section 4 shows that the loan application time series has autocorrelated error term in time, one might worry about a potential autocorrelation in the group shares. Fortunately, Wooldridge (2002) developed a test for autocorrelated error terms in panel data (see "xtserial" algorithm in Stata 10), and this test can not reject the null hypothesis of no autocorrelation in the error terms. As a result, the assumption for ε_{gt} to be iid. normally distibuted error term is not restrictive. Hence, $\varepsilon_{gt} - \varepsilon_{0t}$ is also iid. normal and standard panel data analysis can be performed.

The transformed model is therefore a linear fixed effect panel model: $\alpha_g - \alpha_0$ is the group specific fixed effect that is constant in time and β_k and γ_{kj} parameters can be directly estimated. The results are shown in Table C-1. As a result of the limited sample size and the large number of interactions used as explanatory variables, instead of the standard 5% significance level, the 10% threshold is applied. It is concluded that more young than old customers apply during those weeks when television commercials are running, as shown by the parameters of both TV_t and TV_{t-1}. On the other hand, more rich than poor households apply for personal loans during those weeks when TV advertising is high, as shown the significant parameter of TV_t. While the lagged effect of television is not significant, the joint effect of TV_t and TV_{t-1} is still significant at the 10% significance level. Importantly, all these findings are independent from each other *e.g.,* significant interaction exists between age and television advertising in the determination of loan demand even after controlling for other socio demographic factors, such

who include this step in their algorithm to estimate car price elasticities in the presence of unobserved quality of cars.

as income or marital status. Equally importantly, these results are not driven by a spurious regression, as the model allows different socio-demographic groups to have increasing or decreasing share in time.

The fact that the young and the rich are more sensitive to TV commercials, is further strengthened by looking at the trend of advertising and group shares. The last line of Table C-1 shows that both young and rich have increasing share of total applications in time, and TV GRP has also a small but significantly positive trend in time. This means that it is likely that the positive trend in group shares of young and old segments is induced by the positive trend in TV commercials, which additional correlation is not captured by the γ_{kj} parameters.

Table 3.6: Estimated parameters (β_k and γ_{kj}) of the model predicting groups shares of loan applications using personal loan advertising and time trend
The data is not shown due to confidentiality reasons. Please contact the author for further details.

To sum up the multivariate panel analysis, using careful econometric techniques the empirical result still holds – *i.e.,* the young and the rich react more to TV advertising. Contrasting this result with several straightforward explanations such as targeted media content or different media usage of various segments, this fact is indeed an empirical puzzle and a detailed set of potential economic explanation will be provided in the next section. Interactions between advertising and gender or marital status are weaker, similarly to interactions between newspaper/Internet advertising and socio-demographic variables. Meanwhile all four socio-demographics and all three media GRP series served as important controls in the previous model to strengthen the existence of the empirical puzzle in focus.

3.6 Discussion

Based on the personal loan demand analysis of Sections 4 and 5, which of the three main views of advertising presented in Section 2 is justified by the data? First, the complementary view of Stigler & Becker (1977) is out of scope, as taking out a loan is not likely to create large prestige effects that are necessary for that view. Households are certainly not happy to be in debt, and they are not likely to discuss their choice of lender proudly during social activities, in contrast with other goods as services, such as buying a fancy car.[15] Loan advertising being a com-

[15] Interestingly, Agarwal & Ambrose (2008) equalizes the complementary view with the choice of lender decision of the household, meanwhile brand choice is driven by the informative view in this chapter. However, Agarwal & Ambrose (2008) analyze mortgage, in which case the prestige effect may be more important compared with personal loan, which is more associated with the less wealthy and with the subprime segment.

plement for consumption, or alternatively stating, the existence of a higher level commodity into which consumption and advertising serve as two inputs, does not describe well the personal loan market. Hence, the discussion will cover only the informative and the persuasive views of advertising, similarly to the majority of the related literature.

For the proper interpretation of the results found in the empirical sections, notably that television advertising is the most efficient, and certain customer groups react more to advertising, a structural model is required. The provision of a personal loan is a special financial service, therefore the advertising of personal loans serves different roles compared with traditional goods. Using the wording of Nelson (1974), the personal loan contract is likely to be associated primarily with "search qualities", such as the low interest rate. "Experience qualities", such as brand loyalty and the role of previous experience are assumed to be less important in the decision making process, as if the money is in the customer's hand, he is expected to become more indifferent towards the further services. Additionally, personal loan demand reflects the total consumption of households led by intertemporal optimization, so instead of the standard brand or product choice framework (which is typically modeled with the multinomial logit reviewed in McFadden (2001)), a standard life cycle consumption model has to be developed. Rational customers should use advertising as information, firstly about the fact that a given banking brand is providing a personal loan or not. The price of this specific financial service is the interest rate to be charged, therefore the advertising analysis below has to incorporate the mechanism to provide competitive interest rate information to the customers. Finally, it is also possible that tastes of households change as a result of advertising, which option is modeled accordingly. The three different roles of advertising are merged in one joint model in this section.

After presenting the structural model, the remainder of the section focuses on the two empirical facts – *i.e.,* why television has a higher impact on loan demand than other media, and why rich and young households react more to TV advertising of loans. It is shown that both empirical facts are in line with the persuasive view of advertising, and among other plausible explanations, the second fact is in line with the existence of internal self control mechanisms.

3.6.1 The Three Roles of Advertising in Personal Loan Demand

Let us consider a simple multiperiod consumption model, which is similar to the model in the consumption chapter of Romer (1996). The customer lives from $t = 1, 2, ..., T$ finite time periods, c_t denotes present consumption, y denotes period one observed income, the household has no initial assets or initial debt,[16] and

[16]Otherwise stated, initial debt or assets are spread over the T periods and are included in y income.

accumulates $g^{t-i}y$ income in period t. Income is assumed to grow (or decrease) exponentially, and g is the yearly income growth rate. Prices are constant over time. There is a non-negative i interest on investments, and in the case borrowing the household has to pay $r \geq i$ interest rate. While not essential for the discussion, as a simplification, the investment interest rate is assumed to be lower or equal than the borrowing rate, to avoid risk free arbitrage opportunities. The utility function represents Constant Elasticity of Substition preferences:

$$U = \sum_{t=1}^{T} \frac{1}{(1+\delta)^{t-1}} \frac{c_t^{1-\theta}}{1-\theta}$$

where δ is the discount rate. If the household is borrowing, then the Euler equation is

$$\frac{c_{t+1}}{c_t} = \left(\frac{1+r}{1+\delta}\right)^{\frac{1}{\theta}}$$

If the household has satisfactory income to cover its consumption, then the remainder of its saving gets invested at the interest rate i, so the Euler equation becomes

$$\frac{c_{t+1}}{c_t} = \left(\frac{1+i}{1+\delta}\right)^{\frac{1}{\theta}}$$

The cut-off condition for period 1 loan demand is

$$\left(\frac{1+r}{1+\delta}\right)^{\frac{1}{\theta}} < g$$

showing that the consumption growth rate in the presence of costly borrowing is lower than the income growth rate. The same equation can be expressed in log forms:

$$\widetilde{r} - \widetilde{\delta} < \theta\widetilde{g} \tag{3.2}$$

where $\widetilde{r} = \ln(1+r)$, $\widetilde{\delta} = \ln(1+\delta)$ and $\widetilde{g} = \ln(1+g)$. Suppose that the researcher cannot observe these three economic drivers in the switching equation, only with error. Let us assume that the error term in the switching equation has a logistic distribution, which can be replaced by any other standard distribution without loss of generality. In this case the probability of being in borrowing need is:

$$\Pr(Borrow) = \Lambda(\theta\widetilde{g} + \widetilde{\delta} - \widetilde{r})$$

where $\Lambda(\cdot) = \frac{\exp(\cdot)}{1+\exp(\cdot)}$ is the logistic transformation.

If the household is in borrowing need, it has to select a loan provider from the available brands. This brand selection forms the second hurdle to apply for loan at a given bank. Let us denote the probability of selecting the brand of a specific bank versus selecting the competitor's offer conditional on being in borrowing need by $\Pr(Brand)$. Let us assume that this probability has the formula of

$$\Pr(Brand) = \Lambda(\widetilde{\alpha})$$

where the logistic form is used for the sake of simplicity to get the same functional form as the borrowing probability has. Using these assumptions, the final probability to apply for personal loan at the specific bank is

$$\Pr(Apply) = \Pr(Borrow) \cdot \Pr(Brand)$$

In the case of unsecured lending the most likely use of advertising is to inform the households about the existence of a certain brand on the borrowing market, especially in a competitive market with hundreds of market players. In the presence of advertising activity of the given bank, the probability to select the brand is given by

$$\widetilde{\alpha} = \widehat{\alpha} + \sum_j \beta_j A_j$$

where $\widehat{\alpha}$ drives the probability to chose the brand in the case of no advertising and A_j is a set of dummies of advertising exposure of the bank through media j, which includes TV, newspapers or Internet. Restricting A_j to be a zero-one dummy instead of a continuous variable simplifies further the analysis without the loss of generality. $\beta_j \geq 0$ shows how much the commercials through media j alter the brand choice probability. Note that in fact the level of advertising of the competitors also matters, but that is taken as exogenous in this simple model.

Second, it is possible that the household has adequate information about the existence of the given bank. This may be typical in a less competitive market with a few players, or speaking about a well known bank with high brand awareness, just as in the case of the anonymous European bank analyzed in the empirical section. Similar example would be a Citibank commercial in the U.S.: to the majority of U.S. citizens this advertising contains limited incremental information about the existence of the brand. Nevertheless, commercials may be still useful if a portion of households have incorrect views about the interest rate that a bank would charge them for a personal loan. If Inequality 3.2 does not hold, the optimal decision of these households is not to apply for a personal loan at any bank. These households might learn from the advertisement that for instance, instead of 20% APR they can get a loan for 15% APR. Updating their borrowing interest rate accordingly, these households immediately revisit their previous choice and apply for loan with higher probability, assuming that the advertisements informed them about a lower interest rate compared with their previous expectation. Formally, the households update their interest rate to

$$\widetilde{r} = \widehat{r} - \sum_j \gamma_j A_j$$

where $\gamma_j \geq 0$ shows how much the advertising through media j lowers the logarithm of the interest rate and $\widehat{r}$ represents the high borrowing rate in the lack of any useful advertising information.[17]

As a third but equally important option, advertising can lift the time discount rate of the household to

$$\widetilde{\delta} = \widehat{\delta} + \sum_j \mu_j A_j$$

where just as previously, $\widehat{\delta}$ indicates the time preference in the case of no advertising and $\mu_j \geq 0$ shows the impact of commercials to that discount rate. This approach is consistent with the persuasive view of advertising. The deviation from the rational $\widehat{\delta}$ time discount rate induced by advertising can be an important explanation of the taste for immediate gratification approach recently publicized by Laibson et al. (2003). Otherwise stated, advertising can be interpreted as ”temptation” for higher present consumption (Benhabib & Bisin (2005)). While 30 years ago economists were reluctant to relax the assumption of stable preferences (see the already mentioned complementary view of Stigler & Becker (1977)), in the last decade the fields of behavioral economics and neuroscience provide empirical evidence against stable preferences and model these dynamically.

Note that in terms of functional form, the impact of advertising on the discount rate is identical to the impact of advertising on the interest rate. Both mechanisms introduce advertising linearly into the switching equation and advertising increases the probability of borrow in both cases. However, the differentiation is important. While the lower interest rate increases consumption and loan demand only if the household is in need of credit, the higher discount rate increases consumption in all cases, even if the household does not borrow. Therefore the two mechanisms have different welfare implications. Furthermore, the differentiation enables diverse interpretations and further potential extensions. Finally, the economic drivers of interest rate changes and preference changes are different, while the first is altered through providing information in commercials, the second is modified by persuasion.

Some complications may arise as a result of potentially misleading advertising. For instance, the lender may direct people to think that the currently low

[17]Note that if in the example the household was in borrowing need even in the case of 20% APR and only shops for the best interest rate, then the impact of advertising a competitive interest rate alters the brand choice probability. This shows potential interactions between the two informative advertising mechanisms.

interest rates are likely to last forever, or that the maturity of a particular advertised low-rate personal loan instrument is appropriate for the needs of the given household. Unfortunately, these misleading advertisements weaken the clear cut between persuasive and informative advertising, as the European about a high but seemingly low interest rate contains some persuasive elements. Fortunately, in the current European case example the importance of misleading commercials is minimal: on the one hand, customer protection is at an above average level in the given European country, on the other hand, the anonymous lender provides negligible information on the interest rate, that indeed is flat with minimal additional fees regardless the maturity or the customer segment the individual belongs to. Nevertheless, misleading advertising, similar to other shrouded lending product attributes, are likely to lead to biases in customer demand in more competitive markets, such as in the U.S.

The loan application probability including all three mechanisms of advertising listed above is

$$\Pr(Apply) = \Pr(Borrow) \cdot \Pr(Brand) = \Lambda(\theta\widetilde{g} + \widetilde{\delta} - \widetilde{r})\Lambda(\widetilde{\alpha})$$

The marginal effect of changing advertising to the loan application probability is

$$ME_j = \frac{\partial \Pr(Apply)}{\partial A_j}$$

or

$$ME_j = \Pr(Apply)\{[\gamma_j + \mu_j][1 - \Pr(Borrow)] + \beta_j[1 - \Pr(Brand)]\} \quad (3.3)$$

Consequently, the advertising elasticity of the loan application probability is

$$\varepsilon_j = \frac{\partial \Pr(Apply)}{\partial A_j} : \frac{\Pr(Apply)}{A_j}$$

which directly leads to the simple formula of

$$\varepsilon_j = [\gamma_j + \mu_j][1 - \Pr(Borrow)] + \beta_j[1 - \Pr(Brand)] \quad (3.4)$$

3.6.2 Media Type and Advertising

The empirical fact identified in Section 4, namely that commercials via television have higher impact on credit demand than via Internet or newspapers is an evidence of the persuasive view of advertising. On one hand, it was argued that a potentially longer recall of TV commercials is not a likely explanation of this empirical phenomenon. On the other hand, with the help of Equation 3.3 and the presented model of advertising, it is possible to decompose the various effects of advertising. Assuming that $\Pr(Borrow)$ and $\Pr(Brand)$ are exogenous in Equation 3.3 (which is trivial as these probabilities represent the behavior of the whole portfolio without advertisements), the different marginal effects of advertising has to be driven by the β_j, γ_j or μ_j parameters. β_j is interpreted as the impact of the knowledge about the brand. If a media type has higher β_j, it means that through that media the bank is able to communicate its existence better. It is very unlikely that television is more suitable to communicate a simple brand name that has actually been present on the market for a long time, such as the European bank in the empirical example, so that households should be familiar with it already. The fact that the given bank gives personal loan as a financial service might be a novelty, but this information is again very simple therefore all media should have the same success in transferring this to the audience. In the case of sophisticated messages, or long brand names or web site addresses, written media can be more efficient, but this is not the case in the current example. The impact of the personal loan advertising on the interest rate expectation (γ_j) is likely to be negligible across all media. As it was previously mentioned, the anonymous lender focuses its commercials on a certain life situation and on the brand name, but contains very limited information about the interest rate: only some regulatory compulsory statements on the pricing, depicted with small letters. To further strengthen this argument, even if the customers would be able to capture the pricing information, the same flat interest rate is communicated via all media.

As a result, the heterogeneity in media efficiency can be justified by the different μ_j parameters. As a prerequisite for this, it was previously mentioned that the advertisements contain persuasive elements, specifically the commercials via all media communicate that in the case of windfall consumption shocks the households should rather borrow, instead of smoothing consumption and cutting back from other, probably unnecessary consumption expenditures. This is accompanied with the fact that television is able to alter customer preferences better than other media. This is not surprising given the existing research on this subject *e.g.,* Vakratsas & Ambler (1999) or Abernethy & Franke (1996) provide excellent meta-analysis of marketing advertising papers and list a dozen that demonstrate well that television is more emotional than newspapers, radio or other media, so TV drives customer demand better. Just to mention a few examples, higher emotional state and persuasion can be reached through music, humor, cleverness, entertainment or believability. The current chapter contributes to this literature as in terms of personal loan, evidence of the persuasive impact of television advertising is scarce. This finding is also important as some authors argue that the impact of television on the demand of services is more limited than on consumer goods.[18]

3.6.3 Interactions Between Socio-Demographics and Advertising

Some potential sources of interactions between age or income and the impact of commercials were already discussed in Section 5. Specifically, the targeted media content and the media usage habits of different customer segments could create the observed advertising efficiency differences, but further data analysis pointed towards the rejection of those explanations. This section adds a few economically grounded theories that could similarly lead to the higher advertising elasticities of the young and the rich, but concludes that it is more likely that these segments experience a larger preference change, pointing towards the importance of the persuasive view of advertising.

First, Ackerberg (2001) stresses that previous experience with the product or service can decrease the impact of advertising. His model suggests that poor and old households have higher experience with unsecured lending so they need less information to make their consecutive choices, so react less to advertising. This mechanism directly explains why the rich and the young react to advertising exposure in a higher extent.

Second, the varying level of financial education in different customer segments may alter the impact of advertising. Lusardi & Tufano (2009) show for instance that debt literacy, which negatively alters the cost of debt and the probability of being in financial distress, is lower in the case of the poor and the elderly. Consequently, even if the poor and the elderly faces the same advertising exposure than the young or the rich (including the same creative message and information set), the young and the rich may be able to process this information more efficiently. Otherwise stated, even if the anonymous lender provides better conditions or services, which should attract new customers from all segments, the difference in financial education may lead to the poor and the elderly to neglect this useful information and still engage with an other preferred banking brand. While this explanation is also plausible, note that there is no consensus on the socio-demographic drivers of debt literacy. For instance, Agarwal et al. (2007) analyze the differences in financially relevant cognitive capabilities of households, and in that paper the empirical evidence shows a hump shaped curve in cognitive capabilities through the customer life cycle, middle-aged households being the most efficient in financial planning and decisions.

[18] According to Zeithaml, Parasuraman & Berry (1985), "Television's advertising strengths - which include demonstration as well as sight, sound, and motion benefits - may be less appropriate for services because of their intangibility. Unless a service is associated with relevant tangibles (the equipment in a health club), the service firm may have little to demonstrate. Television, generally the most expensive medium, may also not be feasible for many service firms."

Similarly to the media content and the media usage considerations in Section 4, both the theory of previous experience and financial education fail to explain why the efficiency differences revert in the case of "general advertisements" compared with the "personal loan advertisements". Intuitively, "general advertisements" contain mainly information about the brand and negligible information about the competitive pricing of the bank. As the main difference, "personal loan advertisements" are more successful to alter the discount factor, but one would expect that by removing this difference the rich and the young still react more to "general advertisements". Finding the opposite empirical result is a main reason why this chapter concludes that the source of different reactions to commercials has to arise from the preference changes. The remainder of this section formalizes this logic using the introduced notations of Section 6 blended together with the previous empirical findings.

Let us focus first on the interaction between age and advertising. Let us introduce a second index to the elasticities and to the model parameters that represent a specific socio-demographic group, e.g. β_{TV}^{O} will mean β_{TV} for the old customer group and similarly, Y index refers to the young group. Based on Section 5, the γ_{kj} interaction term between age and TV advertising is positive and statistically significant in the model that estimates group shares, thus

$$ME_{TV}^{Y} > ME_{TV}^{O}$$

These different marginal effects lead to different elasticities as well, due to the previous findings of this chapter. First, both the young and the old face the same television advertising over time, so $\overline{TV}^{Y} = \overline{TV}^{O}$, where the upper bars denote the average of the variable over time. Second, Figure 3.1 in Section 3 shows that young and old groups have almost the same probability to apply at the anonymous bank, so the simplification $\overline{\Pr}(Apply, Y) = \overline{\Pr}(Apply, Y)$ can be also used. As a result, 1% change in TV advertising leads to a higher percentage increase in the number of young applicants than in the number of old applicants:

$$\varepsilon_{TV}^{Y} > \varepsilon_{TV}^{O}$$

Equation 3.4 in Section 6.1 shows that these elasticities are driven by the three different roles of advertising. Due to the limited information contained in the commercials about the interest rates ($\gamma = 0$), this inequality is driven either by the brand information or by the persuasive role of the advertisements. On the other hand, "general advertisements" introduced in the empirical section contain information mainly about the brand (β) but no information about the interest rate ($\gamma = 0$) and no emotional cues that would change the time discount rate ($\mu = 0$). Table 3.5 shows that "general advertisements" lead to higher demand shift in the case of the old. Therefore, by taking the difference of the elasticities of "personal loan" and "general" advertisements (after the proper scaling due to the different β parameters), the following inequality has to hold:

$$\mu_{TV}^{Y}[1-\Pr(Borrow,Y)] >> \mu_{TV}^{O}[1-\Pr(Borrow,O)]$$

As the final step, it is possible to simplify this inequality with the probability to borrow at both sides due to two reasons. First, it was already mentioned that the market penetrations of old and young individuals are almost identical. Second, the life cycle model of consumption suggests that the young should borrow more often, so $[1-\Pr(Borrow)]$ is theoretically lower for the young, leading to an even stronger inequality after the simplification.[19]

$$\gamma_{TV}^{Y}+\mu_{TV}^{Y} >> \gamma_{TV}^{O}+\mu_{TV}^{O}$$

As a result, a likely reason of this empirical pattern is that $\mu_{TV}^{Y} >> \mu_{TV}^{O}$ – *i.e.,* young households experience stronger preferences towards instantaneous consumption in the presence of advertising.[20]

As rich households behave similarly to young customers in terms of the chapter's main empirical finding – *i.e.,* react more to TV commercials, the previous inference used for the young can be repeated. First, the higher marginal effect of advertising in case of rich lead to higher advertising elasticities of demand. This is due to the equal television exposure and to the equal probabilities to apply for personal loan at the given bank. The higher TV advertising elasticity of the rich is not driven by the impact of commercials on brand choice, as general advertisements have stronger impact on the poor compared with personal loan advertisement based on Table 3.5. As the importance of the impact of commercials on the interest rate is negligible, the following inequality has to hold to justify the empirical findings:

$$\mu_{TV}^{R}[1-\Pr(Borrow,R)] >> \mu_{TV}^{P}[1-\Pr(Borrow,P)] \tag{3.5}$$

where R and P indices denote rich and poor groups, respectively. As in the benchmark life cycle model the switching regression does not contain income at all, theoretically, changing income does not change the probability to apply for loan, which latter is driven purely by income growth expectation, interest rate and time

[19]In the demand model presented in Section 6 age differences matter in loan demand even without advertising, as young households have higher income growth expectation for the future than old households, given by the hump shaped age-income profile observed typically in economies. This means that *ceteris paribus,* younger households apply more often for loan, as $\frac{\partial \Pr(Borrow)}{\partial \bar{g}} > 0$.

[20]While the results about TV advertising is satisfactory to discuss the main empirical puzzle and the need for internal self control mechanism, similar analysis can justify the interactions between advertising and other media, and the analysis can be extended to gender and marital status differences as well.

discount rate. The poor and the rich have almost identical probabilities to borrow based on the empirical analysis of Section 3, further justifying the fact that the simplification of Equation 3.5 with $[1 - \Pr(Borrow)]$ at both sides does not alter the sign of the inequality. As a result, $\mu_{TV}^{R} >> \mu_{TV}^{P}$ explains the empirical findings, but the standard life cycle consumption model does not provide immediate explanation for this assumptions, neither for income nor for age differences. Section 6.4 below presents a set of potential justifications of this result.

3.6.4 Further Interactions Arising From the Life Cycle Model

The previous section has enriched the list of explanations of the observed heterogeneity in the impact of advertising among customer groups. To finish the investigation properly, this section adds three extensions of the life cycle model of consumption that are related to this heterogeneity.

First, in the standard model presented in Section 6.1 income y might contain transitory as well as permanent components. If the transitory component is statistically large in the population then *ceteris paribus*, higher income leads to lower the income growth rate. As shown, high income growth g increases the probability to apply for loan at the bank. As a result, $\Pr(Borrow, R) < \Pr(Borrow, P)$ can be justified theoretically with the transitory income - permanent income distinction, and this can lead to Inequality 3.5 to hold. However this argument is undermined by the empirical evidence in Section 3, as Figure 3.1 shows that high income actually does not mean lower response rates in the practice. Second, there is no empirical evidence about a large share of transitory income in the given European country, that would be required for this mechanism to work. Neither would this mechanism resolve the interactions between age and TV commercials.

Second, the existence of a subsistence consumption (such as necessary amounts payed for food and shelter) may be an important feature of the real economy. Consider that the household consumes a fixed subsistence amount ψ, which is identical for the present and future periods as well. In this case, the Euler equation in Section 6.1 can be set up for $c_t - \psi$ and $y - \psi$ which are consumption and income remaining after consuming and paying the subsistence amount, respectively. This model has the same properties as the benchmark model, except the following two features. First, if y is lower than ψ then the household automatically applies in the present time period for loan. Second, if there is a significant subsistence amount, then the income growth rate for $y - \psi$ deviates from the growth rate of y: keeping other model parameters constant, higher income leads to lower income growth rate. The previous analysis shows that high income growth rate leads to higher demand for the loan. Hence, both mechanisms lead to the fact that the poor borrow more, which is accompanied with lower elasticities of advertising based on Equation 3.3. So the presence of large subsistence expenditures theoretically explains the positive interactions between income and advertising in driving loan demand. But again referring to Figure 3.1, the poor do not have higher probabilities to borrow than the rich based on the empirical European data. So this model extension is not likely to explain better the empirical irregularities.

Finally, Section 6.3 have shown that the advertising of personal loans changes more the *preferences* of young and rich individuals. As this contradicts the implications of the simple life cycle model with advertising presented in Section 6.1, an extension of this is necessary. Internal self control mechanisms that are closely related to neuroeconomics can easily justify the interactions between advertising and customer characteristics, presented in detail in Appendix C. Specifically, the application of the addiction model of Bernheim & Rangel (2004) to life cycle consumption provides a parsimonious way to explain why the rich and the young would have higher μ parameters. Intuitively, rich and young households have higher absolute level of consumption, keeping other model variables constant. Under some further assumptions about the decision making process (the consumption of the advertised goods leads to a proportional jump in utilities and if this jump is larger than an absolute threshold, then then the customers "addicted to consumption" can not resist the temptation), the customer segments with higher consumption react more to advertising. In addition to the detailed description and simulation of this model, Appendix C contains some further empirical evidence based on the European data that is in favor of the existence of internal self control mechanisms. Altogether, these considerations justify why this theory is preferred over the other presented theories, that are empirically less solid.

Nevertheless, using field data it is very difficult to unambiguously conclude that internal self control mechanisms are the unique reason behind the observed empirical patterns. Further research in this field is essential, either to justify the hereby listed theories, or to introduce novel economic extensions to the life cycle model that lead to heterogeneity in preference changes as a result of advertising.

3.7 Conclusion

This chapter reports novel empirical evidence from the household unsecured lending market about the importance of the persuasive view of advertising. First, television advertising has a significantly higher impact on the number of applications than other media have. Second, certain large customer segments react to advertising in a way that is unexpected based on the media usage patterns of those segments. Specifically, rich and young households react more to TV advertising. The first fact is fully consistent with the persuasive view of advertising. For the interpretation of the second fact, the chapter lists several potential explanations, out of which the most preferred theory, that is also the best supported by the empirical data, is the existence of the persuasive view together with internal self control mechanisms.

Credit advertising in this chapter is only one observed factor that changes credit demand. The advertising of other goods, seasonality, and other emotions (called affective factors together) continuously change customer's choices and preferences. In the light of the evidence that credit advertising alters consumer's preferences, it is easier to believe that other unobserved affective factors similarly interact with income and other socio-demographics, creating unintuitive non-linearities and non-monotonic relationships in the credit demand, just as in Figure 3.1.

Does the current discussion mean that the informative view of advertising is non-existent in the financial markets? Certainly not, as the reported results also indicate that advertising is a major driver of loan applications in all customer segments. This is a strong evidence towards the informative view of advertising, and therefore the chapter does not contradict the literature that finds information provision as the primary role of commercials. However, empirical evidence toward the persuasive view is rare in the literature of personal loan advertising.

Because of the information asymmetries on the lending market, not all stakeholders may be aware of the fact that commercials of loans shift up present consumption. Banks possess enormous amount of customer information, thus would be able to uncover similar or even deeper insights about the role of advertising. However, banks intend to maximize their profit, and a customer attracted by the brand from the competition generates as much profit as a completely new customer on the lending market attracted by persuasion. Consequently, banks may be probably less interested to hear the findings of this chapter, unless they are committed to responsible lending. On the other hand, the creative messages highlighted in the introduction indicate that some banks already utilize the knowledge about the persuasive role of commercials.

In terms of policy implications, being aware of the fact that advertising changes customer preferences is thus much more important for the regulators and for the customers. In the light of this finding, regulators might fine tune customer protection acts and financial education to maximize welfare in the financial markets. Finally, the individuals might prepare to resist temptations with self control steps, such as muting the television during commercial breaks.

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A Appendix to Chapter 1

A.1 Definition of the Income Quintiles

Table A-1: Minimum household income (in $) as a threshold to define the specific income quintiles

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Quintile 2	31,000	31,057	31,000
Quintile 3	49,156	52,600	53,475
Quintile 4	68,489	79,760	78,362
Quintile 5	100,000	117,028	134,511

Table A-2: Number of observations by income groups and by age

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	657	940	1,003
Quintile 1	128	153	119
Quintile 2	122	151	122
Quintile 3	114	147	129
Quintile 4	122	153	155
Quintile 5	171	336	478

A.2 Robustness Check of the Income-Debt Relationship

Table A-3 shows the 75% percentile of credit card debt-to-income ratio to justify the fact that the middle-income household have higher debt-to-income ratios is not caused by extreme values. Table A-4 shows mean credit card debt-to-income ratios, but only for employees, showing that the debt patterns are not skewed by the behavior of entrepreneurs or inactive households.

Table A-3: 75% percentile of credit card debt-to-income ratio for all households

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	0.46	0.46	0.48
Quintile 1	0.19	0	0.16
Quintile 2	0.09	0.54	0.57
Quintile 3	0.72	1.37	1.04
Quintile 4	0.93	0.85	0.63
Quintile 5	0.48	0.09	0

Table A-4: Mean credit card debt-to-income ratio for households with working household head

Income	$30 \leq Age < 40$	$40 \leq Age < 50$	$50 \leq Age < 60$
Total	0.58	0.68	0.63
Quintile 1	0.72	0.36	0.34
Quintile 2	0.49	0.76	0.58
Quintile 3	0.63	1.20*	1.20
Quintile 4	0.67	0.71*	0.56
Quintile 5	0.43	0.25	0.34

T-tests to compare values in Quintile 2-5 with that of Quintile 1 are shown with (*) if they are significant at the 95% significance level.

A.3 Tobit Model to Estimate Interest Rate Elasticity

This section contains the parameter estimates for the demand model for "low risk" households defined in Section 4.1. This demand model is the extension of Equation 1.1 with interest rate as an additional explanatory variable. Note that the rest of the parameter estimates are not comparable with those in Section 3, as this model is run on a restricted sample: both "high risk" households and those without a credit card are excluded.

Table A-5: Tobit model to estimate credit card debt-to-income ratio for "low risk" households including interest rate as an explanatory variable

Variable	Parameter	Standard error
Variable	Parameter	Standard error
Intercept	2.709	(0.136) *
Interest rate	-0.084	(0.020) *
Quintile 2	0.402	(0.748)
Quintile 3	0.981	(0.697)
Quintile 4	0.190	(0.732)
Quintile 5	-0.632	(0.746)
Age 40-49	0.849	(0.308) *
Age 50-59	0.542	(0.330)
Black	0.843	(0.524)
Hispanic	-0.271	(0.447)
High School	-0.549	(0.282) *
University	-1.115	(0.396) *
Male	0.273	(0.489)
Married	-0.125	(0.458)
Number of kids	0.077	(0.111)
Household owner	0.546	(0.463)
High financial assets	-1.325	(0.261) *
High non-financial assets	-0.173	(0.275)

T-tests are shown with (*) if they are significant at the 95 % significance level. N=1,343.

A.4 Which Segments Are Targeted More with Direct Mail?

Table A-6 shows a result of a probit model that estimates whether the household uses direct mail to make borrowing decisions. The SCF asks the folliwing: "Please tell me which sources of information do you (and your family) use to make decisions about borrowing and credit?" Mutiple sources can be listed by the household. The target variable of the probit model is the direct mail dummy that has the value of one if the "Material in the mail" option is selected by the household. The explanatory variables in the model are the same as in the models to estimate credit card debt in Section 3. Because of missing income data, the correct treatment of income imputation is used, similarly to Section 3.

Table A-6: Probit model to estimate whether a household uses direct mails as information to make borrowing decisions

Variable	Parameter	Standard error
Intercept	-1.120	(0.125) *
Quintile 2	0.341	(0.122) *
Quintile 3	0.573	(0.122) *
Quintile 4	0.497	(0.136) *
Quintile 5	0.282	(0.146)
Age 40-49	-0.046	(0.080)
Age 50-59	-0.118	(0.088)
Black	0.254	(0.101) *
Hispanic	-0.022	(0.113)
High School	0.070	(0.077) *
University	0.073	(0.113)
Male	-0.126	(0.111)
Married	0.012	(0.104)
Number of kids	-0.067	(0.029) *
House owner	0.212	(0.084) *
High financial assets	-0.040	(0.086)

T-tests are shown with (*) if they are significant at the 95 % significance level.

B Appendix to Chapter 2

Stylized Facts from the Holiday Seasons

High consumption and high unsecured loan demand in the U.S. in December are well documented facts. The left hand side of Figure B-1 shows the time development of average revolving loan[21] and average monthly consumption per household between 2003 October and 2008 February, both metrics are deflated to the 2003 October levels using the nationwide Consumer Price Index. The right hand side of the figure shows the average monthly difference of loan and consumption: the October bars show that during the period covered by the time series, unsecured loan in October was slightly less than in September, and consumption decreased more significantly from September to October. One can observe that the high incremental consumption ($472) is accompanied with a high incremental unsecured loan balances in December ($195). Meanwhile this aggregate data does not make it possible to differentiate whether this higher usage rate is due to the life cycle use or to the transactional use of credit card.

The right hand side of Figure B-1 shows that while the high consumption peak in December is followed by a consumption drop of same magnitude in January, the pattern for unsecured loan is not the same. Households accumulate debt in November and December and the payback is spread over January, February and March. This shows that the revolve rate changes after the consumption peak in December, but similarly to the change of the usage rate, it is uncertain whether it is due to life cycle use or to the transactional use.

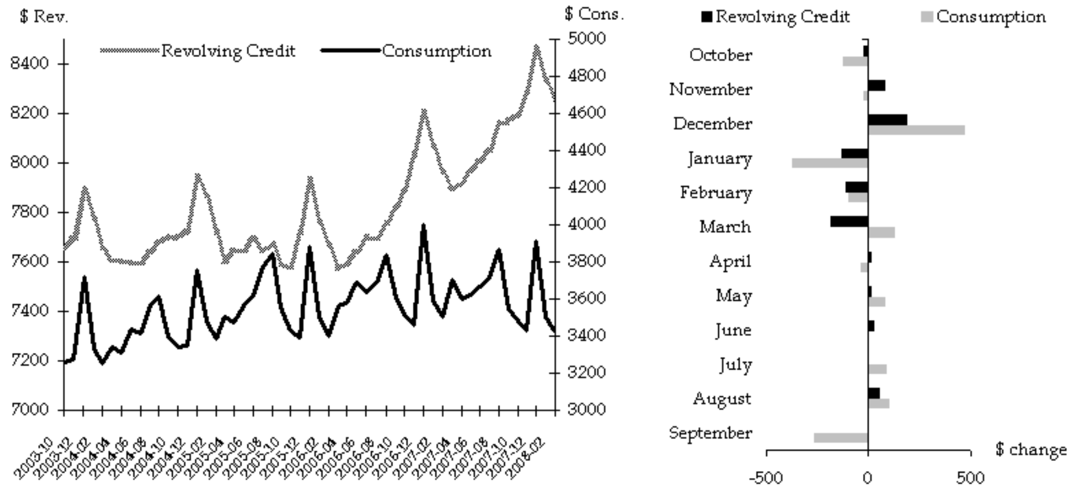
The next stylized fact can be seen on Figure 3.2(a)-3.2(b). Figure 3.2(a) shows statistics from the Survey of Consumer Finances about the yearly credit card usage pattern of households in 2007.[22] About a quarter of households did not have credit card at all during the year, 40% of them are transactors[23] and 18.3% hardly paid

[21] According to the Federal Reserve, 90% of revolving loans contained in the G19 report is credit card debt so the trend of this metric can be used as the best monthly available approximation of credit card debt trend.

[22] The SCF interviews are spread over the year, therefore answers to the usage questions can be taken as a yearly average independent of seasonality.

[23] The exact survey question is: Thinking only about Visa, Mastercard, Discover, American

Figure B-1: Revolving consumer loans and consumption per household in 2003 October USD.

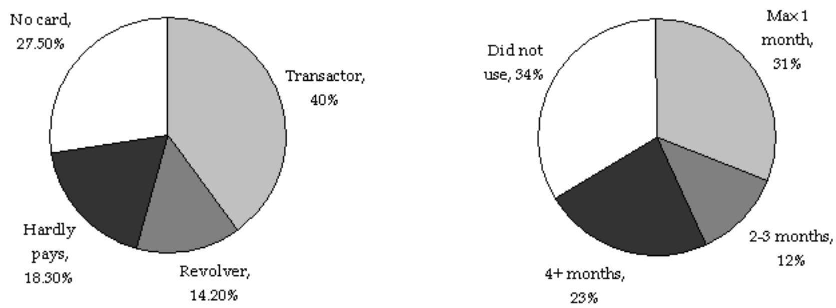


Source: Bureau of Labor Statistics; Federal Reserve

back their balances. Figure 3.2(b) shows comparable statistics from the Deloitte Holiday Survey,[24] and shows that in 2007 December 34% of total households were not using their credit card while 23% of customers accumulated credit card debt and could pay back their loan only in more than 4 months. Also, the share of transactors (those who paid back the holiday loan in less than 1 month) is only 31%. Even after correcting with the slightly less credit card users at Christmas, the share of transactors is lower and consequently, the share of those who revolve longer is higher in the holiday season compared with the full year of 2007. This figure reinstates the fact that households revolve more often with the December debts, consistently with Figure B-1. The exact explanation of the seasonally changing credit card debt patterns is an interesting area for future research, both through the lens of the life cycle consumption model and of the transactional use model.

Express cards you can pay off over time, and store cards, do you almost always, sometimes, or hardly ever pay off the total balance owed on the account each month? Those who respond "Always or almost always" are considered as transactors, those who respond "Sometimes" are considered as revolvers.

[24]www.deloitte.com



(a) All year (b) Holiday season

Figure B-2: Credit card usage statistics, 2007. *Source: Survey of Consumer Finances, Deloitte Holiday Survey*

C Appendix to Chapter 3

Details of the Internal Self Control Mechanisms

Neuroeconomics and advertising are related, for instance Camerer et al. (2005) criticize existing theories of advertising in the following way: "Many of these models seem like strained attempts to explain effects of advertising without incorporating the obvious intuition that advertising taps neural circuitry of reward and desire". Similarly, in his extensive advertising literature review, Bagwell (2005) suggests that "advertising content may be designed to serve as an environmental cue that activates the affective/hot-mode system". Internal self control models can create a direct interaction between advertising and the parameters of the life cycle model.

Using the algorithm of Benhabib & Bisin (2005), this interaction will be negative both in case of income (y) and income growth rate (g), as there is an override system that cancels the impact of advertising (so sets μ_j to zero) if the utility loss due to the suboptimal consumption (evaluated by the deliberative self) is too large, and both y and g increases this utility loss. Based on the algorithm of Bernheim & Rangel (2004), a consumption model creating positive interactions between μ_j and y or g can be constructed with the opposite decision-making process compared with the previous model: if the utility loss generated by not consuming the affective optimum (evaluated by the affective self) is too large, then the decision maker overrides the deliberative optimum and lets μ_j to alter the consumption.

Most easily, the details of these models can be understood by a two period simplified version and simulation shown hereby. One is interested in the optimal consumption for a specific bundle of goods or services if affective shocks (advertising in the specific case) alter the optimum in a simple two period consumption model. In this simple model, the consumer looks at the future as a single time period, where he will spend the remaining money from his wealth to a unique future consumption good. The present and future consumption is denoted by c_1 and c_2, respectively, and as a simplification, it is assumed that c_1 and c_2 are the dollar amount of consumption – *i.e.,* the customer decides how much to spend to the bundle of goods in focus.

The way to include affective shocks is through the utility derived from the present consumption. In the presence of affective shock $\lambda > 1$, the consumption of c_1 is observed as λc_1. Let us introduce y_1 as the period one income, y_2 as the period two income, and $\rho > 0$ as the time discount rate,[25] and suppose that the consumer has to pay r interest rate on $c_1 - y_1$ if $c_1 > y_1$. These assumptions lead to the following utility maximization problem:

$$\max_{c_1,c_2} U(\lambda c_1) + \frac{1}{1+\rho} U(c_2)$$
$$s.t.\ c_1 + c_2 + (c_1 - y_1) \cdot \widetilde{r} \leq y_1 + y_2$$

where $\widetilde{r} = r$ if $c_1 - y_1 > 0$, $\widetilde{r} = 0$ otherwise. The optimal consumption (c_1^*, c_2^*) will lead to $l^* = \max(c_1^* - y_1, 0)$ loan demand.

The rational consumption and loan demand is given by $\lambda = 1$ and is denoted by (c_1^I, c_2^I). The affective consumption and loan demand is given if $\lambda > 1$ and is denoted by (c_1^A, c_2^A).

Benhabib & Bisin (2005) publish a dual self model which is a combination of the previous rational and the affective decision making process. The decision consists of two parts: firstly the automatic processing evaluates and maximizes the affective utility, calculating (c_1^A, c_2^A). Secondly, the controlled processing of the customer's brain evaluates the rational utility, and derives (c_1^I, c_2^I). The final consumption decision will be the affective optimum if the utility loss (by consuming the affective optimum instead of the consumption goal) observed by the controlled processing is smaller or equal than the attention cost b, otherwise the rational consumption goal is realized. One may refer to this model as to the override model, which has the following formal definition:

$$\begin{aligned} &\text{If } U(c_1^I) + \tfrac{1}{1+\rho} U(c_2^I) - U(c_1^A) - \tfrac{1}{1+\rho} U(c_2^A) < b \\ &\text{Then } (c_1^*, c_2^*) = (c_1^A, c_2^A), \\ &\text{Else } (c_1^*, c_2^*) = (c_1^I, c_2^I). \end{aligned} \tag{C-1}$$

The other relevant dual self model is the cold mode - hot mode model, such as that of Bernheim & Rangel (2004). In the discrete choice model of the authors the affective variables has an opposite effect: if the affective shock is greater than a threshold value $(\lambda > \overline{\lambda})$, then the individual enters to a hot mode, where he consumes always the good. Otherwise, the individual behaves as rational utility

[25] One might observe that λ and ρ have the same effect, both parameters are determining the relative weights of c_1 and c_2 in the discounted utility function. However, the distinction is important in case of the dual self models: the two self will evaluate differently relative weight of the present and future consumption. While mathematically it would be identical to use only two discount rates or only two affective factors, the two parameters have different sources: ρ is a rational feature while λ is an affective one, therefore the specification used here is the most beneficial.

maximizer. This model is typically used to explain compulsive behavior such as drug addiction.

There are several ways to map this discrete choice model to continuous optimization. For instance it may be assumed that if $(\lambda > \overline{\lambda})$, then the customer will consume the affective optimum (c_1^A, c_2^A), otherwise the affective shock is small enough to be able to resist, and the customer selects (c_1^I, c_2^I). Secondly, it is possible to arrive to a symmetrical form with the override model, if utility differences are used instead of the affective shock itself. In this case, the final consumption decision will be the affective optimum (c_1^A, c_2^A) if the utility gain (by consuming the affective optimum instead of the consumption goal) observed by the affective processing is larger or equal than the attention cost b, otherwise the consumption goal (c_1^I, c_2^I) will be realized. Formally:

$$\begin{aligned}&\text{If } U(\lambda c_1^A) + \tfrac{1}{1+\rho}U(c_2^A) - U(\lambda c_1^I) - \tfrac{1}{1+\rho}U(c_2^I) < b\\ &\text{Then } (c_1^*, c_2^*) = (c_1^A, c_2^A),\\ &\text{Else } (c_1^*, c_2^*) = (c_1^I, c_2^I).\end{aligned} \tag{C-2}$$

The nice symmetry with the override model is, that this so-called hot mode model is also based on utility differences. However, in the hot mode model the affective shock alters the consumption only if the utility difference is high, as opposed to the override model in which case the utility difference has to be low.

In terms of comparative statics,[26] a quick discussion of the impact of λ is beneficial, and simulated consumption patterns are plotted on Figure 3.2. In the affective model, if λ is increasing then the consumption is also increasing in a non-linear, but continuous way. In the override model it can be observed, that there is a level for λ, below which the consumer behaves as an affective utility maximizer. Meanwhile, when reaching a certain level of the affective shock, the override process starts to work and the customer behaves as a rational utility maximizer. This leads to a downward jump in consumption, and larger affective shocks do not change the consumption level of the individual. The hot-mode model works in the opposite way: for small affective shocks the consumer behaves as rational utility maximizer neglecting the affective shocks, but above a certain λ threshold, the customer switches to the hot mode, where his consumption will jump upwards, and is driven by the level of the affective shock.

The other important model variable to discuss in income. Figure C-1 is showing simulation results by increasing y_1 and y_2 with the same proportion. Because of the CES utility, the relationship between consumption and income is typically linear, but there might be jumps (caused by the dual-self switching equations) and slope changes (caused by the costly loan), therefore the functional form is stepwise linear. In the rational and affective model only slope changes can be ob-

[26]The following simulations are based on Constant Elasticity of Substitution utility functions.

served but no jumps; here only the costly loan has effect on the decision. In the override model one might observe a downward jump in the consumption/income ratio above a certain level of income, because the utility loss in the override model increases with income (through the consumption), and the decision maker will override his affective decision if his attention cost b is achieved. This leads to a downward jump in consumption. Similarly, one might observe an upward jump in the hot mode model in the consumption/income ratio. Here the mechanism is the opposite: higher income will increase both the affective and the rational consumption, and in parallel the utility differences also increase. After a certain attention cost, the decision maker switches to the hot mode. The example of income shows how the dual self effect models are causing upward or downward jumps even if the affective shock is identical, but an other model variable is varying. Hence, this model can explain empirical consumption-income relationship such as hump shaped or non-monotonic curvature. These jumps are similarly generated by changing the discount factor or interest rate as well, therefore the model can explain complex hump shaped relationships between consumption and discount factor drivers as well.

Very similar upward and downward jumps are generated by changing income growth parameter, which is denoted by g in the previous discussions, but is equal to $\frac{y_2}{y_1}$ in the current dual self model setup, keeping y_1 constant. The resulting simulations can be seen in Figure C-3, where higher income growth leads to upward jump in case of the hot mode model, and to downward jump in the override model.

The presented analysis shows that the Bernheim type hot-mode dual self model can create the empirical fact according to which both rich (high y income) or young (high g income growth) households react to advertising more and prefer present consumption to future spending. Intuitively, these households can not resist the larger temptation induced by TV commercials that arises from their relatively larger consumption compared with poor and old households.

Meanwhile this interaction is only a side effect of the hot-mode model, and the primary effect of it is that advertising itself should have an increasing return to scale, matching the simulation results of the "hot mode" model on Figure C-1. Therefore a test of existence of the internal self control mechanism is whether advertising increases demand proportionally more as advertising grows. A simple model to explain the number of loan applications with advertising through the 3 media and with interactions between the 3 media can shed light to this empirical question. To get statistically large population, this model will be run on the $t \times g$ panel data set used before, where t is time and g denotes the customer segments defined previously. Hence, the model is

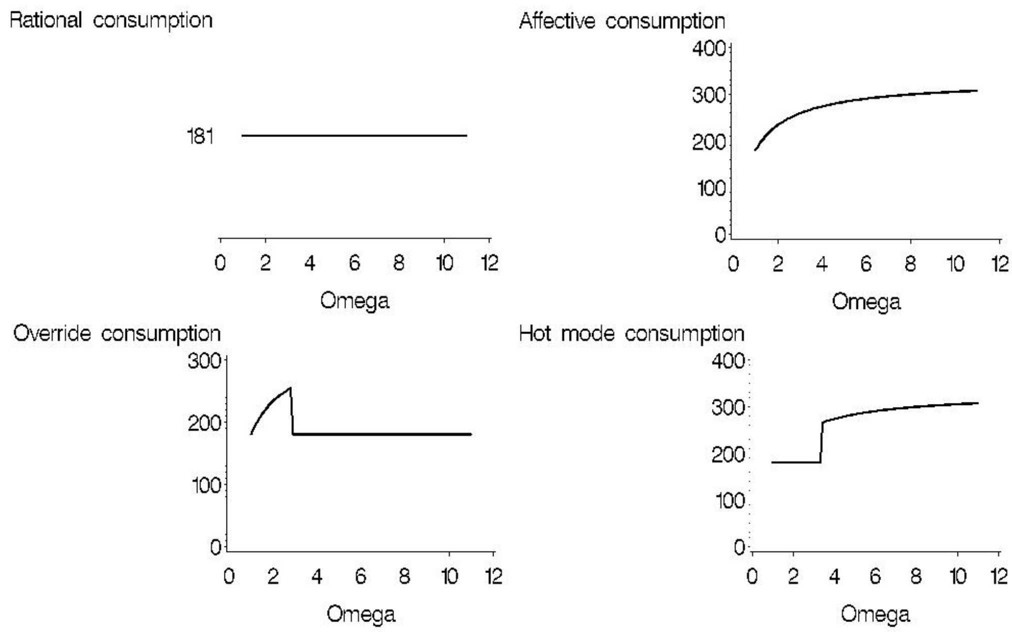


Figure C-1: Consumption as a function λ

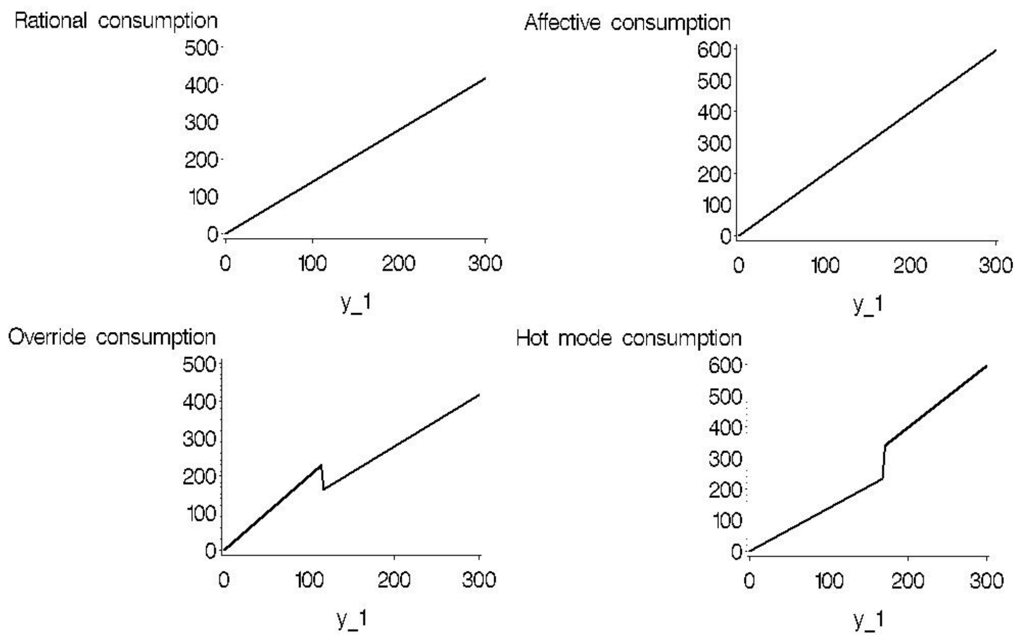


Figure C-2: Consumption as a function of permanent income

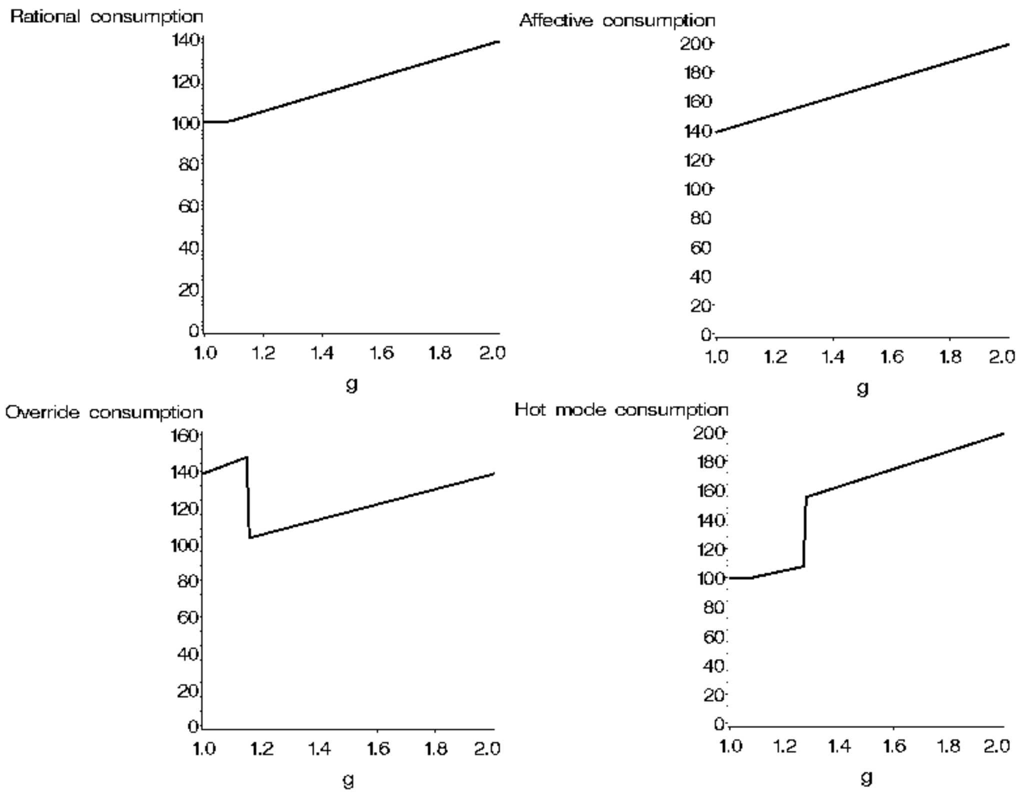


Figure C-3: Consumption as a function of future income growth rate

$$Y_{gt} = \sum_{j=1}^{3} \beta_j A_{jt} + \sum_{j=1}^{3} \sum_{m>j} \gamma_{jm} A_{jt} A_{mt} + u_{gt}$$

and

$$u_{gt} = \delta_g + \varepsilon_{gt}$$

where ε_{gt} is iid. normal. Table C-1 shows that the interaction parameters γ_{jm} are positive and significant in two cases out of the three, specifically between Internet and newspapers, and between TV and newspapers. This regression shows that the internal self control specification seems to fit well the empirical findings as it both explains the interactions between income or age and advertising and the positive economies of scale of advertising.

Table C-1: Estimating loan applications with advertising and first order interactions between different media.
The data is not shown due to confidentiality reasons. Please contact the author for further details.

Note that advertising scale economies are at the heart of the advertising research. For instance Bagwell (2005) identifies this as a main empirical regularity which is frequently discussed in the literature. Internal self control mechanisms create these scale economies *per se* regardless of the market structure and firm behavior, which shows large research potential in modeling the household decision making process itself.