Essays on Credit Card Borrowing Behaviors

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Abstract of the Dissertation

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With the wide usage of credit card and the development of credit card market, new developed credit card borrowing behaviors and payment attitude present unfamiliar challenges to consumer finance researchers, card issuers, and regulators. As the leading unsecured debts, credit card debts become the focus of academic and public policy in recent years with the growth of the number of households carrying credit card debts and the increase of the level of outstanding credit card balance.

The borrowing behaviors of households vary dramatically among different generations due to different social attitudes, varying consumption-savings habits, and enduring effects of historical events, such as early education and peer effects. In addition, the borrowing behaviors of households differ in different economic environments. For example, development of credit card market, availability of card facilities, financial environments, policy, and legislations all impact borrowing behaviors of households. Thus, the differences among generations and changes of economic environments which can be

captured by Age (A), Period (P), and Cohort (C) Estimation Method have implications to estimate and forecast future credit card borrowing patterns.

Due to data limitation, most previous researches on consumer debts are on cross-sectional data. One limitation of these studies is that they overlooked the importance of cyclical influence (period effects) tied to the business cycle and social structural transformation because of population shifts (cohort effects). Applying the Age-Period-Cohort (APC) analysis and utilizing the series of Survey data (1989-2004 Survey of Consumer Finance), this study identifies the existence of Age，Period, and Cohort effects in households' credit card borrowing behavior, and how Period/Cohorts effects are taking into account to modify previous understanding of consumers' credit card borrowing behavior over life cycle. Specifically, two related questions are examined: (1) what is the credit card borrowing pattern across different age groups with and without cohort adjustments (2) what are the underlying factors accounting for consumers' revolving behaviors (propensity to borrow and magnitude of debts) on credit cards.

In order to answer the above two questions, aggregate level APC conventional models are used to identify the existence and pattern of A, P, and C effects. Age profile of credit card borrowing is studied using a two-way fixed effects model. A cross-classified two-level mixed effects model is proposed to disentangle the variance of borrowing behavior between different cohorts and periods and to investigate the determinants of credit card borrowing behaviors. The analysis result shows that younger generations are more inclined to borrow money on their credit cards and to carry more outstanding balance than other generations. Consistent with previous researches, demographic variables are not significant once A, P, and C factors are included in the model. In addition, the residual variation between Cohort variables, or Period variables are significant after controlling the individual-level explanatory variables, which provides the further evidence of the existence of Period and Cohort effects on households' credit card borrowing behavior.

As a complementary analysis to the APC analysis on credit card borrowing behavior using U.S data, a study on credit card borrowing behavior in Taiwan-one of the largest Asia emerging markets-is performed. There is a famous 'puzzle' in both Asia and U.S credit market, that is, consumers may revolve on credit cards while carrying sizable liquidity assets at the same time. In this research, those revolvers on credit card carrying sizable liquidity assets are defined as revolvers 'who do not want to pay' and those without liquidity assets are revolvers 'who cannot pay'. With the availability of a unique credit union panel data from 2008 to 2009, I perform an empirically comparison between these two groups on the underlying determinants of revolving decisions and amount, and try to differentiate those 'who do not want to pay' from 'who cannot pay'.

The findings of this study help to clarify the understanding on credit card debt accumulation pattern and the related determinants of credit card borrowing. The results are useful to researchers, policy makers, and practitioners who need to evaluate or formulate regulations in credit card market.

To my loving family

Table of Contents

List of Tables

List of Figures

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1 Introduction

Credit Card market has changed substantially over past two decades, and credit cards have become increasingly important not only as an important method of money transmission but also as a source of short term borrowing. According to US Census Bureau, there were 176 million credit card holders in 2007 who held around 1,493 million cards, and it is projected that there will be 181 million credit cards holders who hold 1,416 million cards in 2010 . Total credit card purchase volume reached 2,109 billion dollars which account for 50% of total spending volume. The 'buy now-pay later' mechanism of credit cards allows cards users to defer the payment to a future date. When card users decide to invoke the revolving option of credit cards and hold outstanding balance after most recent monthly payment, these card users are known as revolvers and the outstanding balance held by them are credit card debts which will be carried forward to next month billing cycle. Total number of revolvers and substantial credit debt amounts increased over time. According to the latest information of SCF survey provided by Federal Reserve, around half of card holders carry outstanding credit card balance after most recent payment in 2007. The size of total outstanding credit card balances is 962 billion dollars in 2007 and the average household with credit cards carried $10,385 credit card debt, a 7% increase from previous year.

Compared with other consumer debts, credit card debt is flexible, non-secured, and uncommitted, which means that there is no collateral to guarantee the repayment of credit card debt and card holders have the options to decide whether to revolve on credit cards, how much to revolve within the assigned credit limits, and when to pay off on their own convenience. Because of non-secured and uncommitted features of credit card, card debt holders are more likely to default on credit card debt than other secured debts such as home loan, car loan, and installment loan. Since no collateral can be repossessed by card issuers, there is barely any recovery from credit card debts once households default or file bankruptcy. Consequently, bank practitioners usually charge high interest rate and service fees on credit card debt, and it is more expensive to carry unsecured debt than secured debt. As reported by Chu in *USA Today* (July28, 2009), almost one in four households now pay more than 20% interest for credit card debt. Households charged late fees paid an average of four fees during a 12-month period. The high interest rates and fees can upend consumers' budgets and may fasten the speed of the accumulation of credit card debt. Considering the peculiar features of credit card and credit card debt, credit card debt accumulations do not share the same pattern with other secured loans with long history in US. Moreover, the accumulation of credit card debt has spread to impact consumers' living from age 18 to seniors approaching retirement or retired.

Credit card debts have become a focus of academic and public policy in recent years with the growth of the fraction of households carrying credit card debts and the increase of the credit card debts magnitude. For example, some researchers tried to include interest rate of credit card, credit limit or other credit card related features into the life cycle model to understand credit card borrowing behaviors, sticky interest rate in credit card market and the determinants of credit card borrowing decisions theoretically. Some researchers focused on specific card users such as students, women, elderly, low income population, baby-boomer or pre-baby boomers. Other studies focused on revolvers' borrowing decisions and the decision of whether to revolve was usually separated from the decisions on the revolving amount.

One of the main findings from previous research is that demographic characteristics, such as age, race etc., and financial status, such as Income and Net worth etc., impact households' decision of borrowing on credit card and amounts of outstanding credit card balance significantly. Due to lack of data, most previous researches on consumer debts are on cross-sectional data. One limitation is that these studies overlook the importance of cyclical influence that is tied to the business cycle and social structural transformation because of population shifts. Firstly, the borrowing behaviors of households are quite different because of different social attitudes, varying consumption-saving habits and enduring effects of historical events such as early education and peer effects among different generations. As it shows in this research from Survey of Consumer Finance (SCF) data, younger generations are more likely to borrow on credit cards than other generations. The generations approaching retirements are carrying more debts as time goes by. Secondly, development of credit card market, availability of card facilities, and change of financial environments, policy and legislations will impact household's borrowing behaviors dramatically. Thus, in order to understand the credit card borrowing behaviors, it is critical to incorporate a time dimension into the model and conduct a dynamic lifecycle study. Age-Period-Cohort (APC) analysis has been a popular tool to study time-specific phenomena which has been widely used in demographic and social science. In addition, APC analysis makes it possible to account for the effects of variance among generations and changes of economic environments on households' borrowing decisions. Specifically, Age effects represent the effect of different financial needs and available financial resources over life span on credit card borrowing, Cohort effects can represent the difference on credit card borrowing behaviors because of consumers' consumption-saving habits, socioeconomic status, while the difference in financial environment, policy change, and legislation can be captured by Period effects.

Logically, if A, P, and C effects exist and they are not included in the model, A, P, and C effects are confounded and the effects of individual explanatory variables will be biased (that is, either overestimate or underestimate). Current prevailing age-specific measurements and forecasting methods in financial industry, which are not adjusted by different debts accumulation patterns among different generations, will underestimate the probability of default and loss given default. Systematical APC analysis on credit card borrowing has special implications especially when the largest groups of US baby-boomers reach retirement after 2010. Some researchers tried to address credit behaviors in an age-cohorts perspective, and most of these researchers are either simply include cohort dummy into the model or conduct comparative analysis among different cohorts. Different from previous cohort analyses, a systematical APC analysis on credit card debt is performed in this study, using a series of Survey data (1989-2007 Survey of Consumer Finance), to investigate the existence of A, P and C effects, and how the understanding of credit card borrowing is modified by taking A, P, C effects into account .

To carry the APC analysis, the aggregate level conventional APC method is used in order to give the preliminary understanding of APC effects and to assure whether the data are sufficiently described by any a single factor, the combination of any two factors, or all three factors. Then a pseudo-panel data fixed effects method is applied to estimate and simulate the credit borrowing profile in order to investigate how the P and C factors affect the Credit Card Debt-Age profile. After that, the APC hierarchal two-level cross-classified mixed effects model is adopted to study the significance of variance across Period or Cohort groups and the underlying individual level determinants when Period and Cohort level variance allowed.

Besides the rapid growth of the magnitude of outstanding credit card balance, some interesting phenomena in credit market are observed. Hot debates are on the coexistence of credit card debt with high interest rate and sizable liquidity assets with low interest. Literally, those revolvers on credit card carrying sizable liquidity assets are revolvers 'who do not want to pay' and those without liquidity assets are revolvers 'who cannot pay'. Researchers attempted to explain this 'puzzle' by consumer behavior theory. In this research, these consumers are investigated in a different perspective. As a complementary to the APC analysis on credit card borrowing behavior using U.S data, with availability of a unique credit union panel data from the first quarter of 2008 to the fourth quarter of 2009 in Asia emerging market, an empirically comparison between these two groups ('who do not want to pay' and 'who cannot pay') on the underlying determinants of likelihood of being a revolving card user and the amount to revolve on credit card is performed. In addition, these two groups are tried to be differentiated in this study.

Summarizing the above introduction, the layout of this research is as follows. Following the introduction in Chapter One, the Age-Period-Cohort Analysis of credit card borrowing in US credit market is covered in Chapter Two, and Chapter Three investigates the determinants of credit card borrowing behavior for consumers 'who cannot pay' and 'who do not want to pay' based on the unique panel data from Taiwan.

2 Age-Period-Cohort Analysis of Credit card Debt

2.1 Introduction and literature Review

Credit cards become increasingly important not only as a payment tool but also as a source of short term financing. There are two types of card users – revolvers and convenient users. Cards users who hold outstanding card balance after most recent monthly payment are known as revolvers. The total amount of outstanding credit card balance held by revolvers is credit card debt which will be carried forward to next month billing cycle and been charged interest. The fraction of households carrying credit card debts and credit card debts magnitude increases over time. In addition, accumulation of credit card debt spread to affect consumers from age 18 to seniors approaching retirement or retired. Breitbard and Reynolds (2003) found that one-third of 18 and 19 years are credit card users, at least 70% of colleague students held one credit card (Lyons, 2004; Pinto, Mansfield and Parente, 2004), and the percentage reaches to 93% in the senior year of college (Slagel et. al 2006; Norvilitis, Santa Maria, 2002). Severe accumulation of credit card debt among young generations may result in school dropping out, starting off careers with high debts and poor credit ratings (Slagel et. al 2006; Lyons, 2004; Norvilitis and Santa Maria, 2002; Mannix, 1999). Besides college students, early adulthood are found to be heavily in debt among all the debts participations (Slagel et. al 2006; Drentea, 2000). As reported in *USA Today* (Jul28, 2009), older Americans are racking up credit card debt faster than other consumers to stretch their fixed income, to cover rising medical costs and unexpected living costs, or to even help their adult children. A study shows that amount of credit card debt held by those in later adulthood (ages 65-75) and very old age (age 75 and over) rose 89% from 1992 to 2001(Slagel et. al 2006; Hwang, 2004). Chu (2009) shows that low-income and middle-income consumers who are 65 and older carried $10,235 in average card debt in 2008, up 26% from 2005. Card debt for all borrowers rose 3% during the same time span, to $9,827. Consequently, accumulation of credit card debt among seniors may result in insufficient savings for retirement which lead to a lower level of economic well being during retirement. With increased life expectancy and rising medical costs, it becomes the major concern for policy makers as well as households.

Credit card borrowing patterns or trends and determinants of credit card borrowing behaviors are two main research focuses. One of the main finding from previous research is that demographic characteristics, such as Age etc., and financial status, such as Income and Net worth etc., affect the likelihood of being a credit card borrower and amounts of outstanding credit card balance to carry significantly. Due to lack of data, most previous research on consumer debts is on cross-sectional data. One limitation is that it overlooked the importance of cyclical influence tied to the business cycle and social structural transformation because of population shifts. Firstly, the borrowing behaviors of households can be quite different because of different social attitudes, varying Consumption-savings habits and enduring effects of historical events such as early education and peer effects among different generations. As it shows in this research from SCF survey data, younger generations are more likely to borrow on credit cards than other generations. And generations approaching retirements are carrying more debts over time. Secondly, development of credit card market, availability of card facilities, and change of financial environments, policy and legislations will also affect household's borrowing behaviors dramatically. Hence, to understand the credit card borrowing behaviors, it is also necessary to incorporate a time dimension into the model and conduct a dynamic lifecycle study. Age-Period-Cohort (APC) analysis has been a popular tool to study time-specific phenomena which has been widely used in demographic and social science. And APC analysis makes it possible to account for the variance among generations and changes of economic environments. Specifically, Age effects represent the difference because of financial needs and available financial resources over life span and Cohort effects represent the difference of consumers' Consumption-saving habits, socioeconomic status, while the difference in financial environment, policy change, and legislation can be captured by Period effects.

In this analysis, I will conduct a systematical APC analysis on credit card borrowing behaviors to investigate whether the A, P, and C effects on credit card borrowing behaviors exists, and how previous understanding of credit card borrowing behaviors are modified by taking A, P, C effects into account.

To carry the APC analysis, firstly, aggregate level conventional APC method is applied to give the preliminary understanding of APC effects, and to ascertain whether the data are sufficiently described by any one of the single factors, combinations of any two factors or all three factors. Secondly, pseudo-panel data fixed effects method is adopted to estimate and simulate the credit borrowing-age profile to investigate how the P and C factors impact the Credit Card Debt-Age profile. Thirdly, APC hierarchal two-level cross-classified mixed effects model is implemented to study the significance of variance on credit card borrowing behaviors across Period, or Cohort groups and to identify the underlying individual determinants when Period and Cohort level variance allowed.

2.1.1 Age-Period-Cohort Analysis

Age-Period-Cohort (APC) analysis has been a popular tool to study time-specific phenomena in sociology, demography and epidemiology in the past 80 years or so (Yang, 2006, 2008). Generally speaking, APC analysis is a method using Age (A), Period (P) and Cohort (C) membership as explanatory variables to study phenomena of interest (Yang, 2006; Feinberg and Mason 1985). Broadly defined, Age (A) effects represent the difference between specific age groups brought about by accumulation of social experience, physiological, and/or role, status changes. Period (P) effects are the social, cultural or physical environment variance over time that affects all age groups simultaneously. And Cohort (C) effects account for the variances across groups of individuals who share the same initial event such as birth in the same year, whose explanatory power comes from social structural change via replacement of new birth cohort and could be as important in determining behavior as socioeconomic status (Yang 2008; Ryder 1965).

One goal of APC is to identify whether the phenomenon of interest is affected by the combinations of Age, Period and Cohorts and how to estimate distinct contributions of age, period and cohort effects. The multiple classification method, which are referred as conventional APC method are on aggregate population level data which is in a form of rectangular age by period tables of outcome variables/event rates of interest, has been so far the most popular and flexible method to estimate the fixed effects of age, period and cohort with cohorts serving as a special interaction between age and period. Because of dependency relationship among Age (A), Period (P) and Cohort (C) which is incurred from the fact that Cohort Membership can be defined by age and period at which the individual can first enter a data array, APC analysis suffers from the identification problems, consequently, it will cause trouble in statistically estimating and delineating the Age, Period and Cohort effects in practice.

Methodologies being proposed recently to disentangle the identification problem includes proxy variables approach, sequential strategies (Schaie, 1965), bifactorial method(Baltes, 1968), visual inspection (Glenn, 1977), constrained multiple regression method (Mason et al., 1973), triad method (Palmore, 1978), as well as nonlinear parametric transformation method (Glenn 1976, 1977; Fienberg and Mason 1978,1985; Firebaugh 1989; Hobcraft, Menken, and Preston 1982; Wilmoth 1990; O’Brien 2000). Among these strategies, APC multiple classification /accounting model specified by Mason (1973) was most wildly used for estimating age, period and cohort effects in demographic and social research. They proved that the APC will be estimable if at least two age groups, period groups or cohort groups are assumed to have identical effect coefficients. However, the limitation is that researchers need to reply on prior or external information to find constrained groups that hardly exists and cannot be verified. And the patterns of coefficients of age, period and cohort may be different if different constraints are set.

Despite of these limitations, constrained methods can still provide graphical and qualitative understanding of age, period and cohort patterns and variance. It can also provide preliminary knowledge on whether the phenomena under study are sufficiently described by any one, or any combination of two, or all three of these time dimension factors.

APC analysis confronted new challenges and opportunities with the availability of micro data in the form of repeated cross-sectional survey and development of new statistical estimation method, Yang, Land and Schulhofer-Wohl (2008) believed that developments in statistics (e.g., mixed (fixed and random) effects models, MCMC estimation of Bayesian models) lead to better methods for APC analysis that can be applied by ordinary social scientists, which, in turn, lead to the accumulation of more reliable knowledge about age, period, and cohort dynamics. They proposed a new multilevel estimation method to take advantage of the multilevel structure presented in repeated cross-section survey. The repeated cross-sectional data might be aggregated to population level for conventional APC analysis. It can also provide individual level data on the response and other individual-level characteristics that might be related to the response. As an illustration, Yang and Land (2006, 2008) introduced two-level cross-classified mixed model to represent variations in individual level responses by periods (survey years) and cohorts to study verbal acuity on General Social Survey. With the access to individual level survey data, one can group the age, period and/or cohort properties of respondents into time intervals of different lengths. By doing this, it will break the identification problem existing in conventional APC model.

2.1.2 Credit Card Debt

Although development of credit cards has a relatively short history, concerns have been put on the social and financial influence of credit cards usage, especially the usage as a short term revolving tool. To the best knowledge I have, there are very few research on credit cards incorporating Period and Cohort effects into consideration. However, findings from previous studies will be used as reliable 'prior' information in this APC analysis of credit card debts.

One of the earliest hot debates on credit card is on sticky interest rates in credit card market. Some researchers argued that the irrationality of households, failure of competition in credit card market and high search/switching cost account for the high and sticky interest rates (Ausubel, 1991; Mester, 1994; Stavins, 1996; Park 1997; Dunn, et. al 2006; Brito and Hartley, 1995; Calem and Mester, 1995; Crook, 2002; Kim, Dunn, and Mumy, 2005; Kerr and Dunn, 2007). While others argue that rational households may hold credit card debts with high interest rate for liquidity, and the high cost to get other consumer debts may also account for the sticky interest (Brito, Hartley 1995; Telyukova, Wright 2005; Zinman 2007b). From card issuers' perspective of view, in the presence of search or switching cost, issuers would find that lowering interest rate does not necessarily attract customers carrying balance but with good credit risk, and this could contribute to the stickiness of interest rate (Bertaut, Haliassos 2005). Some research are on elasticity of credit card debt to the interest rate (Gross and Souleles, 2002b; Shen and Giles, 2006).

Some existing empirical analysis suggests that there is a link between general household debts and household consumption. However, basic theoretical models (e.g., the life-cycle model and permanent income hypothesis) show that contemporaneous variables such as consumer debts should not affect consumption growth. Some researchers have focused on the relationship between debt growth and sustained consumption or consumption growth (Carroll, Dunn 1997; McCarthy 1997; Ludvigson 1999; Maki 2000;Dunn et. al. 2006; Murphy 2000; Olney 1999; Zhang, Bessler, Leatham 2006).

Another strain of the literature is on credit card debt holders. Main focus is on households' borrowing decision – decision to revolve on credit card and the amount they revolve, which is also one of the main focuses of this research. Another focus is on the impact of credit card debt on households' decision, such as default and bankruptcy decisions (Laderman, 1996; Ausubel, 1997; Dunn and Kim, 1999; Domowitz and Sartain, 1999; Stavins, 2000; Gross and Souleles, 2002a; Fay, Hurst, and White, 2002; Lehnert and Maki 2002; Agarwal, Lui, and Mielnicki, 2003). In these studies, the impact of age, marital status, education, income, race, assets, net worth, homeownership, interest rate on credit card and attitude toward credit card usage etc. are studied, and the results are the starting point of this research. Bird et al. (1999) show that there is a strong increase in the use of credit cards across income groups. Poor households are likely to acquire new cards in good economics period and use it to pay off debt accumulated in bad time. Kim and DeVaney (2001) estimated the factors that affect the outstanding balances among credit card revolvers, and found that the determinants of the likelihood of borrowing and determinants of amounts of credit card borrowing are different. Education and income were positively related to the credit cards debts, while they were negatively related to the probability of carrying credit card debts. Min and Kin (2003) found that the propensity to borrow on credit card and level of credit card debts differs across demographic groups. The preference/attitude toward credit card is positively related to borrowing likelihood and debts level. Researchers also pointed out that credit card balance do not stem primarily from liquidity problems but are a result of a person's behavior (Rutherford and DeVaney 2009; Gross and Souless, 2003). Yilmazer and DeVaney (2005) examined the lifecycle changes in probability of holding and amount of different types of household debt, which includes revolving credit card balances. They found that both Age and Non-financial assets have a negative effect on the ratio of credit card debts compared to the total assets. The marginal effect of financial assets on the ratio of credit card debts to the total assets is significant and negative. Some studies have specifically addressed credit card borrowing behaviors by age groups, for example, on retire or approaching retire population (McGhee, Draut 2004), baby boomers and 'pre-boomers' (Fink, Huston, Sharp 2005).

Some researchers have specifically tried to address credit borrowing behaviors in an age-cohorts perspective. Using Survey of Consumer Finances (1989 through 2001 surveys), McGhee and Draut (2004) investigate credit card debt among seniors (households 65 and over) and "transitioners" (households 55 to 64). They reinforce the importance of income, assets, and gender on the levels of credit card debt held by senior households over time, and noted that transitioners held higher levels of debt than seniors for all years studied.

Using the same series of survey data, Finke, Huston, and Sharpe (2005) provided a descriptive analysis of the balance sheets of the baby boom cohort compared with the “pre-boomers”, they also present some evidence that economic conditions may be as much a factor as age in relation to credit card use. Using 1992 and 2001 Survey of consumer finance, Reynolds, Hogarth and Taylor conduct a comparative study to explore changes over time in consumer credit behaviors with respect to having a credit card and carrying a balance, as well as the amount of the balances carried over by various cohorts, especially those in the pre-retirement and newly-retired age groups.

Several theoretical models have been developed to examine the effects of debt constraints in a lifecycle setting, which includes a three-period pure exchange overlapping generation model (Lambertini 1998, Azariadis Lambertini 2003), a time-varying liquidity constraint model (Ludvigson 1999), and a lifecycle model with payroll taxes and endogenous debt constraints (Andolfatto Gervais 2001). There are other theoretical models are based on Theory of planed Behavior (TpB) (Rutherford and DeVaney, 2009; Ajzen 1988, 1991) , According to TpB, credit card borrowing behaviors can be indirectly predicted by behavioral beliefs, normative beliefs and control beliefs which are influenced by a variety of socio-economic and demographic factors and can be estimated by econometric models. Some other literatures are using self-control theory to explain credit card usage since credit cards separate purchase and payments, which means that benefits of consumption using credit comes earlier than costs (Shefrin, Thaler 1988; Prelec, Simester 2001; Hoch, Loewenstein 1991)

2.2 Data

Data used for this research are 1989 to 2007 Survey of Consumer Finances (SCF) from the Federal Reserve Board. The SCF is a triennial survey of US families' financial portfolios sponsored by the Federal Reserve Board of Governors with the cooperation of the Statistics of Income Division of the Internal Avenue Service (Kennickell, McManus, and Woodburn, 1996). It is considered to be the best source for complete and detailed information on US families' balance sheets, usage of financial services, other socioeconomic status and demographic characteristics.

Table 2.1 lists the key financial and demographic variables from SCF which are considered as the most possible explanatory variables from previous research.

Credit Card Debts are defined as the total outstanding balance owned on all credit cards after most recent payments which will be carried forward to next billing cycle and charged for interest.

Have Credit Card Debts or Not is the binary outcome of the borrowing decision on credit card. It will be coded as 1 when credit card debts are positive, otherwise, 0.

Default History reports whether households had any debt payments more than 60 days past due in last year.

Net Worth is equal to total assets of households minus total debts of the households. Net worth refers to the net financial resource that a household possess and the amount of net worth can be a very important indicator of consumption level of the family (Bryant 1990).

Credit Limit is the total limits held by the households, and it determines the highest level of credit card debt that households could carry. Previous studies have shown that there is a positive relationship between Credit Limit and credit card debts (Lee, Hogarth, 1998).

Debts will be the total household debts excluding outstanding credit card balance. *Total secured debts* will be total household debts secured by collaterals. Total amounts of other debts or other secured debts represent the ability of access to other credit resources and the level of indebtedness or burden of repayment, so it should affect households' decision on credit card use.

Net worth, Income, Liquid Assets, Other Assets and households Debts after excluding credit card debts are considered as the measurement of economic resources, and *Education* have been considered as the human resources. According to human capital theory (Becker, 1975) and household production theory (Bryant, 1990), education can be the proxy of future resource and current human resources, education level of households have significant impact on their economic resources. There exist a significant relationship between education and the households' propensity to borrow on credit card and the amount to carry (Kim, DeVaney 2001). Hazembuller et al. (2007) stressed the importance of education on controlling over credit card balance.

Table 2.1: Variables Definition and Measurements for SCF Data

Measurements of Variables	
Variable	**Definitions of Variables**
Dependent Variables	
HAVE CREDIT CARD DEBT OR NOT	1 if there is positive outstanding balance after the most recent payments
	0 othervise
CREDIT CARD DEBT	Total value of credit card balances held by household after most recent payment
	Balance does not include new charges since last account statement
Independent Variables	
AGE	Age of head of household
EDUC	Total number of years of education that have been completed by head of household
MARRIED	Marital Status of head of household, 1 if married or living with a partner
	0 otherwise
LIFE_CYCLE	1 if age is less than 55, not married and no kids
	2 if age is less than 55, married and no kids
	3 if age is less than 55, married and have kids
	4 if age is less than 55, not married and have kids
	5 if age is greater than 54, currently not work but expect to return to work
	6 if age is greater than 54, currently not work and do not plan to go to work
RACE	1 if white and non-hispannic, 0 otherwise
OCCUPATION CATEGORIES	Occupation categories for head of household, 1 if work for someone else, 2 if self-employment
	/partnership, 3 if retired/disabled + (student/homemaker/misc. not working and age 65 or older)
	4 if other groups not working (mainly those under 65 and out of the labor force)
DEBT PAYMENT	
had any payments more than 60 days past due	1 if yes, 0 if otherwise
No history of payments more than 60 days past due	1 if yes, 0 if otherwise
EXPECTATION FOR FUTURE	
BETTER	1 if yes, 0 if otherwise
WORSE	1 if yes, 0 if otherwise
THE SAME	1 if yes, 0 if otherwise
EXPECTED INTEREST RATE	
HIGH	1 if yes, 0 if otherwise
LOWER	1 if yes, 0 if otherwise
THE SAME	1 if yes, 0 if otherwise
HOME OWNERSHIP	1 if owns a home, 0 otherwise
KIDS	Total number of kids in the household
ASSET	Total value of assets held by household
	It is the sum of both financial and nonfinancial assets
INCOME	Total amount of income of household
Non FINANCIAL ASSETS	Total value of non financial assets held by households
FINANCIAL ASSET	Total value of financial assets held by household
Total Other DEBT	Total value of debt held by household exclude Credit Card Debts
NETWORTH	Difference of Total Assets and Total debts
EDN_INST	Total value of education loans held by household
INSTALLMENT LOAN	Total value of installment loans held by household
Total Secured DEBT	Total value of mortages and home equity loans of household secured by the primary residence
RATIO OF DEBT PAYMENT TO INCOME	Ratio of monthly debt payments to monthly income
Liquidity Assets	Total value of all types of transactions accounts and CDs
CREDIT LIMIT	Sum of total line of available credit from all credit cards
CREDIT CARD INTEREST RATE	The interest rate of credit card having the largest balance

Interest Rate is measured by the interest rate of the credit card having the highest balance and it is the main cost of carrying credit card debt. It is not recorded in 1989 and 1992 SCF. Hence it is not being studied in APC analysis. Compared with other type of consumer debt, Interest rate charged on credit card debt is usually very high, and it means that the expenses of holding a credit card balance is high. Interest Rate is hypothesized negatively related to being revolver and the amount to revolve. Canner and Luckett (1992) found that credit card revolvers were more likely to be sensitive to the level of interest rates than convenience users, while interest rate is not a big concern for convenience users.

Households Characteristics includes age, race, occupation status and occupation category and marital status of the household head, number of children in the household, house ownership. These characteristic variables represent the consumption needs and the availability of financial resources of the households. Previous studies have addressed that younger and married households are more likely to borrow and borrow more than older and single headed households.

Time Horizon and other attitudinal Variables demonstrate households' attitude to borrow and time preference. Previous research argued that high credit card balance does not stem primarily from liquidity needs but are results of individual's motivation, attitude and other affective factors. For example, households may have higher probability to borrow on credit card for current consumption if they value now more than future. They can also help us to determine whether households are irrational or not.

Business cyclical influence, according to previous research, increase or decrease of credit card debt is highly affected by economic condition. For example, increases in outstanding credit card debt may indicate a strong economy, as confident consumers spend more., and increase in outstanding credit card balance may also indicate a bad economy, as more consumers find it harder to pay off their credit card bills when they experience downturn of economy tied with high level unemployment, fallen home value and tightened mortgage loan standards etc..

In order to provide reliable information that is representative the whole population, SCF employs a dual-frame sample design when choose sample respondents. It requires that data from SCF should be weighted in descriptive analysis (Kennickell et al., 1996). The SCF also uses multiple imputation techniques to deal with missing data, which create implicate data sets. Both the descriptive and regression analysis in this study are weighted and first implicate data are used.

Respondents included in this study are those with at least one credit/charge card from 1989 to 2007 SCF. In total, there are 27,172 households included in this study. Starting from 1995, there are on average around 3,500 households are selected each year. Exact number can be found in the bottom panel of Table 2.2. The variables with dollar amounts used in this sample are converted to 2007 dollars using the current version of the Consumer Price Indexes for Urban Consumers. Table 2.2 contains the weighted descriptive summary of dependent variables and all possible explanatory variables from 1989 to 2007.

The first section of Table 2.2 reports the mean incidence of credit card debt holders and amounts of outstanding credit card balance from year 1989 to year 2007. From cross section view, increasing patterns across survey years are identified for both the proportion of households holding credit card debt and average amounts of outstanding credit card balance. More than 43% card holders revolved on credit cards in 1989 and the ratio reached 47.95% in 2007. The average credit card outstanding balance among the card holders increased from $1566.9 in 1989 to $3722 in 2007.

Section 2 of Table 2.2 reports the trends of average level of financial status, as can be seen, income, assets, and other debts increased significantly from 1989 to 2007 which resulted from the economy expansion in 1990s and early 2000s. However, the average level of income, assets, and net worth reported here is clearly influenced by extreme value. To smooth out the noise, income, net worth, and assets variables are capped at 95% quartile. Credit card utilization rate decreased significantly from 88% in 1989 to 38% in 2007, and the average total credit limit increased from $9,330 in 1989 to $47,995 in 2007, given the increase of outstanding credit card balance, it indicates the credit expansion and relaxation of credit constraints. The average interest rate charged on outstanding credit card balance is around 13% and did not experience significant change from 1995 to 2007. Rate of Total Payments to Total Income, which measures the share of disposal income dedicated to the payment of mortgage and consumer debts, increased gradually from 14.6% in 1989 to 17.6% in 2007.

Table 2.2: Descriptive Statistics Summary of SCF

Variables	1989	1992	1995	1998	2001	2004	2007	Total
CC Borrowing								
HCCBAL	43.67%	45.56%	47.66%	45.89%	44.90%	46.60%	47.95%	46.15%
CCBAL	1354.5	1605.98	1981.35	2541.95	2171.6	2788.5	3721.62	2365.44
DEFAULT HISTORY	2.36%	2.73%	3.32%	3.71%	3.76%	4.35%	2.47%	3.30%
NO DEFAULT HOSTORY	97.64%	97.27%	96.68%	96.29%	96.24%	95.65%	97.53%	96.70%
Financial Assets and Other Key Factors								
CC_UTILIZATION	87.57%	73.35%	61.84%	69.02%	48.24%	47.21%	37.62%	59.06%
interest_rate	.	.	13.48%	13.61%	13.93%	10.68%	12.68%	1286.31%
TOT_LIMIT	9330.15	11230.28	16439.24	22893.67	26785.31	36472.8	47994.46	25439.66
num_cards	7	6	6	6	5	5	5	6
tot_other_debt	150652.77	138491.36	150767.05	178573.99	180116.35	239194.96	274666.21	190229.69
tot_secured_debt	105107.04	107981.56	114535.48	124739.14	129967.46	179802.39	216337.25	142098.92
tot_liq	191362.26	205925.65	186061.38	160811.13	253341.75	303471.74	323615.49	235149.07
TPAY	1739.69	1660.34	1647.39	2075.07	1840.47	1941.1	2385.92	1908.53
PIRTOTAL	14.61%	16.46%	18.30%	18.32%	15.21%	16.75%	17.60%	16.84%
INCOME	374320.52	344408.92	369322.83	462769.27	594383.62	890978.27	1149384.82	614251.49
FIN	1360295.57	1949406.98	2667438.75	3310028.41	4012986.97	4395521.79	5498847.55	3435221.2
NFIN	3470259.65	6154923.68	4698968.39	5539005.47	5839874.83	8199511.13	9485724.81	6335792.39
NETWORTH	3991942.25	5741018.88	5785156.38	6954790.34	8122493.55	10748545.1	12681854.2	7942726.67
Demographic								
AGE	51	50	50	50	50	51	52	51
white	87.39%	85.21%	86.48%	86.07%	85.24%	83.44%	83.84%	85.28%
married	76.07%	72.35%	73.13%	72.43%	72.44%	71.78%	73.53%	72.97%
EDUC	13.98	14.26	14.19	14.33	14.33	14.54	14.59	14.34
EDCL1	11.65%	8.79%	8.18%	6.95%	7.22%	5.68%	5.28%	7.47%
EDCL2	24.26%	22.33%	24.40%	22.65%	22.64%	21.91%	22.31%	22.87%
EDCL3	15.76%	16.52%	18.23%	17.32%	17.00%	15.68%	14.76%	16.50%
EDCL4	48.32%	52.36%	49.19%	53.08%	53.14%	56.74%	57.65%	53.27%
KIDS	0.93	0.85	0.81	0.83	0.86	0.85	0.84	0.85
hhouse	83.58%	78.44%	80.26%	78.65%	78.74%	81.32%	83.32%	80.51%
occupation_status1	51.80%	47.55%	51.12%	49.93%	51.56%	50.95%	50.99%	50.56%
occupation_status2	26.92%	29.87%	27.46%	29.84%	29.22%	29.95%	28.25%	28.86%
occupation_status3	19.29%	18.77%	18.09%	17.35%	16.62%	16.15%	18.06%	17.66%
occupation_status4	1.99%	3.82%	3.32%	2.89%	2.60%	2.95%	2.70%	2.92%
occupation_type1	39.36%	40.23%	36.24%	41.30%	44.93%	46.93%	47.57%	42.58%
occupation_type2	21.03%	22.59%	23.00%	20.29%	20.29%	18.68%	17.80%	20.46%
occupation_type3	18.33%	14.60%	19.34%	18.17%	15.57%	15.29%	13.87%	16.38%
occupation_type4	21.28%	22.59%	21.41%	20.24%	19.21%	19.10%	20.76%	20.58%
exp_eco_better	24.68%	43.95%	29.62%	22.95%	27.07%	49.02%	27.96%	32.45%
exp_eco_worse	26.34%	21.40%	19.26%	27.48%	33.87%	14.94%	29.54%	24.64%
exp_eco_same	48.98%	34.65%	51.12%	49.57%	39.07%	36.04%	42.49%	42.92%
exp_IR_higher	49.32%	75.87%	58.39%	62.65%	65.50%	85.20%	61.58%	66.21%
exp_IR_lower	14.85%	4.68%	8.97%	6.75%	6.17%	2.09%	7.67%	6.97%
exp_IR_same	35.84%	19.44%	32.63%	30.60%	28.34%	12.70%	30.75%	26.82%
N	2411	3117	3521	3395	3617	3629	3483	27173

Section 3 of Table 2.2 reports the demographic characteristics of households included in this analysis. Average age of the head of households included in this research is around 50, and quite stable across survey years. White population and married population decreased slightly. Average years of education increased slightly from 1989 to 2007. On average, above 80% of credit card owners own their own house and the percentage did not vary much from 1989 to 2007. Share of population expect good/bad economic and high/low interest show no monotonic trend.

2.3 Conventional Age-Period-Cohort (APC) Analysis

The common aim of fitting APC model is to assess the effects of three elements - Age, Period and Cohorts- on the phenomena of interest, which are the propensity to borrow on credit card and total amount of outstanding credit card balance in this analysis. In the early stage of APC model development, more attention is put on the study on percentages or occurrence/exposure rates of events such as births, deaths, disease incidence, crimes, and so on. Data required for such analysis is on aggregate cohort level and in the form of age-by-time period contingency tables. Advantage of using aggregate/ cohort average is that it will reduce the impact of idiosyncratic variability of individuals in certain level.

In conventional APC analysis, Descriptive and graphical analysis are usually used to provide qualitative understanding of patterns of age, period, cohort variations, or two-way age by period and age by cohort variations. In other words, aggregate level model is usually constructed to assure whether the data are sufficiently described by any a single factor, combinations of any two factors or combination of all three.

2.3.1 Conventional APC analysis – Descriptive and Graphical Analysis

In conventional APC descriptive and graphical analysis, these 7 survey data serials are aggregated into 23 3-year age groups, which coincide with the interval of survey years.

Sorting data by 23 cohorts and 7 survey years, I calculate the weighted sample mean of the proportion of credit card debt holders, level of credit card debt for each cohort-year cell and list them in Table 2.3 and Table 2.4. Table 2.3 shows the share of households carrying credit card debt, and Table 2.4 illustrates the average credit card debts (in 2007 dollar). In both of the two tables, age groups forms the row, survey years (period groups) form the column and birth cohorts are represented by the diagonals that run from upper left to lower right. Respondents from the sample who were born in the same 3-year interval share the same cohort. In order to gain more insights, I plot the share of households carrying credit card debt (Table 2.3), sample means of credit card debt amount for each cohort-year cell (Table 2.4), in both cohort view and cross-sectional view figures to capture the patterns of credit card borrowing for different cohorts. Figure 2-1 is a cross-sectional view of fractions of credit card debt holders by connecting the points in the same survey year, and each line represent one survey year.

Figure 2-2 is the cohort view of fractions of credit card holders by connecting the points sharing the same birth cohort. From left to right, the first line represents the youngest cohort in the sample who was born in the years 1988-1990, the second line represents the second youngest cohort born in the years 1985-1987, and so on up to the oldest cohort born in the years 1897-1900. Each point on a line corresponds to a different survey year. Figure 2-3 and Figure 2-4 are the corresponding cross-sectional and cohort view figures of total amount of outstanding credit card debt for Table 2.4.

As it shows in Figure 2-1, a monotonic negative relationship between the share of households carrying credit card debt and age is identified, in other words, it suggests that probability of households revolving on credit card decreases with the ages. From 1989 to 2007, the line gets flatter with year increase, which means percentage of households holding credit card debts in elderly group get higher over time. Reading diagonals from upper left to lower right of Table 2.3, we can see that younger cohorts are more likely to borrow on credit card. However, as it shows in the cohort view (Figure 2-2), most of the lines are compiled together, we cannot conclude that lines representing younger cohorts are steeper than older cohorts, further investigation required to tell the existence of cohort effects on households' propensity to borrow on credit card.

Table 2.3: Fractions of Households Carrying Credit Card Debt

				Year			
Age	**1989**	**1992**	**1995**	**1998**	**2001**	**2004**	**2007**
17 - 19	80%	65%	71%	72%	64%	62%	100%
20 - 22	53%	82%	76%	79%	80%	73%	68%
23 - 25	73%	77%	78%	83%	73%	71%	76%
26 - 28	78%	75%	74%	82%	69%	71%	72%
29 - 31	76%	68%	76%	76%	71%	72%	68%
31 - 34	69%	75%	78%	69%	70%	70%	79%
35 - 37	68%	73%	74%	61%	68%	77%	76%
38 - 40	67%	71%	73%	69%	70%	72%	69%
41 - 43	70%	62%	68%	68%	62%	74%	69%
44 - 46	59%	62%	72%	67%	62%	70%	81%
47 - 49	68%	69%	74%	68%	62%	67%	70%
50 - 52	64%	57%	61%	61%	60%	66%	64%
53 - 55	65%	49%	62%	63%	52%	60%	64%
56 - 58	63%	62%	61%	61%	59%	56%	60%
59 - 61	36%	44%	48%	42%	44%	49%	64%
62 - 64	40%	39%	52%	56%	53%	45%	57%
65 - 67	44%	46%	38%	41%	40%	46%	48%
68 - 70	31%	43%	38%	39%	41%	38%	46%
71 - 73	33%	36%	41%	31%	29%	38%	39%
74 - 76	18%	38%	24%	19%	35%	42%	36%
77 - 79	23%	30%	28%	21%	25%	46%	35%
80 - 82	18%	25%	32%	9%	17%	19%	19%
above 83	17%	27%	29%	18%	31%	0%	22%

Figure 2-1: **Fractions of Households Carrying Credit Card Debt (Cross Section View)**

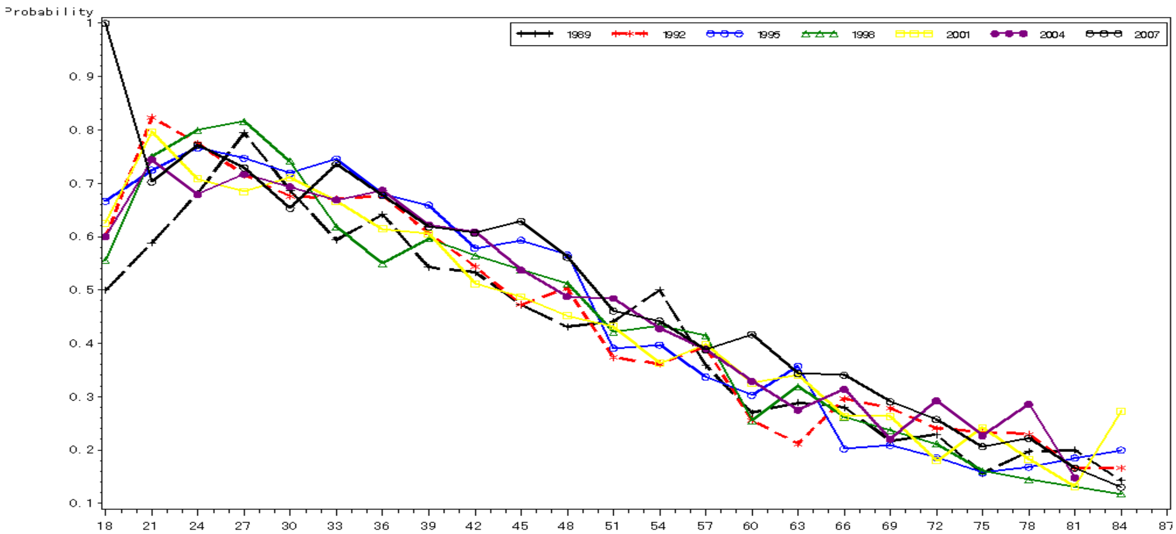


Figure 2-2: **Fractions of Households Carrying Credit Card Debt (Cohort View)**

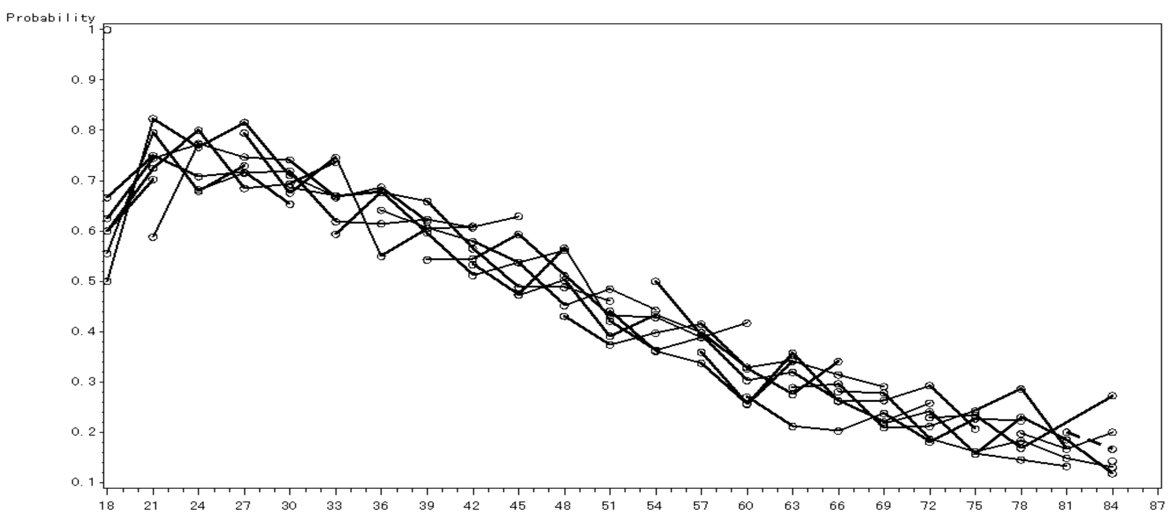


Table 2.4: Average Amount of Outstanding Credit Card Balance

	Year						
Age	**1989**	**1992**	**1995**	**1998**	**2001**	**2004**	**2007**
17 - 19	$128	$1,279	$459	$3,532	$1,154	$248	$389
20 - 22	$818	$1,213	$1,796	$1,548	$1,929	$1,365	$1,496
23 - 25	$1,645	$1,829	$2,756	$2,873	$2,647	$2,447	$2,131
26 - 28	$2,636	$2,378	$2,495	$2,905	$3,168	$2,326	$3,231
29 - 31	$2,576	$1,990	$2,305	$4,021	$3,350	$3,314	$3,949
31 - 34	$1,920	$1,993	$3,461	$3,375	$3,867	$3,817	$5,890
35 - 37	$1,934	$2,366	$3,079	$3,629	$2,990	$4,116	$4,273
38 - 40	$2,383	$2,164	$3,252	$3,786	$3,290	$4,058	$4,880
41 - 43	$2,251	$2,994	$2,809	$3,754	$2,980	$4,099	$5,964
44 - 46	$1,788	$2,515	$3,378	$3,498	$2,789	$4,671	$5,965
47 - 49	$1,720	$2,896	$3,654	$3,779	$2,773	$4,389	$5,757
50 - 52	$1,999	$2,422	$2,646	$2,827	$2,855	$3,776	$4,799
53 - 55	$1,817	$1,788	$2,063	$3,172	$2,825	$3,943	$4,976
56 - 58	$1,354	$1,312	$2,164	$3,227	$2,568	$3,783	$4,884
59 - 61	$1,351	$1,532	$2,335	$3,591	$2,678	$2,031	$5,057
62 - 64	$965	$1,375	$1,642	$3,467	$1,485	$2,715	$4,270
65 - 67	$701	$906	$1,074	$2,422	$2,003	$3,130	$3,931
68 - 70	$714	$711	$1,458	$1,527	$1,062	$1,985	$1,675
71 - 73	$385	$1,025	$502	$757	$898	$1,355	$2,081
74 - 76	$269	$589	$332	$894	$653	$2,634	$2,815
77 - 79	$92	$1,140	$430	$673	$462	$1,944	$896
80 - 82	$254	$354	$627	$329	$361	$376	$397
above 83	$30	$263	$81	$437	$100	$0	$99

Figure 2-3: Outstanding Credit Card Balance after Last Payment (Cross Section View)

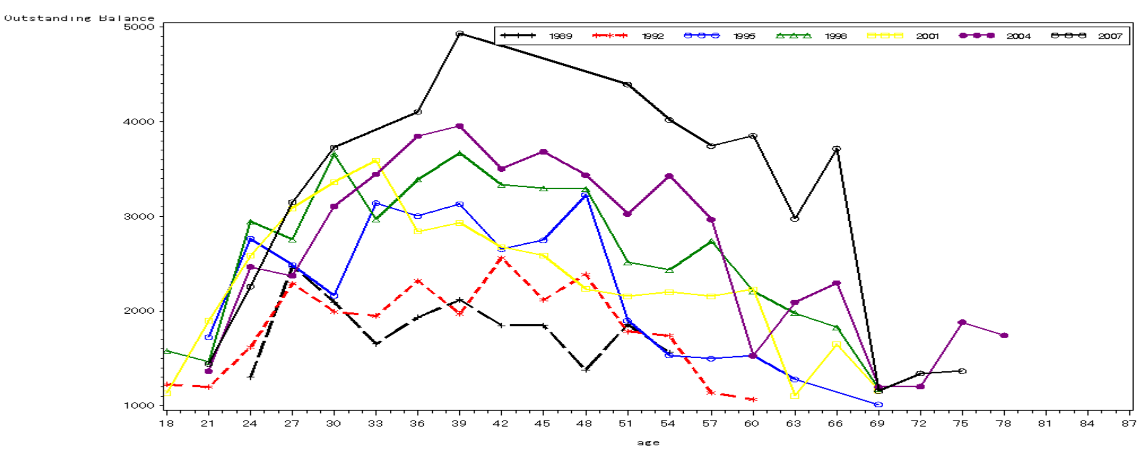
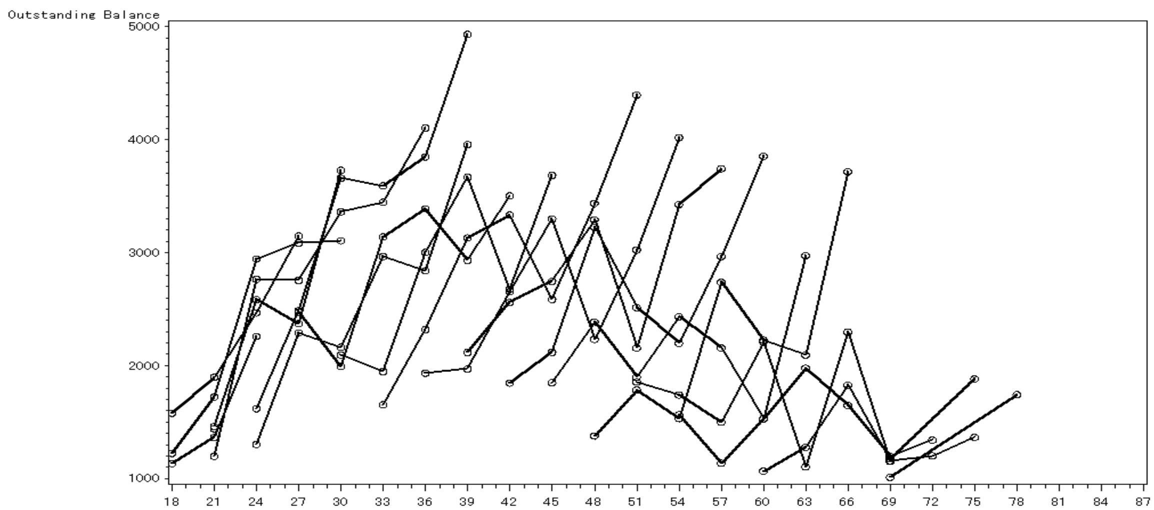


Figure 2-4: Outstanding Credit Card Balance after Last Payment (Cohort View)



As it shows in Figure 2-3, cross-sectional view of outstanding credit card debt amount exhibits a humped shape-visible life-cycle pattern, it suggests that credit card debts accumulate at younger age, peaks at middle age around 40-60 and then decrease with advancing ages. From 1989 to 2007, the graphs of latter years in most cases are above that of previous years, and peak age shit to the right, it suggests that the average amount of credit card debt held by credit card holders is increasing, and debt accumulation stage in life cycle is increasing over time. For example, line of average amount of credit card debt of year 2007 is above lines of year 2004, 2001 etc.

Figure 2-4 is the cohort view of total outstanding credit card balance. Comparing adjacent cohorts, we can see that the line of the younger cohort lies above the line of the older cohort. It suggests that on average the younger cohort carries more credit card debt than the older cohort, and there may be a cohort effects pattern on credit card borrowing behaviors of households. However, further analysis should be conducted to investigate whether cohort effects persist statistically and how Cohort element working together with Age element and Period element to influence households' decision on the amount to revolve on credit card.

2.3.2 Conventional APC Analysis-Population Level Aggregate Model

In order to differentiate the conventional aggregate level APC method to the following APC analysis on individual level data, the conventional aggregate level APC model introduced here is referred as Conventional APC. One objective of conventional APC model is to provide qualitative understanding of patterns of age, period, cohort variations, or two-way age by period and age by cohort variations, and to ascertain whether the data are sufficiently described by any a single factor or combinations of any two dimensions or if it is necessary to include all three factors.

$$PHCCBAL_{ij} = u + a_i + \varepsilon_{ij} \quad (2.1)$$

$$CCBAL_{ij} = u + a_i + \varepsilon_{ij} \quad (2.2)$$

$$PHCCBAL_{ij} = u + p_j + \varepsilon_{ij} \tag{2.3}$$

$$CCBAL_{ij} = u + p_j + \varepsilon_{ij} \tag{2.4}$$

$$PHCCBAL_{ij} = u + c_k + \varepsilon_{ij} \tag{2.5}$$

$$CCBAL_{ij} = u + c_k + \varepsilon_{ij} \tag{2.6}$$

Consistent to previous APC analysis, Equations 2.1, 2.3, and 2.5 are referred as one factor APC models on households' probability of borrowing on credit card. Equations 2.2, 2.4, and 2.6 are one factor APC model when dependent variable is amount of total credit card debt. According to APC theory, model 2.1 and 2.2 are also referred as age effects models as they contains only variable Age, model 2.3 and 2.4 are period effects models as only variable Period included, and model 2.5 and 2.6 are cohort effects models as only variable Cohort included. Equations with any possible combinations of two of these three factors are referred as two factor model, namely, AP model if only age and period are included in the model, PC model if period and cohort are included in the model, and AC model if age and cohort are included in the model.

As stated previously, if we want to test and separate A, P, and C effects on households' decision on credit card borrowing separately, all three factors have to be included into one equation. A major methodological challenge in the three factors APC analysis of is the ''identification problem'' induced by the exact linear dependency between age, period, and cohort- Period = Age + Cohort. Mason, et al. (1973) developed an approach to estimate age, cohort and period effects using multiple classification analysis. Mason et al. (1973) formally showed that one needed to constrain the three factor equation in order to estimate it. In other words, to estimate the parameters of Equation 2.7 and 2.8, any two age groups, periods, or cohorts must be constrained to have identical effect parameters. By doing this, linear dependency in conventional APC model is eliminated and the parameters of the model are estimable. The constrained method proposed by Mason et al. is considered to be the most appealing conceptually and statistically (Rentz, Reynolds, and Stout, 1983; Reynolds and Rentz, 1981). The advantage of this method is that constrained equal coefficients can be based on priori reasons, and other predictive variables can be easily incorporated into the model along with A element, P element and C element.

$$PHCCBAL_{ij} = u + a_i + p_j + c_k + \varepsilon_{ij} \tag{2.7}$$

$$CCBAL_{ij} = u + a_i + p_j + c_k + \varepsilon_{ij} \tag{2.8}$$

The assumptions and explanation of these two equations (restricted full APC) are as below:

- $PHCCBAL_{ij}$ is the percentage of credit card holders having outstanding credit card balance for the age group i at the time period j; $CCBAL_{ij}$ is the average outstanding credit card balance held by the respondents in age group i at the time period j, the averaging within cohorts has the advantage of reducing the impact of outliers and measurement error without suffering problems such as data attrition and small sample size that common with longitudinal data.
- u denotes the intercept or adjusted mean
- a_i is the i^{th} row age effect or the coefficient for the i^{th} age group

- b_j is the j^{th} column period effect or the coefficient for the j^{th} time period
- c_k is the k^{th} cohort effect or the coefficient for the k^{th} cohort for $k = 1,...,(a + p - 1)$ cohorts, with $k = a - i + j$.
- ε_{ij} denotes the random errors with expectation $E(\varepsilon_{ij}) = 0$
- Coefficients Equality constraint in APC models, Maximum separation method are used to detect constrained groups in this analysis
  - when estimating Level of outstanding credit card balance, Period 1995 and 2004, Cohort 1899 and Cohort 1902 are constrained to be equal
  - When estimating households' propensity of revolving on credit card, age group 21 and 24, cohort 1899 and cohort 1902 are constrained to be equal

Table 2.5: Goodness-of-fit of Aggregate APC Model

Dependent Variables	Goodness-of-Fit of Aggregate Age-Period-Cohort Model							
	Model	Root MSE	Model DF	Error DF	R-Square	Adj-R-Sq	AIC	BIC
Credit Card Debt Level	A	831.45	22	138	0.63681	0.57891	2186.04	2195.66
	P	1160	6	154	0.21111	0.18037	2278.93	2281.56
	C	851.84	28	132	0.63535	0.55801	2198.69	2213.33
	AC	486.24	50	110	0.90099	0.85599	2032.79	2081.65
	AP	550.13	28	132	0.84791	0.81565	2057.9	2072.54
	PC	653.88	34	126	0.79491	0.73957	2118.04	2139.33
	APC	437.29	55	105	0.92356	0.88352	2001.13	2062.3
Credit Card Borrowing Decision	A	0.05872	22	138	0.93362	0.92304	-891.687	-882.076
	P	0.21478	6	154	0.00897	-0.02964	-488.44	-485.807
	C	0.0709	28	132	0.90744	0.88781	-826.159	-811.513
	AC	0.04871	50	110	0.9636	0.94705	-932.4	-883.539
	AP	0.05583	28	132	0.94259	0.93042	-903.065	-888.419
	PC	0.05946	34	126	0.93785	0.92108	-878.272	-856.982
	APC	0.04847	55	105	0.96559	0.94757	-931.472	-870.308

Table **2.5** exhibits all the goodness-of-fit statistics which were calculated to select the best fitting model. Because likelihood ratio tests tend to favor models with a larger number of parameters, instead, two most commonly used penalized-likelihood model selection criteria are reported, namely, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), each of which adjust the impact of model dimensions on model deviances (Yang, 2006). Based on the adjusted-r-sq, AIC and BIC, full APC three-factor model performs better than two-factor or one-factor models when estimating level of credit card debt.

Figure 2-5: Age Effects

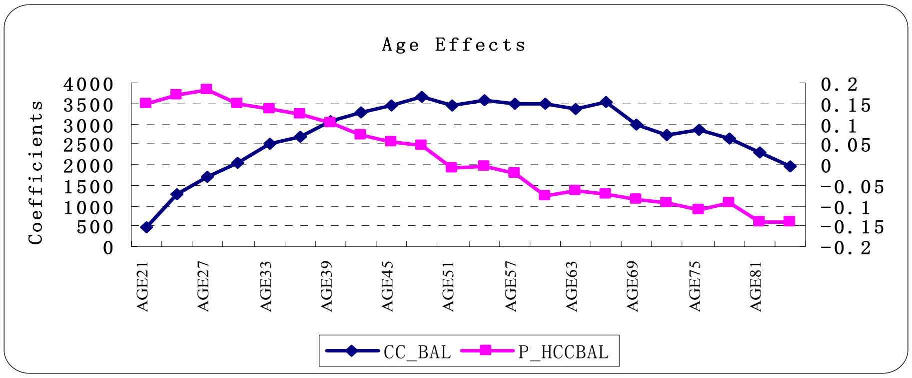


Figure 2-6: Cohort Effects:

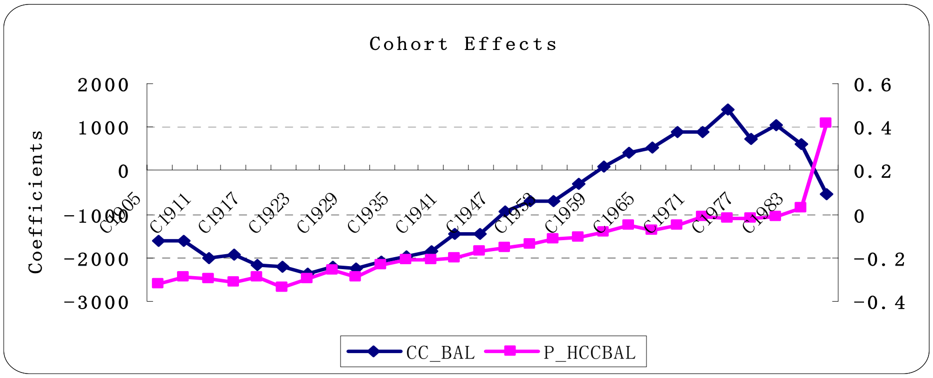
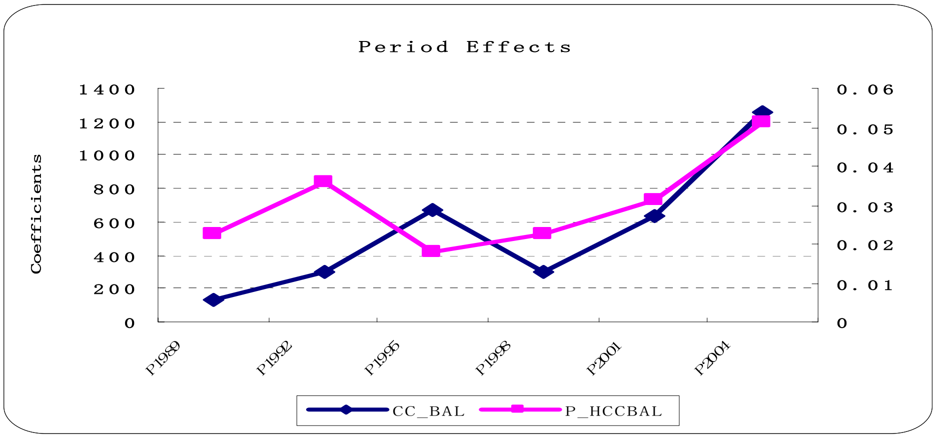


Figure 2-7: Period Effects



Regression coefficients of the restricted three factors APC model are plotted into Figure 2-5, Figure 2-6, and Figure **2-7** to demonstrate the pattern of Age, Cohort and Period effects on credit card borrowing. Figure 2-5 is the coefficient of age dummies and it shows that age effect on credit card debt level is increasing and reaching the highest value at middle age then taping off, while the age effect on households' probability to borrow on credit card is decreasing. Figure 2-6 is the coefficients of Cohort Dummies. According to Figure 2-6, with few exceptions, cohort effects on both households' probability to borrow on credit card and amount of credit card debt are decreasing, which suggests that younger cohorts are more likely to borrow on credit card and tend to hold more credit card debt than older cohorts. Figure **2-7** reports the period effects, and it demonstrates an increasing trend except the kick points in 1990s which suggests amounts of credit card borrowing is related to economic conditions.

2.4 Age-Period-Cohort (APC) Analysis for repeated cross sectional data: Age Profiles of households' credit card borrowing

Preliminary conclusions draw from conventional APC in section 2.3 are that Period and Cohort effects on credit card borrowing exist and we could fit a better model for propensity to borrow on credit card and amount of outstanding credit card balance if we incorporate Age, Period and Cohort factors into estimation. In another word, the exhibited pattern of credit card debt across lifespan is determined jointly by age, period and cohort. The purpose of this section is to show how Period and Cohort factors affect the Credit Card Debt-Age profile.

Different to previous conventional APC model which is on aggregate level of data, Individual level micro data provides us with more opportunities on APC analysis. One opportunity of using micro data for APC analysis is that analyst can group the individuals into cohorts and periods of any lengths which will break the perfect linearity among Age, Period and Cohort and hence break the identification problem of APC model. Specifically, one common technique in previous literature is to replace age dummies of aggregate level APC with single year age of household head and expand 3 year interval birth year cohort to 5 year interval birth year cohort. By doing this, the analysis is actually in individual level in contrast to previous section. The basic model set up is as Equation 2.9 and Equation 2.10. A pseudo-panel data fixed effects estimation method (Thomas, Ostrovsky 2003) is adoped to estimate the age, period, and cohort effects and simulate age profiles of credit card borrowing with and without cohort adjustment

.

$$\log(HCCBAL_{ijt} / 1 - HCCBAL_{ijt}) = u_{ijt} + g(a_i) + p_j + c_k \tag{2.9}$$

$$CCBAL_{ijt} = \beta_{ijt} + f(a_i) + P_j + C_k + \varepsilon_{ijt} \tag{2.10}$$

Instead of tracking the credit card borrowing behavior of individuals, the key idea of 'pseudo' panel is that we form various cohorts defined by birth date and then track the average credit card borrowing behaviors of the same birth cohort across survey years. To estimate Equation 2.9 and Equation 2.10, 7 years SCF Survey data are pooled together, and 18 5-year cohorts are defined. $f(a)$ and $g(a)$ are 5th order polynomials of AGE which appears to smooth out much of the noise while still being flexible enough to illustrate the shape of the underlying age profile (Attanasio 1998; Gibson, Scobie 2001). P_j is a 5-year interval birth year cohort which is conventional in demographic analysis and qualitatively meaningful to distinguish cohorts. And C_k is the 3-year interval survey year which is fixed. Other explanatory variables are not included in this model since no significant correlation between age and income, number of cards and other explanatory are identified in this data, that is, we could assume that the inclusion or exclusion of other explanatory variables won't affect the shape of age profiles of credit card borrowing, which is consistent to the assumptions and findings from previous research (Jiang, 2007; Slagel et. al. 2006).

Given the perfect linear relationship between age, cohort, and year ($a + c = p$), any trends exhibited in data can be attributed to a combination of age and cohort effect, or to year effects (Deaton, Paxson 1994). In order to derive the age profiles of credit card borrowing behavior, instead of dropping the period element from the model, the Deaton-

Paxson normalization is adopted, and it is equivalent to assume that year dummies sums to zero and orthogonal to time trend. By this assumption, time effects reflect additive macroeconomic shocks or the residual influence of non-systematic measurement error (Jappelli 1999). The youngest cohort (born after 1985) is set as the reference group.

In order to show the importance of adjusting for cohort effects on the age profile on credit card borrowing, the other pair of cross-sectional regression was estimated by including only age polynomials. Table 2.6 shows the cross-sectional and cohort adjusted regression results of Propensity to Borrow on Credit Card. Table 2.7 demonstrates the regression coefficients for the level of credit card borrowing.

As it shows in Table 2.6, Age polynomials are not significant in estimating households' propensity to borrow on credit card with and without. The youngest cohort ($cohort17$) who were born after 1985 is served as the reference cohort. After including Cohort dummies into the estimation and restricting Year dummies, T-test shows that Cohort dummies are jointly significant. Based on the coefficients of age polynomials estimated, the shape of age profile of propensity to borrow can be determined.

Table 2.6: Parameter Estimates for the Propensity to Borrow on Credit Card

	Cohort Adjusted			Cross sectional		
Individual Effects	**Coefficient**	**SE**	**Chi Square**	**Coefficient**	**SE**	**Chi Square**
Intercept	1.175	3.6925	0.1013	-1.4279	3.4021	0.1762
AGE	-0.0112	0.4274	0.0007	0.3115	0.3882	0.6437
age2	0.000619	0.0186	0.0011	-0.0132	0.0169	0.6035
age3	-0.00005	0.000389	0.0154	0.000233	0.000355	0.4303
age4	8.16E-07	3.917E-6	0.0433	-2.04E-6	3.585E-6	0.3232
age5	-4.26E-09	1.527E-8	0.0777	7.143E-9	1.399E-8	0.2608
cohort1	-0.4854	0.9334	0.2704			
cohort2	-0.5241	0.8334	0.3955			
cohort3	-0.6129	0.7794	0.6185			
cohort4	-0.6455	0.7322	0.7772			
cohort5	-0.5068	0.6879	0.5427			
cohort6	-0.4211	0.6460	0.4250			
cohort7	-0.2547	0.6045	0.1776			
cohort8	-0.2269	0.5645	0.1616			
cohort9	-0.0655	0.5273	0.0154			
cohort10	0.0345	0.4923	0.0049			
cohort11	0.0636	0.4608	0.0190			
cohort12	0.2054	0.4323	0.2258			
cohort13	0.2182	0.4059	0.2889			
cohort14	0.28	0.3846	0.5300			
cohort15	0.3194	0.3681	0.7529			
cohort16	0.1026	0.3623	0.0802			
cohort17	0	0	0			
year1	0.0518	0.0989	0.2747			
year2	0.038	0.0699	0.2960			
year3	0.0847	0.0453	3.5016			
year4	-0.0402	0.0342	1.3783			
year5	-0.1245	0.0448	7.7125			
year6	-0.0391	0.0686	0.3253			
year7	0.0293	0.0433	0.2356			

Figure 2-8: Propensity to borrow on credit card -Age Profile:

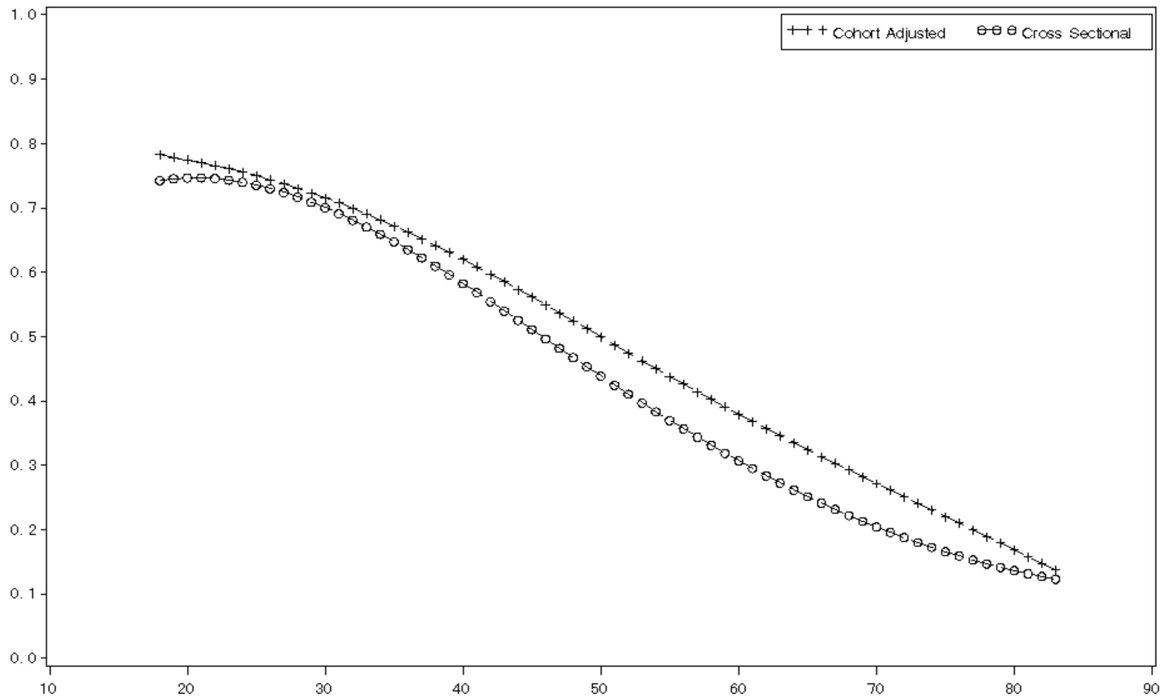


Figure 2.8 is the plot for the age profile of households' propensity to borrow on credit card simulated from both the cross-sectional model and cohort –adjusted model. In order to show a full image of the profile across all age spans from 18 to 90, only age profile for younger cohort is demonstrated. As Figure 2.8 shows, age profile of households' propensity to borrow on credit card with cohort adjusting is above the age profile without cohort adjusting, which is consistent to the findings from previous chapter, that is, younger cohorts are more likely to borrow on credit card and share of credit card debt holders is increasing across survey years. Figure 2.8 also demonstrates that households' propensity to borrow on credit card is decreasing with aging, but the rate of decreasing

slows down among younger cohort. Since cross-sectional profile confounds both the age effects (net lifecycle pattern) and cohort effects together, if we do not account for cohort effects, the estimation or forecasting of households' likelihood of revolving on credit card based on the cross-sectional profile will be biased and underestimated.

Table 2.7: Parameter Estimates for Amounts of Credit Card Debt

	Cohort Adjusted			Cross sectional		
Individual Effects	**Coefficient**	**SE**	**t Value**	**Coefficient**	**SE**	**t Value**
Intercept	-15026	16180	-0.93	**-26168	15453.00	-1.69
AGE	1801.14142	1910.19478	0.94	**3137.11596	1811.85	1.73
age2	-79.03717	85.87703	-0.92	**-134.65311	81.25	-1.66
age3	1.76074	1.84882	0.95	**2.96027	1.75	1.69
age4	-0.01858	0.01915	-0.97	**-0.03172	0.02	-1.76
age5	0.00007285	0.00007652	0.95	**0.00012911	0.00	1.79
cohort1	532.92417	2094.02736	0.25			
cohort2	46.08118	1862.52325	0.02			
cohort3	-441.60117	1723.64687	-0.26			
cohort4	377.20279	1578.66842	0.24			
cohort5	316.74172	1460.62541	0.22			
cohort6	652.74767	1330.23164	0.49			
cohort7	1506.66295	1199.90253	1.26			
cohort8	*1770.02358	1078.37435	1.64			
cohort9	**1873.68485	968.13829	1.94			
cohort10	***2332.95117	865.60045	2.7			
cohort11	***2236.88305	769.1809	2.91			
cohort12	***2324.97857	681.63045	3.41			
cohort13	***1975.68605	622.43183	3.17			
cohort14	***1426.42429	604.65819	2.36			
cohort15	0	0	0			
year1	-1591.37396	311.06902	-5.12			
year2	-1236.97431	241.2063	-5.13			
year3	-758.86135	185.29791	-4.1			
year4	481.37092	169.68212	2.84			
year5	-233.12436	184.61074	-1.26			
year6	794.83284	230.93409	3.44			
year7	***2544.13022	294.28415	8.65			

Note: *** Significant at 1% or better ** Significant at 5% or better * Significant at 10%

Table 2.7 reports the regression results on amounts of credit card debt, as illustrated in Equation 2.10, which is estimated on the population of revolvers. As it shows in Table 2.7, Age polynomial is significant in cross-sectional regression. In order to keep roughly same size cohort and eliminate the impacts of outliers, the younger cohort 1975-1979, 1980-1984 and later than 1985 are combined as the youngest cohort and is set as a reference group. After cohort dummies are included in the estimation, age polynomial is no longer significant, while cohort dummies are jointly significant. Coefficients of cohort dummies represent the average magnitude deviate from Cohort 15, and it shows an overall increasing trend from older cohort to younger cohort, the magnitude of the coefficients of Cohort dummies also determines the relative position of the age profiles of level of credit card debt for different cohorts. Based on the estimated coefficients from the two regressions, simulated age profiles of level of credit card borrowing with cohort adjusting and without cohort adjusting (cross-sectional) are plotted to compare the profiles under these two scenarios and illustrate the importance of controlling cohort effects.

Figure 2-9: Amounts of Credit Card debt -Age Profile

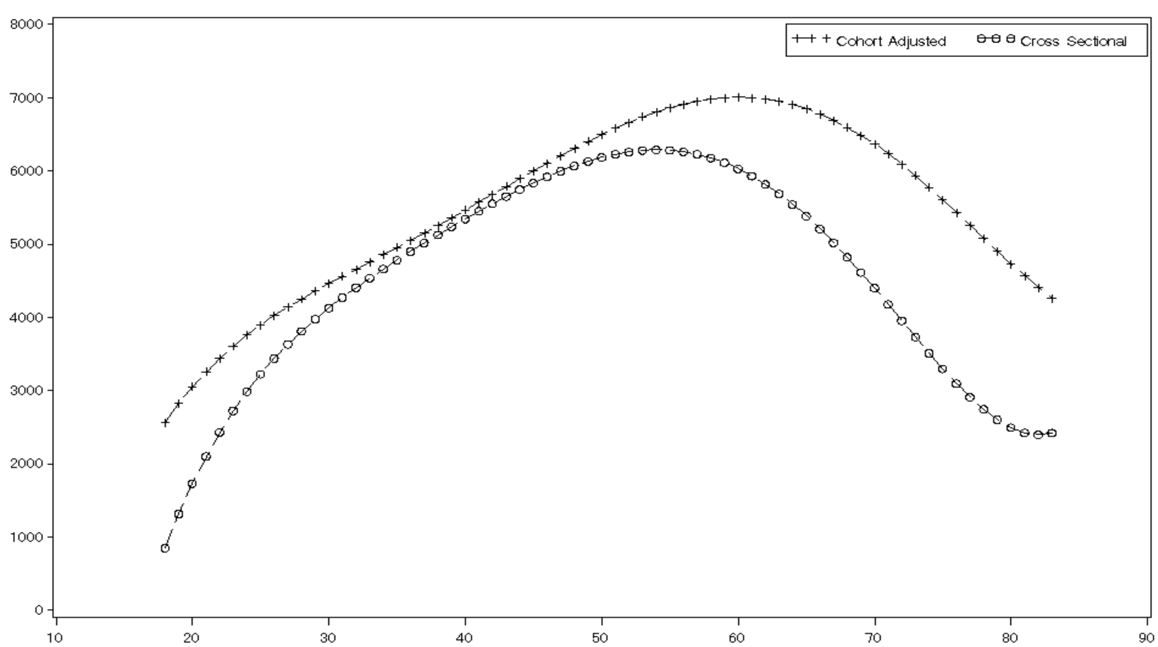


Figure 2-9 shows the age profiles of level of credit card debt with and without cohort adjusting. In order to show a full image of the profile across all ages from 18 to 90, we only demonstrate the profile for younger cohort. Both the cross-sectional and cohort adjusted age profile of amounts of credit card debt are humped-shaped. Cohort adjusted profile is above the cross-sectional age profile, and cohort adjusted age profile of amounts of credit card debt peaks about 10 years later than cross-sectional profile. It suggests that revolvers in younger cohort are carrying more credit card debt and the debt accumulation stage across life cycle is longer than other cohorts.

In conclusion, younger cohorts are more likely to revolve on credit cards than older cohorts. And younger revolvers are inclined to carry more debts than older revolvers. Although carrying more credit card debts may not necessarily be an indication of financial risk by itself, the 'buy now-pay later' mechanism of credit cards requires that households are be able to pay back later. If credit cards debts accumulation pattern is persistent among younger generations over time, more and more aged households are inclined to borrow on credit cards and carry more credit card debts, it will be a threat to the financial health, especially for financial health of elderly who are more vulnerable to financial risk. While current prevailing age-specific measurement and forecasting method used in financial industry, which do not adjust the cohort difference among different generations, will underestimate the probability of default and loss given default. As a consequence, credit card issuers will take on more credit risk and the financial distress may increase sharply when economy turns down. So the difference among generations has implications to estimate and forecast future credit card borrowing patterns. And it is very important to investigate the existence of difference of credit card borrowing behaviors among generations.

2.5 Age-Period-Cohort (APC) Analysis for repeated cross sectional data: Hierarchical Two Level Cross-Classified Model

Fixed effect models in previous section assume that Period and Cohort effects are fixed and Period and Cohort Variations are adequately modeled as fixed. In fact, it is possible that respondents surveyed in the same survey year or of the same birth cohorts may subject to same unobserved events that affect their credit card borrowing decisions, that is, respondents surveyed in the same survey year or of the same birth cohort may share same random errors on credit card borrowing unique to their survey years or birth cohorts. Therefore, there is cluster-level heterogeneity leading to dependence between responses of units in the same (Skrondal and Rabe-Hesketh, 2004). It indicates that the assumption of independence of error terms may be violated. Fail to assess this potentially more complicated error structure may have serious consequences for statistical inference in APC model, and multilevel or hierarchical regression model should be adopted to assess this possibility.

Using Cross-classified Random Effects model, Garner and Raudenbush conducted a study of neighborhood and school effects on educational attainment in Scotland in 1991. Here the attainment data of students are cross-classified by two higher level social contexts - neighborhood and school. Yang and Land (2006) stated that respondents are nested in and cross-classified by two higher level social contexts defined by survey year and birth year in repeated cross-sectional survey data. In recognition of this multiple level structure in repeated survey data, they proposed the Cross-classified two-level APC model using micro level survey data and named it as Hierarchical APC model. The two-way cross-classified structure of micro level survey data enable us not only can take influences of Cohort and Period according to life course approach but to assess the importance of these two 'context' in evaluating credit card borrowing behavior. In this section, the Cross-classified two-level APC Model will be employed to assess the possibility that respondents who share the same Cohort and Survey Year could share unobserved random effects, and to explain the variance in the Period and Cohort level after controlling for individual fixed effects. The practice of the Cross-classified two-level model also provides a possibility to accommodate the Period and Cohort level grouping factors on Credit Card Borrowing in future.

Table 2.8 reports the two-way cross-classified data structure of survey data. Each row is a Cohort J and each column is a survey year K. Each cell represents the number of respondents (n_{jk}) of a given cohort who were surveyed in a given year. There are 17 5-year birth cohorts and 7 3-year survey periods. All respondents are assigned into these 17*3 'cells'. Birth cohort 1905 is those respondents who were born before 1909, and respondents who were born between 1910 and 1914 are in birth cohort 1910, and so on. Birth cohort 1985 is those respondents who born after 1985.

Table 2.8: Two-way cross-classified structure: Frequency of respondents by Cohort & Year

Birth Cohort J	Year (K)						
	1989	**1992**	**1995**	**1998**	**2001**	**2004**	**2007**
1905	42	12	.	.	.	.	.
1910	106	93	51	.	.	.	.
1915	150	146	148	97	36	.	.
1920	217	237	213	145	132	73	23
1925	232	293	275	225	208	159	132
1930	227	260	291	244	225	211	158
1935	271	281	297	273	257	239	234
1940	258	341	367	350	322	364	332
1945	309	370	405	446	426	454	417
1950	244	317	410	409	477	475	437
1955	189	318	359	408	490	456	465
1960	125	246	302	316	384	398	360
1965	39	164	267	215	244	311	312
1970	2	39	123	190	238	216	240
1975	.	.	13	76	141	167	192
1980	.	.	.	1	37	101	140
1985	.	.	.	.	.	5	41

This data structure shows that respondents of any birth cohorts can be interviewed in multiple survey years, and respondents surveyed in any particular survey year are from different birth cohorts.

2.5.1 Propensity to Borrow on Credit Card

Namely, two-level cross-classified model contains Level I and Level II models. Level I model is also referred as 'Within Cell' model, individuals' credit borrowing behavior within each cell are modeled as a function of age, age polynomials, education, other demographic characteristics, financial and attitude variables. The Intercept of level I model varies across birth cohorts and survey years, Level II model, which is also referred as 'Between Cell' model, modeled the intercept of level I model as a function of residual random effects of cohort and of time period.

Detailed specifications of multiple models to analyze credit card borrowing decisions (propensity to borrow) are as follow:

$$\log\left(\frac{HCCBAL_{ijk}}{1-HCCBAL_{ijk}}\right) = \beta_{0jk} + g(a) + \tilde{z}_{ijk} \qquad (2.11)$$

$$\beta_{0jk} = \gamma_0 + u_{0j} + v_{0k}, u_{0j} \sim N(0,\tau_u), v_{0k} \sim N(0,\tau_v) \qquad (2.12)$$

Where $i\,(i=1,2,...,n_{jk})$ denotes individual, $j\,(j=1,2,...,17)$ denotes 17 birth cohorts and $k\,(k=1,2...7)$ denotes 7 survey years. In level I model, as it shows in Equation 2.11, within cohort j and survey year k, the propensity of individual i carrying credit card debts is modeled as a function of intercept β_{0jk}, age polynomials $g(a)$, number of kids, marital status, occupation, and other financial, credit borrowing behaviors, attitudes variables $\widetilde{z_{ijk}}$. All the continuous covariates are centered on the group means. Level II model, as it shows in Equation 2.12, modeled the intercept of level I model as the residuals of random effects of cohort u_{0j} and survey year v_{0k}. The specifications of Level II model allow only the Level I intercept vary randomly across cohorts and periods (survey years). And the centering of continuous variables in level I model makes the model more interpretable.

To obtain estimates of Level I intercept that are easier to interpret and get a statistical inference that related to the motivation of this research, it is very important to choose the appropriate method to center individual-level explanatory variables. According to Kreft and De Leeuw, centering the continuous variables can also help to remove high correlations between the random intercept and slopes, high correlation between level I and Level II variables and cross-level interactions. However, the meaning and interpretation of coefficients in the model is dependent on the type of centering used. In this research, the explanatory variables are centered on group means, which mean the continuous explanatory variables in level I model are transformed to deviations from the 'cell' means.

In this model, the level I intercept β_{0kj} represents the mean proportion of individuals of birth cohort J and surveyed in year K, and the variance of β_{0kj} represents the between group variance in households' propensity to borrow. Apply the interpretation of components of level II model in HAPC model from Yang and Land (2006) and Yang (208) here, the model intercept γ_0 is the overall proportion of individuals carrying credit card debt, u_{0j} is the residual random effect of cohort J, which is the contribution of cohort J averaged over all periods. v_{0k} is the residual random effects of survey year K, which is the contribution of survey year K averaged over all cohorts.

For comparative purpose, a fixed effect model is also estimated, where the cohort effects and period effects are assumed fixed rather than variable and random. In practice, as it shows in Equation 2.13, two sets of cohort and period dummies are incorporated into estimation to account for the cohort effects and period effects. It assumes that variance of intercept β_{0kj} is totally captured by cohort and period dummies. To estimate Equation 2.13, youngest cohort (later than 1985) and most recent year (2007) are set as the reference group and are not included in the model.

$$\beta_{0jk} = \gamma_0 + \gamma_{1j} \sum Cohort_j + \gamma_{2k} \sum Period_k \qquad (2.13)$$

Table 2.9 reports the parameter estimates and model fit statistics, and Table 2.10 reports the covariance parameter estimates.

First part of Table 2.9 shows estimates of individual level fixed effects. Individual level variables included in the model are Age, education level, occupation type, race, number of kids, marital status, total income, total amount of other type of debts, whether have late payment on any type of debt in past 60 days, total amount of payment to debt, total credit card limit, total number of cards, whether own a house or not, whether have sizeable liquidity assets. The parameter estimates of individual-level covariates from random effects models are remarkably similar to those from fixed effects model. It suggests that assumption of random effect model is appropriate (Yang, 2006; Yang and Land (2008)).

Table 2.9: Estimates of two-level cross-classified random effect (CCREM) and fixed (CCFEM) model

	CCFEM			CCREM		
Individual Effects(HCCBAL=1)	Coefficient	SE	Wald Chi-Square	Coefficient	SE	t Value
Intercept	5.4514	1.1873	21.0823	7.17	0.38	18.82
c_educ	***-0.1451	0.00749	375.5318	***-0.1702	0.01	-23.41
c_kids	***0.0735	0.0147	25.1329	***0.05825	0.01	4.16
MARRIED	***-0.0689	0.0195	12.4466	***-0.2498	0.04	-6.50
MARRIED				0.00	.	.
C_INCOME	***-8.19E-7	4.267E-8	368.6344	-8.16E-7	.	.
c_tot_other_debt	***-7.13E-7	9.514E-8	56.1472	-7E-7	.	.
LATE60=0	***-0.7257	0.0655	122.6550	***-1.6098	0.13	-12.25
LATE60				0.00	.	.
C_TPAY	***0.000095	0.000010	84.4898	***-0.00003	4.706E-6	-5.46
C_TOT_LIMIT	***-0.00000486	6.031E-7	64.8531	***-4.44E-6	.	.
HOUSECL=0	***-0.2114	0.0233	82.2471	***-0.4373	0.04613	-9.48
HOUSECL				0.00	.	.
HLIQ500 =0	***0.447	0.0331	182.8872	***0.9240	0.06633	13.93
HLIQ500				0.00	.	.
c_num_cards	***0.0718	0.00409	308.8351	***0.05232	0.003646	14.35

cont.

	Fixed Effects			Random Effects		
	Coefficient	SE	t Value	Coefficient	SE	t Value
Year						
1989	-0.2320	0.2054	1.2760	-0.3187	0.1010	-3.16
1992	-0.0345	0.1402	0.0605	-0.1362	0.09796	-1.39
1995	0.0276	0.0781	0.1251	-0.08435	0.09680	-0.87
1998	0.0127	0.0388	0.1061	-0.03190	0.09662	-0.33
2001	-0.00425	0.0762	0.0031	-0.01752	0.09673	-0.18
2001	0.0953	0.1400	0.4632	0.1878	0.09728	1.93
2007	.	.	.	0.4009	0.09845	4.07
Cohort						
1905	-0.2849	0.9410	0.0917	-0.04	0.1657	-0.24
1910	-0.2923	0.7889	0.1373	-0.06	0.1382	-0.45
1915	-0.3574	0.6717	0.2831	-0.14	0.1178	-1.20
1920	-0.5199	0.5593	0.8641	-0.26	0.1012	-2.59
1925	-0.4122	0.4486	0.8440	-0.10	0.08782	-1.08
1930	-0.3861	0.3406	1.2854	0.00	0.08181	0.02
1935	-0.2667	0.2333	1.3074	0.10	0.07647	1.37
1940	-0.1991	0.1335	2.2243	0.12	0.07221	1.59
1945	0.0130	0.0770	0.0285	0.2414	0.06957	3.47
1950	0.1723	0.1344	1.6430	0.2212	0.06975	3.17
1955	0.1641	0.2321	0.5000	0.1166	0.07147	1.63
1960	0.3623	0.3377	1.1506	0.1382	0.07628	1.81
1965	0.4604	0.4475	1.0588	0.07720	0.08445	0.91
1970	0.5724	0.5571	1.0560	0.08404	0.09681	0.87
1975	0.5789	0.6713	0.7437	-0.06515	0.1139	-0.57
1980	0.3995	0.7829	0.2605	-0.2419	0.1320	-1.83
1985	.	.	.	-0.1937	0.1692	-1.14

Model Fit Statistics		
AIC	24410.863000	
SC	24748.994000	
-2 Log L	24326.863	
-2 Res Log Pseudo-Likelihood		108024.7
Generalized Chi-Square		24356.67
Gener. Chi-Square / DF		1.05

Note: *** Significant at 1% or better ** Significant at 5% or better * Significant at 10%

Table 2.10: Covariance parameter estimates of two-level cross-classified random effect (CCREM) model

Covariance Parameter Estimates		
Subject	**Estimate**	**Standard Error**
Cohort	0.004333	0.005107
Year	0.04365	0.02791

As reported in Table 2.9, results from both models show that Occupation and Race are not significant in predicting households' likelihood of revolving on credit card while other characteristic variables such as education, number of kids and marital status are significant. According to previous research, a consumers' age, marital status, and household size represent the consumption needs of household and might affect the propensity of a card holder to borrow on credit card. A negative relationship between age and the propensity of being a credit card revolver is identified from both the fixed effects and random effects models. And this finding is consistent with previous research (Kim & Devaney, 2001; Bei, 1993; Canner & Cyrnak, 1985; Choi & DeVaney, 1995; Steidle, 1994; Wasberg, Hira & Fanslow, 1992). This finding also implies that households with younger head are more likely to use credit cards as borrowing instruments than households headed by an older individual.

Marital status is another important factor in explaining the propensity of a card holder to revolve on credit card (Canner & Cyrnak (1985)). As it shows in this research, since consumers who are married are likely to have higher expenditures than non-married consumers, married householders are more likely to borrow on credit card. Household size is positively related to the consumption need and demand, so household with larger size usually more likely to borrow on credit card to finance a larger amount of living expenses. As an important measurement of household size, number of kids in the households is expected to have a positive effect on the likelihood of being a revolving credit card user. More kids in a household incur more expenses and other consumptions need which may leads to a higher propensity to borrow on credit card.

Theoretically, education is considered as one of the human resources. Education can increase the demand of current consumption (Kim & DeVaney 2001). According to Becker (1975), education can also be a future resource which suggests high future income, as well as a current human resource. High future income is likely to increase the demand for consumption and for borrowing more money in the current period. Hence, education is expected to have a positive effect on the propensity of borrowing from credit card. However, different to previous research, negative relationship is identified between education and the likelihood of being a revolving card user, and it suggests that individuals with higher levels of education will less likely to borrow on credit card debt. The reasonable explanation is that individuals with higher education level are possible have higher income, they may also have a better control on credit card borrowing since they possible have more information on other credit options and have a better understanding of credit card contract terms, they less likely to borrow.

The financial resource that a household hold or be able to access constrain and determine a household's level of consumption. The typical measurements of financial resource in SCF survey data include Total Income, Liquidity Assets, Financial Assets, Investment Assets, Real Assets, Amount of Net Worth, Total Debt Amount and Total Other Debt Amount etc.. Total Income, Total Amount of Other Debt and binary transformation of Liquidity Assets are included in the final model and significantly related to the propensity of borrowing on credit card. It is argued that households with less income, fewer liquid assets, fewer investment assets, fewer real assets, and more debt are expected to be more likely to revolve on credit cards (kim & DeVany, 2001), that is, households with substantial financial recourses or have a higher debt burden are less likely to borrow on credit card. As Table 2.9 reports, there is a negative relationship between Total Income and likelihood of being a revolving credit card user. Contrary to previous research, Total Amount of Other Debts has a negative relationship with the likelihood of being revolving on credit card. One reason is that households holding larger amount of other type of debts are able to access financing instruments other than credit card debt. And these households possibly prefer other type of financing instruments than credit card debt. According to Duca and Whitesell (1995), total amount of liquid assets held by household can be an important indicator of consumers' repayment ability and patterns because only consumers with substantial balances of liquid assets can decide whether to revolve on credit cards and how much to revolve. The binary transformation of liquidity assets is included in this analysis, and regression results show that consumers with sizeable liquidity assets are less likely to borrow on credit card. Some previous research also shows that households with high liquid assets are more likely to pay their debt in full each month (Canner & Cyrnak, 1985; Zhang &DeVaney, 1999). However, more and more customers holding substantial liquidity assets revolve on credit card. Hot debates are put on the coexistences of high-interest credit card debt and low-interest liquidity assets. Since repayment to other type of debt will eat the liquidity assets held by consumers, total amount of payment to other debt is expected to have a positive relationship with the likelihood of being a revolving credit card user.

Holding credit cards allow households being able to access to credit. A higher credit limit or more credit cards represent more credit sources available to consumers. Obviously, more credit sources provide the opportunity that lead consumers to borrow more money. Hence, total number of credit cards and the credit limit are hypothesized to have a positive effect on the likelihood of being revolving on credit card and the amount of the outstanding credit card balance. While in this research, credit limit shows a negative impact on the likelihood of being a revolving card user after controlling for Cohort and Period effects. One reason is that financial institute usually assign high credit limit to customers with higher credit worthiness that should at least make few months of on time payments. In this case, customers with higher limit may not have higher propensity to borrow on credit card.

Habit formation affects the utility obtained from current consumption (Kim & DeVaney 2001; Warneryd, 1999). Habit implies that a consumer will have a tendency toward repetitive and routine behavior (Kim & DeVaney 2001). Therefore, having an outstanding credit card balance could be influenced by loan repayment habit. If consumers have history of missing payments or pay behind schedule, they are more likely to revolve on credit card than those always pay on schedule. As it shows in Table 9, customers who ever making late or behind-schedule payments in past 60 days are more likely to revolve on credit card.

Whether owning a house or not is also very important in predicting the consumers' propensity to borrow on credit card. The expenses of owning a house is much higher than renting a house or apartment. Besides the monthly mortgage and tax payment, the house owner also will bear the substantial cost of maintaining a house. Hence, house owner usually has higher demand for liquidity assets and credit, and they are hypothesized to be more likely to borrow on credit card than those renting. In this research, it shows that house owners are more likely to be revolving credit card users.

According to previous research, Preferences and attitude are also critical to estimate the probability of being revolving on credit card (Kim & DeVaney 2001). Major findings are customers who have a positive general attitude toward credit and positive specific attitudes toward he use of credit for vacation, living expenses, and luxury goods are more likely to borrow on credit card. And customers who have a short planning time horizon are more likely to be revolving credit card. However, Attitude variables and time horizon variables are not significant in predicting the propensity of borrowing in this research.

Second part of Table 2.9 shows the estimated fixed effects and random effects for 17 cohorts and 7 survey years. In random effect model, residual random effects for all 17 cohorts and 7 survey years are listed. And the coefficients are average residual effects of the cohorts and periods across all time periods and cohorts. By comparison, coefficients estimates for 16 cohorts and 6 time periods from fixed model specification are listed with the youngest cohort and most recent year being the reference groups. These coefficients represent the net effect of each cohort and period, and they are estimated jointly as deviations from reference group after controlling for all other cohorts and periods.

As it can be seen from Table 2.10, controlling for all the individual-level explanatory variables, the residual variation between years is still significant and is estimated to 0.04365 which is consistent with previous findings that economic condition is one of the important factor to estimate households' borrowing decisions on credit card.

2.5.2 Outstanding Balance of Credit Card

As stated previously, the decision to hold revolve on credit card may be separated into two level choices: firstly, consumers need to decide whether to revolve or not (Reynolds & Hogarth & Taylor, 2006), that is, whether to pay off the entire balance from prior month (the participation decision); and secondly, how much to revolve (the consumption decision). Hence amount of credit card debt carried over from prior month is another important dependent variable we will investigate. The detailed specification of the two-level cross-classified APC model is as Equation 2.14 and Equation 2.15. Equation 2.14 is the level I (within cell) conventional fixed effects model, and Equation 2.15 is the level II (between cell) model.

$$CCBAL_{ijk} = \beta_{0jk} + f(a) + \widetilde{x_{ijk}} + \varepsilon_{ijk}, \varepsilon_{ijk} \sim N(0, \sigma^2) \quad (2.14)$$

$$\beta_{0jk} = \gamma_0 + u_{0j} + v_{0k}, u_{0j} \sim N(0, \tau_u), v_{0k} \sim N(0, \tau_v) \quad (2.15)$$

Where i ($i = 1, 2, ..., n_{jk}$) denotes individual, j ($j = 1, 2, ..., 17$) denotes 17 birth cohorts and k ($k = 1, 2...7$) denotes 7 survey years. In level I model, as it shows in Equation 2.14, within cohort j and survey year k, the total amount of credit card outstanding balance of individual i is modeled as a function of intercept β_{0jk}, age polynomials $f(a)$, number of kids, marital status, net worth, total secured debt, late payment indicator in last 60 days, total liquidity assets and other financial, credit borrowing behaviors, attitudes variables $\widetilde{x_{ijk}}$. Level II model, as it shows in Equation 2.15, modeled the intercept of level I model as the residuals of random effects of cohort u_{0j} and survey year v_{0k}. The specifications of Level II model allow only the Level I intercept vary randomly across cohorts and periods (survey years).

However, we have selection bias when estimate Equation 2.14 and Equation 2.15 since the amount of credit card debt can only be observed when card users revolve, we expect to observe zeros credit card debt for convenience card users and positive credit card balances for card revolvers.

Sample selection problem is more frequently used in studies using cross-sectional data and less common to estimate with panel data, even less in multilevel modeling. Since this research is on pooled repeated cross-sectional data, I borrowed the idea from Wooldridge 1995 and adopt Heckman selection two-stage to correct selection bias. Firstly, 7 Probit regressions are run on cross-sectional data of 7 survey years separately to calculate the inverse Mills ratio for each i, T. The model specification is as Equation 2.16, and significant explanatory variables in Equation 2.11 are included in Equation 2.16. Where $HCCBAL$ indicates households revolving status ($HCCBAL$ = 1 if the respondent is revolving on credit card and $HCCBAL$ = 0 otherwise), Z is a vector of explanatory variables which are significant predictive variables from Equation 2.12, γ is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution.

$$\Pr ob(HCCBAL_{it} = 1/Z) = \phi(Z\gamma) \tag{2.16}$$

Secondly, taking lambda calculated from Equation 2.16 as an omit variable, I include it into the estimation of two-level cross-classified model to study the amount to borrow on credit card. Model is specified as Equation 2.17:

$$CCBAL_{ijk} = \beta_{0jk} + \widetilde{f(a)} + \lambda_{it} + \widetilde{x_{ijk}} + \varepsilon_{ijk}, \varepsilon_{ijk} \sim N(0, \sigma^2) \tag{2.17}$$

$$\beta_{0jk} = \gamma_0 + u_{0j} + v_{0k}, u_{0j} \sim N(0, \tau_u), v_{0k} \sim N(0, \tau_v) \tag{2.18}$$

Not all the variables that affect the participation equation are also determinants to estimate the Equation 2.17. To make the intercept interpretable, the level I explanatory variables are also centered on 'cell' means. In this model, the level I intercept β_{0kj}

represents the mean credit card debt held by individuals of birth cohort J and surveyed in year K, and the variance of β_{0kj} represents the between group variance in the credit card amount. Apply the interpretation of components of level II model in HAPC model from Yang and Land (2006) and Yang (208) here, the model intercept γ_0 is the grand mean of credit card debt, u_{0j} is the residual random effect of cohort J, which is the contribution of cohort J averaged over all periods. v_{0k} is the residual random effects of survey year K, which is the contribution of survey year K averaged over all cohorts.

Similarly to the study on individual's propensity to borrow on credit card, a fixed effect model is also estimated for comparative purpose, where the cohort effects and period effects are assumed fixed rather than variable and random. In practice, as it shows in Equation 2.19, two sets of cohort and period dummies are incorporated into estimation to account for the cohort effects and period effects. It assumes that variance of intercept β_{0kj} is totally captured by cohort and period dummies. To estimate Equation 2.19, youngest cohort (later than1985) and most recent survey year (2007) are set as the reference group and are not included in the model.

$$\beta_{0jk} = \gamma_0 + \gamma_{1j} \sum Cohort_j + \gamma_{2k} \sum Period_k \qquad (2.19)$$

Table 2.11: Estimates of two-level cross-classified random effect (CCREM) and fixed (CCFEM) model of Amounts of Credit Card Debt

	Heckman Adjusted CCREM Results			CCREM			CCFEM		
Individual Effects(CCBAL/HCCBAL=1)	Coefficient	SE	t Value	Coefficient	SE	t Value	Coefficient	SE	t Value
Intercept	3241.240000	1393.740000	2.33	5833.15	1166.37	5.00	-49.68	1438.87	-0.03
c_age	***-177.75	20.622300	-8.62	***-177.58	19.7526	-8.99	43.30	53.69	0.81
c_age*c_age	***1.0257	0.113900	9.01	***0.9548	0.1037	9.21	-0.63	0.41	-1.53
c_educ	*75.8950	43.041800	1.76	-33.7499	24.1490	-1.40	**95.04473	37.19	2.56
c_kids	-47.2372	48.756100	-0.97	-18.0373	47.7125	-0.38	-59.89	52.30	-1.15
MARRIED	-79.5215	136.690000	-0.58	**-240.54	125.84	-1.91	4.26	134.31	0.03
MARRIED	0	.	.	0	.	.	0.00	.	.
C_NETWORTH	***-0.00015	0.000030	-5.15	***-0.00014	0.000028	-4.95			
c_tot_secured_debt	***-0.01312	0.000833	-15.75	***-0.01347	0.000829	-16.24	***-0.011345	0.00	-13.75
LATE60	-341.110000	307.920000	-1.11	***-1007.71	215.17	-4.68	-347.06	272.08	-1.28
LATE60	0.000000	.	.	0	.	.	0.00	.	.
OCCAT2	198.550000	197.950000	1.00	134.20	196.83	0.68	271.81	200.21	1.36
OCCAT2	-151.930000	202.690000	-0.75	91.7467	186.08	0.49	-72.15	195.94	-0.37
OCCAT2	-246.720000	219.810000	-1.12	68.8031	193.22	0.36	-142.03	208.29	-0.68
OCCAT2	0.000000	.	.	0	.	.	0.00	.	.
EXP_IR_HIGHER	*-225.49	126.000000	-1.79	-201.16	125.69	-1.60	-204.68	127.20	-1.61
EXP_IR_LOWER	-27.919000	233.850000	-0.12	-25.9827	233.93	-0.11	-3.53	236.73	-0.01
EXP_IR_SAME	0.000000	.	.	0	.	.	0.00	.	.
RACE	258.010000	287.480000	0.90	222.33	287.40	0.77	251.73	291.16	0.86
RACE	-844.110000	392.860000	-2.15	-155.00	319.05	-0.49	-846.32	362.53	-2.33
RACE	-181.850000	357.180000	-0.51	119.81	342.28	0.35	-212.60	353.24	-0.60
RACE	0.000000	.	.	0	.	.	0.00	.	.
C_TPAY	***2.3336	0.077990	29.92	***2.3473	0.07804	30.08	***2.122619	0.08	28.29
C_TOT_LIMIT	***0.09201	0.002910	31.62	***0.08959	0.002857	31.36	***0.076977	0.00	27.62
HOUSECL	***-817.89	166.200000	-4.92	***-1081.70	140.95	-7.67	***-776.333784	155.60	-4.99
HOUSECL	0.000000	.	.	0.00	.	.	0.00	.	.
c_tot_liq	***-0.00332	0.000730	-4.54	***-0.00369	0.000718	-5.14	***-0.004963	0.00	-6.67
c_num_cards	***252.57	19.446300	12.99	***290.99	15.4391	18.85	***294.845841	18.42	16.01
lambda	***-2013.5	661.680000	-3.04	.	.	.	***-1900.111565	502.97	-3.78

	Random Effects			Random Effects			Fixed Effects		
	Coefficient	SE	t Value	Coefficient	SE	t Value	Coefficient	SE	t Value
Year									
1989	-838.200000	255.85	-3.28	-1112.39	296.22	-3.76	-3462.08	727.56	-4.76
1992	245.640000	236.04	1.04	119.42	282.30	0.42	-2626.61	615.71	-4.27
1995	-43.433200	227.92	-0.19	-126.39	276.45	-0.46	-2341.76	505.04	-4.64
1998	-104.810000	226.62	-0.46	-178.94	275.14	-0.65	-1289.57	403.96	-3.19
2001	-2.454700	223.60	-0.01	-9.3683	273.07	-0.03	-1703.74	310.81	-5.48
2001	668.340000	237.32	2.82	870.27	282.13	3.08	-820.88	225.43	-3.64
2007	74.914300	266.35	0.28	437.40	297.25	1.47	0.00	.	.
Cohort									
1905	-5.843600	582.01	-0.01	-11.1606	501.03	-0.02	5959.61	3613.23	1.65
1910	269.910000	507.61	0.53	223.22	448.52	0.50	5754.52	3054.86	1.88
1915	-86.982900	447.48	-0.19	-137.57	402.46	-0.34	4715.34	2829.90	1.67
1920	462.080000	384.22	1.20	278.19	347.66	0.80	4097.68	2625.00	1.56
1925	229.18	332.64	0.69	129.73	303.74	0.43	4071.30	2444.53	1.67
1930	271.54	316.50	0.86	252.61	290.42	0.87	3532.48	2261.76	1.56
1935	242.42	297.05	0.82	307.88	273.31	1.13	3410.05	2086.06	1.63
1940	-584.46	291.00	-2.01	-481.71	266.98	-1.80	2861.22	1908.31	1.50
1945	-1518.92	262.73	-5.78	-1301.59	238.28	-5.46	2351.46	1743.05	1.35
1950	-609.48	248.34	-2.45	-417.24	223.43	-1.87	2303.91	1583.24	1.46
1955	-124.02	242.48	-0.51	4.8552	218.89	0.02	2563.70	1429.52	1.79
1960	182.53	245.79	0.74	312.08	219.80	1.42	2247.38	1284.36	1.75
1965	-150.280000	264.05	-0.57	-70.0258	238.18	-0.29	1963.50	1150.55	1.71
1970	349.110000	295.54	1.18	402.53	267.00	1.51	1856.14	1042.71	1.78
1975	258.940000	338.74	0.76	161.78	309.40	0.52	1353.17	960.24	1.41
1980	519.870000	400.01	1.30	262.98	362.07	0.73	815.16	936.11	0.87
1985	294.410000	514.85	0.57	83.4102	453.77	0.18	0.00	.	.

Model Fit Statistics		
-2 Res Log Likelihood	217677.3	217700.5
AIC	217683.3	217706.5
AICC	217683.3	217706.5
BIC	217677.3	217700.5

Note: *** Significant at 1% or better ** Significant at 5% or better * Significant at 10%

Table 2.12: Covariance parameter estimates of two-level cross-classified random effect (CCREM) model

Covariance Parameter Estimates			
Subject	**Estimate**	**Standard Error**	**P value**
Cohort	401205	265117	0.0651
Year	271163	141444	0.0276

Table 2.11 displays the parameter estimates on amounts of credit card debt and model fit statistics, and Table 2.12 reports the covariance parameter estimates. Compared to Table 2.9 and Table 2.10, the factors that are statistically significant are not the same as those in the first stage which suggests the differences in the determinants of propensity to borrow on credit card and amount to borrow. As it can be seen from the first part of Table 2.11, lambda is significant in both random effects and fixed effects model. Similar to the model on households' propensity to borrow on credit card, the parameter estimates of individual-level covariates from random effects models are similar to those from fixed effects model. It suggests that assumption of random effect model is appropriate.

As stated in previous section, a consumers' age, marital status, and household size represents the consumption needs, and these variables probably will affect consumers' borrowing decision. Age plays an important role in the consumer decision-making process (Schwarz, 2003). Previous studies have tested the age effects on amount of credit card debt, the curvilinear relationship between age and outstanding credit balance identified in this research is consistent with Kim and DeVaney's findings in 2001. According to Kim and DeVaney, age follows the life-cycle hypothesis pattern which result in the curvilinear relationship with credit card debt. The curvilinear relationship suggests that younger consumers have a stronger incentive to borrow on credit card because younger consumers usually face with financial obstacles, such as lower-paying jobs and high expenses of raising a family. It may also suggest the existence of generation effects, where younger generations are more conformable with borrowing money (Rutherford and DeVaney, 2009). However, what merits our particular mention is that age is not significant to predict amount of credit card balance in fixed effects model using Cohort and Period dummies to account for cohort and period difference.

Married households intend to carry more credit card balance than single households, however, the difference between married and single households are not significant after selection bias correction. Households with more kids usually bear more living expenses and more financial needs and it is surprisingly to identify the negative relationship between the numbers of kids and amount to borrow on credit card.

Different to propensity to borrow on credit card, household with highly educated head is more likely to carry more credit card debt than those less educated. According to Becker (1975), education can be a future resource, high future resources suggest that high future income is likely to increase the demand for consumption and for borrowing more money in the current period (Kim & DeVaney 2001). Another explanation is that highly educated individuals may still carry a certain amount of student loan, and monthly payment of student loan incurs higher needs for cash or cash equivalents. Hence, education is expected to have a positive effect on total amount of credit card debt.

The financial resource that a household hold or be able to access constrain and determine a household's level of consumption. The typical measurements of financial resource in SCF survey data include Total Income, Liquidity Assets, Financial Assets, Investment Assets, Real Assets, Amount of Net Worth, Total Debt Amount and Total Other Debt Amount etc.. Total Net worth, Total Amount of Debt Secured by Collaterals and binary transformation of Liquidity Assets are included in the final model

Total Credit limit represent credit sources available to consumers. Obviously, more credit sources provide the opportunity that lead consumers to borrow more money. Hence, Total Credit Limit is hypothesized to have a positive effect on the amount of the outstanding credit card balance. As it exhibits in Table (11), with an increase of $1000 in credit limit, the average increase of total amount of outstanding balance is $92, which is consistent to previous findings (Kim and DeVaney, 2001). Total number of credit cards also reflects the accessible credit resources to consumers, one additional credit card will increases $253 credit card debt on average.

It is argued that previous experience is the best predictor of the future behavior (Coner and Armitage, 1998; Sutton, 1994). And past payment habits were a significant predictor for credit card debt. It suggests that if consumers have history of missing payments or pay behind schedule, they are more likely to revolve on credit card and carry more outstanding credit card balance than those always pay on schedule. As it can be seen from Table 2.11, customers who ever making late or behind-schedule payments in past 60 days are carrying more credit card debts. However, after controlling for selection bias, it is not significant anymore.

Whether owning a house or not is also very important in predicting outstanding credit card balance. The expenses of owning a house is much higher than renting a house or apartment. Besides the monthly mortgage and tax payment, the house owner also will bear the substantial cost of maintaining a house. Hence, house owner usually has higher demand for liquidity assets and credit, and they are hypothesized to be more likely to borrow on credit card and carry more debt than those renting. As it shows in Table (10), on average, those who own a house carry around $800 amount of balance than those who rent.

Preferences and attitude variables are also tested in this model. It hypothesized that customers who have a negative general attitude toward credit would adjust and control their behavior to avoid paying interest and other financial charges. As a result, they will less likely being a revolving card user and carrying less debt. However, these preference and attitude variables are not significant in predicting amount to borrow on credit card allowing for Cohort and Year level variance.

Second part of Table 2.11 shows the estimated fixed effects and random effects for 17 cohorts and 7 survey years. In random effect model, residual random effects for all 17 cohorts and 7 survey years are listed. And the coefficients are average residual effects of the cohorts and periods across all time periods and cohorts. By comparison, coefficients estimates for 16 cohorts and 6 time period from fixed model specification are listed with the youngest cohort and most recent year being the reference groups. These coefficients represent the net effect of each cohort and period, and they are estimated jointly as deviations from reference group after controlling for all other cohorts and periods.

As it can be seen from Table 2.12, controlling for individual-level explanatory variables, the residual variation between years and cohorts are still significant and is consistent with previous findings that cohort difference and economic condition are the important factors to determine amount of outstanding credit card balance.

2.6 Conclusions

A contribution of this analysis is to conduct the systematically APC analysis on credit card debt and to provide the theoretical and empirical evidence of the existence of Age (A), Period (P) and Cohort (C) effects on consumers' propensity to borrow on credit card and amount of the credit card debt and how the taking A, P, C effects into account modified previous understanding of credit card borrowing behaviors.

To carry the APC analysis, firstly, I adopted aggregate level conventional APC method to give the preliminary understanding of Age, Period and Cohort effects, and ascertain whether the data are sufficiently described by any single factor, combinations of any two factors or all three factors. Graphical analyses show that consumers are more likely to borrow on credit card at younger age and the probability to borrow decreases with ages. From year 1989 to year 2007, the share of households holding credit card debts in elderly group gets higher over time. On the other hand, average credit card debt is increasing over time, and debt accumulation stage in life span is increasing over time. In cohort view of amount of outstanding balance of credit card, the line of the younger cohort lies above the line of the older cohort, and it suggests that on average the younger cohort carries more credit card debt than the older cohort. AIC and BIC fitting statistics from constrained conventional APC also suggests the existence of APC effects and that full APC three-factor model performs better than two-factor or one-factor models when estimating Credit Card Debt Level.

Secondly, I conducted a Pseudo-Panel data fixed effects method and simulate the credit borrowing profile to investigate how the P and C factors affect the Credit Card Debt-Age profile. Specifically, I did a comparison between the cross-sectional profile and cohort adjusted Debt-Age profile. In order to show a full image of the profile across all age spans from 18 to 90, only profiles for younger cohort are demonstrated. Cohort adjusted Propensity to Borrow-Age profile is flatter than cross-sectional profile and located above the cross-sectional profile. The results suggested that younger cohorts are more likely to borrow on credit card and share of credit card debt holders is increasing over time, while rate of decreasing for younger cohort slows down. Both the cross-sectional and cohort adjusted Debt Amount-Age profile are humped-shaped and cohort adjusted Debt Amount-Age profile is above the cross-sectional profile. Cohort adjusted Debt-Age peaks about 10 years later than cross-sectional profile. It suggests that revolvers in younger cohort are carrying more credit card debt and the debt accumulation stage across life cycle is longer than other cohorts.

Thirdly, I adopted a two-level cross-classified random effects model to study the significance of variance across Period & Cohort groups and the underlying individual determinants when Period and Cohort level variance allowed. After controlling for individual-level explanatory variables, the residual variation between years is still significant in the propensity to borrow model, which suggests that propensity to borrow on credit card is highly related to economic conditions. While in the amount of outstanding credit card balance model, residual variation between both periods and cohorts are significant after controlling for individual level fixed effects.

Allowing for Period and Cohort level variance, difference among the determinants of propensity to revolve on credit card and amount of outstanding credit card balance is identified. Occupation and Race are not significant in predicting probability of being revolving on credit card and revolving amount while other characteristic variables such as Education, Number of kids and marital status are significant.

A negative relationship between age and the propensity of being a credit card revolver is identified from both the fixed effects and random effects models. This finding also implies that households with younger head are more likely to use credit cards as borrowing instruments than households headed by an older individual. Relationship between age and outstanding credit card balance is curvilinear. The curvilinear relationship suggests that younger consumers have a stronger incentive to borrow because younger consumers usually face with financial obstacles, such as lower-paying jobs and high expenses of raising a family. And it may also suggest the existence of generation effects. However, what merits our particular mention is that age is not significant to predict amount of credit card balance in fixed effects model using Cohort and Period dummies to account for cohort and period difference.

Since consumers who are married are likely to have higher expenditures than non-married consumers, married householders are more likely to borrow on credit card and carry more credit card debt. Number of kids, as an important measurement of household size, is expected to have a positive effect on the likelihood of being a revolving credit card user. More kids in a household will incur more expenses and other consumptions need which may leads to a higher propensity to borrow on credit card, while it is surprisingly to exhibit a negative relationship between number of kids and amount of outstanding credit card balance.

Different to previous research, negative relationship is identified between education and the likelihood of being a revolving card user, and it suggests that individuals with higher levels of education will less likely to borrow on credit card debt. The reasonable explanation is that individuals with higher education level are possible have higher income, they may also have a better control on credit card borrowing since they possible have more information on other credit options and have a better understanding of credit card contract terms, they less likely to borrow. However, once consumer default, household with highly educated head is more likely to carry more credit card debt than those less educated.

Households with higher Total Income are less likely to be a revolving credit card user. The higher the net worth of a household hold, the less amount of debt they are inclined to carry. Contrary to previous research, Total Amount of Other Debts has a negative relationship with the likelihood of being revolving on credit card. And total secured debt has a negative relationship with the amount of credit card debt. One explanation is that households holding larger amount of other type of debts are able to access financing instruments other than credit card debt. And these households possibly prefer other type of financing instruments than credit card debt. Total amount of liquid assets held by household indicates consumers' repayment ability and patterns because only consumers with substantial balances of liquid assets can decide whether to revolve on credit cards and how much to revolve. Consumers with sizeable liquidity assets are less likely to borrow on credit card and carry less amount once revolve.

Credit limit and number of credit cards represent credit sources available to consumers. Opposite to previous research, credit limit shows a negative impact on the likelihood of being a revolving card user and positive impact on the revolving amount after controlling for Cohort and Period effects. One explanation is that financial institute usually assign high credit limit to customers with higher credit worthiness that should at least make few months of on time payments. In this case, customers with higher limit may not have higher propensity to borrow on credit card, however, high credit limit provide the opportunity for households to borrow more on credit card.

Customers who ever making late or behind-schedule payments in past 60 days are more likely to revolve and carry more debt than those who always pay on schedule. The expenses of owning a house is much higher than renting a house or apartment. Hence, house owner usually has higher demand for liquidity assets and credit, and those who own a house are more likely to be revolving credit card users and borrow more on credit card. Preferences and attitude variables are not significantly related to the probability of being revolving on credit card allowing for Cohort and Year level variance.

3 Determinants of Credit Card Borrowing for Consumers 'Who cannot pay' and 'who do not want to pay'

3.1 Introduction and literature Review

Besides the rapid growth of the magnitude of outstanding credit card balance, some interesting phenomena in credit market are observed. Hot debates are on the coexistence of credit card debt with high interest rate and sizable liquidity assets with low interest.

Because of its non-secured, uncommitted feature, credit card debt holders are more likely to default on credit card debt than other secured debts such as home loan, car loan and installment loan. Since no collateral can be repossessed by card issuers, there is barely any recovery from credit card debts once households default or file bankruptcy. Consequently, bank practitioners usually charge high interest rate and service fees on credit card debt. As it shows by Chu in *USA Today* (July28, 2009), almost one in four households now pay more than 20% interest for credit card debt. And households charged late fees paid an average of four fees during a 12-month period. Bertaut and Halisassos (2006) showed that most habitual credit card revolvers pay relatively high interest rate. For those households who sometimes paid off the card balance in full, the median interest rate charged ranged from 13% to 14.8%, while typical interest rate was 15% to 16 % for households who usually did not pay off the card balance in full, vary in Survey years. It is obvious that cost of carrying credit card debt is much higher than other type of debt. However, researchers found that a large share of credit card revolvers hold a certain amount of liquidity assets in checking and saving accounts yielding at 1 to 2 percent, which is against the arbitrage considerations that a rational should have (Gross and Souleles (2002a)). To look at this phenomenon in credit card market in a more conservative stance, Bertaut and Halisassos (2006) found that a remarkably numerous credit card holders appear to have more than enough financial assets to pay off credit card balance in full.

Researchers have attempted to explain this 'Puzzle of Debt Revolvers' from different perspectives. Firstly, assumption of the lack of information or irrationality of consumer is ruled out by most of researchers since the large share of the population have tendency to carry both credit card debt and liquidity assets. Some argued that debt revolvers find it difficult to access other financing media and need liquid assets for transactions which credit cards are not accepted. Telyukova (2009) quantitatively evaluate the demand for liquidity as an explanation for this puzzle and he argued that households holding positive balances in liquid accounts both for transactions and precautionary purposes. Some researchers argued that revolvers may hold liquidity assets strategically to prepare for a bankruptcy filing since credit card debt will be discharged while liquid assets are easily to be converted to bankruptcy exemptible assets when declaring bankruptcy. Lehnert & Maki (2001) found that the puzzle is more prevalent in the states where bankruptcy exemption levels are higher. However, further studies show that this explanation may be compelling only to a small percentage of households, as most of them would be unlikely to file for bankruptcy since they hold significant and positive financial and nonfinancial wealth (Telyukova, 2009). Alternatively, some researchers deviated from the default motivation and yet adopted the theory of self-control to understand this behavior. They elaborated that earner of the household will manipulate the amount of credit card payment and choose not to pay credit card debt in full in order to leave less of the credit line open for the shopper to spend (Bertaut and Haliassos (2002), and Haliassos and Reiter (2003)). This again seem unlikely to account for the widespread nature of this phenomenon and was disagreed by some researchers since there are less expensive control options such as cutting credit limit or holding few credit cards (Telyukova, 2009).

However, most of previous researches on this credit card debt puzzle are for mature US credit card market. To the best knowledge I have, there are few researches on Asia credit card market and debt puzzle issues in Asia market. It would be meaningful and interesting to study whether Asia credit market suffer from the same puzzle as Asia rising and becoming increasingly integrated into the global economy.

Firstly, in this research those revolvers on credit card carrying sizable liquidity assets are defined as revolvers 'who do not want to pay' and those without liquidity assets are revolvers 'who cannot pay'. Even both 'cannot payers' and 'won't payers' are revolving on credit card, but the motivations and purpose of carrying debts are totally different. And they are assumed to respond differently to financial policy, economic stimulus and change of market environments. This analysis is motivated by this possible difference of response to the determinants of credit card borrowing between 'cannot payers' and 'won't payers'. Due to data restrictions, I will focus on Taiwan credit card market only in this research. As a complementary analysis to the APC analysis on credit card borrowing behavior using U.S data, with availability of a unique credit union panel data from first quarter of 2008 to the fourth quarter of 2009 from Taiwan- one of the largest Asia emerging market, I perform an empirically comparison between these two groups on the underlying determinants of the likelihood of being revolving credit card users and level of credit card debt, and try to differentiate those 'who do not want to pay' from 'who cannot pay'.

3.2 Asia Credit Card Market

Contrary to the maturity of US credit market, unsecured borrowing started to expand rapidly and is still developing in Asia, as housing financing of households has so far still dominated the household lending.

Since 1997-98 Asia financial crises, lending to households increased significantly and has led to a marked turnaround in the balance sheets of financial institutions in Asia. Credit card lending has been growing exceptionally fast even though quantitatively not significant. Take Malaysia as an example, house financing accounted for 55% of total household debt and credit card debt accounted for 5% of total household debt as at end of 2007. Although the amounts of credit card debts are less significant, outstanding credit card balance increased by 17.8% a year on average from 2001 to 2007. The strong demand for unsecured loans for consumption spending accounted for the rapid growth of credit card debt. Economic recovery after Asia financial crisis in the region brought higher income to households and hence improved consumer confidence, together with the low interest rate which reduced the cost of borrowing, households with prospects of higher income have become more willing to borrow in order to smooth their consumption. Aggressive marketing and advertising strategies adopted by banks and financial institutes to attract customers are also attributable to the rapid increase of credit card debt (Endut and Hua, 2009). Many banks and other financial institute started to develop their household loan sector as a new source of loan growth and profits since these lenders suffered large losses from their corporate loan portfolios during the Asian financial crisis (He, Dong, Yao, Effie and Li, Kim-hung, 2008). In some cases, governments encouraged financial institutions to lend to the household sector to stimulate economic growth through boosting domestic consumption and hence to reduce reliance on external demand at the mean time.

Lending through credit cards has helped smooth consumer spending and improved profitability of financial institutions, on the other hand, it also raise a number of issues. Firstly, credit card market and credit lending is emerging or newly industrialized in most of Asia countries, lenders may have difficulty to manage the risks correctly particularly when facing volatile borrowing behavior patterns and changing external economic environment. Secondly, although credit card loans account for a small ratio of the lending portfolio of major financial institutions in Asia, it can also affect the financial health of this region in many channels. Thirdly, Because of the family tradition in Asia, the consequences of credit card borrowing on private consumption growth can be larger and more protracted than we can expect.

The expansion of credit card debt in different region in Asia market has different paths.

Credit card market experienced an explosive growth during 2004-2007 and started to develop in India and China, the annual compound growth of total credit card receivables has averaged 47% for India and 76% for China. Credit card lending and debt in Malaysia, Singapore and Australia has shown the relatively steady growth that might characterize a smooth convergence to the level of such receivables in relation to household income in mature markets. In contrast, credit card lending in Hong Kong, Korea and Taiwan has exhibited large fluctuations of a boom-bust nature in each case (Endut and Hua, 2009). Fluctuations in credit card lending in these three markets can create potential systemic risks and present new challenges to its region's regulators. Behind these big fluctuations in credit card receivables would be costly adjustments on the part of both card issuers and cardholders, if not investors and taxpayers. More broadly, such lending booms and busts can be viewed as part of a more general problem involving the build-up and subsequent unwinding of financial imbalances observed not just in emerging Asia. "The recent crisis in the US subprime mortgage market testifies the need for a better understanding of potential financial imbalance associated with excessive risky lending. However, these patterns can have important implications for the real economy, financial stability and in turn the design of policies and regulatory frameworks" (Kand and Ma (2008); Borio and Lowe (2002), Borio and Shim (2007)). Due to data restriction, I will focus on Taiwan market, and conclusions draw from Taiwan market, which has the 3rd largest banking sector by assets in Asia, may be valuable to policymakers in other Asian markets that are starting to experience a rapid expansion in credit card lending, especially for the most populous Asian markets like China, India and Indonesia.

3.3 Credit Card Market in Taiwan

First credit card in Taiwan was issued in 1973. In May 1992, Bureau of Money Affairs announced “The Management Statute of Credit Card Affairs” to regulate credit card market. Because of the increasing demand on consumer financing and high profits in credit card sector, Credit card industry experienced a significant expanding from 90s to 2005. According to the most recent report of Bureau of Monetary Affairs, total number of credit cards in force, total volume of credit card transaction and total revolving credit card balance reached their peaks in 2005. Specifically, total number of credit card in force increased significantly from 927 thousand in 1990 to 45,494 thousand in 2005 followed by a dramatic decrease from 2005 to 2009. Total volume of credit card transactions increased from 37,355 million NT$ in 1990 to 1,420,984 million NT$ in 2005, and total volume of credit card transactions account for around 20.5% of total private personal consumption in Taiwan in 2005. Total amount of revolving credit card balance was first recorded in 1998, since then, it increased with average 20% annual growth rate and peaked with 494,711 million NT$ in 2005, which is around 4 times of the value in 1998. However, Taiwan was hit by credit card crisis starting from late 2005. The explosive growth of credit card sector resulted in a surge of credit card debt. Together with the accumulation of high interests, a large share of consumers is unable to pay off their credit card bills. To overcome this crisis, governments stepped in and strengthened legislations on financial cards. Banks and other financial institutes suspend or stop issuing new card, card issuers have also attempt to propose repayment and interest rate solutions to consumers or write off their card loan problems. The involvement of government and the strategies taken by the banks led to a dramatic fall in the number of cards in circulation and in outstanding loan balances from late 2005. As it shows in Table 13, in 2009, Total number of cards in circulation shrank to around 30 Million, and around 63% of these cards are active cards. Total amount of credit card transactions dropped to 1,365,434 million NT$ which accounts for 17.9% of total private personal consumption expenditure in Taiwan.

Table 3.1: Historical Statistics of Credit Card in Taiwan Market

Year	Total Number of Cards in Force (Thousand)	Toal Volume of Credit Card Transactions (NT$ Million)	% of Total Volume of Credit Card Transactions on Total Private Consumption Expenditure	Total Outstanding Credit Card Balance (NT$ Million)	% of Credit Card Outstanding Balance on Total Consumer Debt
1991	927	37,355	1.40	—	-
1992	1,503	64,841	2.14	—	-
1993	2,051	94,991	2.81	—	-
1994	2,709	131,553	3.45	—	-
1995	3,676	190,653	4.58	—	-
1996	5,467	272,387	5.86	—	-
1997	7,665	374,425	7.42	—	-
1998	10,640	491,097	9.03	124,908	-
1999	13,575	597,786	10.38	152,768	-
2000	18,276	719,770	11.82	205,656	-
2001	24,135	771,861	12.59	259,875	-
2002	31,591	873,599	13.96	316,328	7.12
2003	37,850	998,885	15.87	399,847	8.05
2004	44,182	1,254,482	18.95	457,932	7.81
2005	45,494	1,420,984	20.48	494,711	7.46
2006	38,324	1,380,462	19.04	350,430	5.28
2007	36,437	1,413,455	18.83	284,700	4.23
2008	33,950	1,394,056	18.28	253,662	3.82
2009	30,567	1,365,434	17.94	208,107	3.06

Besides the rapid increase in magnitude of total credit card transactions and credit card debt, the boom-bust of Taiwan credit card industry also affects economic growth deeply. Credit card debt and its impacts on national economic has been a focus of researchers in past decade. Credit card issuers started to realize that it is critical to understand the borrowing behavior of customers in order to implement customer-related strategies to maintain credit card debt in a healthy level. Data used in this study is a quarterly customer level panel maintained by an anonymous credit risk rating agency in Taiwan. In this data sample, each customer is tracked from first quarter of 2008 to the fourth quarter 2009. In addition to the basic demographic information, data used in this research also contains the credit history and financial status of customers. Key variables are:

Demographic variables: Age, sex, marriage, industry and education level of the customer.

Average credit card utilization rate: it is defined as total credit card balance divided by total credit limit held by customers. The utilization rate in past 6 months is calculated. Most card issuers believe that lower utilization rate usually related to less risky.

Number of Cards with 0 Balance: Total number of credit card with 0 balances is usually considered as an indicator of whether customers experience credit constraint. However, more cards 0 balance do not necessary indicator that customers are less likely to revolve on credit cards.

Average Interest paid is last 6 months: It actually is the average expenses that a customer paid for carrying credit card. Besides the interest accrued, it also contains fees in relative to the outstanding credit card balance such as late payment fee.

Default History: customer default when they fail to pay off the minimum required amount due for three continuous business cycles. It indicates the risk category of the customers.

Delinquent on other credit account: whether customers are delinquent on other credit product such as cash cards, installment loan, and mortgage in current period.

Other Financial characteristics: total household income, liquidity assets, financial assets etc..

With the availability of the customer level credit card debt, I revisit the coexistence phenomena of credit card debt with high interest rate and liquidity assets with low yield rate by conducting an empirically comparison on the underlying determinants of revolving decision on credit card and amount to revolve separately for households with and without liquidity, efforts are also put to differentiate those 'who do not want to pay' from 'who cannot pay'. Table 3.2 and Table 3.3 list the descriptive statistics of customers with and without sizable liquidity assets separately. Compared with US credit market, the average age of population using credit card is around 38, which is younger than the population using credit cards in US. To be consistent with previous research, the credit card debts here are also referred as the total amount of outstanding balance after most recent payment and will be carried to next billing cycle and charged interest. The average percentage of population carrying credit card balance is around 9% in Taiwan, and it is significantly less than the percentage in US which is around 50%. The average amount of credit card debt is increasing across years and demonstrate significant seasonal trend.

The level of credit card debts among revolvers is also higher than those in US credit market. Average credit card utilization in last 12 months is around 14%, together with the average 0 balance cards of 2 of each customer, it shows that Taiwanese experience no budget constraint; it also shows the excessive issuing of credit cards in Taiwan. Not surprisingly, customers with liquidity are less likely to borrow on credit card and carry significantly less credit card debt than those without liquidity assets. As it exhibits in Table 3.2 and Table 3.3, the percentage of customers without liquidity assets revolving on credit card are twice as much as the percentage of revolvers with liquidity assets. Compared with those holding liquidity assets, the utilization of credit card of customers without liquidity assets in past 12 months is on average around 5% higher, and they are more likely to default on credit card and revolve on other credit products, less likely to hold an installment loan, but more likely to hold a cash card or mortgage loan.

Table 3.2: Descriptive Statistics for Customers with Liquidity Assets

Variable	2008q1	2008q2	2008q3	2008q4	2009q1	2009q2	2009q3	2009q4	Total
HCCBAL	3.03%	3.65%	3.64%	4.60%	5.78%	7.31%	6.90%	7.06%	5.31%
CCBAL	1565.15	2185.9	3534.23	4309.28	6352.68	5792	5300.14	11151.6	5106.07
age	38	38	38	39	39	39	39	40	39
Married	54.30%	54.75%	54.75%	54.72%	54.35%	54.54%	54.42%	54.58%	54.55%
Average Util Rate in Last 6 Mths	9.89	9.71	9.67	9.68	10.45	10.63	10.70	10.61	10.19
Average Expenses for carrying Credit Card Debt in Last 6 Mths	262.03	243.75	254.49	238.94	272.54	255.85	236.56	213.79	247.24
Number of Cards with 0 Balance	2.35	2.39	2.34	2.32	2.30	2.28	2.23	2.15	2.29
Default history	0.00%	0.00%	0.00%	0.00%	0.00%	0.04%	0.09%	0.09%	0.03%
Total accumulated Card Balance	102080.35	96224.07	95108.26	89759.93	100000.56	92810.19	97052.38	94585.38	95968.9
Limit	119872	118677	118391	117921	119388	117396	120599	118490	118847
Delinquent on Installment Loan	0.0961%	0.1919%	0.3356%	0.3878%	0.4376%	0.4380%	0.4867%	0.4470%	0.3568%
Delinquent on Mortgage Loan	0.1922%	0.2879%	0.5753%	0.5332%	0.5689%	0.3942%	0.7080%	0.6705%	0.4949%
Delinquent on Cash Card	0.0481%	0.2399%	0.3356%	0.0969%	0.4376%	0.4380%	0.2655%	0.4023%	0.2877%
Have cash card account	26.7179%	25.7198%	24.4008%	22.8793%	23.7637%	22.6018%	22.0797%	21.4573%	23.6550%
Have installment account	41.2782%	40.8829%	41.5628%	40.3781%	40.3939%	40.5607%	41.2832%	41.4394%	40.9690%
have mortgage account	26.1413%	21.3532%	20.7095%	19.4862%	20.9628%	20.3241%	18.4513%	14.9307%	20.2371%
Total HH Income	708111.48	702001.44	700436.24	722744.55	716981.18	706677.62	703238.05	702163.61	707773.06
Total liquidity assets	14844.65	15101.81	13798.41	14642.55	14071.01	13459.53	13160.15	12947.84	13979.03
N	2,081	2,084	2,086	2,063	2,285	2,283	2,260	2,237	17,379

Table 3.3: Descriptive Statistics for Customers without Liquidity Assets

Variable	2008q1	2008q2	2008q3	2008q4	2009q1	2009q2	2009q3	2009q4	Total
HCCBAL	11.12%	10.96%	9.79%	12.37%	10.68%	15.25%	14.15%	18.98%	12.83%
CCBAL	3053.6	3531.82	4473.19	4693.41	5711.74	7071.34	7448.7	18217.82	6652.84
age	37	37	37	38	38	38	38	39	38
Married	54.96%	54.73%	54.61%	54.46%	54.65%	54.54%	54.61%	54.34%	54.62%
Average Util Rate in Last 6 Mths	14.5972383	14.9793839	15.1782534	15.3514444	15.4536731	15.43191	15.8589775	16.3645959	15.3862868
Average Interest paid for Credit Card Debt in Last 6 Mths	358.41	348.77	366.41	377.98	384.28	357.06	373.48	354.83	365.09
Number of Cards with 0 Balance	2.6669593	2.689483	2.6092598	2.5287897	2.3983612	2.3490805	2.2930542	2.2048	2.4737043
Default history	0.09%	0.06%	0.06%	0.18%	0.22%	0.29%	0.16%	0.32%	0.17%
Total accumulated Card Balance	116943.67	116427.37	116548.2	116693.01	112105.21	107910.72	112177.18	112386.13	114004.61
Limit	107765	107225	105906	106871	102353	99874.76221	101499	98765.856	103908
Delinquent on Installment Loan	0.6438%	0.3819%	0.8847%	1.0870%	0.7879%	0.8244%	0.7929%	1.7920%	0.8924%
Delinquent on Mortgage Loan	0.7902%	0.8226%	1.2091%	1.4689%	1.4497%	1.4268%	1.6492%	2.6240%	1.4149%
Delinquent on Cash Card	0.4683%	0.3232%	0.6193%	0.6169%	0.8509%	1.0463%	1.0783%	1.3440%	0.7818%
Have cash card account	28.6509%	28.1140%	26.9537%	26.0576%	25.3073%	24.8256%	24.7701%	24.7680%	26.2309%
Have installment account	29.8215%	30.3760%	30.6399%	31.1692%	30.8856%	30.9131%	30.9864%	30.5280%	30.6586%
have mortgage account	32.4846%	30.9342%	29.9617%	29.7004%	27.9861%	27.2987%	25.5630%	22.2080%	28.3704%
Total HH Income	566029.56	565215.04	565392.80	592570.21	588359.28	579967.03	576701.87	571828.48	575639.98
N	3,417	3,104	3,391	3,404	3,173	3,154	3,153	3,125	26,221

3.4 Methodology

As stated previously, credit card borrowing decisions always involves two levels of decisions: firstly, consumers need to decide whether to revolve or not (Reynolds & Hogarth & Taylor, 2006), that is, whether to pay off the entire balance from prior month (the participation decision); and secondly, how much to revolve (the consumption decision), that is the amount of credit card to carry. The purpose of this research is to perform an empirical analysis on the phenomena of coexistence of high-interest credit card debt and low-yield liquidity assets. To accomplish this purpose, firstly, I split the whole population into two groups based on whether they have liquidity assets or not. Revolvers with sizable liquidity assets are defined as consumers ‘who do not want to pay’ and those without sizeable liquidity assets are defined as ‘who cannot pay’. Secondly, I will conduct the empirical comparison on these two groups on the two level choices on credit card borrowing.

To avoid the incidental parameter problem (Arellano-Hanhn, 2007; Kalbfleisch and Sprott, 1970), Conditional Maximum Likelihood Fixed Effects (Chamberlain 1980) method is adopted to estimate the propensity to revolve on credit card of customers with and without liquidity assets separately. Namely, each customer is treated as a separate stratum, which has the consequence of grouping together the 8 observations for each customer in the process of constructing the likelihood function (Allison, 2005). Equation 3.1 is the detailed specification. In this equation, $i,(i=1,...N)$ denotes the individual and $t,(1,...T)$ denotes the panel. u_t is an intercept that is allowed to vary with time. z_i is a column vector of variables that describe the individuals but do not vary over time. c_i represents all differences between persons that are time invariant and not accounted for in z_i. x_{it} are the independent variables which includes demographic variables such as age, and age polynomials, financial status and credit history of the customers. In this equation,

For comparisons purpose, equations on households' propensity to borrow for customers with and without liquidity assets, overall population have the same set of explanatory variables. The predictive variables perform significantly different for these three different populations.

$$\log\left(\frac{HCCBAL_{it}}{1-HCCBAL_{it}}\right)=u_t+c_i+\beta x_{it}+\gamma z_i \tag{3.1}$$

Since the amount of credit card debt can only be observed when card users revolve, we expect to observe zeros credit card debt for convenience card users and positive credit card balances for card revolvers. When we try to estimate the underlying determinants on amount of credit card debt, we have selection bias problems,

$$HCCBAL_{it} = 1[X\alpha + w_i + b_{it} > 0] \tag{3.2}$$

$$CCBAL_{it} \mid (HCCBAL_{it} = 1) = Z\beta + \theta_i + a_{it} \tag{3.3}$$

as it shows in Equation 3.2 and Equation 3.3, $CCBAL_{it}$ can only be observed if $HCCBAL_{it}$ greater than 0. Selection bias is more frequently used in studies for cross-sectional and less common to estimate with panel data. Wooldridge proposed a semi-parametric method to correct the sample selection, and the estimator he proposed can be estimated based on applications of conventional methods.

Following his procedure, I firstly run 8 cross-sectional probit models and calculated $\hat{\lambda}_{it}$ each time, I then run the conventional fixed effects linear regression with the observed data to estimate the parameters of β and ρ in Equation 3.4. In particular, some variables appear in the selection equation (cross-sectional probit model), yet they do not appear in the equation on level of credit card borrowing.

$$CCBAL_{it} = Z\beta + \theta_i + \rho\hat{\lambda}_{it} + a_{it} \tag{3.4}$$

Z is the set of explanatory variables including credit card related variables, financial status of the customer, and their demographic characteristics. θ_i describes all the difference among individuals. a_{it} is the residuals terms.

3.5 Results and Conclusions:

For comparison purpose, parameters on the overall population, customers with liquidity assets and customers without liquidity assets are estimated separately. Table 3.4 demonstrates the regression estimation results of customers' propensity to borrow on credit card. Consistent with analysis using US credit card data, demographic variables such as race, occupation, marital status and sex are not significant in predicting the likelihood of being a revolving credit card user once credit card usage variables/ credit history variables are included in the model. However, for customers without liquidity assets, age is significant associated with the decisions of revolving on credit card. Holding other variables constant, the probability of being a revolving credit card user is quadratic in age. Another interesting finding is that Total Liquidity Assets hold by customers are not significantly related to customers probability to borrow on credit card, while other major predict variables perform differently on modeling customers with and without liquidity assets.

Table 3.4: Estimation Results of the Propensity to Borrow on Credit Card in Taiwan Credit Market

	Overall Population			With Liquidity Assets			Without Liquidity Assets		
HCCBAL	Estimate	Standard Error	Wald Chi-Square	Estimate	Standard Error	Wald Chi-Square	Estimate	Standard Error	Wald Chi-Square
age	-0.163	0.128	1.6199	-0.3332	0.3129	1.1337	-0.1377	0.1437	0.9186
age*age	0.00166	0.00142	1.3654	0.00587	0.00364	2.6072	***0.00101	0.0016	0.4016
Avg util in Last 6 mth	***0.0283	0.00255	123.6691	***0.0284	0.00591	23.1237	***0.0243	0.00295	68.0791
# of cards with 0 bal	***-0.2661	0.0207	165.6871	***-0.2282	0.0464	24.1586	***-0.2989	0.0239	156.2324
limit	***0.000047	0.000014	11.4104	**-0.00005	0.000027	3.5545	***0.000088	0.000018	25.1706
Revolve on cashcard	***1.7635	0.1697	107.9616	***1.4933	0.4602	10.529	***1.8177	0.1916	89.978
Revolve on installment	***1.6861	0.1479	130.0489	***1.8403	0.3608	26.0178	***1.6693	0.168	98.6825
Revolve on Mortgage	***1.2692	0.2081	37.2089	0.9498	0.5216	3.3164	***1.2569	0.2413	27.1349
income	8.19E-07	6.51E-07	1.5835	1.34E-07	7.08E-07	0.0357	*0.000002412	1.51E-06	2.5629
Average interest	0.00006	0.000041	2.1636	-0.00003	0.000058	0.2844	***0.000178	0.000061	8.486
Liquidity Assets	5.21E-08	4.59E-08	1.2864						

Model Fit Statistics		
Criterion	Without Covariates	With Covariates
AIC	14452.826	13449.429
SC	14452.826	13605.72
-2 Log L	14452.826	13413.429

Model Fit Statistics		
Criterion	Without Covariate s	With Covariates
AIC	2748.681	2576.819
SC	2748.681	2708.79
-2 Log L	2748.681	2542.819

Model Fit Statistics		
Criterion	Without Covariates	With Covariates
AIC	11168.333	10388.519
SC	11168.333	10527.482
-2 Log L	11168.333	10354.519

Unutilized credit limit of the credit cards and number of cards with 0 balances measures the actual credit capacity available to a customer. Hence, average utilization rate in last 6 months and number of cards with 0 balances is significantly related to consumers' decision of revolving on credit card. As reported in Table 3.4, customers with higher average utilization rate in past 6 months are more likely to revolve on credit cards, and Number of cards with 0 balance of a customer held negatively related to the likelihood of being a revolving credit card user. Utilization rate in last 6 months and number of cards with 0 balances exhibit no significantly different effects on customers with and without liquidity assets.

The probability of being a revolver is significantly greater for customers with a delinquent history than those never delinquent on any lending product. Revolving on other credit products or not is expected to be positively related to customer's decision of revolving on credit card. As it shows in Table 3.4, when estimating on overall population, the probability of customers' decision of revolving on credit card increased significantly if customers ever revolve on cash card, installment loan, or mortgage. The magnitude of the effects of revolving history varies between customers with and without liquidity assets. Ever revolving on mortgage or not is not significant in predicting the probability of borrowing on credit card of customers with liquidity assets, while it is significant for customers without liquidity assets. If a customer is revolving on mortgage, the odds of revolving on credit card of customer with liquidity assets increased 2.59, comparison to the 3.51 increase in odds of customers without liquidity assets. Similarly, if a customer revolves on cash card, odds of customer with liquidity assets revolving on credit card is 4.45 while 6.15 for customers without liquidity assets.

A higher credit limit or more credit cards represent more credit sources available to consumers, as more credit sources provide the opportunity that lead consumers to borrow more money. Hence, total number of credit cards and the credit limit are hypothesized to have a positive effect on the likelihood of being revolving on credit card and the amount of the outstanding credit card balance. However, as it shows in Table 3.5, for customers with liquidity assets, Total credit limit has significant negative relationship with their decisions of revolving on credit, while it is positively related to the borrowing decision of customers without liquidity assets. Given that total credit limit of customers is the sum of credit limit on all credit cards held by the customers, customers with higher credit limits may reallocate their outstanding credit card balances into other credit cards to avoid high interest rate incurred or reduce their minimum payments. Since customers with liquidity assets hold higher level of income and total credit limit than customers without liquidity assets (According to Table 3.2 and Table 3.3), higher total credit limit may reduce the probability of borrowing on credit card of customers with liquidity assets. Another possible explanation is that assignment of credit limit is highly correlated to the level of credit worthiness of customers, from card issuers' view of point, a customer with sizable liquidity assets are usually correlated to higher level credit worthiness. In this case, customers with higher limit may not have higher propensity to borrow on credit card.

Researchers have found that the 'sticky' interest for credit card debt as interest rate changed a little while other interest rates rose or fall. As the expenses of carrying credit card debt, Interest and Fees Incurred, is expected to have a negative relationship with customers' decisions to borrow on credit card. In this research, as reported in Table 3.4, interest is negatively related to the revolving decision of customers with liquidity assets while positively related to the revolving decision of those without liquidity assets. It suggests that customers with liquidity assets are 'rational', customers may pay off their outstanding balance when interest occurs is high enough. The difference response to interest between customers with and without liquidity assets explains partially the existence of higher 'sticky' interest in credit card market, that is, those irrational 'who cannot payers' experienced troubles to get rid of their credit card debt.

Table 3.5: Estimation Results on the Amount of Outstanding Balance in Taiwan Credit Card Market

Overall Population				With Liquidity Assets			Without Liquidity Assets		
CCBAL/HCCBAL=1	Estimate	Standard Error	t value	Estimate	Standard Error	Wald Chi-Square	Estimate	Standard Error	Wald Chi-Square
age	-49.48136	1433.3827	-0.03	2174.27799	4255.7087	0.51	*-2432.05229	1358.39999	-1.79
age*age	11.61707	16.57974	0.7	0.62586	48.27632	0.01	**36.00784	15.78176	2.28
Avg util in Last 6 mth	***1346.95328	75.77975	17.77	***2195.48638	191.05476	11.49	***926.26782	71.41749	12.97
# of cards with 0 bal	***-7855.88637	1099.4089	-7.15	***-11251	3235.896	-3.48	***-4752.9950	1049.68271	-4.53
limit	***3.13797	0.30008	10.46	***3.31448	0.7922	4.18	***2.12453	0.30049	7.07
income	***0.0154	3.90E-03	3.95	0.009370	9.32E-03	1	***0.01911	3.96E-03	4.83
interest	***12.44266	1.73322	7.18	**7.90925	3.70269	2.14	***19.60064	1.87038	10.48
Liquidity Assets	***-0.00007027	2.25E-03	-0.03						
Lambda	***-753.02	6.52E+01	-11.55	***-860.36	1.37E+02	-6.29	***-631.66	6.64E+01	-9.51

Table 3.5 lists the regression estimates on the amount of credit card debt for overall population, customers with liquidity assets, and customers without liquidity assets after selection bias correction. Not surprisingly, demographic variables such as race, occupation, marital status and sex are not significant determinants on the level of credit card debt once credit card usage variables/ credit history variables are included in the model. However, Age plays an important role in the consumer decision-making process (Schwarz, 2003). Significant quadratic relationship between age and outstanding credit card balance is identified for customers without liquidity assets in this research.

The number of credit cards with 0 balances and the total credit limit is expect to have positive effects on credit card debt because these two variables represent the total actual credit capacity available to customers that constrains the customer's borrowing capacity. As the upper bound of credit card debt, total credit limit are found to be positively correlated to the outstanding credit card balance. On average, $1000 increase in total limit will increase the amount of outstanding credit card balance by $331 for customers with liquidity assets and $212 for customers without liquidity assets. However, number of credit card with 0 balances are negatively related to the amount of credit card debt. One additional card with 0 balances will lead to $11251 decrease in credit card debt for customers with liquidity assets and $4752 for customers without liquidity assets. Since unutilized credit limit measures the credit capacity available to the customers, more unused credit capacity are expected to encourage more outstanding credit card balance, however, as it shows in Table 3.5, the average utilization rate in last 6 months are significantly positively related to the level of outstanding credit card balance. One average, one unit increase in credit card utilization rate in past will increase the credit card debt by $21.95 for customers with liquidity assets, and $9.26 for customers without liquidity assets.

The interest rate is the price of borrowing on credit card, so people should tend to carry less credit card debts when the costs are high. However, according to the estimated coefficient reported in Table 3.5, $1 increase in Interest and fee incurred will lead to a $7.9 increase in credit card debt for customers with liquidity assets and a $19.6 increase for customers without liquidity assets.

Summarizing above results, credit card borrowing in Taiwan credit market share some similarities with the credit market in U.S, for example, both the markets experienced rapid growth of total outstanding credit card balance and the coexistence of credit card debt with high interest rate and low yield liquidity assets. In contrast to U.S market, younger population are using credit cards in Taiwan, and the percentage of revolvers of credit card user are around 10% in Taiwan , which is around 40% less than U.S credit card market. However, the average level of outstanding credit card balance among revolvers is significantly higher than that of in U.S market. Comparison between customers with and without liquidity assets show that the underlying determinants of likelihood of being a revolving card user and the amount to revolve on credit card performed significantly different between these two groups.

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