AN INVESTIGATION OF CREDIT CARD HOLDING, BORROWING, AND PAYOFF

DISSERTATION

Presented in Partial Fulfillment of the Requirements for
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By

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ABSTRACT

The widespread use of credit cards has challenged the traditional lifecycle hypothesis and introduced new uncertainties into U.S. financial markets. Based on a set of new survey data, this dissertation empirically investigates two critical issues in the credit card market: 1) the lifecycle borrowing and payoff profiles of credit card revolvers adjusting for cohort effects, 2) the underlying determinants of the consumer’s choices regarding holding, borrowing, and payment on credit cards.

Due to data limitations, most previous studies analyzed consumer debt in a static or comparative static context. Using a synthetic cohort approach, this research tracks the changing behavior of credit card borrowing and payoff in a lifecycle framework for different birth cohorts observed in a time series of cross sections. A two-way fixed effect, pseudo-panel data model is proposed to disentangle cohort effects from age and time effects and to estimate the cohort-adjusted profiles. The fitted profiles show very different patterns compared with the unadjusted cross-sectional profiles implied by the simple lifecycle hypothesis. The results suggest that younger American consumers are borrowing more heavily and repaying
at lower rates on credit cards than older generations. If the current borrowing and repayment habits persist, a substantial buildup of credit card debt at a later period in life may jeopardize the financial well-being of the elderly and cause instability in the credit card market.

For effective policy-making and regulation in consumer finance, it is necessary to understand the underlying determinants of consumer behavior in credit card holding, borrowing and payoff. This study examines a variety of factors, including credit related variables, socioeconomic variables, and expectations variables, in determining household behavior related to credit card use. Specifically, the analysis focuses on three aspects of the consumer’s choices: 1) credit card ownership, i.e. whether or not to hold a credit card, 2) credit card borrowing, i.e. whether or not to borrow on a credit card, and 3) determinants of the levels of credit card debt and payoff rates. Analyzing credit card debt and payoff rates in the context of ownership choice and borrowing choice helps to provide an understanding of how consumers maximize utility by switching between different roles, and allows us to look at consumer behavior in the credit card market from a broader perspective.
Dedicated to my advisor, Professor Lucia Dunn.
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First and foremost, I would like to express my deepest gratitude to my advisor Professor Lucia Dunn. She is not only a great advisor who gives inspiring insights on my academic research, but also an intelligent mentor who teaches me wisdom in many aspects of life. Here I am dedicating this dissertation to her with all my respect and thanks.

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also want to give thanks to all my colleagues and friends who have made my school life in Columbus a joyful experience.
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CHAPTER 1

INTRODUCTION

After credit cards became a popular product in the U.S. financial market, the past two decades have observed a continuous increase in credit card debt and bankruptcy filings. Compared with other types of consumer debt, credit card debt has its unique features, of which two most important ones are non-security and flexibility. First, credit card debt is non-secured in the sense that there is no required collateral to guarantee the repayment of the debt. This non-security feature makes it very risky for the lenders to manage the credit card loan; therefore credit card contracts usually specify high interest rates and many kinds of related fees, including membership fees, late payment fees, over-the-limit fees, and other services fees. On the other hand, the options to default and to file for bankruptcy under certain circumstances encourage irresponsibility of the borrowers in paying off their credit card debt. The feature of flexibility refers to the fact that within given credit limits consumers can discretely make decisions on when, where, and how much to borrow.
on their credit cards and the flexible payment arrangement also allows them to decide on the payment amount and payoff plan to their own conveniences. The only restriction on the amount of payment is the minimum required payment, which is usually a very small percentage of the total balance due on the statement. With the rapid development of the credit card market, many researchers have turned their attention to this unique financial instrument with non-secured borrowing and flexible repayment.

Recently there has been an increasing concern among policymakers and banking practitioners that if the current debt accumulation pattern persists, people will not be able to pay off their debt in the future. Are American consumers paying off or accumulating their credit card debt? To the best of my knowledge, there are few studies in the existing literature that have attempted to answer this question. Based on original household data on consumer finances, this dissertation tries to address this issue with the intention of shedding some light on the prospects of credit card payoff for future generations as well as evaluating relevant policies that will influence consumer behavior. The analysis is focused on two critical issues in the credit card market: 1) the lifecycle borrowing and payoff profiles of credit card revolvers adjusting for cohort effects, 2) the underlying determinants of the consumer’s choices.
regarding holding, borrowing and payment on credit cards. The above two issues are separately discussed in Chapter 3, *A Synthetic Cohort Analysis of Credit Card Debt and Payoff Rates*, and in Chapter 4, *Consumer Choices in Credit Card Holding, Borrowing, and Payoff*. The two chapters correspond to the two steps in the two-step estimation procedure for the proposed two-way fixed effect, pseudo-panel data model, and they investigate consumer behavior in the credit card market at the aggregate cohort level and at the individual household level, respectively.

There is strong evidence that nowadays the young Americans are getting more and more addicted to borrowing on credit cards to satisfy their consumption needs, but they are less responsible in repaying their increasing credit card debt comparing with people in earlier generations. The average generation difference in credit card debt is estimated to be $3000, and the average generation difference in credit card payoff rate is estimated to be 10 percentage points. Consumers are borrowing on credit cards so extensively that the relatively higher payments after retirement are far from enough to recover their credit card debt accumulated in early life. If the current pattern persists, most people will carry a considerable amount of credit card debt to the end of their lifecycles, which would jeopardize the financial well-being of the elderly and cause instability in the credit card market.
In order to take effective procedures to revert this trend, it is important for policymakers to have a better understanding of the underlying factors that determine the consumer’s choices related to credit card use. Using recent consumer finance data, this research also empirically tested the effects of a variety of variables, including credit related variables, socioeconomic variables, and expectations variables, in determining credit card holding, borrowing, and payoff. The results have important policy implications and are especially relevant for evaluating recent policy actions by federal banking authorities. It is found that increasing the minimum required payment will increase the actual payoff rate more than proportionately and dramatically shorten the timeframe necessary to achieve a total payoff of the running balance.
CHAPTER 2

DATA

The data used in this dissertation come from two large monthly surveys – one conducted by The Ohio State University Center for Survey Research and known as the Ohio Economic Survey (OES), and one conducted by the Center for Human Resource Research at The Ohio State University and known as the Consumer Finance Monthly (CFM). These surveys collect original household data on consumer finances and have many unique variables that are not available in other consumer finance surveys. Compared with the Survey of Consumer Finances (SCF), which is the most widely used public dataset covering credit card issues, the OES and the CFM provide more detailed information on the credit card market and consumer behavior. Furthermore, the SCF takes place every three years and the data are two years old when published; while the OES and the CFM are monthly surveys and provide the most up-to-date data on consumer finances to reflect the newest changes of American consumers’ spending habits and financial management.
The *OES* is a state-wide telephone survey of Ohio residents conducted between November 1996 and April 2002. The sample was selected using Random Digit Dialing to obtain at least 500 completed cases each month. The final dataset consists of 40,320 cases, among which 30,557 were credit card holders. Considering possible non-response error, the data were weighted to take into account the number of telephone lines in each household and to adjust for variations in the sample from U.S. population related to various demographic and socioeconomic factors. Respondents were encouraged to consult their most recent credit card statements in order to facilitate the recall of the credit card information. This could include terminating the phone call with scheduling a callback when the respondent had all the information. Usual survey quality standards were enforced to ensure high quality data, including third party monitoring and extensive checks for internal consistency in the responses using filtering algorithms. There is a variety of variables on credit card use in the *OES*, including monthly charges, cash advances, monthly payments, revolving balances, minimum required payments, credit limits, annual percentage rates, number of cards charged on, number of cards maxed out, and number of times missing minimum required payments. In addition, the *OES* contains consumer
confidence measures, price expectations, and debt stress variables. There is also extensive demographic and socioeconomic information available in this survey.

The CFM is an on-going national survey, which started in February 2005 and is adding up at least 300 new cases each month. By the end of 2006, about 7,000 cases have been completed and are available for research. Similar to the OES, the CFM is also a monthly telephone survey using Random-Digit-Dialing techniques. The CFM questions have been constructed to be as individualized as possible. When the respondents say “don’t know” or “refuse” to answer, a series of unfolding bracket questions are used in order to get as much information as possible. In all unfolding bracket questions, a threshold is presented, and the respondent is asked whether or not the amount is “less than” or “more than” the threshold. Based on the thresholds and the answers to the unfolding brackets, an estimated value can be calculated to reflect the true value of the data. The set of questions addressing credit card use in the CFM survey is greatly expanded and includes a more detailed inventory of household credit cards and additional facets of their use, such as balance switching, credit knowledge, and bill payment. Another major aspect of the CFM is the inclusion of a battery of questions which elicit complete information on household assets and liabilities. This balance sheet information allows us to look at the consumer’s credit
card debt in a context of their overall financial well-being so that we can better understand consumer behavior and forecast economic activities.

The population characteristics of the state of Ohio closely approximate those of the nation as a whole; and for this reason, it is one of the most commonly used test market states in the U.S. Table 2.1 demonstrates that the sample characteristics for the Ohio sample in the OES are very close to those characteristics of the national sample in the SCF and the CFM. The main difference occurs with gender and employment status. The disproportionate number of males and employed respondents in the SCF arises from its personal interviewing of household heads in a sample that over-represents the wealthy. The breakdowns of the OES and the CFM are closer to the actual national proportions, which results from the random sampling techniques. The closeness of sample characteristics for the OES and the CFM provides reliability for combining the two datasets to obtain a time series of cross sections used in this research.
<table>
<thead>
<tr>
<th>Variables</th>
<th>OES Mean</th>
<th>SCF Mean</th>
<th>CFM Mean</th>
</tr>
</thead>
<tbody>
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<td>11.10</td>
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</tr>
<tr>
<td>APR (annual percentage rate)</td>
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<td>Ethnicity: percentage white</td>
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<tr>
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<td>Age</td>
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<td>50.02</td>
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<tr>
<td>Gender: percentage males</td>
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<td>0.76</td>
<td>0.43</td>
</tr>
<tr>
<td>Employment: percentage employed</td>
<td>0.61</td>
<td>0.76</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Note: The statistics for the SCF are taken from Min and Kim (2003), Table 2.

Table 2.1: Descriptive Statistics for the OES, 1998 SCF, and 2005 CFM
CHAPTER 3

A SYNTHETIC COHORT ANALYSIS OF CREDIT CARD DEBT AND PAYOFF RATES

3.1 Introduction

Consumer debt has traditionally been analyzed within the Fisher framework of shifting consumption between periods and smoothing consumption over the lifecycle. While the shifting of consumption to earlier periods via various debt instruments will necessarily have a negative impact on future consumption as debt is repaid with interest, the assumption is usually made that consumers will indeed over time successfully repay the debt acquired earlier in life. However, with the introduction of non-secured lines of credit with flexible payments - i.e., credit cards - the traditional patterns of consumption smoothing and debt repayment may no longer be the same for U.S. households. According to the Federal Reserve Board, U.S. consumers are currently carrying about $800 billion in revolving debt, mostly credit card balances, which represents a six-fold increase in the last two decades. Unlike mortgages, student loans, auto loans, and other installment loans with which the U.S.
population has a relatively long history, substantial credit card debt is a fairly recent phenomenon, and predictable debt accumulation and repayment trends have yet to be firmly established. Besides the flexible repayment feature of credit card debt, the possibility of default and bankruptcy poses further uncertainties about how consumers will repay their debt over the lifecycle.

There is particular concern about how credit card debt will affect the future financial security of the elderly. At present, credit card debt and default are more prevalent among younger cardholders. However, as the population ages, these credit card trends could well persist and result in a dramatically changed debt landscape for the elderly. Approximately three-quarters of Americans over the age of 65 hold credit cards according to the SCF data; and the mean revolving credit card balances for indebted senior households are on the rise, increasing by about 89 percent from 1992 to 2001 (McGhee and Draut 2005). The number of older Americans filing for bankruptcy tripled in this same time period, according to the National Association of Consumer Bankruptcy Attorneys. Depending on variations of payoff rates over the lifecycle, the long term aftermaths of these trends could include a serious deterioration of living standards for the elderly, a possible increase in estate bankruptcies, and a consequent rise in interest rates. New interventions may be
needed to regulate credit card market and guide consumer behavior in order to maintain market stability and protect consumer interests.

To understand debt accumulation and repayment patterns over time and make reliable predictions, a lifecycle analysis on credit card debt and payoff rates is necessary. Due to data limitations, most previous studies analyzed consumer debt in a static or comparative static context. Using a synthetic cohort approach, this research incorporates a time dimension to provide evidence on credit card debt and payoff rates from a lifecycle perspective. The objective of this chapter is to empirically estimate the lifecycle profiles of credit card borrowing and repayment behavior for 14 different birth cohorts and compare the patterns with the implications of the simple lifecycle model. A two-way fixed effect, pseudo-panel data model is proposed to characterize both the cohort effects and the time effects, and a two-step estimation procedure is utilized in the regression which greatly simplifies the estimation process and allows for more flexibility in model specification. The results suggest that younger American consumers are borrowing more heavily and repaying at lower rates on credit cards than earlier generations. If the current borrowing and repayment habits persist, a substantial buildup of credit card debt at a
later period in life may jeopardize the financial well-being of the elderly and cause instability in the credit card market.

A synthetic cohort approach is used in this study to disentangle cohort effects from age and time effects based on a time series of cross sections or pseudo-panel data. This technique provides a feasible way for lifecycle analysis when genuine panel data are not available. Compared with cross sectional data, pseudo-panel data have a time dimension and thus can track the behavioral trend of cohorts over time. The cohorts are synthetic in the sense that instead of tracking the same people, we are tracking individuals born in the same birth year interval from consecutive cross sectional surveys. At the same time, synthetic cohort analysis has the advantage of reducing measurement error by taking averages within cohorts without having to suffer from problems such as data attrition and small sample sizes that are common with longitudinal data. The importance of cohort effects is worth emphasizing because people belonging to different generations tend to differ in consumption habits and macroeconomic environments. The unadjusted profiles derived from cross sectional data are misleading because cohort differences are entangled with the lifecycle trend. Controlling for cohort effects, the adjusted lifecycle profiles are able to track the actual behavioral pattern for each cohort. To the best of my knowledge
this research is the first study that applies the synthetic cohort technique to the investigations of the consumer’s borrowing and repayment behavior in the credit card market.

3.2 Previous Research

Consumption, saving and income have been extensively studied in the literature under a lifecycle framework to examine how individuals allocate time, labor and money intertemporally (Heckman 1974, Deaton and Paxson 1993, Browning and Crossley 2001, Gourinchas and Parker 2002). However, due to data limitations, relatively few empirical lifecycle studies have been conducted to analyze debt issues, especially unsecured credit card debt. There are several theoretical models which examine the effects of debt constraints in a lifecycle setting, including a pure exchange overlapping generation model (Lambertini 1998, Azariadis and Lambertini 2003), a time-varying liquidity constraint model (Ludvigson 1999), and a lifecycle model with payroll taxes and endogenous debt constraints (Andolfatto and Gervais 2001). Lifecycle modeling has also been applied to understand the coexistence of high-interest credit card debt and low-yielding liquid assets (Laibson, Repetto and Tobacman 2003). Most of the above studies used simulation methods to make
predictions from the proposed models. This study utilizes a fixed effect, pseudo-panel data model to determine the lifecycle profiles of cohort debt accumulation and repayment behavior based on microeconomic household data.

Most consumer finance data come from cross sectional surveys. When panel data are not available, a time series of cross sectional data allows the tracking of cohorts in the sample, a technique which has been referred to as synthetic cohort analysis or pseudo-panel data modeling in the literature (Deaton 1985, Baltagi 2001, Verbeek 1995, Wooldridge 2003). One line of study has focused on pseudo-panel data where the number of individuals observed in each period is small relative to the number of time periods (Deaton 1985, Collado 1997), while another line of research has investigated pseudo-panel data where the number of individuals observed in each period is large relative to the number of time periods (Moffitt 1993, Girma 2000, Verbeek and Vella 2004). Many datasets from public surveys fall into this latter category, including the OES and the CFM. Pseudo-panel data modeling technique has been applied to various areas of research. Deaton and Paxson (1993) investigated the saving, growth, and aging issues of Taiwanese households. Using repeated cross sectional data in Italy, a series of studies were conducted to estimate the lifecycle profiles of consumption, income, saving, and wealth for Italian
households (Jappelli and Modigliani 1998, Jappelli 1999, Jappelli and Pistaferri 2000). The synthetic cohort approach was also employed to analyze the housing arrangements of Canadian households (Crossley and Ostrovsky 2003). In this study we will apply this technique to track the behavioral patterns of different cohorts in credit card borrowing and repayment over the lifecycle.

3.3 Descriptive Statistics

The data used in this chapter are a time series of cross sections combining two monthly surveys - the OES (1997-2002) and the CFM (2005). The combined data span a period of nine calendar years, with individual observations being taken in 75 different months from 1997 through 2005. To reduce the potential biasing effects due to small sample sizes, the 1996 OES data are excluded because the OES started in November 1996 and there are only two months of data collected in 1996. As discussed in Chapter 2, the sample characteristics of the OES are very close to those of the CFM. Therefore we are combining the two datasets to give a longer time span of the observations. To eliminate outliers, the total annual household income is restricted to be less than $1,000,000, and the age of the respondents is restricted to be between 18 and 85 years old. Only revolvers who have a positive amount of credit
Credit card debt is defined as the total amount owed on all credit cards after the most recent payments, which will have to be carried over to the next period and be charged for interests at the end of the billing cycle. The payoff rate refers to the percentage of the statement balance that is actually paid off before the minimum required payment is past due. If the amount of actual payment is less than the minimum required payment, the cardholder is in default. The payoff rate is an important indicator of the consumer’s behavior on repaying and accumulating credit card debt. While the data for credit card debt are available in most consumer finance surveys including the SCF, the OES and the CFM are the only datasets that allow for the computation of actual payoff rates. Thus “payoff rate” is a unique variable obtained in the OES and the CFM. The payoff rate from these datasets is computed as the ratio of the payment to the statement balance. The statement balance is computed from separate questions which obtain the amount of payment on the most recent billing statement and the amount owed, or debt, after that payment. The pre-payment balance is the sum of the amount of payment and the amount owed after the most recent payment.
Since people born at different times encounter different macroeconomic environments and tend to form different consumption habits, they are very likely to behave differently in debt accumulation and repayment on their credit cards. So it is important to take cohort effects into consideration and separate cohort effects from age and time effects. In this study, we will examine the credit card debt and payoff rates for 14 different birth year cohorts. As shown in Table 3.1, cohort 1 includes respondents who were born between 1915 and 1919, cohort 2 includes those born between 1920 and 1924, and so on up to cohort 14 which includes those born between 1980 and 1984. Each cohort is composed of respondents from the sample who were born in the same five-year interval. For convenience of comparison in later sections, we also define the oldest cohort in the sample, cohort 1, to be the “grandparents’ generation”; the middle-aged cohort in the sample, cohort 7, to be the “parents’ generation”; and the youngest cohort in the sample, cohort 14, to be the “children’s generation”. Columns (3), (4), and (5) in Table 3.1 report the average ages of each cohort observed in 1997 and in 2005, as well as the sample sizes for each cohort. The last four columns report the weighted means and medians of credit card debt (in 2005 dollar) and payoff rates (in percentage point) for each cohort. The differences between the means and medians suggest skewness in the distributions of credit card
debt and payoff rates. If we look at the columns (6) and (8) vertically, the average debt and the average payoff rate illustrate a concave pattern and a convex pattern, respectively. However, this illusory cross sectional observation confounds cohort, age, and time effects and therefore cannot give us any clue about the shapes of the profiles for debt accumulation and repayment behavior.

To gain more insights on the age-debt and age-payoff profiles, we generate two graphs to capture the trends of credit card debt and payoff rates for different cohorts in the sample. Sorting the data by 14 birth cohorts and 7 survey years results in $14\times7=98$\textsuperscript{1} different cohort-year cells. We calculate the sample means for each cohort-year cell and plot them in Figure 3.1 and Figure 3.2. In both figures there are 14 different graph segments each corresponding to a different birth cohort. Going from left to right, the first line represents the youngest cohort in the sample who was born in the years 1980-1984, the second line represents the second youngest cohort born in the years 1975-1979, and so on up to the oldest cohort born in the years 1915-1919. Each point on a line corresponds to a different survey year. The first point on a line represents the average debt or payoff rate for that birth cohort observed

\textsuperscript{1} There are actually 94 cohort-year cells because when the age of the respondents is restricted to be between 18 and 85 years old, the youngest cohort in the sample has only four years of observations and the oldest cohort has only six years.
in year 1997, and the last point on the line represents those statistics in year 2005. Thus each of the 14 segments in the graphs follows the behavioral pattern of a particular cohort over time. The survey data span a time period of nine calendar years from 1997 to 2005, so the segments in the figures overlap by four years for adjacent cohorts. These are synthetic cohorts in the sense that, while we do not track the same people, each segment tracks individuals born in the same birth year interval from successive cross sectional surveys.

Figure 3.1 shows strong evidence of cohort effects. Comparing adjacent cohorts, especially those segments in the middle, we can see that the line of the younger cohort lies above the line of the older cohort, which suggests that on average the younger cohort carries more credit card debt than the older cohort. Looking at the debt profile over the lifecycle, credit card debt tends to accumulate fast at younger ages, steadily grow over middle ages, and then taper off with advancing ages. As shown in Figure 3.2, the shape of the payoff profile mirrors the debt profile: the payoff rate declines fast at younger ages, becomes steady at middle ages, and starts to increase in later life. Cohort effects, however, are not as obvious in the payoff figure and need to be tested in the econometric model. In the next section, the above observations from descriptive statistics will be broadly supported by empirical results,
accurate shapes of the profiles will be presented, and the magnitudes of cohort differences will be estimated.

3.4 Two-Way Fixed Effect Pseudo-Panel Data Model

3.4.1 Model Specification

Since genuine panel data on consumer finances are not publicly available, we use the synthetic cohort approach to analyze the pseudo-panel data obtained from combining 7 repeated cross sections from the 1997-2002 OES and the 2005 CFM. The analysis is focused on two primary estimations: one is an estimation of credit card debt, and the other is an estimation of payoff rates. To separate cohort effects, age effects, and time effects, a two-way fixed effect, pseudo-panel data model is proposed as follows:

Debt: \[ D_{i,j,t} = \alpha_{1,j} + \gamma_{1,t} + x_{i,j,t}^i \beta_1 + \epsilon_{i,j,t} \] (3.1)

Payoff Rate: \[ P_{i,j,t} = \alpha_{2,j} + \gamma_{2,t} + z_{i,j,t}^i \beta_2 + \eta_{i,j,t} \] (3.2)

where \( D_{i,j,t} \) and \( P_{i,j,t} \) are credit card debt and payoff rates respectively, \( x_{i,j,t} \) and \( z_{i,j,t} \) are vectors of explanatory variables including age, \( \alpha_{1,j} \) and \( \alpha_{2,j} \) are cohort-specific effects, and \( \gamma_{1,t} \) and \( \gamma_{2,t} \) are time-specific effects. Observations are indexed by year, \( t = 1,2,\ldots,T \), by cohort, \( j = 1,2,\ldots,M \), and by individual household within each...
year and cohort, $i = 1, 2, \ldots, N_{j,t}$. The repeated cross sectional data consist of $T$ independent cross sections observed at different points of time, with each being a random sample of some underlying population. As the individual respondents in the survey are not the same people interviewed over time, the index $i$ merely identifies observations and does not refer to specific individuals. The two-way fixed effects in the model allow the parameters $\alpha_{1,j}$ and $\alpha_{2,j}$ to capture the differences between birth cohorts and the parameters $\gamma_{1,t}$ and $\gamma_{2,t}$ to capture the fluctuation over time due to exogenous shocks in macroeconomic environments.

One implicit assumption of this model is habit persistence. We assume that over time the behavioral trend of the younger cohort is consistent with that of the older cohort, except at a different level. For example, a current 20 year-old’s consumption habits will be similar to those observed from a current 30 year-old when this consumer actually reaches 30 years of age. Therefore the age-debt profiles and the age-payoff rate profiles have similar shapes for different cohorts as they pass through the same stages in life. The only differences between cohorts are the cohort-specific effects, which determine the relative levels of the profiles for different cohorts. This assumption has been widely used in the literature of synthetic cohort
3.4.2 Two-Step Estimation Procedure

Theoretically, estimating the debt equation (3.1) and the payoff equation (3.2), will simultaneously give us two results: 1) the shapes of the age-debt profiles and the age-payoff rate profiles for different birth cohorts, and 2) the effects of other explanatory variables on debt and payoff rate levels. However, it is not feasible in practice due to data limitations. The early years of the OES data do not include several important variables such as APR, minimum required payment, and other debts. And assets data were not collected in any year of the OES. These variables are potentially important in determining credit card debt and payoff rates and thus cannot be omitted. At the same time, the estimation of the age-debt profiles and the age-payoff rate profiles requires all of the available seven years of cross-sectional surveys. Data imputation is an option to remedy the conflict between the time-expansion and the number of variables, but it would add extra uncertainty to the estimation. To avoid data imputation, a two-step estimation procedure will be used in the regression to deal with the two aspects separately.
Equations (3.1) and (3.2) can be rewritten as:

Debt: \[ D_{i,j,t} = \alpha_{1,j} + \gamma_{1,i} + f(a) + \bar{x}_{i,j,t}^\prime \beta_1 + \epsilon_{i,j,t} \] (3.3)

Payoff Rate: \[ P_{i,j,t} = \alpha_{2,j} + \gamma_{2,i} + g(a) + \bar{z}_{i,j,t}^\prime \beta_2 + \eta_{i,j,t} \] (3.4)

where \( f(a) \) and \( g(a) \) are functions of age, and \( \bar{x}_{i,j,t} \) and \( \bar{z}_{i,j,t} \) are vectors of explanatory variables excluding age. Other notations remain the same as those in equations (3.1) and (3.2). If there are no interactions between age and other explanatory variables, then the shapes of the age-debt profiles and the age-payoff rate profiles depend only on the coefficients of the age functions \( f(a) \) and \( g(a) \). Other factors, including cohort effects, time effects, and other explanatory variables, determine the positions of the profiles through the intercepts without affecting the shapes of the profiles. Therefore we can separately estimate the shapes and the positions of the profiles in two steps. The two-step procedure is empirically supported by the data. Preliminary investigations of the data find no significant correlations between age and other explanatory variables, and adding those explanatory variables into the regression does not change the basic shapes of the profiles. As we will see in later sections, the two-step procedure will greatly simplify the estimation process and allow more flexibility in the model specification.
In the first step, we leave out other explanatory variables and consider only
the effects of age, cohort, and time on debt and payoff rates. The regression
equations can thus be expressed as:

Debt: \[ D_{i,j,t} = \alpha_{1,j} + \gamma_{1,t} + f(a) + \varepsilon_{i,j,t} \] (3.5)

Payoff Rate: \[ P_{i,j,t} = \alpha_{2,j} + \gamma_{2,t} + g(a) + \eta_{i,j,t} \] (3.6)

The model will be fitted using a full set of cohort dummies, a set of restricted year
dummies, and a fifth-order polynomial in age. The youngest cohort is omitted in the
estimation, thus the reference group is the youngest cohort consisting of those who
were born between 1980 and 1984. The estimated coefficients of the cohort
dummies then represent the relative cohort differences compared with the youngest
group. The estimation method is similar to the standard Dummy Variable Least
Squares (LSDV) or Fixed Effect (FE) estimation for genuine panel data models. To
highlight the importance of controlling for cohort effects, the cross-sectional model
will also be estimated to compare with the cohort-adjusted model. The
cross-sectional model is specified below:

Debt: \[ D_{i,j,t} = f(a) + \varepsilon_{i,j,t} \] (3.7)

Payoff Rate: \[ P_{i,j,t} = g(a) + \eta_{i,j,t} \] (3.8)
The year dummies are restricted in order to solve the identification problem. The perfect collinearity between age, cohort, and year has been well known in the literature (Mason and Fienberg 1985), and additional restrictions have been proposed to identify the age, cohort, and year effects. One option is to eliminate all the year dummies, as used by Chiuri and Jappelli (2003) in estimating the profile of homeownership. Here we take a less restrictive approach, which will be later referred to as the Deaton-Paxson normalization (Deaton and Paxson 1993; Deaton 1997). Deaton-Paxson normalization assumes that the year dummies sum to zero and are orthogonal to the time trend. Specifically, in our model the time-specific effects have to satisfy the following conditions:

Debt: \[ \sum_{t=1}^{T} \gamma_{1,t} = 0; \sum_{t=1}^{T} t \gamma_{1,t} = 0 \]

Payoff Rate: \[ \sum_{t=1}^{T} \gamma_{2,t} = 0; \sum_{t=1}^{T} t \gamma_{2,t} = 0 \]

Under the Deaton-Paxson normalization, we are attributing all trends to age and cohort effects rather than to time. Therefore the coefficients of year dummies reflect only the residual fluctuations relative to a linear trend due to exogenous macroeconomic shocks.

The second step of the two-step estimation procedure focuses on the effects of other explanatory variables on credit card debt and payoff rates. Since in this step...
we are not interested in estimating the changes of debt and payoff rates over time, one
or two cross sections which contain all the important explanatory variables would be
sufficient. Only the CFM data will be used in this step because they contain more
variables of interests as an expansion of the OES with detailed balance sheet
information on assets and liabilities. Another advantage of the CFM is that it is an
on-going monthly survey on consumer finances, and thus can provide the most
up-to-date information on the consumers’ behavioral changes in the credit card market.
Explanatory variables that will be used in the estimation include credit-related
variables, socioeconomic variables, and expectations variables. Details of the
second step estimation are discussed in Chapter 4. The rest of this chapter will focus
on the first step of the two-step estimation procedure to find out the shapes of the
age-debt profiles and the age-payoff rate profiles for different birth cohorts.

3.5 Age-Debt Profiles

Age-debt profiles can be derived from the regression results of the
cohort-adjusted model expressed by equation (3.5). For comparison purpose,
regression results of equation (3.7), the cross-sectional (unadjusted) model, are also
presented. Table 3.2 shows the estimated coefficients for both the cohort-adjusted
model and the cross-sectional model. In the cohort-adjusted model, the youngest cohort (cohort 14) is the reference group which is omitted in the regression. The coefficients of all the other cohort dummies (cohort 1 - cohort 13) are tested to be jointly significant, which suggests that the cohort effects are important in this model. The coefficients of year dummies are not jointly significant, thus time effects are trivial and can be ignored in forecasting. Under the assumptions of Deaton-Paxson normalization, this indicates that the general profile of debt accumulation is not influenced by additive macroeconomic fluctuations relative to a linear trend. Therefore in this model, credit card debt profiles and relative levels are predictable by age and cohort, and business cycling effects can be neglected.

Based on the regression results in Table 3.2, the age-debt profiles for the cohort-adjusted model and the cross-sectional model are plotted together in Figure 3.3. Recall that under the assumption of the cohort-adjusted model, the shapes of the age-debt profiles for different cohorts are the same except that they have different intercepts. For illustration, the plot in Figure 3.3 only shows the age-debt profile for the youngest cohort in the sample, which is also the reference group in the estimation. The cross-sectional profile is the typical humped shape implied by the simple lifecycle hypothesis: credit card debt increases at younger age, peaks at middle age
and then tapers off at older age. The maximum amount of debt appears around 40-45 years of age, and at age 80 debt declines to the same level as for those who are 20 years old. It seems that people smooth consumption by borrowing using credit cards at younger ages, and they gradually pay off their credit card debt in later life. This conclusion, however, is misleading because the cross-sectional model confounds the age effects and the cohort effects. The decomposition of the age effects and the cohort effects is important because it enables us to track the real trend of debt accumulation over the lifecycle net of the cohort complication. The cohort-adjusted profile shows a very different pattern from the cross-sectional profile: it peaks at around 70-75 years of age, which is 30 years later than the cross-sectional maximum, and the decumulation of debt is much less thereafter. This suggests that people are actually borrowing using credit cards and accumulating credit card debt most of their lifetime, and they only start to pay down their debt after retirement. The amplitude of debt decumulation in later life is so small that the credit card debt is not likely to be paid off by the end of the lifecycle. Unlike other debt, credit card debt is non-secured, so the unpaid debt cannot be recovered from collateral. If people keep their current consumption patterns, we can expect more people to carry a substantial amount of credit card debt at death, which will constitute a considerable loss for the
credit card issuing banks. On the other hand, this also serves as a warning for the current young generations to manage their debt wisely in order to avoid potential financial problems when they grow old.

Since the shape of the age-debt profiles only depends on the parameter estimates of the age polynomial, i.e. \( f(a) \), the fitted profiles for all other cohorts (cohort 1 - cohort 13) should have the same shape as for the youngest cohort (cohort 14) plotted in Figure 3.3, except at different levels. The relative positions of the age-debt profiles for different cohorts are determined by the coefficients of the cohort dummies. Figure 3.4 is a plot of the relative cohort effects for all 14 different cohorts against their birth year intervals. The 14 marks on the dotted line corresponds to the 14 birth cohorts: going from left to right the first dot represents the oldest cohort in the sample who were born between 1915 and 1919, and the last dot represents the youngest cohort born in the years 1980-1984. Cohort effects are tested to be jointly significant in the regression, and the increasing trend across cohorts is obvious from this plot: the younger cohorts tend to have higher levels of credit card debt than the older cohorts. To illustrate the significance of cohort effects, we compare three different generations - children (cohort 14), parents (cohort 7) and grandparents (cohort 1) - and plot their age-debt profiles in Figure 3.6. On average,
the children’s credit card debt is about $2,300 higher than their parents and about
$6,400 higher than their grandparents. Note that in Figure 3.6 and Figure 3.10 the
age-debt profiles for the parents’ generation and the grandparents’ generation are
missing in early life. This is due to the fact that credit cards did not become a
popular financial instrument until the 1980s, and back then the older cohorts did not
even have a credit card. The youngest cohort has a complete profile starting from 18
years of age, because this generation was born at a time when credit cards were
already widely used in U.S. financial market.

The decomposition of the age effects and the cohort effects is worth
emphasizing because it enables us to track the real trend of debt accumulation over
the lifecycle net of the cohort complication. This can be clearly seen from
comparing the age-debt profiles in Figure 3.3 and the plot of cohort effects against
age in Figure 3.5. Since birth year and age are negatively correlated, the plot of
cohort effects against age in Figure 3.5 is mirrored with the plot of cohort effects
against birth year in Figure 3.4. The horizontal axes for both Figure 3.3 and Figure
3.5 are age; therefore we can compare the two plots directly and find out how cohort
effects have made the shapes of the cross-sectional profile and the cohort-adjusted
profile different. The cross-sectional profile in Figure 3.3 is hump-shaped because
the cohort effects are not separated. We observe a decreasing trend after middle ages from the cross-sectional data because the lower levels of debt for older cohorts drag down the actual profile. The cohort-adjusted profile is net of cohort effects, thus it lies above the cross-sectional profile and the gap between the two profiles becomes greater as cohort effects increase with age.

3.6 Age-Payoff Rate Profiles

Payoff rates represent the speed of debt accumulation and thus the age-payoff rate profiles, together with the age-debt profiles, will give us a more complete picture of the consumer’s behavior in the credit card market over the lifecycle. The regression results of payoff equations (3.6) and (3.8) are presented in Table 3.3, providing estimated coefficients for the cohort-adjusted model and the cross-sectional model, respectively. The cross-sectional model is estimated to emphasize the importance of adjusting for cohort effects in determining the shape of the age-payoff rate profiles. Similarly, the omitted cohort is cohort 14, which is the youngest cohort in the sample and the age variable used in the regression is expressed in deviations from 45. T-test on all cohorts shows that the coefficients of cohort dummies are jointly significant. Based on the estimated coefficients of the age polynomial, the
shape of the age-payoff rate profiles can be determined. The relative levels of the profiles for different cohorts depend on the magnitudes of the cohort effects.

Figure 3.7 is a plot of age-payoff rate profiles for the cohort-adjusted model and the cross-sectional model. Since the age-payoff rate profiles for all cohorts are assumed to have the same shape, here we also plot the cohort-adjusted profile only for the reference group for illustration purpose. The cohort-adjusted profile and the cross-sectional profile indicate very different patterns of repayment behavior: people are paying off a much lower percentage of their credit card balances than they seem to be doing by cross-sectional observations. Although the cross-sectional profile shows an increasing trend in repaying debt starting around 30 years of age, the prediction from the cohort-adjusted profile is not as optimistic. Looking at the cohort-adjusted profile, the payoff rate decreases rapidly at younger ages, keeps declining through middle ages at relatively lower rates, bottoms out around age 60, and then increases in later life. The lowest payoff rate is reached about 30 years later in the cohort-adjusted model than in the cross-sectional model, which is consistent with the results from the age-debt profiles. Notice that the maximum amount of debt appears about 10 years later than the minimum level of payoff rate. The reason is that the payoff rate, as an indicator of the speed of debt accumulation, is the decision the
The consumer has to make immediately after receiving his/her credit card bills. The amount of the total debt will then change as a result of the actual payments made. The payoff rate is an instantaneous choice, while debt accumulation is gradual. It will take some time for the changes in payoff rates to be reflected in the changes in the amount of debt. Therefore it is reasonable that the lowest payoff rate in the age-payoff rate profile appears ahead of the maximum amount of debt in the age-debt profile. The shape of the age-payoff rate profile, which is opposite of the shape of the age-debt profile, reinforces the conclusion we had before: people are borrowing on credit cards so extensively that the low payoff rates are not enough to recover their credit card debt by the end of the lifecycle.

The difference made by disentangling the age effects and the cohort effects can be clearly seen from comparing the age-payoff rate profiles in Figure 3.7 and the plot of cohort effects against age in Figure 3.9. Similarly, the plot of cohort effects against age in Figure 3.7 is mirrored with the plot of cohort effects against birth year in Figure 3.6, as a result of the perfectly negative correlation between their horizontal axis variables, birth year and age. The cross-sectional profile is misleading because it mixes the age effects with the cohort effects. The higher payoff rates at older ages observed in the cross-sectional profile is partially attributable to the positive cohort
effects of the older cohorts. The gap between the cross-sectional profile and the cohort-adjusted profile is caused by the cohort effects: as cohort effects increase with age, the gap also becomes greater over time.

The relative levels of the profiles for different cohorts are determined by cohort effects, which are estimated in the model by the coefficients of the cohort dummies. Figure 3.8 is a plot of the cohort effects against birth years for all cohorts in the sample. The 14 marks on the dotted line correspond to the 14 birth cohorts: going from left to right the first dot represents the oldest cohort in the sample who were born between 1915 and 1919, and the last dot represents the youngest cohort born between 1980 and 1984. The decreasing trend indicates that the older cohorts generally have higher payoff rates than the younger cohorts as they pass through the same stages of their lifecycles. This can be clearly seen in Figure 3.10 which compares the age-payoff rate profiles for three different generations - children, parents, and grandparents - in the same figure. On average, the estimated difference in payoff rates between generations is about 10 percentage points: the children’s payoff rate is 10 percentage points lower than their parents and 20 percentage points lower than their grandparents. This adds to the evidence that nowadays the young
Americans are getting more addicted to borrowing on credit cards, but they are less responsible for paying off the debt comparing with people in earlier generations.

So far we have determined the shapes of the age-debt profiles and the age-payoff rate profiles, as well as the relative positions of the profiles for different cohorts. We find that, on average, the younger cohorts have more credit card debt and lower payoff rates than the older cohorts, and over time people are accumulating debt so tremendously that they are unlikely to be able to pay off their credit card debt by the end of the lifecycle. However, it is important to notice that the data used in the debt and payoff regressions only include the revolvers in the sample, so it is better to regard the above conclusions as pertaining to the aggregate behavior of all revolvers in each cohort, rather than to the individual choices of a representative household. Actually it is difficult to define a representative household in the credit card market due to the complete heterogeneity in household behavior. At individual household level, credit card borrowing and repayment decisions frequently change due to unobservable psychological factors and are often influenced by unexpected events such as unemployment, divorce, and health problems (Draut et al. 2005). In addition, the common phenomenon of switching roles between transactors and revolvers makes the situation even more complicated. In reality, the behavior of
individual households is so unstable that it is hard to find two households which have
the same shapes of age-debt profiles and age-payoff rate profiles. Therefore it is
only possible and reasonable for us to track the aggregate behavioral trend for
different cohorts rather than for individual households. In the next chapter, we
extend our analysis from the aggregate cohort level to the individual household level
and estimate the effectiveness of a variety of factors in determining the credit card
debt and payoff rates for a particular household.

3.7 Conclusion

This chapter empirically estimated the age-debt profiles and age-payoff rate
profiles for 14 different birth cohorts over their lifecycles. A two-way fixed effect,
pseudo-panel data model is utilized to analyze the consumer’s debt accumulation and
repayment behavior based on recent developments in the literature for handling time
series of cross sectional data. The OES and the CFM data used in this research
contain an array of new variables that have not been available in other public datasets,
and they allow for the unique computation of payoff rates. The data span a period of
nine calendar years, with individual observations being taken in seven different
survey years from 1997 through 2005. Thus they are particularly well-suited for a
synthetic cohort analysis. Most previous studies have analyzed debt in a static or comparative static context; the synthetic cohort approach used here can track the behavioral patterns of different cohorts through their lifetime and thus contribute a lifecycle framework to the previous investigations in this area.

The results suggest that the younger cohorts tend to borrow more on credit cards and repay at lower rates than the older cohorts. Within each cohort, the profiles of payoff rates show a declining trend over young and middle ages which causes credit card debt to accumulate substantially to its maximum level around retirement age. Although the payoff rates become relatively higher in later life, the extent of debt decumulation is much too limited to recover the considerable amount of debt acquired in early life. Therefore if people keep their current consumption patterns, we can expect more people to be in deep credit card debt by the end of their lifecycles, which will threaten the financial well-being of the elderly and cause instability in the credit card market. This implies that policy interventions are needed to regulate the credit card market and guide consumer behavior. Recent policy changes, such as the bankruptcy law revision and the doubling of minimum required payments, are steps in this direction.
The Deaton-Paxson normalization is used to solve the identification problem caused by the collinearity between age, cohort, and year. It is assumed that the year dummies sum to zero and are orthogonal to the time trend. Therefore we are attributing all trends to age and cohort rather than to time. The coefficients of year dummies reflect only the residual fluctuations relative to the time trend which might be caused by exogenous macroeconomic shocks or non-systematic measurement errors. Although the synthetic cohort approach can successfully separate the cohort effects from the age and year effects, it remains unknown as to whether the patterns of debt accumulation and repayment behavior are driven by aging (age effects) or by economic growth (time trend). It is arguably possible that the substantial debt accumulation in early life is due to the rapid development of the credit card market during the same time period rather than as a result of the consumer’s allocation of resources over the lifecycle. To solve this problem, genuine panel data are needed to track the behavioral trend of real cohorts where the same individuals are observed over time.
<table>
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<th>Cohort</th>
<th>Birth Year Interval</th>
<th>Average Age in 1997</th>
<th>Average Age in 2005</th>
<th>Cell Size (mean)</th>
<th>Debt (mean)</th>
<th>Debt (median)</th>
<th>Payoff Rate (mean)</th>
<th>Payoff Rate (median)</th>
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<td>88</td>
<td>144</td>
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Note: The amount of credit card debt is expressed in 2005 dollar. The descriptive statistics are computed using sample weights.

Table 3.1: Descriptive Statistics for Credit Card Debt and Payoff Rates
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<th>Variables</th>
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<td>Intercept</td>
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<td>903.39478</td>
</tr>
</tbody>
</table>

Note: The age used in this regression is in deviations from 45.

*** significant at 1% level or better;
**  significant at 5% level or better;
*   significant at 10% level or better

Table 3.2: Parameter Estimates for Age-Debt Profiles
<table>
<thead>
<tr>
<th>Variables</th>
<th>Cohort Adjusted</th>
<th>Cross Sectional</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std Error</td>
</tr>
<tr>
<td>Age</td>
<td>-0.31885</td>
<td>0.16413</td>
</tr>
<tr>
<td>Age(^2)</td>
<td>***-0.02479</td>
<td>0.00949</td>
</tr>
<tr>
<td>Age(^3)</td>
<td>**0.00081694</td>
<td>0.00041365</td>
</tr>
<tr>
<td>Age(^4)</td>
<td>***0.00004675</td>
<td>0.00001222</td>
</tr>
<tr>
<td>Age(^5)</td>
<td>***-0.00000114</td>
<td>3.781787E-7</td>
</tr>
<tr>
<td>Cohort1</td>
<td>**21.67751</td>
<td>8.82257</td>
</tr>
<tr>
<td>Cohort2</td>
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<td>7.63008</td>
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<tr>
<td>Cohort3</td>
<td>***24.43852</td>
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<td>Cohort4</td>
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<td>6.43585</td>
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<td>Cohort5</td>
<td>***19.72956</td>
<td>6.02100</td>
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<td>Cohort6</td>
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<td>Cohort7</td>
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<td>5.28595</td>
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<td>Cohort8</td>
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<td>Cohort9</td>
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<td>4.77265</td>
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<td>Cohort13</td>
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<td>Year97</td>
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</tr>
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<td>Year98</td>
<td>***-2.90805</td>
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<td>Year99</td>
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<td>Year00</td>
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</tr>
<tr>
<td>Year02</td>
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<tr>
<td>Year05</td>
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<td>0.54394</td>
</tr>
<tr>
<td>Intercept</td>
<td>***21.95258</td>
<td>4.86691</td>
</tr>
</tbody>
</table>

Note: The age used in this regression is in deviations from 45.

*** significant at 1% level or better;
**  significant at 5% level or better;
*   significant at 10% level or better

Table 3.3: Parameter Estimates for Age-Payoff Rate Profiles
Figure 3.1: Plot of Cohort Mean Credit Card Debt for Revolvers

Figure 3.2: Plot of Cohort Mean Credit Card Payoff Rates for Revolvers
Figure 3.3: Age-Debt Profiles

Figure 3.4: Plot of Cohort Effects vs Birth Year for Debt Equation
Figure 3.5: Plot of Cohort Effects vs Age for Debt Equation

Figure 3.6: Age-Debt Profiles for Children, Parents, and Grandparents
Figure 3.7: Age-Payoff Rate Profiles

Figure 3.8: Plot of Cohort Effects vs Birth Year for Payoff Equation
Figure 3.9: Plot of Cohort Effects vs Age for Payoff Equation

Figure 3.10: Age-Payoff Rate Profiles for Children, Parents, and Grandparents
CHAPTER 4

CONSUMER CHOICES IN CREDIT CARD HOLDING, BORROWING, AND PAYOFF

4.1 Introduction

The past two decades have witnessed great expansion in credit card ownership and substantial increase in credit card debt. According to the 1983 SCF, 65% of U.S. households have at least one credit card; while in 2005 the rate of ownership has increased to 80% based on the CFM data. Whether or not to hold a credit card is the first choice a consumer has to make when facing credit card offers, and this “market entry decision” will influence the consumer base in the credit card market as well as the sequential choices related to credit card use. The most important choice for cardholders is whether or not to borrow on credit cards, and this “borrowing decision” categorizes the consumers in the credit card market into two types - revolvers and transactors. Revolvers use credit cards as a financing instrument. They pay financial charges for the outstanding balances and their credit card debt keeps revolving to later periods until being paid off. Transactors, also
called convenience users, usually pay off the entire balances in their credit card statements before the payment due dates. They use credit cards as a convenient transacting instrument, and along with the transactions, they often receive extra benefits from various perk programs such as cash back and frequent flier miles. Consumers can also freely switch roles between revolvers and transactors: when a revolver pays off all of the credit card debt and starts using credit cards for transaction purposes, this consumer becomes a transactor; when a transactor fails to pay off the entire balance on the bill and begins to revolve credit card debt, this consumer has switched to a revolver. According to the OES and the CFM data, in 1998 about one third of the credit card holders do not carry a balance after the most recent payment, and by 2005 the percentage of convenience users has increased to around one half of all cardholders.

With the rapid development of the credit card market, the composition of consumers in terms of non-cardholders, revolvers, and transactors also changed over time. The changes of the consumer composition will inevitably have an impact on the total amount of revolving credit card debt. Therefore, analyzing the consumer’s ownership choice (cardholder vs non-cardholder) and borrowing choice (revolver vs transactor) will give us a better understanding of the underlying determinants of the
credit card debt and payoff rates and allow us to look at the consumer’s behavior in the credit card market from a broader perspective. In this chapter I will use the most recent consumer finance data - the 2005 and 2006 CFM - to analyze three aspects of the consumer’s choices related to credit card use for U.S. households: 1) determinants of credit card ownership, i.e. whether or not to hold a credit card, 2) determinants of credit card borrowing, i.e. whether or not to carry over a balance on a credit card, and 3) determinants of the levels of credit card debt and payoff rates, i.e. the amount of borrowing and the rate of repayment on a credit card. The logit estimation is used for both the ownership decision and the borrowing decision to model the binary choices of “cardholder vs non-cardholder” and “revolver vs transactor”. A tobit model is used to estimate the effects of a variety of factors, including credit related variables, socioeconomic variables, and expectations variables, in determining the levels of credit card debt and payoff rates. The tobit model adjusts for sample selection bias by considering both revolvers and transactors so that the results can reflect the aggregate response of all cardholders in the population. Corresponding to the second step of the two-step estimation procedure proposed in the previous chapter, this part of the dissertation allows us to look at the consumer’s choices and behavioral patterns in the credit card market at the individual household level. The results have
important policy implications and are relevant for evaluating recent policy actions by federal banking authorities.

4.2 Previous Research

Much of the early work on the credit card market focused on the high and sticky interest rates of credit card debt. Ausubel (1991) was one of the first to carry out an empirical study of this market, finding high profits as well as high and sticky interest rates in spite of a seemingly competitive structure in the credit card industry. He speculated that search/switching costs and a type of irrational consumer behavior might be involved in these paradoxical outcomes. Countering this reasoning, Brito and Hartley (1995) argued theoretically that the aspect of liquidity service of credit cards saves consumers the opportunity cost of holding money for payment and makes it rational for them to hold balances even with high interest rates. Mester (1994), Stavins (1996), and Park (1997) also addressed the issue referring to information problems, high interest elasticities for defaulters, and the open-ended nature of credit card loans respectively, all of which create high risks for banks. Consumer search or the lack of it also became a strand of research aimed at explaining the high and sticky interest rates. Calem and Mester (1995), using the 1989 SCF data, find that
consumers with high balances are discouraged from searching because of their greater likelihood of rejection. Using the 1998 SCF data, Crook (2002) finds, however, that this discouragement to search no longer exists. Indeed, credit card interest rates have fallen in recent years, and this highlights the changing nature of this market.

With the decline of interest rates, researchers began to turn their attention to the all-time high credit card debt and the underlying consumer behavior related to credit card borrowing. Using the 1998 SCF and the Heckman two-stage model, Kim and DeVaney (2001) estimated the variables that affect the outstanding balances among credit card revolvers, and found that the factors related to the probability of borrowing on credit cards are different from the factors related to the amount of borrowing. Using probit and tobit models on the 2001 SCF, Yilmazer and DeVaney (2005) examined the lifecycle changes in likelihood and amount of holding for different types of household debt, including credit card debt. The results show that probability of holding each type of debt tends to be lower for the elderly, so does the amount of each type of debt. Based on the 1998 SCF, Min and Kim (2003) compared the results of type I and type II tobit approaches in modeling credit card borrowing. Type II tobit procedure is proved to be more appropriate for analyzing the behavior of credit card users and for predicting household credit card debt.
Using the same data, Castronova and Hagstrom (2004) investigated credit card demand in a two-stage procedure, with consumers obtaining limits in the first stage and then borrowing some fraction of the limits in the second stage. The results suggest that consumers tend to borrow a constant fraction of the limits as debt; therefore credit card demand is mainly for limits rather than for debt.

Credit card ownership is an area that has not been extensively studied in the credit card literature. Many previous studies on credit card ownership focused on the effect of credit cards on money demand as a transaction medium which can substitute the use of deposits such as checking or savings accounts (Feige 1974, White 1976). Due to econometric techniques and data limitations, however, early studies did not control for sample selection bias and balance sheet variables of the households. Using the 1983 SCF data, Duca and Whitesell (1995) conducted a cross-sectional study on the relationship between credit card ownership and deposit accounts, which was one of the first to take into considerations of the self-selection problem and the impact of assets or wealth on money demand. Consistent with previous studies, their results provide new evidence for the hypothesis that credit cards contribute to the reduction of household demand deposits. A more recent study that has addressed the issue of credit card ownership is Bertaut and Haliassos (2006). By comparing data
from several waves of the *SCF*, their paper documented the changes in credit card ownership and borrowing across different demographic groups. The results suggest that the percent of cardholders has increased over time, but the rate of increase has slowed down in recent years as the credit card market is becoming more saturated.

### 4.3 Data and Variables

The data used in the empirical analysis come from the 2005 and 2006 *CFM*. Compared with the *OES*, the *CFM* has several advantages for the study in this chapter. First, the *CFM*, as a national survey, can represent the characteristics of U.S. consumers better than the *OES* which is a state-wide survey for the Ohio residents. Second, the *CFM* is an on-going monthly survey; the data collected in the years of 2005 and 2006 provide the most up-to-date information on the consumer’s choices in the financial market. Moreover, besides a more detailed inventory of household credit card use, the *CFM* includes a series of questions which elicit complete information on household assets and liabilities that allows us to analyze the consumers’ behavior related to credit cards in the context of their overall financial situation.
The original sample in the 2005 and 2006 CFM includes 7,275 households. Among them 1,498 are non-cardholders, 2,221 are revolvers, and 3,556 are transactors or convenience users. On average, about 80% of the households in the U.S. population have at least one credit card, and among all cardholders about 45% have unpaid balances on their credit cards.\footnote{The summary statistics reported here are weighted percentages.} There are three stages related to the consumer’s choices in the credit card market that will be addressed in the following sections. The first stage focuses on the ownership decision and examines the probability of holding a credit card, the second stage focuses on the borrowing decision and examines the probability of borrowing on a credit card, and the third stage examines the underlying determinants of the levels of credit card debt and payoff rates for revolvers. In the first stage, both cardholders and non-cardholders are considered and the sample size is 7,275. In the second and third stages, only those who have at least one credit card are considered, which will give us a sample size of 5,777 households including both revolvers and transactors.

The variables used in the analysis can be grouped into three broad categories: credit related variables, socioeconomic variables, and expectations variables. Credit related variables reflect the consumer’s credit card use and credit history and can be
further divided into two subgroups - contractual variables and behavioral variables. APR, credit limit, and minimum required payment are three important contractual variables in the sense that they are all predetermined in the credit card contract, through which credit card issuers or policymakers can influence consumer behavior in order to achieve particular goals in the market. Behavioral variables include total number of credit cards, credit card debt, credit card payoff rates, default history, and bankruptcy history, because they are mainly the results of the consumer’s own choices. Banks and policymakers usually do not have direct influences on issues such as how many credit cards to hold, whether or not to make payments on time, and whether or not to file for bankruptcy. Socioeconomic variables can also be divided into two subgroups - financial variables and demographic variables. Income, net worth, assets (financial assets, physical assets), debts, and homeownership are financial variables because these factors represent the overall financial situation of a household. Controlled in the regression are also demographic variables including age, race, marital status, education, and household size. Expectations variables include unemployment expectations, interest rate expectations, and price expectations. They can help us to determine whether or not the consumer’s choices are rational. Detailed variable definitions and summary statistics are provided in Table 4.1. The
means and medians in the table are computed using sample weights so that the descriptive statistics are representative of the U.S. population. Only households who have at least one credit card are considered in the calculation of the descriptive statistics.

### 4.4 Determinants of Credit Card Ownership

#### 4.4.1 Descriptive Statistics

Table 4.2 compares the sample characteristics of cardholders and non-cardholders. T-tests and chi-square tests are conducted respectively for continuous variables and categorical variables to examine the differences between the two groups. The results suggest significant differences between cardholders and non-cardholders by age, race, marital status, education, household financial situation, and credit history. Consumers who are white, married, better-educated, and wealthier are more likely to hold a credit card probably because they have greater consumption needs and are more confident about their financial management abilities. Compared with cardholders, a higher percentage of non-cardholders have bankruptcy record because they are less likely to be approved or pre-approved for credit cards by the issuers. Credit card ownership is the equilibrium of the consumer’s credit
demand and the bank’s credit supply in the market. Age, race, marital status, education, income, net worth, and homeownership can reflect both credit demand and credit supply. Bankruptcy history is primarily an indicator of credit supply.

4.4.2 Logit Model

If we consider the decision of whether or not to hold a credit card as a binary choice, then a logit model can be used to analyze the probability of credit card ownership. The logit specification is of the following form:

\[
\Pr(C_i = 1) = F(x_i^\prime \theta) = \frac{\exp(x_i^\prime \theta)}{1 + \exp(x_i^\prime \theta)}
\]

(4.1)

\[
C_i = \begin{cases} 
1 & \text{if } i = \text{cardholder} \\
0 & \text{if } i = \text{non-cardholder}
\end{cases}
\]

where \(C_i\) is the binary dependent variable indicating whether or not household \(i\) holds a credit card. When household \(i\) holds at least one credit card, \(C_i\) takes the value 1; otherwise \(C_i\) is equal to 0. The estimation method for the logit model is maximum likelihood. The log-likelihood function is:

\[
\ln L(\theta | x_{it}) = \sum_{i=1}^{n} \left[ C_i \ln \frac{\exp(x_{it}^\prime \theta)}{1 + \exp(x_{it}^\prime \theta)} + (1 - C_i) \ln(1 - \frac{\exp(x_{it}^\prime \theta)}{1 + \exp(x_{it}^\prime \theta)}) \right]
\]

\[
= \sum_{i=1}^{n} \left[ C_i x_{it}^\prime \theta - \ln(1 + \exp(x_{it}^\prime \theta)) \right]
\]
Unlike linear regression models, the estimated coefficients of the tobit model indicate only the direction of the relationship between the dependent variable and independent variables. To provide information on the estimated effect of a particular independent variable \( (x_k) \) on the probability of credit card ownership \( (Pr(C_i = 1)) \), we need to calculate the marginal effect for household \( i \) based on the following formula:

\[
\frac{\partial E(C_i)}{\partial x_k} = \frac{dF(x_i \hat{\theta})}{dx_i \hat{\theta}} \hat{\theta}_k
\]

\[
= \frac{\exp(x_i \hat{\theta})}{1 + \exp(x_i \hat{\theta})} \left[ 1 - \frac{\exp(x_i \hat{\theta})}{1 + \exp(x_i \hat{\theta})} \right] \hat{\theta}_k
\]

\[
= \frac{\exp(x_i \hat{\theta})}{[1 + \exp(x_i \hat{\theta})]^2} \hat{\theta}_k
\]

In addition, the predicted probability of credit card ownership for household \( i \) can also be calculated using the tobit estimates:

\[
F(x_i \hat{\theta}) = \frac{\exp(x_i \hat{\theta})}{1 + \exp(x_i \hat{\theta})}
\]

### 4.4.3 Empirical Results

The results of the logit estimation are presented in Table 4.3. In addition to the parameter coefficients and standard errors, marginal effects are also reported to reflect the estimated changes in the probability of credit card ownership. The marginal effects are calculated for a representative household with sample mean.
characteristics. For continuous independent variables, the marginal effect is the estimated effect on the probability with a unit change in the given independent variable. For categorical variables, marginal effect is the estimated effect on the probability when the dummy variable changes from 0 to 1. The predicted probability of holding a credit card for a representative household with sample mean characteristics is 85.45%.

Holding other variables constant, the probability of being a cardholder is hump-shaped with respect to age. The young and the old have lower probabilities of holding credit cards than those consumers in the middle. This is consistent with the fact that younger and older applicants are more likely to be denied a credit card because they are usually less financially sufficient than middle-aged consumers who are at the peak of their income and wealth profiles. On the demand side, transaction needs and borrowing needs tend to be relatively lower in the earlier and later stages of the lifecycle. Also, some elderly consumers may prefer the traditional payment media such as cashes or checks to credit cards.

The probability of being a cardholder is significantly greater for white, married, and better-educated consumers. According the marginal effect, the probability of holding a credit card for a white household with sample mean
characteristics is 4.98 percentage points greater than the probability for a non-white household with similar socioeconomic background. Holding other factors constant at sample mean levels, the difference between married households and non-married households in the probability of credit card ownership is 7.89 percentage points. Similarly, college graduates are 5.89 percentage points more likely to be a cardholder than those who did not finish college education.

Financial variables, including income, net worth, and homeownership, are positively related to the probability of credit card holding. This perhaps reflects the greater demand for credit of wealthier households as well as the abundant credit supply to them due to their potential of paying off the debt. For a household with sample mean characteristics, a one percentage point increase in income will increase the probability of credit card ownership by 3.01 percentage points, and a one percentage point increase in net worth will increase the probability by 0.44 percentage point. Homeowners are more likely to be a cardholder than renters, and the estimated difference in the probability of credit card holding is 8.46 percentage points. Notice that the effect of income is greater than that of net worth on the probability of credit card ownership. One reason may be that, other than net worth, income is usually asked in credit card applications and the information will be used by the banks
in risk management models as an element to evaluate the consumer’s credit
worthiness in order to determine whether or not to issue a credit card.

Bankruptcy record is negatively associated with the likelihood of being a
cardholder. Consumers who have a record of bankruptcy are usually high risk
people with low credit scores. They have greater chances of being rejected for credit
cards and even approved, the terms in their credit card contracts tend to be stricter,
such as lower credit limits and higher interest rates. Holding other variables constant,
consumers who have filed for bankruptcy are less likely to hold a credit card than
households without bankruptcy history. The marginal effect of bankruptcy history
on the probability of credit card ownership is 8.29 percentage points for a
representative household.

In summary, credit card ownership is the equilibrium of credit demand and
credit supply. Lower probability of credit card ownership by less-educated,
lower-income, and minority households suggests the importance of credit supply
factors that are utilized by the credit card issuers to identify the risk levels of
consumers. Credit demand factors also play an important role in determining the
consumer’s choice of owning a credit card. Married, middle-aged, and wealthier
households would like to hold credit cards since they tend to have greater transaction
needs and borrowing needs. Better-educated consumers choose to hold a credit card maybe because they have higher levels of financial literacy and therefore are more confident about their abilities in managing credit card debt. Furthermore, there are some other unobserved variables on the demand side such as religious, traditional, cultural, and psychological factors that may also influence the consumer’s decision on credit card ownership.

4.5 Determinants of Credit Card Borrowing

4.5.1 Descriptive Statistics

The sample characteristics of revolvers and transactors are compared in Table 4.4. T-tests are conducted for continuous variables and chi-square tests are conducted for categorical variables to examine the differences between households with and without a positive amount of credit card debt. Among the list of independent variables considered in the analysis, significant differences between revolvers and transactors are shown to exist for all demographic variables (age, race, marital status, education, and household size), for some of the credit related variables (number of cards, default history), and for some of the financial variables (net worth, homeownership). Consumers who are white, married, better-educated, and wealthier are more likely to be convenience users perhaps because they have lower borrowing
needs and are also more responsible and capable in managing their finances. Compared with transactors, revolvers tend to have more credit cards as well as a higher probability of default. There is a significant difference in homeownership between households with and without revolving credit card debt - 76.93% of revolvers are homeowners compared with 85.50% for transactors. Unlike credit card ownership which is determined by both credit demand and credit supply, credit card borrowing is primarily the consumer’s own decision based on predetermined terms in the credit card contract. In other words, a credit card represents a line of credit made available to the consumers, and whether or not to borrow on it has nothing to do with the credit card issuers.

### 4.5.2 Logit Model

Similarly, for the binary choice of whether or not to borrow on a credit card, we also use a logit model to analyze the probability of being a credit card revolver.

The logit model for credit card borrowing is specified as follows:

\[
Pr(R_i = 1) = F(x_i, \phi) = \frac{\exp(x_i, \phi)}{1 + \exp(x_i, \phi)}
\]  
(4.2)

\[
R_i = \begin{cases} 
1 & \text{if } i = \text{revolver} \\
0 & \text{if } i = \text{transactor}
\end{cases}
\]
where \( R_i \) is the binary dependent variable indicating whether or not household \( i \) revolves balances on a credit card. When household \( i \) is a revolver, \( R_i \) takes the value 1; \( R_i \) is 0 if household \( i \) is a transactor. The estimation method for the logit model is maximum likelihood. The log-likelihood function is:

\[
\ln L(\phi|x_{2i}) = \sum_{i=1}^{n} \left[ R_i \ln \left( \frac{\exp(x_{2i}^\prime \phi)}{1 + \exp(x_{2i}^\prime \phi)} \right) + (1 - R_i) \ln(1 - \frac{\exp(x_{2i}^\prime \phi)}{1 + \exp(x_{2i}^\prime \phi)}) \right]
\]

To provide information on the estimated effect of a particular independent variable \( x_k \) on the probability of credit card borrowing \( (\Pr(R_i = 1)) \), the marginal effect for household \( i \) is calculated according to the following formula:

\[
\frac{\partial E(R_i)}{\partial x_k} = dF(x_{2i}^\prime \hat{\phi}) \cdot \frac{\partial}{\partial x_k} \left( \frac{\exp(x_{2i}^\prime \hat{\phi})}{1 + \exp(x_{2i}^\prime \hat{\phi})} \right)
\]

\[
= \left( \frac{\exp(x_{2i}^\prime \hat{\phi})}{1 + \exp(x_{2i}^\prime \hat{\phi})} \right) \left[ 1 - \frac{\exp(x_{2i}^\prime \hat{\phi})}{1 + \exp(x_{2i}^\prime \hat{\phi})} \right] \hat{\phi}_k
\]

\[
= \frac{\exp(x_{2i}^\prime \hat{\phi})}{[1 + \exp(x_{2i}^\prime \hat{\phi})]^2} \hat{\phi}_k
\]

Moreover, the predicted probability of credit card borrowing for household \( i \) can also be calculated based on the tobit estimates as follows:

\[
F(x_{2i}^\prime \hat{\phi}) = \frac{\exp(x_{2i}^\prime \hat{\phi})}{1 + \exp(x_{2i}^\prime \hat{\phi})}
\]

65
4.5.3 Empirical Results

Table 4.5 presents the results of the logit estimation for credit card borrowing. Besides the parameter coefficients and standard errors, marginal effects are also reported to reflect the estimated changes in the probability of borrowing on a credit card. The marginal effects are calculated for a representative household with sample mean characteristics. For continuous independent variables, the marginal effect is the estimated effect on the probability with a unit change in the given independent variable. For categorical variables, marginal effect is the estimated effect on the probability when the dummy variable changes from 0 to 1. The predicted probability for a representative household to be a credit card revolver is 58.59%.

Among credit related variables, number of cards, APR, and default history are significantly related to the consumer’s decision of revolving on credit cards. The number of credit cards is positively related to the likelihood of being a revolver and the marginal effect is 2.88 percentage points with one additional card the representative household has. Revolvers tend to hold more credit cards because they can save money by switching balances from credit cards with higher interest rates to those with lower interest rates. APR is negatively related to credit card borrowing decision because the interest rate is the price of borrowing and it is more expensive to
borrow on credit cards with higher interest rates. When shopping for credit cards in the market, revolvers usually prefer offers with lower interest rates, although convenience users are not as sensitive to the interest rate as revolvers (Canner and Luckett 1992). A one percentage point increase in APR will decrease the likelihood of borrowing on a credit card by 0.53 percentage point for a representative household. The probability of being a revolver is significantly greater for households with a default history than those who have never missed the minimum required payment. The estimated difference in the likelihood of credit card borrowing between defaulters and non-defaulters is 19.66 percentage points. The credit limit, however, is not a significant determinant of credit card borrowing. This makes sense because the consumer’s choice of using the credit card as a financing instrument to smooth consumption over time is independent of the amount of accessible credit supplied by issuers. As the upper bound of the consumer’s borrowing capacity, the credit limit has influences on the amount of borrowing instead of the initial decision of whether or not to borrow (see Table 4.6).

Among demographic variables, age and education are significantly associated with the decision of revolving credit card debt. Holding other variables constant, the probability of being a revolver is quadratic in age. The maximum probability occurs
for consumers who are at the age of 45, with lower probabilities for those who are younger and older. Credit cards are often temporarily used by consumers as a financing instrument for short-term borrowing when they are short of liquid assets. This may indicate that middle-aged consumers have greater financing needs through credit cards than those who are younger and older. Education is negatively correlated with credit card borrowing, with a marginal effect of 5.18 percentage points on the likelihood of revolving credit card debt for a representative household. Race, marital status, and household size are found to be insignificantly related to the probability of being a credit card revolver.

As far as financial variables are concerned, net worth is more important in determining the consumer’s borrowing choice than income and homeownership. Wealthy people tend to use credit cards for transaction convenience rather than for consumption smoothing. The poor are more likely to revolve outstanding balances on credit cards, and one percentage point increase in net worth will decrease the probability of borrowing on a credit card by 1.79 percentage points. Recall that the effect of income is greater than that of net worth on the probability of credit card ownership. As to the probability of credit card borrowing, however, net worth has a greater marginal effect than income since net worth is a better indicator of the
household’s overall financial well-being than income. Wealthy people with low income do not necessarily borrow on credit cards especially when they have enough liquid assets; high income people with low net worth may still have to borrow on credit cards to satisfy their consumption needs.

4.6 Determinants of Credit Card Debt and Payoff Rates

4.6.1 Tobit Model

After examining the decision of credit card borrowing, in this section we will analyze the extent of credit card borrowing. In particular, the analysis is focused on the determinants of the levels of credit card debt and payoff rates. Since a significant fraction of the population do not carry a revolving balance on their credit cards, we observe zero credit card debt for those transactors who use credit cards as a transacting instrument and positive credit card debt for those revolvers who use credit cards as a financing instrument. Therefore the data for credit card debt is left-censored at zero, and the tobit model will be used in the regression. The tobit model combines both the discrete and the continuous parts of the censored distribution, thus both transactors and revolvers are considered in the estimation. The tobit specification for credit card debt takes the following form:
\[ D^*_i = x'_i \beta + \xi_i, \quad \xi_i \sim N(0, \sigma^2_\xi) \] (4.3)

\[
D_i = \begin{cases} 
D^*_i & \text{if } D^*_i > 0 \\
0 & \text{if } D^*_i \leq 0 
\end{cases}
\]

where \( D^*_i \) is a latent variable that indicates the desired amount of credit card debt and \( D_i \) is the amount of credit card debt that is actually observed from the data.

The estimation method for the tobit model is maximum likelihood. For those observations where credit card debt is greater than zero, the contribution to the likelihood is:

\[
[\Pr(D_i > 0)] f_D(D_i \mid D_i > 0) = \Phi\left(\frac{x'_i \beta}{\sigma_\xi}\right) \cdot f_D(D_i \mid x_i) / \Phi\left(\frac{x'_i \beta}{\sigma_\xi}\right)
\]

\[
= \frac{1}{(2\pi)^{1/2} \sigma_\xi} \exp \left[ -\frac{1}{2} \left( \frac{D_i - x'_i \beta}{\sigma_\xi} \right)^2 \right]
\]

For those observations where credit card debt is equal to zero, the contribution to the likelihood is:

\[
\Pr(D_i = 0) = \Pr(D^*_i \leq 0) = \Pr(\xi_i \leq -x'_i \beta) = 1 - \Phi\left(\frac{x'_i \beta}{\sigma_\xi}\right)
\]

where \( \Phi \) is the cumulative distribution function of the standard normal. Thus the likelihood function is:

\[
L_D = \prod_{D_i > 0} f_D(D_i \mid x_i) \prod_{D_i = 0} \left[ 1 - \Phi\left(\frac{x'_i \beta}{\sigma_\xi}\right) \right]
\]

\[
= \prod_{D_i > 0} \frac{1}{(2\pi)^{1/2} \sigma_\xi} \exp \left[ -\frac{1}{2} \left( \frac{D_i - x'_i \beta}{\sigma_\xi} \right)^2 \right] \prod_{D_i = 0} \left[ 1 - \Phi\left(\frac{x'_i \beta}{\sigma_\xi}\right) \right]
\]
Similarly, the payoff rates are right-censored at 100% because the transactors always pay off the debt in full and their payoff rates are 100%. The payoff rates are also left-censored at zero because negative payoff rates cannot be observed either. Negative payoff rates occur when consumers keep borrowing on credit cards when they already failed to pay for the existing balances. The two-sided tobit model for payoff rates then takes the form:

$$P_i^* = z_i^\prime \beta_2 + \tau_i, \quad \tau_i \sim N(0, \sigma_\tau^2) \tag{4.4}$$

$$P_i = \begin{cases} P_i^* & \text{if } 0 < P_i^* < 100 \\ 100 & \text{if } P_i^* \geq 100 \\ 0 & \text{if } P_i^* \leq 0 \end{cases}$$

And the likelihood function is:

$$L_p = \prod_{0 < P < 100} f_p(P_i | z_i) \prod_{P = 100} \left[ 1 - \Phi\left(\frac{100 - z_i^\prime \beta_2}{\sigma_\tau}\right)\right] \prod_{P = 0} \left[ 1 - \Phi\left(\frac{z_i^\prime \beta_2}{\sigma_\tau}\right)\right]$$

where the first product is contributed by those payoff rates that are observed between zero and 100, the second product is contributed by those payoff rates observed to be 100, and the third product by those payoff rates observed to be zero.

The coefficients of the tobit model represent the estimated effects of the independent variables on the latent dependent variable. In order to find out the aggregate behavioral trend of all consumers including both revolvers and transactors, it is necessary to calculate the marginal effects which reflect the effects of
independent variables on the observed dependent variable. The following is the formula for calculating the marginal effect of independent variable \(x_k\) on the credit card debt in household \(i\):

\[
\frac{\partial E(D_i)}{\partial x_k} = \partial \left[ 1 - \Phi(-\frac{x_i\hat{\beta}_1}{\sigma}) \right] \left( x_i\hat{\beta}_1 + \frac{\sigma \phi(-\frac{x_i\hat{\beta}_1}{\sigma})}{1 - \Phi(-\frac{x_i\hat{\beta}_1}{\sigma})} \right) / \partial x_k
\]

\[
= \partial \Phi(\frac{x_i\hat{\beta}_1}{\sigma})[x_i\hat{\beta}_1 + \frac{\sigma \phi(\frac{x_i\hat{\beta}_1}{\sigma})}{1 - \Phi(\frac{x_i\hat{\beta}_1}{\sigma})}] / \partial x_k
\]

\[
= \Phi(\frac{x_i\hat{\beta}_1}{\sigma})\hat{\beta}_k
\]

Similarly, the marginal effect of independent variable \(z_k\) for the credit card payoff rate in household \(i\) can be calculated as follows:

\[
\frac{\partial E(P_i)}{\partial z_k} = \partial \left[ 1 - \Phi(-\frac{z_i\hat{\beta}_2}{\sigma}) \right] \left( z_i\hat{\beta}_2 + \frac{\sigma \phi(-\frac{z_i\hat{\beta}_2}{\sigma})}{1 - \Phi(-\frac{z_i\hat{\beta}_2}{\sigma})} \right) / \partial z_k
\]

\[
= \partial \Phi(\frac{z_i\hat{\beta}_2}{\sigma})[z_i\hat{\beta}_2 + \frac{\sigma \phi(\frac{z_i\hat{\beta}_2}{\sigma})}{1 - \Phi(\frac{z_i\hat{\beta}_2}{\sigma})}] / \partial z_k
\]

\[
= \Phi(\frac{z_i\hat{\beta}_2}{\sigma})\hat{\beta}_k
\]
4.6.2 Empirical Results

The tobit models expressed by equations (4.3) and (4.4) are estimated respectively for the credit card debt and the credit card payoff rate. The independent variables included in the regressions fall into three broad categories as described in section 4.3: credit related variables (number of cards, APR, credit limit, minimum payoff rate, and default history), socioeconomic variables (age, race, marital status, education, household size, income, assets, debts, and homeownership), and expectations variables (unemployment expectations, interest rate expectations, and price expectations). The debt and payoff equations have the same set of explanatory variables except that minimum payoff rate is not included in the debt equation. Minimum payoff rate is predetermined by the card issuing banks based on the consumer’s performances on a particular credit card. Normally consumers who have lower credit scores and higher outstanding balances will be required to have a higher minimum payoff rate in order to force them to payoff the debt faster. So the level of credit card debt might contribute to the changes of minimum payoff rate instead of being determined by it. However, the change of minimum payoff rate will directly influence the actual payoff rate, as shown by the parameter estimate in Table 4.7.

The tobit estimates for the credit card debt equation (4.3) are presented in Table 4.6. The reported marginal effects in the table are the weighted sample means
of individual households’ marginal effects. Compared with the marginal effects for a representative household with sample mean characteristics, these can better reflect the aggregate effects of given independent variables on the observed credit card debt. All credit related variables, including the number of cards, APR, credit limit, and default history, are significant in determining the amount of credit card debt. The number of credit cards and the total credit limit have positive effects on credit card debt because these two variables represent the total available credit that constrains the consumer’s borrowing capacity. According to the marginal effects, on average, one additional card will increase the average credit card debt by $322, and an additional $1,000 in credit limit will lead to a $45 increase in credit card debt. Using different datasets and econometric models, Kim and DeVaney (2001) and Gross and Souleles (2000) also find a positive relationship between credit card borrowing and credit supply. The APR is negatively related to credit card debt because it determines the amount of financial charges. The interest rate is the price of borrowing, so people tend to borrow less on credit cards when the costs are high. According to the estimated coefficient, when APR increases by one percentage point, average credit card debt will decrease by about $80. Default history indicates the risk categories of consumers: those who have missed the minimum required payments belong to the
high risk category and those who have never missed the minimum required payments belong to the low risk category. High risk consumers who have a default history tend to carry more credit card debt than low risk consumers, and the average difference between the two categories is $2,151.

In previous studies the effect of income as a determinant of credit card debt is significant, but the sign has not been consistent. The influence of income on credit card debt can be explained by two related factors: borrowing needs and credit access. Although both borrowing needs and credit access affect credit card debt positively, the opposite relationships of these two factors with income cause the ambiguity. High income people borrow less since they do not have a lot of borrowing needs, but they could also borrow more because they are usually eligible to have more credit cards and higher credit limits due to their high payoff potential. Low income people, on the other hand, tend to borrow more on credit cards to meet their current consumption needs, but their borrowing capacity is constrained by their limited access to credit. The negative relationship between income and credit card debt in Table 4.6 indicates that in our data borrowing needs dominate credit access in determining the consumer’s credit card borrowing. An augmented model with a quadratic term in income is also estimated to test for possible curvilinear relationship between income
and debt. The estimated coefficients for income and squared income are 2500.01 and -156.19 respectively and they are both significant. The negative sign of the quadratic term suggests that credit card debt is actually concave in income, with middle income people revolving more credit card debt than low income and high income classes. The 2004 SCF data also support this conclusion: credit card outstanding balances are substantially lower among the highest and the lowest income groups (Bucks, Kennickell and Moore 2006).

As far as assets are concerned, financial assets are more important in determining credit card borrowing than physical assets. In the CFM survey, the amount of financial assets is calculated as the aggregate of bank accounts, stocks, bonds, mutual funds, retirement plans, and life insurances; the amount of physical assets is calculated as the aggregate of real estate, business equity, vehicles, and other possessions. The negative relationship between financial assets and credit card debt is consistent with our intuition because financial assets are usually of better liquidity than physical assets, and thus can be used for instantaneous consumption needs or credit card payments, either of which will decrease the total amount of credit card debt.
The amount of other debts is another important determinant of credit card debt. According to the 2004 SCF, mortgages, student loans, auto loans, and other installment loans constitute more than 90% of total household debt, and they all require fixed monthly payments. Credit cards, which require only a small amount as the minimum payment, are therefore employed by consumers to offset some of the other debt burden or free some existing assets for other purposes. Thus households with higher levels of other debts probably induce higher outstanding balances on their credit cards.

Homeownership shows a significant relationship with credit card borrowing: homeowners carry an average of $801 less credit card debt than renters. Homeownership may influence credit card borrowing through home equity lines of credit (HELOC). HELOCs, as a substitute for credit cards, provide another financing instrument for consumers who are homeowners. Homeowners have the option of borrowing from HELOCs instead of from credit cards, and they can also choose to pay down their credit card debt using HELOCs. According to a 2005 consumer finance survey conducted by Demos, a non-profit public policy organization, a substantial number of homeowners use HELOCs or proceeds from mortgage refinancing to pay down their credit card debt (Draut et al. 2005).
The effects of psychological factors on consumer behavior have been investigated extensively in the psychology and marketing literature. With the availability of new survey data, the psychological aspect began to receive more attention in the consumer finance area. Several recent studies have made some attempts to empirically test the effects of psychological factors on credit card debt using household data (Kim and DeVaney 2001, Yilmazer and DeVaney 2005, Ekici 2005). In this study, we find that the consumer’s expectations on future unemployment and prices are significant in determining their current credit card borrowing behavior. Since the unemployment rate is one of the most important indicators of macroeconomic prosperity, high unemployment expectations suggest low expectations for macroeconomic well-being. People tend to borrow more on credit cards in the current period if they expect the economy to be depressed in the future. Thus consumers with high unemployment expectations are likely to carry more credit card debt than their counterparts. High inflationary expectations also lead the consumers to borrow more on credit cards because future depreciation increases the value of money in the current period. Among the three expectations variables in the regression, the expected interest rate for borrowing seems to be the least significant factor in determining the consumer’s credit card borrowing.
Table 4.7 presents the tobit estimates for the credit card payoff equation (4.4). Similarly, the reported marginal effects in the table are calculated as the weighted sample means of individual households’ marginal effects. Comparing the results with Table 4.6, most of the significant determinants for debt - including the number of cards, APR, default history, income, financial assets, homeownership, and price expectations - are also shown to be significant in determining payoff rates, except with opposite signs. For example, APR affects payoff rates positively: one additional percentage point increase in APR will increase the average payoff rate by 0.63 percentage point. One noteworthy exception is the credit limit, which shows no significant effects in determining payoff rates. Credit limit is important in determining debt because it places an upper bound on the consumer’s borrowing capacity, and once the limit is increased, more accessible credit will allow more credit card borrowing and induce higher credit card debt. The payoff rate, however, is not affected by credit limit, probably due to the fact that credit limit places no restrictions on the amount of payment.

As discussed Chapter 1, credit card debt is non-secured with flexible payments. The only restriction on the amount of payment is the minimum required payment, which establishes a lower standard for the consumer’s repayment behavior.
without falling into delinquency. The minimum required payment is typically
determined as follows:

\[ M_{\text{min}} = \begin{cases} 
\alpha_{\text{min}} B, & \text{if } B > m / \alpha_{\text{min}} \\
m, & \text{if } m \leq B \leq m / \alpha_{\text{min}} \\
B, & \text{if } 0 < B < m 
\end{cases} \]

where \( M_{\text{min}} \) is the minimum required payment, \( \alpha_{\text{min}} \) is the minimum payoff rate, \( B \) is
the statement balance, and \( m \) is a constant representing the threshold. Most banks set
the threshold to be $10 or $20 and the minimum payoff rate to be 2%. When the
statement balance is below the threshold, consumers are required to pay off the entire
balance; when the statement balance is above the threshold, consumers are required to
pay the threshold amount or a certain percent (\( \alpha_{\text{min}} \)) of the balance, whichever is
greater. The Office of the Comptroller of the Currency and Board of Governors of
the Federal Reserve System have for some time been discussing possible steps which
would assist consumers with their debt management. One recent policy change that
has received a lot of attention is the raising of the minimum required payments on
statement balances from the typical average level of around 2% to around 4%. In
2006, banks began to gradually implement these new minimum required payment
rates. Will this policy be effective in helping the consumers to pay off their credit
card debt faster? Our analysis shows the following empirical relationship: one
additional percentage point increase in the minimum payoff rate on credit cards will increase the average payoff rate by 1.7 percentage points. Therefore increasing the minimum payoff rate from 2% to 4% will increase the average payoff rate by 3.4 percentage points across cardholders. This will make a significant difference in the time that consumers take to pay off their credit card balances. For example, making only the 2% minimum payment each month on a balance of $1,000 at an interest rate of 19% will take eight years four months to repay the balance in full. However, holding other factors constant, if the actual monthly payment increases from 2% to 5.4% as a result of the new policy, it will take only one year and ten months to pay off the debt.

The estimated marginal effect of 1.7 percentage points on the actual payoff rate with respect to the minimum required payoff rate is powerful. Based on our intuition, when the minimum required payment increases, those marginal consumers who are actually paying off the minimum are most likely to respond. If this is the case, we would expect the aggregate effect on the actual payoff rate to be less than one percentage point since among all cardholders only a small percent of consumers (less than 10% in the CFM data) are making only the minimum required payments. Our estimated marginal effect of 1.7 percentage points indicates that not only the
consumers on the margin but also those who are above the margin are responding to the increased minimum required payment rate. It would thus appear that there are some psychological factors at play in required payment rates. Seeing increases in required payments may well increase the uncertainty of cardholders about future required payment rates. An environment of increased uncertainty may motivate cardholders to draw down their credit card debt as quickly as possible in order to avoid future default should those rates rise again. Although all cardholders, including those who are paying the minimum and those who are paying more than the minimum, are responding to the increase of required payment rates, the potential differences of their responses are not further explored in this chapter due to the small number of marginal consumers in the current dataset. When more data are available, future research can be conducted to investigate the sensitivity of consumer responses in more details.

4.7 Conclusion

In order to take effective measures in the credit card market, it is important for policymakers to understand the underlying determinants of the consumer’s choices in credit card holding, borrowing, and payoff. Using recent CFM data, this chapter
empirically tests the effects of a variety of factors, including credit related variables, socioeconomic variables, and expectations variables, in determining household behavior related to credit card use. Specifically, the analysis is conducted in three stages: the first stage focuses on credit card ownership and examines elements on both the demand and the supply sides, the second stage estimates the effects of various factors on the likelihood of being a revolving credit card user who carries over credit card balances, and the third stage investigates the determinants of the levels of credit card debt and payoff rates. Analyzing credit card debt and payoff rates in the context of credit card ownership and credit card borrowing provides us with a broader perspective to look at the changing credit card market.

In the past 10 years, the percentage of credit card ownership has increased very slowly with an average of 80% of the population. This may indicate that the U.S. credit card market is approaching saturation in terms of new customer acquisition. During the same time period, however, among all cardholders the percentage of transactors has increased much faster from 34% in 1998 to 49% in 2005. The fact that more consumers began to use credit cards for transaction convenience might suggest an increased awareness of the financial problems brought by excessive borrowing on credit cards. Although the percentage of revolvers is decreasing over
time, the average household credit card debt never stopped growing. Apparently, those who are already indebted keep going deeper in debt either due to lack of self-discipline or limited financial literacy. The unique CFM data used in this chapter provide the most up-to-date information on the consumers’ recent behavioral changes in the credit card market that is not available in any other public consumer finance dataset.

The estimation results provide insights for policy-making and banking regulation in the credit card market. It is found that increasing the credit limit will lead to more credit card borrowing - $45 more debt per $1,000 increase in credit limit - but have no significant effects on average payoff rates. A one percentage point increase in the required minimum payment rate on credit cards will increase the actual payoff rate by 1.7 percentage points and dramatically shorten the time necessary to pay off the balances in full. This result shows that the on-going federal policy “doubling the minimum required payments” will be very effective in helping consumers to pay off credit card debt faster. Based on the estimated marginal effect, regulators can also adjust their future policies to achieve particular goals in the credit card market.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition of Variables</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit card debt</td>
<td>Amount owed on all credit cards after the most recent payments</td>
<td>2,501</td>
</tr>
<tr>
<td>Payoff rate</td>
<td>The ratio of actual payments to statement balances on all credit cards (in percentage)</td>
<td>54.15</td>
</tr>
<tr>
<td>Number of cards</td>
<td>Total number of credit cards</td>
<td>2.94</td>
</tr>
<tr>
<td>APR</td>
<td>Annual Percentage Rate on the credit card that has the largest balance (for revolvers) or most frequently used (for transactors)</td>
<td>12.07</td>
</tr>
<tr>
<td>Credit limit</td>
<td>Sum of total line of available credit from all credit cards (in thousands of dollars)</td>
<td>25.89</td>
</tr>
<tr>
<td>Minimum required payoff rate</td>
<td>The ratio of minimum required payments to statement balances on all credit cards (in percentage)</td>
<td>6.23</td>
</tr>
<tr>
<td>Default history</td>
<td>Dummy=1 if the respondent has missed making the minimum payment at least once in the past 6 months; Dummy=0 otherwise</td>
<td>14.56%</td>
</tr>
<tr>
<td>Bankruptcy history</td>
<td>Dummy=1 if the respondent has filed for personal bankruptcy; Dummy=0 otherwise</td>
<td>9.11%</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>Log of total annual household income</td>
<td>10.68</td>
</tr>
<tr>
<td>Log(Assets)</td>
<td>Log of total household assets</td>
<td>12.01</td>
</tr>
<tr>
<td>Log(Financial)</td>
<td>Log of total household financial assets</td>
<td>9.29</td>
</tr>
<tr>
<td>Log(Physical)</td>
<td>Log of total household physical assets</td>
<td>11.45</td>
</tr>
<tr>
<td>Log(Debts)</td>
<td>Log of total household debts excluding credit card debt</td>
<td>7.25</td>
</tr>
<tr>
<td>Log(Networth)</td>
<td>Log of total household net worth</td>
<td>11.10</td>
</tr>
<tr>
<td>Age</td>
<td>Number of years old of the respondent</td>
<td>51.57</td>
</tr>
<tr>
<td>White</td>
<td>Dummy=1 if the respondent is white; Dummy=0 otherwise</td>
<td>82.23%</td>
</tr>
<tr>
<td>Marital status</td>
<td>Dummy=1 if the respondent is married; Dummy=0 otherwise</td>
<td>64.94%</td>
</tr>
<tr>
<td>Education level</td>
<td>Highest level of education completed by the respondent: =1 if less than high school grad; =2 if high school grad; =3 if some college; =4 if college grad; =5 if more than college</td>
<td>3.42</td>
</tr>
<tr>
<td>Household size</td>
<td>Total number of adults and kids in the household</td>
<td>2.76</td>
</tr>
<tr>
<td>Homeownership</td>
<td>Dummy=1 if the respondent is a homeowner; Dummy=0 otherwise</td>
<td>81.64%</td>
</tr>
<tr>
<td>Expect higher unemployment</td>
<td>Dummy=1 if the respondent thinks unemployment will be higher in a year; Dummy=0 otherwise</td>
<td>37.64%</td>
</tr>
<tr>
<td>Expect higher interest rates</td>
<td>Dummy=1 if the respondent thinks interest rates for borrowing will be higher in a year; Dummy=0 otherwise</td>
<td>74.28%</td>
</tr>
<tr>
<td>Expect higher prices</td>
<td>Dummy=1 if the respondent thinks prices will be higher in a year; Dummy=0 otherwise</td>
<td>81.06%</td>
</tr>
</tbody>
</table>

Table 4.1: Defined Variables and Summary Statistics
<table>
<thead>
<tr>
<th>Variables</th>
<th>Cardholders</th>
<th>Non-cardholders</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>51.57</td>
<td>51.05</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>White</td>
<td>82.25%</td>
<td>68.19%</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Marital status</td>
<td>64.94%</td>
<td>43.10%</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Education level</td>
<td>3.42</td>
<td>2.65</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>10.68</td>
<td>9.89</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Log(Networth)</td>
<td>11.10</td>
<td>9.23</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Bankruptcy history</td>
<td>9.11%</td>
<td>16.79%</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Homeownership</td>
<td>81.64%</td>
<td>56.17%</td>
<td>&lt; 0.0001</td>
</tr>
</tbody>
</table>

Table 4.2: Sample Characteristics of Cardholders vs Non-cardholders
<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>Mrg Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>*** 0.0406</td>
<td>0.0126</td>
<td>0.08</td>
</tr>
<tr>
<td>Age²</td>
<td>*** -0.000333</td>
<td>0.000115</td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>*** 0.3709</td>
<td>0.0935</td>
<td>4.98</td>
</tr>
<tr>
<td>Marital status</td>
<td>*** 0.5602</td>
<td>0.0761</td>
<td>7.29</td>
</tr>
<tr>
<td>Education level</td>
<td>*** 0.4735</td>
<td>0.0328</td>
<td>5.89</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>*** 0.2423</td>
<td>0.0258</td>
<td>3.01</td>
</tr>
<tr>
<td>Log(Networth)</td>
<td>*** 0.0354</td>
<td>0.0098</td>
<td>0.44</td>
</tr>
<tr>
<td>Homeownership</td>
<td>*** 0.6068</td>
<td>0.0874</td>
<td>8.46</td>
</tr>
<tr>
<td>Bankruptcy history</td>
<td>*** -0.5712</td>
<td>0.1042</td>
<td>-8.29</td>
</tr>
<tr>
<td>Intercept</td>
<td>*** -4.8825</td>
<td>0.4088</td>
<td></td>
</tr>
</tbody>
</table>

Note: Marginal effects are in terms of percentage points.
*** significant at 1% level or better;
** significant at 5% level or better;
* significant at 10% level or better

Table 4.3: Logit Estimates for Credit Card Ownership
<table>
<thead>
<tr>
<th>Variables</th>
<th>Revolvers</th>
<th>Transactors</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cards</td>
<td>3.34</td>
<td>2.63</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>APR</td>
<td>11.86</td>
<td>12.32</td>
<td>0.0663</td>
</tr>
<tr>
<td>Credit limit</td>
<td>25.49</td>
<td>26.28</td>
<td>0.3970</td>
</tr>
<tr>
<td>Default history</td>
<td>22.11%</td>
<td>7.47%</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Age</td>
<td>48.18</td>
<td>54.39</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>White</td>
<td>77.92%</td>
<td>85.79%</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Marital status</td>
<td>61.56%</td>
<td>67.71%</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Education level</td>
<td>3.28</td>
<td>3.54</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Household size</td>
<td>2.92</td>
<td>2.63</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>10.69</td>
<td>10.68</td>
<td>0.6596</td>
</tr>
<tr>
<td>Log(Networth)</td>
<td>10.42</td>
<td>11.66</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Homeownership</td>
<td>76.93%</td>
<td>85.50%</td>
<td>&lt; 0.0001</td>
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</tbody>
</table>

Table 4.4: Sample Characteristics of Revolvers vs Transactors
### Table 4.5: Logit Estimates for Credit Card Borrowing

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>Mrg Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cards</td>
<td>*** 0.1187</td>
<td>0.0259</td>
<td>2.88</td>
</tr>
<tr>
<td>APR</td>
<td>*** -0.0220</td>
<td>0.00753</td>
<td>-0.53</td>
</tr>
<tr>
<td>Credit limit</td>
<td>-0.00107</td>
<td>0.00208</td>
<td>-0.03</td>
</tr>
<tr>
<td>Default history</td>
<td>*** 0.8852</td>
<td>0.1535</td>
<td>19.66</td>
</tr>
<tr>
<td>Age</td>
<td>*** 0.0681</td>
<td>0.0216</td>
<td>-0.26</td>
</tr>
<tr>
<td>Age^2</td>
<td>*** -0.000765</td>
<td>0.000213</td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>-0.1695</td>
<td>0.1404</td>
<td>-4.07</td>
</tr>
<tr>
<td>Marital status</td>
<td>-0.1759</td>
<td>0.1174</td>
<td>-4.25</td>
</tr>
<tr>
<td>Education level</td>
<td>*** -0.2135</td>
<td>0.0464</td>
<td>-5.18</td>
</tr>
<tr>
<td>Household size</td>
<td>0.0232</td>
<td>0.0348</td>
<td>0.56</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>-0.0395</td>
<td>0.0436</td>
<td>-0.96</td>
</tr>
<tr>
<td>Log(Networth)</td>
<td>*** -0.0736</td>
<td>0.0165</td>
<td>-1.79</td>
</tr>
<tr>
<td>Homeownership</td>
<td>0.00653</td>
<td>0.1394</td>
<td>0.16</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.0116</td>
<td>0.6742</td>
<td></td>
</tr>
</tbody>
</table>

Note: Marginal effects are in terms of percentage points.

*** significant at 1% level or better;
** significant at 5% level or better;
* significant at 10% level or better
<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>Mrg Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cards</td>
<td>*** 645.824921</td>
<td>117.089220</td>
<td>321.924</td>
</tr>
<tr>
<td>APR</td>
<td>*** -160.061461</td>
<td>41.782862</td>
<td>-79.786</td>
</tr>
<tr>
<td>Credit limit</td>
<td>*** 89.516029</td>
<td>11.220487</td>
<td>44.621</td>
</tr>
<tr>
<td>Default history</td>
<td>*** 4315.330710</td>
<td>730.315492</td>
<td>2151.06</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>*** -693.529291</td>
<td>243.324314</td>
<td>-345.704</td>
</tr>
<tr>
<td>Log(Financial)</td>
<td>*** -247.874090</td>
<td>84.933976</td>
<td>-123.558</td>
</tr>
<tr>
<td>Log(Physical)</td>
<td>99.240088</td>
<td>173.821381</td>
<td>49.468</td>
</tr>
<tr>
<td>Log(Debts)</td>
<td>** 200.767976</td>
<td>78.748016</td>
<td>100.077</td>
</tr>
<tr>
<td>Age</td>
<td>* 197.203418</td>
<td>103.750258</td>
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<tr>
<td>Age^2</td>
<td>** -2.528674</td>
<td>1.094674</td>
<td>-335.410</td>
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<tr>
<td>White</td>
<td>-672.878605</td>
<td>702.462233</td>
<td>-372.725</td>
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<tr>
<td>Marital status</td>
<td>-747.737383</td>
<td>646.439325</td>
<td>-253.238</td>
</tr>
<tr>
<td>Education level</td>
<td>** -508.030973</td>
<td>258.329963</td>
<td>-800.973</td>
</tr>
<tr>
<td>Household size</td>
<td>262.388841</td>
<td>192.842582</td>
<td>130.793</td>
</tr>
<tr>
<td>Homeownership</td>
<td>* -1606.862772</td>
<td>869.846561</td>
<td>-659.312</td>
</tr>
<tr>
<td>Expect higher</td>
<td>** 1322.671133</td>
<td>557.801630</td>
<td>659.312</td>
</tr>
<tr>
<td>unemployment</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Expect higher</td>
<td>983.542547</td>
<td>622.258913</td>
<td>490.267</td>
</tr>
<tr>
<td>interest rates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expect higher</td>
<td>** 1476.591770</td>
<td>698.481163</td>
<td>736.037</td>
</tr>
<tr>
<td>prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>*** 1745.631699</td>
<td>42.662393</td>
<td></td>
</tr>
</tbody>
</table>

*** significant at 1% level or better;
** significant at 5% level or better;
* significant at 10% level or better

Table 4.6: Tobit Estimates for Credit Card Debt
<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>Mrg Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cards</td>
<td>** -1.297186</td>
<td>0.591103</td>
<td>-0.898</td>
</tr>
<tr>
<td>APR</td>
<td>*** 0.907742</td>
<td>0.197686</td>
<td>0.629</td>
</tr>
<tr>
<td>Credit limit</td>
<td>0.026273</td>
<td>0.054689</td>
<td>0.018</td>
</tr>
<tr>
<td>Minimum required payoff rate</td>
<td>*** 2.454485</td>
<td>0.201176</td>
<td>1.700</td>
</tr>
<tr>
<td>Default history</td>
<td>*** -16.398483</td>
<td>3.633434</td>
<td>-11.357</td>
</tr>
<tr>
<td>Log(Income)</td>
<td>** 3.045535</td>
<td>1.415913</td>
<td>2.109</td>
</tr>
<tr>
<td>Log(Financial)</td>
<td>*** 1.384910</td>
<td>0.457618</td>
<td>0.959</td>
</tr>
<tr>
<td>Log(Physical)</td>
<td>-0.667011</td>
<td>0.917010</td>
<td>-0.462</td>
</tr>
<tr>
<td>Log(Debts)</td>
<td>*** -1.33811</td>
<td>0.405633</td>
<td>-0.924</td>
</tr>
<tr>
<td>Age</td>
<td>*** -2.466488</td>
<td>0.640699</td>
<td>0.092</td>
</tr>
<tr>
<td>Age^2</td>
<td>*** 0.026725</td>
<td>0.006499</td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>2.173343</td>
<td>3.991588</td>
<td>1.505</td>
</tr>
<tr>
<td>Marital status</td>
<td>** 6.802938</td>
<td>3.250051</td>
<td>4.711</td>
</tr>
<tr>
<td>Education level</td>
<td>*** 3.683389</td>
<td>1.349071</td>
<td>2.551</td>
</tr>
<tr>
<td>Household size</td>
<td>*** -2.901909</td>
<td>1.023420</td>
<td>-2.010</td>
</tr>
<tr>
<td>Homeownership</td>
<td>*** 12.751038</td>
<td>4.574328</td>
<td>8.830</td>
</tr>
<tr>
<td>Expect higher unemployment</td>
<td>-2.583484</td>
<td>2.881957</td>
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<tr>
<td>Expect higher interest rates</td>
<td>0.208441</td>
<td>3.280208</td>
<td>0.144</td>
</tr>
<tr>
<td>Expect higher prices</td>
<td>** -9.020283</td>
<td>3.545663</td>
<td>-6.247</td>
</tr>
<tr>
<td>Intercept</td>
<td>* 36.753786</td>
<td>22.073056</td>
<td></td>
</tr>
</tbody>
</table>

*** significant at 1% level or better;
** significant at 5% level or better;
* significant at 10% level or better

Table 4.7: Tobit Estimates for Credit Card Payoff Rates
APPENDIX A

RELEVANT SURVEY QUESTIONS IN THE CONSUMER
FINANCE MONTHLY SURVEY
A1. Credit Related Variables

1. Currently, does your household have any credit cards? How many credit cards do you have?
2. If you had an unpaid balance on your credit card, what interest rate would you have to pay on the balance?
3. Speaking of all your credit cards, all together, how much have you paid or will you pay on the most recent bills you have received?
4. For all your credit cards taken together, after any payments you have made or will make on your most recent bills, how much will you still owe on them?
5. For all of your credit cards together, what is the maximum amount you could borrow; that is, what is the total credit limit considering all of them?
6. According to your most recent credit card statements, if you add up the minimum required payment for all your credit cards, what would it come to?
7. In the past 6 months, have you ever missed a credit card payment by 60 days or more?
8. Have you ever filed for personal bankruptcy?
A2. Socioeconomic Variables

1. Approximately, what was your total household income from all sources before taxes last year?
2. Created variable “financial assets” is the aggregate of the following asset categories: checking and savings accounts, CDs, stocks, bonds, mutual funds, retirement plans, life insurances, and money owed by others.
3. Created variable “physical assets” is the aggregate of the following asset categories: real estate, business equity, vehicles, and other possessions.
4. Created variable “debts” is the aggregate of the following debt categories: credit card debt, mortgages, home equity loans, student loans, installment loans, bank loans, payday loans, and personal loans.
5. Created variable “assets” is the sum of financial assets and physical assets.
6. Created variable “net worth” is the difference of assets and debts.
7. Is the house/apartment in which you live either owned or being bought?
8. What year were you born?
9. Are you white, black, Asian, or something else?
10. What is your current legal marital status?
11. How many members of your household are 17 years or younger?
12. Counting yourself, how many members of your household are 18 or older?
13. What is your highest level of education completed?
A3. Expectations Variables

1. One year from now, do you think unemployment will be higher, lower, or about the same as today?
2. One year from now, do you think interest rates for borrowing will be higher, lower, or about the same as today?
3. One year from now, do you think prices in general will be higher, lower, or about the same as today?


