A Synthetic Cohort Analysis of Credit Card Debt and Payoff Rates

Sarah S. Jiang*

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Abstract

Using a synthetic cohort approach, this paper tracks the changing behavior of credit card borrowing and payoff in a lifecycle framework for different birth cohorts. 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 based on a time series of cross sections. The fitted profiles show very different patterns compared with the cross-sectional profiles implied by the simple lifecycle hypothesis. The results suggest that young American consumers are borrowing more heavily and repaying at lower rates on credit cards than older generations. A tobit model is used to examine the underlying determinants of credit card debt and payoff rates, and the results are relevant for evaluating recent policy actions by federal banking authorities. It is found that a one percentage point increase in the minimum required payment on credit cards will increase the actual payoff rate by 1.6 percentage points.

Key words: cohort, lifecycle, credit card debt, payoff rate

JEL codes: D12, D91

I. 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

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* Ph.D. Candidate, Department of Economics, The Ohio State University. Email: jiang.103@osu.edu. I would like to thank my advisor Professor Lucia Dunn for suggestions and guidance, and Professor Stephen Cosslett, Professor Richard Steckel, Professor Randall Olsen and Professor Huston McCulloch for the helpful comments and advice. Provision of data from Center for Survey Research and Center for Human Resource Research at The Ohio State University is greatly acknowledged.

debt repayment may no longer be the same for U.S. households. 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.

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 objectives of this study are: 1) 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, and 2) to examine the financial, socioeconomic, demographic, and psychological determinants of credit card debt and payoff rates. 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 which greatly simplifies the estimation process and allows for more flexibility in model specification is utilized in the regression to separately address the above two objectives. 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. Therefore, new policies are needed to regulate the credit card market and guide consumer behavior.

The paper proceeds as follows. The next section briefly reviews relevant literature on credit card debt and lifecycle modeling. Section III discusses the data and descriptive statistics. Section IV proposes the econometric model and estimation procedure. Section V presents the empirical results. Section VI concludes with a discussion of future research directions.

II . 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. Several theoretical models have been developed to examine the effects of debt constraints in a lifecycle setting, including a three-period pure exchange overlapping generation model without commitment to debt (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 used 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 profiles of cohort debt accumulation and repayment behavior and estimates the effects of a variety of variables on credit card debt and payoff rates based on microeconomic household data.

One of the main objectives of this research is to estimate the age-debt profiles and the age-payoff rate profiles over the lifecycle. 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). Most data from public surveys fall into this latter category, and the 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).

Another objective of this research is to examine the determinants of credit card debt and payoff rates at the individual household level. Since data on payoff rates have not been available in any other public surveys, the existing studies in the literature mainly focused on credit card debt. Using the 1998 *Survey of Consumer Finances (SCF)* and the Heckman two-stage model, Kim and DeVaney (2001) estimated the factors that affect the outstanding balances among credit card revolvers, people who use their credit cards as a borrowing instrument (as opposed to transactors who simply use the cards in lieu of cash and pay their balance in full every month), and found that the factors related to the probability of borrowing from credit cards are different from the factors affecting 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 balances. The rationality of consumer behavior in the credit card market is supported by the study of Ekici (2005) using the *OES* data, which empirically tested the effects of price expectations and consumer confidence measures on credit card borrowing.

III. Data and Descriptive Statistics

The data used in this paper come from two large monthly surveys – one conducted by The Ohio State University Center for Survey Research known as the *Ohio Economic Survey* (*OES*) and one conducted by the Center for Human Resource Research at The Ohio State University 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 *SCF*, which is the most widely used publicly available data set covering credit card issues, the *OES* and the *CFM* provide more detailed information on credit card usage 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 which provide the most up-to-date data on consumer finances reflecting the newest information on the American consumer's spending habits and financial management. The closeness of the samples' characteristics ensures reliability when combining the two datasets - the *OES* (1997-2002) and the *CFM* (2005) - to obtain a time series of cross sections. The combined data span a period of nine calendar years, with individual observations being taken in 75 different months from 1997 through 2005. 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 card debt are considered in estimating the profiles. The final sample size includes 17,160 households.

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 on which interest will be charged 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. In this study, we will examine the credit card debt and payoff rates for 14 different birth cohorts. Cohort 1 includes those who were born between 1915 and 1919, cohort 2 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 the 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 "grandparent generation"; the middle age cohort in the sample, cohort 7, to be the "parent generation"; and the youngest cohort in the sample, cohort 14, to be the "child generation". Sorting the data by 14 birth cohorts and 7 survey years results in 14*7=98[1] different cohort-year cells. We calculate the sample means for each cohort-year cell and plot them in Figure 1 and Figure 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 in the year 1997, and the last point on a segment represents the year 2005. Thus each of the 14 segments in the graph follows the behavioral pattern of a particular birth cohort over time. 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.

[1] There are actually 97 cohort-year cells because the oldest cohort in the sample has only six years of observations when the age of the respondents is restricted to be between 18 and 85 years old.

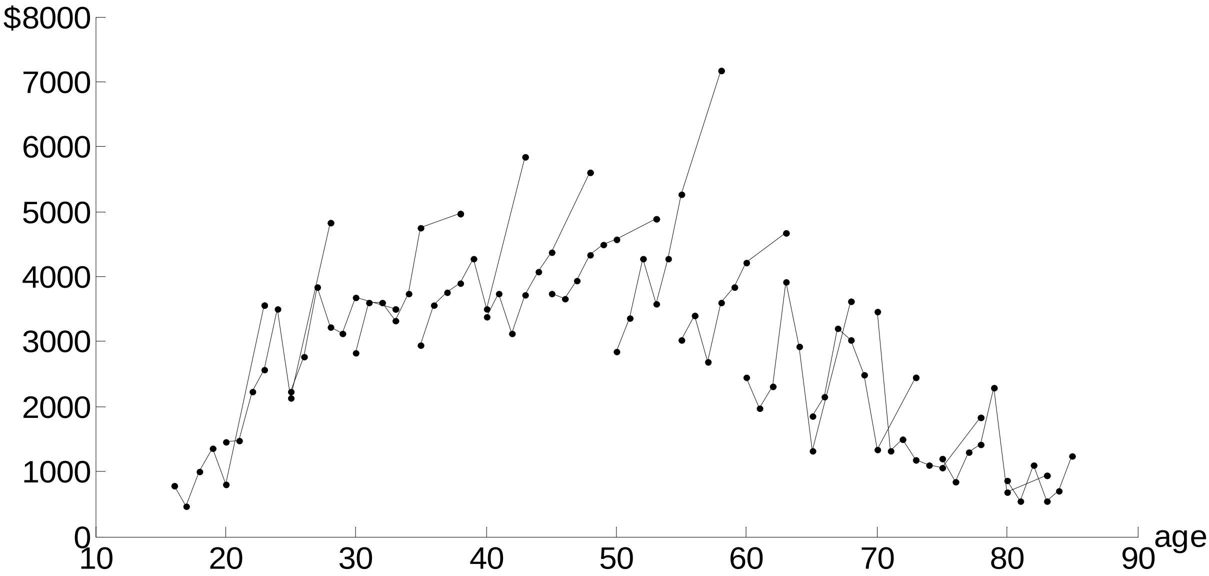

Figure 1: Plot of Cohort Mean Credit Card Debt

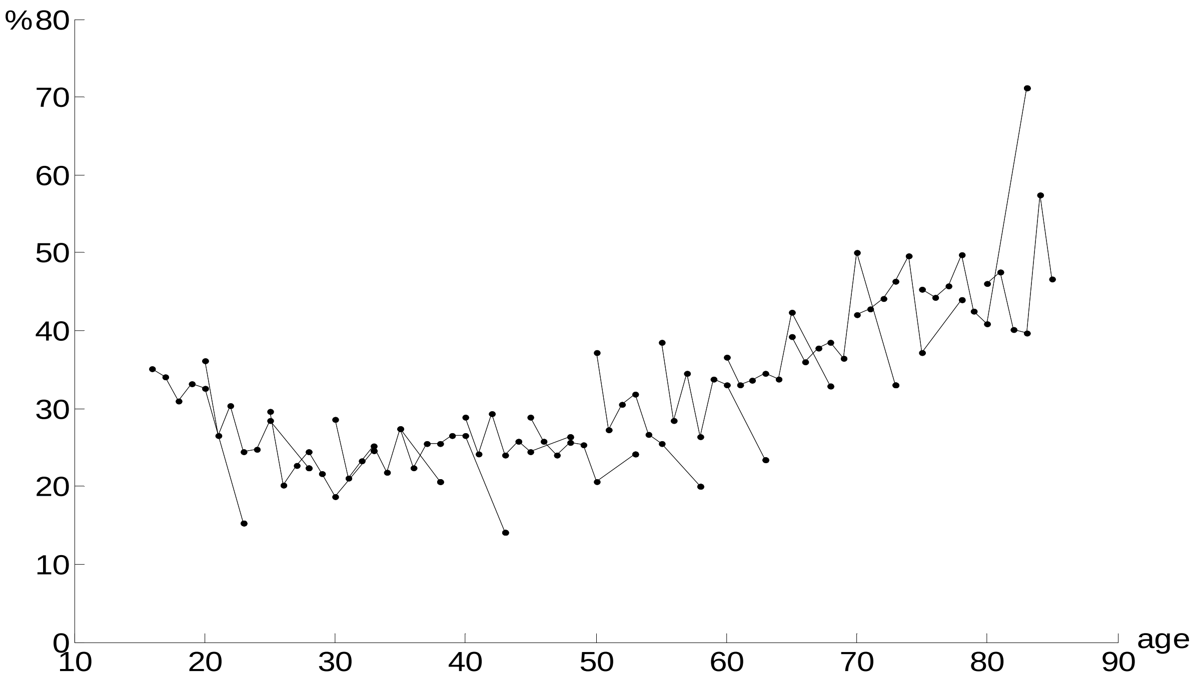

Figure 2: Plot of Cohort Mean Credit Card Payoff Rates

Figure 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 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 from 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.

IV. Econometric Model

i. Model Specification

This study focuses 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: $$D_{i,j,t} = \alpha_{1,j} + \gamma_{1,t} + x'_{i,j,t}\beta_1 + \varepsilon_{i,j,t} \tag{1}$$

Payoff Rate: $$P_{i,j,t} = \alpha_{2,j} + \gamma_{2,t} + z'_{i,j,t}\beta_2 + \eta_{i,j,t} \tag{2}$$

where $D_{i,j,t}$ and $P_{i,j,t}$ are the 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 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 will be consistent with that of the older cohort, except at a different level. For example, a current 20 year-old will have consumption habits similar to those observed from a current 30 year-old consumer when he actually reaches 30 years of age. Therefore the age-debt and age-payoff rate profiles have similar shapes for different cohorts as they pass through the same life stages. 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 analysis (Deaton and Paxson 1993, Jappelli 1999), and its theoretical basis is the simple lifecycle hypothesis.

ii. Two-Step Estimation Procedure

There are two main objectives of this study: 1) to estimate the shapes of the age-debt profiles and the age-payoff rate profiles for different birth cohorts, and 2) to evaluate the effects of a variety of variables on debt and payoff rate levels. Technically both objectives can be achieved in one step by estimating equations (1) and (2); however, it is not feasible 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. Asset data were not collected in any year of the *OES*. These variables are theoretically important in determining credit card debt and payoff and thus cannot be omitted. At the same time, the estimation of the age-debt profiles and the age-payoff rate profiles needs 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 and measurement errors into the estimation. To avoid data imputation, a two-step estimation procedure will be used in the regression to deal with the two objectives separately.

Equations (1) and (2) can be rewritten as:

Debt: $$D_{i,j,t} = \alpha_{1,j} + \gamma_{1,t} + f(a) + \tilde{x}'_{i,j,t}\,\beta_1 + \varepsilon_{i,j,t} \qquad (3)$$

Payoff Rate: $$P_{i,j,t} = \alpha_{2,j} + \gamma_{2,t} + g(a) + \tilde{z}'_{i,j,t}\,\beta_2 + \eta_{i,j,t} \qquad (4)$$

where *f*(*a*) and *g*(*a*) are functions of age, and $\tilde{x}_{i,j,t}$ and $\tilde{z}_{i,j,t}$ are vectors of explanatory variables excluding age. Other notations remain the same as in equations (1) and (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 the next section, 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: $$D_{i,j,t} = \alpha_{1,j} + \gamma_{1,t} + f(a) + \varepsilon_{i,j,t} \quad (5)$$

Payoff Rate: $$P_{i,j,t} = \alpha_{2,j} + \gamma_{2,t} + g(a) + \eta_{i,j,t} \quad (6)$$

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 effects 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 year dummies are restricted in order to solve the identification problem due to the perfect collinearity between age, cohort and year. Here we follow the normalization method proposed by Deaton and Paxson (Deaton and Paxson 1993; Deaton 1997) to assume 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: $$\sum_{t=1}^{T} \gamma_{1,t} = 0; \qquad \sum_{t=1}^{T} t\gamma_{1,t} = 0$$

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

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 estimation focuses on the effects of other explanatory variables on credit card debt and payoff rates. In this step we are not interested in estimating the changes over time, thus one cross section which contains all the variables of interest will be sufficient. We use the 2005 *CFM* in this step because, as an expansion of the *OES*, it contains more variables of interest with detailed balance sheet information on assets and liabilities. Another advantage of the 2005 *CFM* is that it reflects the most up-to-date behavioral changes of consumers in the credit card market. Since a significant fraction of the population does 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:

$$D^*_{i,j,t} = x'_{i,j,t}\beta_1 + \varepsilon_{i,j,t}, \qquad \varepsilon_{i,j,t} \sim N(0,\sigma^2_\varepsilon) \tag{7}$$

$$D_{i,j,t} = \begin{cases} D^*_{i,j,t} & if \quad D^*_{i,j,t} > 0 \\ 0 & if \quad D^*_{i,j,t} \le 0 \end{cases}$$

where $D^*_{i,j,t}$ is a latent variable that indicates the desired amount of credit card debt and $D_{i,j,t}$ is the amount of credit card debt that is actually observed from the data. Similarly, the payoff rates are right-censored at 100% because the transactors always pay off their 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 their credit cards when they already failed to pay for the existing balances. The two-sided tobit model for payoff rates then takes the form:

$$P^*_{i,j,t} = z'_{i,j,t}\beta_2 + \eta_{i,j,t}, \qquad \eta_{i,j,t} \sim N(0,\sigma^2_\eta) \tag{8}$$

$$P_{i,j,t} = \begin{cases} P^*_{i,j,t} & if \quad 0 < P^*_{i,j,t} < 100 \\ 100 & if \quad P^*_{i,j,t} \ge 100 \\ 0 & if \quad P^*_{i,j,t} \le 0 \end{cases}$$

V. Empirical Results

i. Age-Debt Profiles and Age-Payoff Rate Profiles

Parameter estimates for the debt equation (5) and the payoff equation (6) are presented in Table 1. The cross-sectional models are estimated to highlight the importance of

Table 1: Parameter Estimates for Age-Debt Profiles and Age-Payoff Rate Profiles

	Debt		***Payoff Rate***	
	Cohort-adjusted	Cross-sectional	Cohort-adjusted	Cross-sectional
Age	**122.58195	-3.97404	†-0.31885	**0.28644
Age^2	*3.98984	-1.30157	**-0.02479	0.00253
Age^3	-0.06927	-0.03568	*0.00081694	0.00031322
Age^4	**-0.00793	**-0.00382	**0.00004675	**0.00002219
Age^5	*0.00014412	*0.00010977	**-0.00000114	**-7.20998E-7
Cohort1	**-6386.03132		*21.67751	
Cohort2	**-6265.29143		**23.52013	
Cohort3	**-6133.79617		**24.43852	
Cohort4	**-5531.09963		**21.96321	
Cohort5	**-4862.00452		**19.72956	
Cohort6	**-3512.73023		**15.08735	
Cohort7	*-2341.15809		*11.38203	
Cohort8	-1313.65828		4.46229	
Cohort9	-991.75458		3.64712	
Cohort10	-624.62435		1.66620	
Cohort11	-392.99049		1.85556	
Cohort12	-290.06774		1.60819	
Cohort13	-87.97723		1.58750	
Year97	-93.71021		**3.19285	
Year98	113.51132		**-2.90805	
Year99	113.08983		-0.25669	
Year00	-35.94830		-0.44262	
Year01	108.30842		-0.45246	
Year02	†-325.64293		0.12555	
Year05	120.39186		0.74142	
Intercept	**5535.24362	**4329.02613	**21.95258	0.40550

Note: ** significant at 1% or better; * significant at 5% or better; † significant at 10% or better

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

adjusting for cohort effects in determining the shapes of age-debt profiles and age-payoff rate profiles. In the cohort-adjusted models, the youngest cohort (cohort 14) is the reference group, so it is omitted in the regression. The coefficients of the other cohort dummies are found to be jointly significant, which suggests that the average levels of credit card debt and payoff rates are different for different cohorts. The coefficients of year dummies are not jointly significant, thus time effects are trivial and can be ignored in forecasting. Under the assumptions of the Deaton-Paxson normalization, this indicates that, other than a linear trend, debt accumulation and payoff patterns are not influenced by exogenous macroeconomic fluctuations. Based on the estimated coefficients of the age polynomials, the age-debt profiles and age-payoff rate profiles are plotted in Figure 3 and Figure 4 respectively. Recall that under the assumption of the cohort-adjusted model, the shapes of the profiles for different cohorts are the same except that they have different intercepts. For illustration, only the plots for the youngest cohort are shown to represent the shapes of the cohort-adjusted profiles. The cross-sectional profiles, however, involve all cohorts in the sample.

Let us first look at the age-debt profiles in Figure 3. 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 age effects and 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

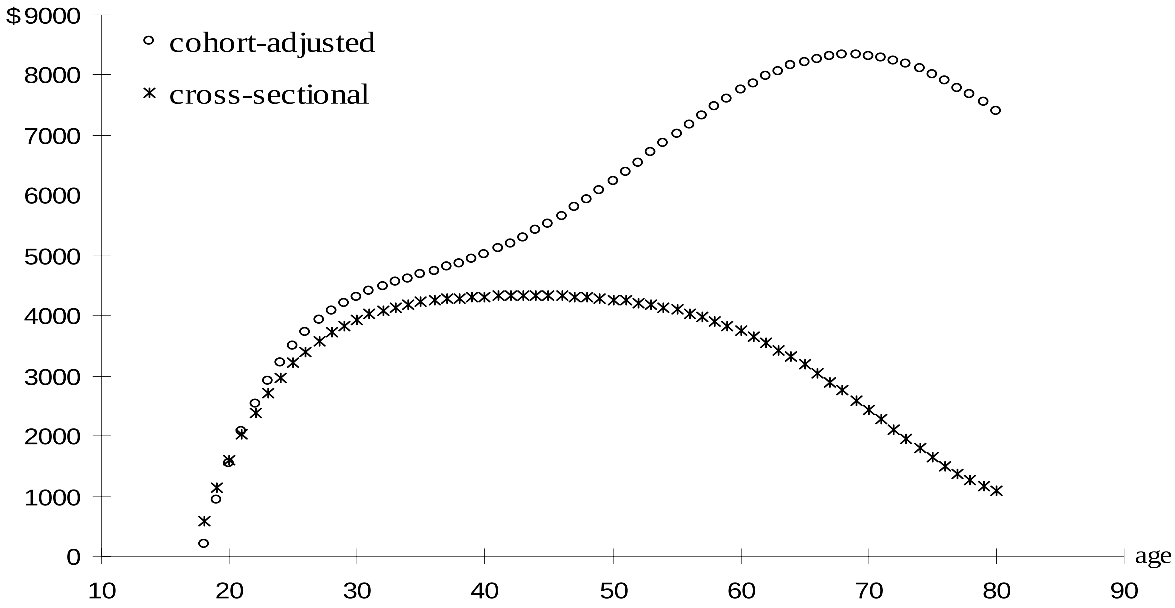

Figure 3: Age-Debt Profiles

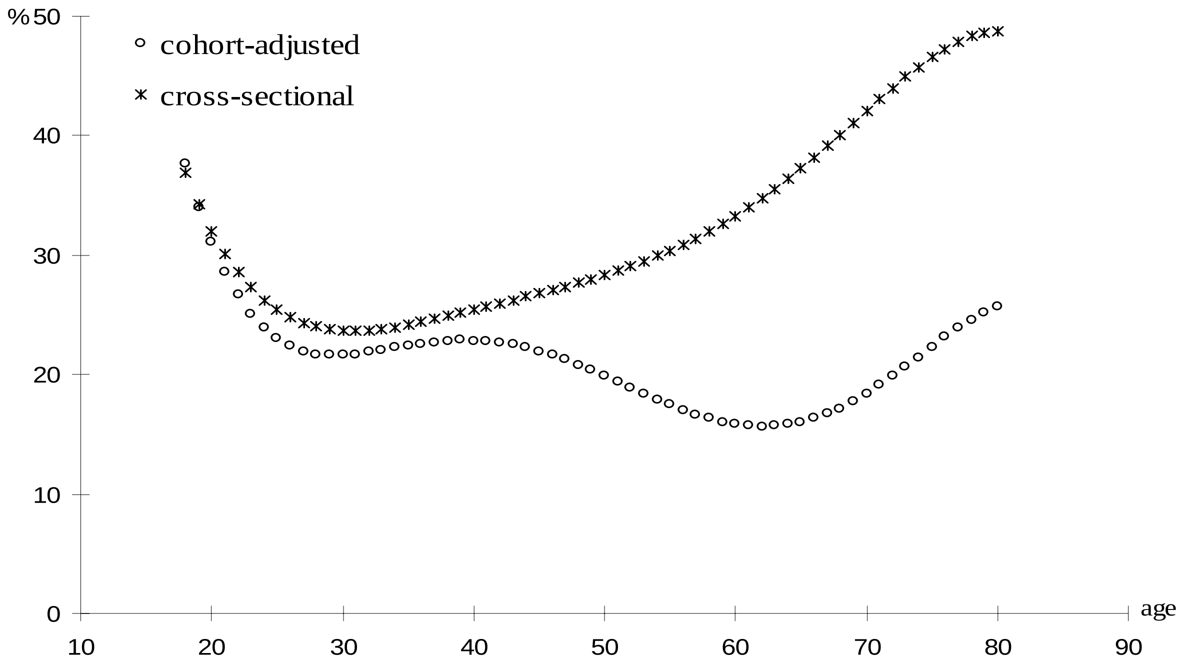

Figure 4: Age-Payoff Rate Profiles

different pattern from the cross-sectional profile: it peaks 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. This also serves as a warning for the current younger generations to manage their debt wisely in order to avoid a potential financial crisis when they grow old.

Similarly in Figure 4, the profiles of the cohort-adjusted model and the cross-sectional model show 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 minimum 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 payoff rate. The reason is that the payoff rate, as an indicator of the speed of debt accumulation, is the decision 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 a while for the changes in payoff rates to be reflected in changes in the amount of debt. Therefore it is reasonable that the minimum payoff rate in the age-payoff rate profile appears ahead of the maximum 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 above: people are borrowing from their credit cards so extensively that the low payoff rates are not enough to recover their credit card debt by the end of the lifecycle.

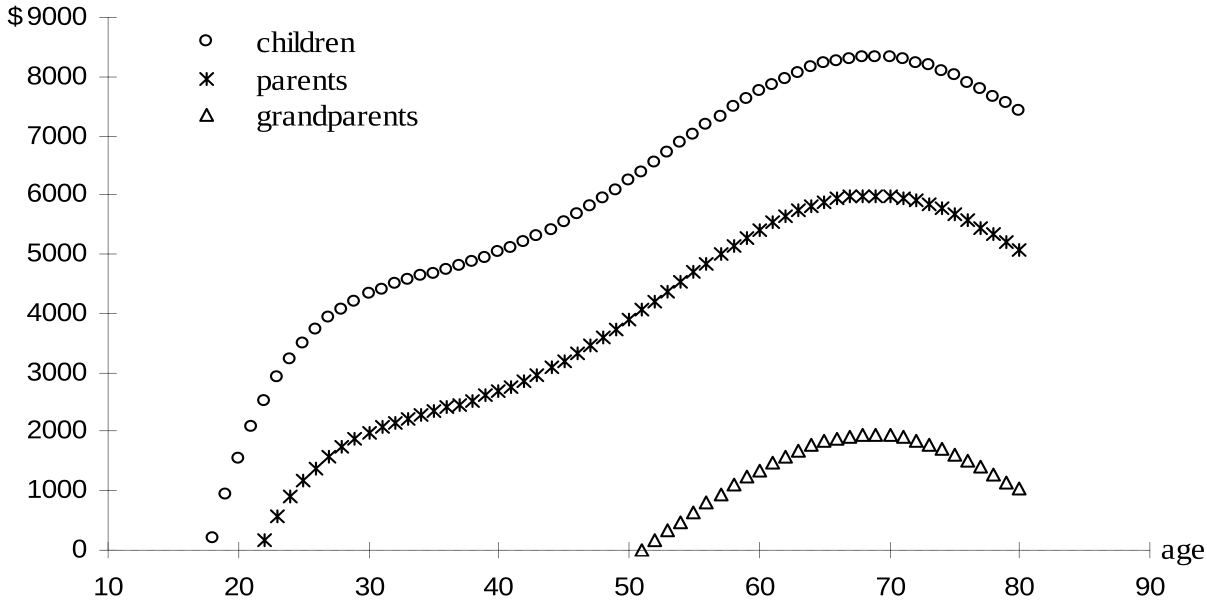

Figure 5: Age-Debt Profiles for Children, Parents, and Grandparents

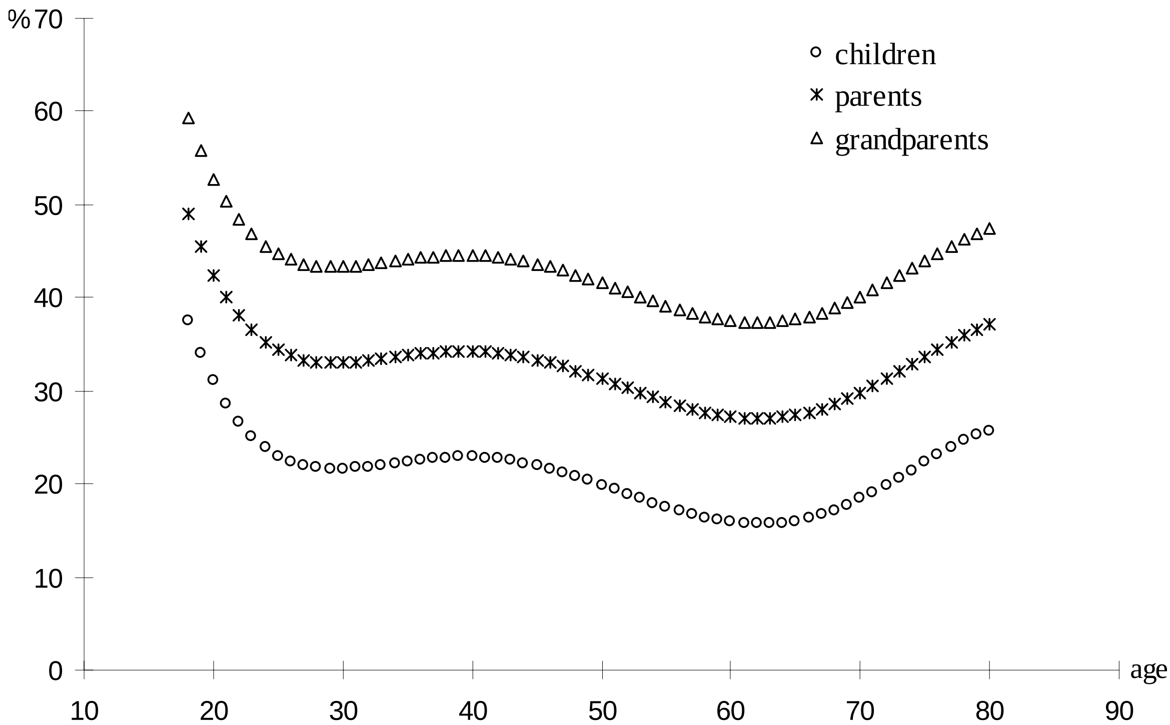

Figure 6: Age-Payoff Rate Profiles for Children, Parents, and Grandparents

The relative levels of the age-debt profiles and age-payoff rate profiles for different cohorts are determined by the coefficients of the cohort dummies. 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 debt and payoff rate profiles in Figure 5 and Figure 6 respectively. On average, the children's credit card debt is about $2,300 higher than their parents and about $6,400 higher than their grandparents. The estimated difference in payoff rates between generations is 10 percentage points: the children's payoff rate is 10 percentage points lower than their parents and 20 percentage points lower than their grandparents. Note that in Figure 5 the age-debt profiles for the parent's generation and the grandparent's 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 the financial market.

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 conclusion as pertaining to the aggregate behavior of the revolvers in each cohort, instead of a representative household. Actually it is difficult to define a representative household in the credit card market due to the complete heterogeneity of household behavior. At an individual level, the credit card borrowing and/or repaying decision frequently changes with unobservable psychological factors and is 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 volatile that it is hard to find two households which have the same shapes for their 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 section, we extend our analysis from the cohort level to the household level and estimate the effectiveness of a variety of variables in determining the credit card debt and payoff rates for a particular household.

ii. Determinants of Credit Card Debt and Payoff Rates

Listed in Table 2 are all the variables used in the tobit estimation for debt and payoff rates. The weighted sample means are computed based on all valid cases in the sample including both transactors and revolvers. Credit card debt and the payoff rate are the two dependent variables for the tobit models as presented in equations (7) and (8), respectively. Other variables are independent variables which are potentially important in determining the levels of credit card debt and payoff rates. These independent variables can be grouped into four broad categories: credit related variables (number of cards, APR, credit limit, minimum required payoff rate, and default history), balance sheet variables (income, assets, other debts, and homeownership), demographic or socioeconomic variables (age, marital status, education, and household size), and psychological factors (unemployment expectation, interest rate expectation, and price expectation). The debt and payoff equations have the same set of explanatory variables except that the minimum required payoff rate is not included in the debt equation. Minimum required payoff rates are prescribed by credit card issuing banks according to the consumer’s credit history and other relevant background information. People

Table 2. Defined Variables and Summary Statistics

Variable	*Definition of Variables*	*Mean (Median)*
Credit card debt	Amount owed on all credit cards after the most recent payments	2,482 (50)
Payoff rate	The ratio of actual payments to statement balances on all credit cards	62.47 (92.31)
Number of cards	Total number of credit cards	3.33 (3.00)
APR	Annual Percentage Rate on the credit card that has the largest balance (for revolvers) or most frequently used (for transactors)	12.66 (12.00)
Credit limit	Sum of total line of available credit from all credit cards (in thousands of dollars)	25.82 (15.30)
Minimum required payoff rate	The ratio of minimum required payments to statement balances on all credit cards	6.04 (3.33)
Default history	Dummy=1 if the respondent has missed making the minimum payment at least once in the past 6 months; Dummy=0 otherwise	13.12
Log(Income)	Log of total annual household income	10.64 (10.82)
Log(Assets)	Log of total household assets	11.92 (12.44)
Log(Debts)	Log of total household debts excluding credit card debt	7.32 (10.04)
Age	Number of years old of the respondent	50.90 (50.00)
Marital status	Dummy=1 if the respondent is married; Dummy=0 otherwise	64.60
Education level	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	3.39 (3.00)
Household size	Total number of adults and kids in the household	2.72 (2.00)
Homeownership	Dummy=1 if the respondent is a homeowner; Dummy=0 otherwise	80.94
High expected unemployment	Dummy=1 if the respondent thinks unemployment will be higher in a year; Dummy=0 otherwise	40.51
Low expected unemployment	Dummy=1 if the respondent thinks unemployment will be lower in a year; Dummy=0 otherwise	16.76
High expected interest rates	Dummy=1 if the respondent thinks interest rates for borrowing will be higher in a year; Dummy=0 otherwise	79.33
Low expected interest rates	Dummy=1 if the respondent thinks interest rates for borrowing will be lower in a year; Dummy=0 otherwise	2.88
High expected prices	Dummy=1 if the respondent thinks prices will be higher in a year; Dummy=0 otherwise	81.00
Low expected prices	Dummy=1 if the respondent thinks prices will be lower in a year; Dummy=0 otherwise	1.13

Note: Means are computed using sample weights. Means for dummy variables and (minimum required) payoff rates are expressed in percentage points.

who have lower credit scores and higher outstanding balances will be required to have higher minimum required payoff rates in order to force them to pay off their debt faster, so the level of credit card debt might contribute to changes in minimum required payoff rates instead of being determined by them. Changes in minimum required payoff rates, however, will directly influence the actual payoff rates because most consumers make at least the minimum required payments to avoid default.

Table 3: Tobit Estimates for Credit Card Debt

Variables	***Coefficient***	***Std Error***
Number of cards	*332.775728	137.653798
APR	*-141.908763	59.693486
Credit limit	**94.638219	12.825005
Default history	**3081.579383	275.506508
Log(Income)	*-663.193246	261.952502
Log(Assets)	-122.566008	201.287824
Log(Debts)	**336.908702	89.209081
Age	†236.926576	122.843719
Age^2	†-2.469491	1.281183
Marital status	193.968851	751.323809
Education level	-507.753569	326.168136
Household size	275.750273	284.508672
Homeownership	**-2707.131464	300.439221
High expected unemployment	702.749561	628.965299
Low expected unemployment	*-817.483258	364.118565
High expected interest rates	380.952165	821.821619
Low expected interest rates	67.612370	127.541834
High expected prices	†1660.079804	865.939488
Low expected prices	**-648.054772	55.952051
Intercept	**264.124362	30.632027

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

The tobit estimates for the debt equation (7) are presented in Table 3. 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 cards and 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. On average, one additional card will increase the average credit card debt by $333, and an additional $1,000 in credit limit will lead to a $95 increase in credit card debt. Using 1998 *SCF* data and the Heckman selection model, Kim and DeVaney (2001) estimated the effect of the credit limit on the amount of outstanding credit card balance to be $93, which is very close to our result. The comparative study of consumer response to changes in credit supply by Gross and Souleles (2000) also supports the 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: people tend to borrow less from credit cards when the costs are high. According to the estimated coefficient, when the APR increases by one percentage point, average credit card debt will decrease by $142. Default history indicates the risk categories of the consumers: people who have missed the required minimum payments belong to the high risk category and those who have never missed the required minimum 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 people, and the average difference between the two categories is $3,082.

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 can also borrow more because they are usually eligible to have more credit cards and higher credit limits due to their high potential to pay off the debt. Low income people, on the other hand, tend to borrow more from 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 indicates that in our data borrowing needs dominate credit access in determining the consumer's credit card borrowing behavior. 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 1277.2 and -105.7 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* from the Federal Reserve Board support this conclusion by reporting that credit card outstanding balances are notably lower among the highest and lowest income groups (Bucks, Kennickell and Moore 2006).

Total assets seem to be an insignificant determinant for credit card borrowing. Intuitively assets are supposed to be negatively related to credit card debt because households with more assets - especially liquid assets - are more likely to pay off their credit card debt and revolve lower balances. Contrary to intuition, the effect is not significant in our estimation although the sign of the estimated coefficient for assets is negative. This result is consistent with the literature on the "debt puzzle", which refers to the coexistence of high-interest credit card debt with low-interest liquid assets and the considerable accumulation of retirement assets. Hyperbolic discounting has been proposed to explain the first coexistence (Laibson, Repetto, and Tobacman 2003), and an accountant-shopper framework has been shown to be consistent with both types of coexistence (Haliassos and Reiter 2003, Bertaut and Haliassos 2006).

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 debt, and they all require a fixed amount in monthly payments. Credit cards, which only require a small percentage 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 a higher level of other debts probably also have a higher outstanding balance on their credit cards.

Homeownership shows a significant relationship with credit card borrowing: homeowners carry on average $2,707 less credit card debt than renters. Homeownership is grouped into the category of balance sheet variables because it influences 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 consumer finance survey conducted at Demos, in the past three years 40% of homeowners refinanced or got a second mortgage, among whom over 50% paid down their credit card debt with proceeds from the mortgage refinancing or HELOCs (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 (Ekici 2005, Yilmazer and DeVaney 2005, Kim and DeVaney 2001). 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 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 that the economy will be depressed in the future. Thus consumers with high unemployment expectations will carry more credit card debt than their counterparts. High inflationary expectations also lead the consumers to borrow more on their credit cards because future depreciation makes the present money more valuable. Using data from the *OES*, Ekici tested the rationality of consumer behavior by examining the effects of price expectations and consumer confidence measures, and his results are very similar to our findings above. Among the three psychological variables in the regression, the expected interest rate for borrowing does not significantly affect consumer behavior. This result resonates with the empirical study of Min & Kim (2003), who found that credit card interest rates are important in determining the consumer's decision to borrow, but not the amount actually borrowed.

Table 4 shows the tobit estimates for the payoff equation (8). Comparing it with Table 3, most of the significant determinants for debt - including the number of cards, APR, default history, income, homeownership, and expectations for unemployment and prices - are also shown to be significant in determining payoff rates, except with opposite signs. For example, the APR affects payoff rates positively: one additional percentage point increase in APR will increase the average payoff rate by 1.5 percentage point. One exception is the credit limit, which shows no significant effects in determining payoff rates. The 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 more credit card debt. The payoff rate, however, is not affected by the credit limit, probably due to the fact that the credit limit places no restrictions

Table 4: Tobit Estimates for Credit Card Payoff Rates

Variables	*Coefficient*	*Std Error*
Number of cards	†-1.539649	0.917863
APR	**1.512622	0.423970
Credit limit	-0.035850	0.084649
Minimum required payoff rate	**1.634471	0.341925
Default history	**-25.006691	7.345249
Log(Income)	**7.626406	2.305359
Log(Assets)	0.057090	1.497713
Log(Debts)	-0.950765	0.639023
Age	*-2.715446	1.115038
Age^2	**0.029385	0.010998
Marital status	8.253232	6.064372
Education level	*5.496341	2.316883
Household size	**-5.716186	2.067388
Homeownership	**22.852246	7.959696
High expected unemployment	†-10.566009	5.460693
Low expected unemployment	-4.864519	7.340871
High expected interest rates	-6.379358	6.845753
Low expected interest rates	-22.486689	15.247302
High expected prices	**-21.260728	6.516340
Low expected prices	-31.537207	22.691606
Intercept	23.203445	35.791787

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

on the amount of payment. The only restriction on payments is the minimum required payment, which establishes a lower standard for the consumer's repayment behavior without falling into delinquency. Since 2005, the Office of the Comptroller of the Currency and the Board of Governors of the Federal Reserve System have been discussing procedures to regulate credit card banks and assist consumers with their debt management. One possible policy change that has received a lot of attention is to double the minimum required payments on statement balances from the current level of 2% to 4%. Will this policy be effective in helping the consumers to pay off their debt faster? Our results provide optimistic empirical estimates: one additional percentage point increase in the minimum required payoff rate will on average increase the actual payoff rate by 1.6 percentage points. Therefore increasing the minimum required payoff rate from 2% to 4% will increase the average payoff rate by 3.2 percentage points for all cardholders. This will make a substantial difference in the time that consumers have to take to pay off their credit card debt. 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 and four months to repay the balance in full. If the monthly payment increases from 2% to 5.2% in response to the doubling of the minimum required payoff rate, however, it will take only two years to pay off the debt holding other factors constant.

Unlike debt, payoff rates are also shown to differ with demographic groups and socioeconomic status. Well-educated people tend to pay off more on their credit cards, and bigger households are significantly related with lower payoff rates. Payoff rates are convex in age, which is consistent with the age-payoff rate profiles discussed before.

VI. Conclusions

This paper 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 *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 from their 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 causing 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, there will be more people who fail to pay off 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 paper 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.

In order to take effective measures, it is important for policymakers to have a better understanding of the factors that determine credit card debt and payoff rates. This research empirically tested the effects of a variety of variables, including financial, socioeconomic, demographic and psychological factors, in determining credit card debt and payoff rates. 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 - $95 more debt per $1,000 increase in credit limit - but have no significant effect on average payoff rates. Doubling the minimum required payments on statement balances from 2% to 4% will increase average payoff rates by approximately 3.2 percentage points and dramatically shorten the time required to pay off the balances in full.

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 only reflect the residual fluctuations relative to the time trend that might be caused by exogenous macroeconomic shocks or non-systematic measurement errors. Although the synthetic cohort approach can successfully separate the cohort effects from 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.

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