An Investigation on Balance Switching Behavior in Credit Card Market

DISSERTATION

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By

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ABSTRACT

Research on the behavior of credit card balance switching is underdeveloped because data on the phenomenon are quite limited. The few previous studies show that consumers’ choice of accepting a low introductory interest rate and then switching a balance to it depends on two major factors: one is the difference between the current credit card rate and the interest rate offered, and the other is the total amount of outstanding balances. This dissertation uses data from a new nationwide survey – the *Consumer Finance Monthly* – with much richer information about consumers’ credit history and card holding conditions to investigate several fundamental factors in balance switching. A theoretical model is developed to rationalize revolvers’ decision about balance switching. An exercise of dynamic optimization is conducted to reveal the relationship between switchers’ reservation rate, payment process, and the predicted duration spell. Econometric methods are used to do the empirical analysis. Two endogenous switching regression models are applied to inspect two distinct responses on the switchers’ side. The commonly used Cox-proportional duration model is shown to be invalid for fitting our data. The accelerated lifetime model is adopted instead to capture the impact of the credit card debt and other relevant factors on the duration spell for holding an initial card. Last, we address the issue of unobserved heterogeneity in a structural Weibull-Gamma duration model.
The two theoretical predictions in this paper are consistent with the primary findings in our empirical study. Switchers wait for an interest rate that is regarded as sufficiently low. Consumers with worse payment history have to wait longer to receive such a low rate. Our survival analysis shows that the degree of stress over the debt rather than the amount of credit card debt itself hastens consumers’ switching decision. The fitted hazard rate is bell-shaped both in the accelerated lifetime model with Gamma distribution and in the structural duration model. Cardholders are most likely to switch in the window of the sixth to twelfth month staying with old cards.

Our empirical findings include evidence for the existence of the "winner’s curse" as in Ausubel (1999) and his "underestimation hypothesis". Switchers improved their debt situation right after switching. But the impact has very a short memory. Balance switching could only bring symptomatic relief but not a credit cure. Switchers still bear a heavier burden of credit card debt in the long run. This result supports "adverse selection" as in Ausubel (1991), but it does not support his later finding in Ausubel (1999).
Dedicated to my daughter Elaine
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CHAPTER 1

Introduction and Literature Review

1.1 Introduction

In recent years, balance switching behavior has drawn more and more attention as balance switching service became a significant part of credit card market. Facilitated by the relatively richer information from Consumer Finance Monthly private data from the Center of Human Resource Research, this dissertation attempts to investigate the factors that determine consumers’ decision of balance switching and the factors that impact their duration spells staying with old cards before switching.

The content is organized as follows: chapter 1 describes the background of balance switching in credit card market and introduces the related literature; chapter 2 introduces the CFM data used in this dissertation and compares some main characteristics between switchers and non-switchers. Section 2.2.2 focuses on the introductory interest rate and its corresponding duration period. They are the two major terms in the offers accepted by switchers and in the mail offers received by non-switchers. The question about consumers’ response to the mail offer solicitation is elaborated in 2.2.3. In 2.2.4, the significance of difference between new card rate and old card rate is rejected, which is against the result of the previous study based on the Ohio Economic Survey (OES) data. Sections 2.2.5 – 2.2.11 compare switchers’ and non-switchers’
default history, balance carrying history and asset holding status, as well as some socio-economic and demographic characteristics. Based on the statistical descriptions, three hypotheses are proposed about the interactional relationship between balance switching, default history and interest rates. In section 2.2.5, the ratios of credit card debt-to-income and credit card minimum monthly payment-to-income are regarded as the indices of debt burden in the short run and long run respectively. The existence of "adverse selection" (more precisely, the version of "adverse selection" in Ausubel (1991)) is confirmed in section 2.2.8: although we believe that switchers temporarily improved their current default situation after switching, they still bear a heavier debt burden and are more likely to default in the future default risk than non-switchers. The fact that bad consumers are more sensitive to card rates leads to downward sticky interest rate in this market.

Chapter 3 does theoretical model analysis. Section 3.1 builds a theoretical model to rationalize consumers’ choice of timing to switch a balance. Two predictions are derived through the simulation analysis. One is consistent with the third hypothesis we proposed in chapter 2. The other is to be tested in survival analysis. Section 3.2 uses the recursive dynamic optimization to mimic the equilibrium strategy. The important results in this section include the reservation rate and the predicted duration spell at equilibrium.

Chapter 4 sets up two endogenous switching regression models to test the first two hypotheses listed in section 2.2 and the theoretical prediction in section 3.1: first, the link between switchers’ default history and credit card debt burden \( CCDTI \) is broken, implying that their default situation could have been changed after they switched a balance; second, although switchers who experienced different default histories receive
different interest rates, they wait for a rate that is sufficiently low to switch to. The multi-imputation method is introduced and employed in this section to hurdle the problem of missing values. Four estimation approaches (Heckman two-stage method with two ways of imputation, FIML method, and OLS method directly based on original data) are used. Their corresponding estimation results are compared.

Chapter 5 employs duration models to do the survival analysis. In section 5.1, the most commonly used Cox-proportional hazard rate model is proved invalid due to the violation of the proportionality assumption. We adopt parametric models—the accelerated lifetime model. We assign five different distributions for the duration spell and compare the model performance. Section 5.2 further addresses the issue of unobserved heterogeneity and confirms the bell shape of the hazard rate. Section 5.3 concludes.

1.2 Background and Related Literature

1.2.1 Background of Balance Switching in Credit Card Market

With the increasing credit card debt and consequent delinquency, debtors seek ways to cut down their monthly payment on interest charges and to decelerate the balance accumulation. Balance switching service was created in mid 1990’s and prospered in the boom in recent years. In credit card market, all kinds of balance switching offers, especially the mail-out solicitations grow rapidly. Balance switching is considered as a short-term remedial solution, commonly adopted as an option of debt consolidation. By transferring the outstanding balances from one or several cards to another one with a lower interest rate, the balance carriers could make immediate savings on interest charges. As a result, this considerable reduction of monthly
payment leads to a temporary fall in the delinquency risk for consumers who were swamped in the credit card debt.

Like other commodities that compete against their substitutes, balance switching offers vary in the combinations of their terms, such as the introductory interest rate (referred as intro-rate hereafter) on transferred balance, the interest rate on new purchase, the duration period of intro-rates (referred as intro-period hereafter), transaction fees, perks like cash back and rewarded flying miles and so on. Sensitive shopping around will help debtors settle down their plastic debt to a right card and to improve their financial situation. Due to the lean data and the few investigations in this area heretofore, however, factors taken into account when consumers make balance switching decision are still behind the veil.

1.2.2 Related Literature about Balance Switching, Searching, and Responding to Credit Card Offers

The research on consumers’ behavior of balance switching in credit card market was only a few up to now because the data about it were quite limited. Frank (1999) first examined this activity based on a small sample of credit card holders. He claimed that the outstanding balance and the interest rate were the two most important triggers of switching activity. Kim (2000)\(^1\) investigated the factors that affect consumer’ decision of balance switching in a nested multinomial logit model, based on the Ohio Economic Survey (OES)\(^2\) data. In his study, there are two crucial determinants of balance switching. One is the difference between the new card rate

\(^1\)In chapter 5 of his dissertation paper: introductory credit card interest rates and balance switching behavior of cardholders

\(^2\)The Ohio Economic Survey (OES), also known as Buckeye State Poll (BSP), is an original data set collected by the Center for Survey Research (CSR) at the Ohio State University between November 1996 and April 2002.
and the old card rate and the other is the total amount of credit card debt, partially supporting Frank (1999). Two demographic variables such as education level and number of children in the family are also found to have positive effects. In other words, highly educated consumers and those households with more children are more likely to switch a balance. Another recent study on balance switching is conducted by Ekici, Dunn and Kim (2007). They studied consumers’ sequential decisions: accepting an intro-rate card and then switching a balance to it. Their basic results are: the major behavior factors involved with accepting an intro-rate card is significantly related to the APR difference and card holders’ risk types; APR difference and balance to income ratio are significantly related to switching. The risk type, however, is not found influential on balance switching. The home ownership shows a positive effect, implying that the competing effect of Heloc option is not as high as some may have expected. This dissertation uses the CFM data with more comprehensive information in balance switching section to test all these results and to further explore some new findings.

Although the research focused on balance switching is handful, we can still facilitate our study with the literature on consumers’ other behaviors related to balance switching, such as searching for desirable cards, responding to mail solicitations and their defaulting behaviors (including late payment to credit card debt, accounts collected by collection agencies, and bankruptcy filings). In general, consumers who are prone to switch a balance are considered more likely to have a bad payment history and a higher default risk in the future. Looking at how these consumers search around for credit cards and respond to mail offers will shed some lights on the question that how long they wait until they take their first move of switching.
Among all the literature on default risk, the debt burden index—debt to income ratio ($DTI$) or debt service coverage ratio ($DSCR$) is widely used as a powerful predictor of future default risk. Higher $DTI$ reveals lower financial solvency of debtors and indicates higher likelihood of delinquency or even default. Since we focus on credit card market in this paper, we use the ratio of credit card debt to income ratio ($CCDTI$) as the index of card holders’ credit card debt burden and regard it as the predictor of future default on credit card payment. Dunn and Kim (2002) further shows that the monthly minimum payment-to-income ratio ($MMP TI$), the balance utilization rate and the number of "maxed-out" cards also have significant prediction power for households' future default. In this dissertation, we treat $MMP TI$ as an index of more urgent credit card debt burden and a predictor of short-term default risk. While $CCDTI$ is used to predict the probability of default in the relatively far future, in line with the prevailing measurement.

In retrospective of the research on sticky prices in credit card market, three versions of "adverse selection" appeared. By and large, they had reverse effects against each other based on different assumptions on risky borrowers’ response to interest rates. Stiglitz & Weiss (1981) claims that the credit card rate is upward sticky. If all banks currently charge the same rate, no banks will deviate to a higher rate since the only borrowers who are willing to take this high rate are riskier consumers. Ausubel (1991) proposes an opposite version by asserting that the credit card rate is downward sticky. Banks hesitate to decrease the card rate; otherwise they only draw the bad consumers who are sensitive to the low rates. Ausubel (1999) again puts forward a new version of "adverse selection" which is against his old one: consumers who take the high rate offers are borrowers with high default risk. In his 1999 paper, he
also borrows the term of "winner’s curse" in auction theory to explain the findings in credit card market: the respondents with higher default risk get relatively inferior offers. In this dissertation, we attempt to prove that the "winner’s curse" also exits in balance switching section. We also probe the existence "adverse selection" in balance switching. Our findings support the earlier version in Ausubel (1991) instead of Ausubel (1999).

Consumers’ waiting time until switching probably involve their searching behavior, which also exhibits their sensitivity to card offers. There were two arguments about consumers’ searching behavior in different default categories. The first one is represented by Calem & Mester (1995): consumers with poor payment history tend to search less because they are aware of the high probability of being rejected by low rate cards. The second argument prevails in later studies. Kim (2000) finds that "defaulters’ usage of intro-rate is 5.3% higher than their non-default counterparts on average", implying that defaulters are more willing to utilize a low rate. Crook (2002) also finds that households with poor payment history do not appear to search more or less than those with better payment histories. Kerr & Dunn (forthcoming 2008 in JBES) further proves that high-balance consumers have lower interest rates due to their higher searching effort. Our findings about the waiting time of switchers with different risk types and the heterogeneity in their rates support Kim (2000), Crook (2002) and Kerr & Dunn (forthcoming 2008 in JBES).

The switching behavior is also seen in other markets, such as refinancing on a mortgage loan or brand switching on consumption goods. Studies on these areas could lend some insights on investigation on balance switching. Agarwal et al (2002) used an option pricing model to address the issue of refinancing on mortgage loans. Lee
and Rosenfield (2005) adopted a dynamic programming approach as an alternative way to be more appropriate for shorter term mortgages. Some researchers are devoted to the brand loyalty and switching analysis. Sun, Neslin and Srinivasan (2002) did such marketing research on the effect of promotions on brand switching.

1.2.3 Related Literature about Econometric Methods Used

Endogenous switching models are widely used in labor economics, consumer finance and other fields. It distinguishes from the mixture model with conditional densities by the feature of self-selection. The significant difference in two or more types of subjects can be conveniently discovered and displayed by the comparison of the regression result cross type. The interpretation of the standard endogenous switching regression model was made in Maddala & Nelson (1975). The applications include the labor-supply model (Heckman (1974)), the union-nonunion-wage model (Lee (1978)), and recently the home bank-external bank model (Kerr & Cosslett & Dunn (2004)) and the collateral and sorting model (Dey & Dunn (2007)), etc.

Two endogenous switching models are used in this dissertation. One is to test the link between card holders’ default history and their debt burdens. The other is to investigate the determinants of switchers’ acceptance of intro-rate.

The estimation of factors’ effects on the waiting time before switching is obtained in duration models. Duration models were most seen in labor economics and now spread in the field of consumer finance in more complicated forms, thanks to the increasingly available data. A big family of duration models is based on Cox-proportional hazard rate. It is widely used owing to its mathematical convenience by
separately factoring the hazard rate into a function of time and a function of characteristic variables. Another advantage of Cox-proportional hazard rate model is that the parameters are estimated without necessary consideration of the base line hazard function, given the proportionality assumption holds. But if this assumption does not hold obviously, previous study shows that the estimates from Cox proportional hazards regression might not be consistent. Another family of duration models is called accelerated lifetime models. Kiefer (1988) makes an instructive comparison between these two families: in the former family, the model is linear in characteristic variables \( X \), but the dependent variable is \( \ln \Lambda_0 (t) \). While in the latter family, the model is linear in characteristic variables \( X \) and the dependent variable is \( \ln (t) \). The proportional hazard rate models restrict the error term to a unique distribution- type one extreme value distribution, but allows for a large class of specifications of \( \Lambda_0 (t) \). While the accelerated lifetime models restrict the transformation of duration, they do not restrict the distributions of error terms. This kind of parametric models might not capture the base line very well. If the distribution of error term is miss-specified, the gains in efficiency fostered by parametric models may be lost.

Literature that involves proportional hazard could be found in Lancaster (1979) that studies the duration of unemployment, Andrew & Haurin & Munasib (2001) that compares the time prior to first-time home ownership of young adults in Britain and the U.S., Omori (2002) that applies a discrete proportional duration model to Japanese diffusion index, Kuo & Chen (2004) employs a mixed multinomial logit model and Cox-proportional hazard model to study the brand choice and inter-purchase time, etc. Literature that involves accelerated hazard was relatively thinner

\[
0 (t) = \int_0^t h_0 (u) \, du.
\]

\(^3\)Let \( h_0 (t) \) be the baseline of hazard rate function. \( \Lambda_0 (t) = \int_0^t h_0 (u) \, du. \)
but develops rapidly. Li (1999) adopts three most commonly used hazard formulations in his accelerated lifetime model and applies the Bayesian model comparison criterion to determine which formulation should be used. Gyimah & Ghilagaber (2004) employs an accelerated lifetime model based on each of five commonly used distributions for the error term and studies the child-spacing in sub-Saharan Africa. These two kinds of duration models are both studied in this dissertation, while the accelerated lifetime model turns out fitting our data better.

The duration analysis with unobserved heterogeneity is conducted at last. In proportional hazard models, the scale parameter $\lambda$ is set as $\exp(-X\beta)$. As a result, the hazard ratio is completely determined by the independent variables, i.e., the individual characteristics. This assumption is seldom fulfilled and in most cases proved to be inappropriate. Due to the omission of some important explanatory variables, unobserved heterogeneity is of growing awareness as existing cross sample members or over time for the same sample members. It is well known that the duration analysis produces inadequate or misleading results if unobserved heterogeneity is ignored. The impact is stronger in hazard models than in other types of regression models. Blossfeld & Hamerle (1992) demonstrated the effect of unobserved heterogeneity in event history models by comparing the result of Weibull and Generalized Gamma model. In their paper, the Gamma shape and scale parameters in the generalized Gamma model are not equal to 1, indicating that there is unobserved heterogeneity that can not be neglected in the Weibull model. In their paper, they also showed that a decreasing hazard rate is more likely to occur in case of omitted unobserved heterogeneity. Heckman & Singer (1984) provided similar proof of this statement. Blossfeld & Hamerle (1992) also proposed a score test that is used to detect the
miss-specification of omitted variables, based on previous study by Lancaster (1985), Kiefer (1984) and Burdeltt et al. (1985).

Estimates are proved to be sensitive to the distribution of the heterogeneity (Heckman & Singer (1984), Keiding (1987), et al.). Major effort has been made on finding an appropriate functional form of the distribution. Blossfeld & Hamerle (1989) used the Exponential distribution and found that the mixtures model with Weibull duration and Exponential heterogeneity was exactly the Log-logistic duration model. Others like Lancaster (1979) and Nickell (1979) made other choices. As a pioneer study in this area, Lancaster (1990) dealt with the unobserved reasons of leaving the state of interest and the selection effect on the survivors. He first adopted a proportional hazard model with multiplicative unobserved heterogeneity. This model is now called mixed proportional hazard (MPH) model and most commonly used in econometrics. The MPH model needs to be estimated by parametric methods of the assumptions on the distribution of the heterogeneity. In his study, Lancaster pointed out that in practice, Gamma distribution is the most preferred due to both computational and expositional reasons: all functions of interest have simple explicit expressions in this case. Abbring & Van den Berg (2006) rationalizes the preference for the gamma distribution by proving that the distribution of the heterogeneity among survivors converges to a Gamma distribution, and rapidly in most cases. Their results suggest that it is appropriate to use the Gamma distribution with a survey that misses the early-exit individuals. Our empirical results strongly favor the Gamma distribution over a number of other standard distributions. So the Gamma distribution is assigned to the unobserved heterogeneity for the sample members in our study. The mixed proportional duration model with Gamma distributed heterogeneity now is widely
used. Duration analysis that adopted Gamma heterogeneity could be seen in Andersen et al. (1993), Murphy (1994, 1995), Petersen et al. (1996) and Brusilovskiy (2006).

In line with Lancaster (1990) and Brusilovskiy (2006), we adopt a structural duration model with Weibull duration and Gamma heterogeneity as an adjustment to our Weibull accelerated lifetime model.
CHAPTER 2

The Data and Descriptive Statements

2.1 *CFM* Introduction

The data used in this dissertation is called *Consumer Finance Monthly* Private data. It is an ongoing monthly telephone survey conducted by Center for Human Resource Research (CHRR) at the Ohio State University. The data set started from February, 2005 and continuously adds in about 300 new observations each month. Up to January, 2007, it has accumulated to 7275 observations. It provides relatively more up to date information and covers a wide range including credit card history, track of bill payment, measures of stress over debt, households’ preference and expectation and detailed balance sheet information. Among the investigation on consumers’ behavior in all aspects of the financial market, this survey contributes an exclusive array of questions about balance switching which facilitates the study in this particular area\(^4\).

The data are weighted to gain a better performance on representing the population in U.S. The weight variable is created by choosing income category and race (Black vs. non-Black) as the stratification factors and equalizing the cell percentages to those of the latest Current Population Survey from U.S. Census Bureau. All values are transformed to 2007 dollars with inflators of CPI-U from Bureau of Labor Statistics.\(^4\)The survey questions are provided in the appendix.
The mean and median of CFM essential variables are comparable with those from Survey of Consumer Finance Public data, which is mostly used in the academic research. The reliability of this data set is thus guaranteed in this sense.

The total sample size is 7275, among which 3230 comes from 2005 survey, 3762 comes from 2006 survey and 283 comes from 2007 survey. Seventy-eight percent (5660) of consumers hold at least one credit card. Since we analyze balance switching behaviors, our targeted consumers are card holders only.

In the full sample of card holders, eleven percent of them switched a balance during the past six months (they are referred as switchers and their counterparts are referred as non-switchers). Cardholders’ default history is tracked: eight-five percent of them never missed the minimum payment on loan or credit card in the past six months; fourteen percent of them missed at least once for less than 60 days, only two percent of them missed payments 60 days or longer, they are regarded as defaulters. Nine percent of them once reported bankruptcy.

Eighty-three percent of cardholders in our sample are home owners. Among these home owners, about 20.5% own their house outright and do not need to pay any home loans; seventy-one percent own a house (not completely) and never pay their home loan late; the rest 0.5% once paid their home loan late in the past 12 months. This home loan delinquency rate seems a little lower than the industry standard, which is somewhere around 2%. The created dummy variable about home loan delinquency (yes=1, no=0) is all 0 for switchers. It is not statistically significant in all the regressions. So we exclude it from both regression and statistics analysis.

One limitation of this original data set is caused by the missing observations. As a result, the number of observations that could be used in estimations would be less than 7275.
Some might argue that the analysis should be conducted only on revolvers since balance switching is an "exclusive" activity for current balance carriers. While we believe cardholders provides a more appropriate sample set than revolvers to calibrate the model for several reasons: first of all, it is a widely misconceived conception that balance transfer activities are limited to revolvers. In practice, if one opens his mail, he could find checks attached with the balance transfer offer. Even a transactor could take advantage of the lower intro-rate by using these checks to take a vacation, pay off holiday expenses, or make any big-ticket purchases. Card holders could activate their approved balance transfer offers with an exiting balance or even a balance that is created later. Besides this fact, a transactor could also switch a balance one month before its payment is due. And last, in our data, the switching proportion in transactors is five percent. When we look at the switchers, twenty-seven percent of them are currently holding zero credit card debt. All of these speak out that eliminating transactors from the data would lose a strip of scope of applications as well as a fair amount of useful information from a quarter of card holders.

The main body of the statistical description is displayed by making a comprehensive comparison between switchers and non-switchers from the following aspects: intro-rate, intro-period, default history, balance-carrying history, asset status, social economic characteristics and geographic regions. In different scenarios, cardholders are classified into groups like revolvers vs. transactors; low risk type vs. middle risk type vs. high risk type, and so on.

The definitions and means of variables used in this dissertation are shown in Table 1 by non-switchers and switchers separately. Quite a few variables are of categorical type. Besides the binary variables indicated in the table, there are some variables that
have ordinal values. For credit card late payment, −1 denotes never had credit card late payment in the past six months; 0 denotes the delinquency is less than 60 days; 1 denotes otherwise longer than 60 days. For whether accounts have been collected by collection agencies, −1 denotes never paid a loan late; 0 denotes paid a loan late but accounts never have been collected, and 1 denotes accounts once have been collected. Rank of ratio of monthly minimum credit card payment to income takes value from 1 to 10. Stress over credit card debt takes value from 1 to 5. Education takes value from 1 to 7.

2.2 Comparison between Switchers and Non-switchers Based on CFM Data

2.2.1 Number of Credit Cards in Hand and the Current Interest Rate

We start comparing switchers and non-switchers by looking at how many credit cards in their hands. Because the number of credit cards is discrete, the normality assumption is not satisfied for the two sample t-test. The non-parametric tests are regarded more powerful in detecting population differences in this case. The Wilcoxon Mann-Whitney test, a.k.a. the rank sum test, is one of the most powerful non-parametric tests for comparing two populations when the observations are ordinal data rather than direct measurements.

On average, non-switchers hold less than three credit cards, while switchers hold more than four. The Wilcoxon Mann-Whitney test result is shown in Table 2. CFM survey asked about the interest rates of three cards in holders’ hand, including the newly opened one, the most charged one and the one carrying the highest balance. The new survey conducted from June, 2006 compressed the question list in the credit
card section and only asked for the interest rate of the most used card. We compare switchers’ and non-switchers’ interest rates on these cards. The two sample t-test in Table 3 finds that switchers enjoy lower interest rates on all these cards than non-switchers. The bigger number of cards in hand and the lower rates on these cards reveal a higher searching effort that switchers are made. They are inclined to apply for new cards and take advantage of the lower teaser rates.

2.2.2 Intro-rate and Intro-period in the Mail Offers

The two major terms in the mail offers that are received by non-switchers and accepted by switchers are intro-rate and intro-period.

As shown in Figure 1, seventy-five percent of switchers switched a balance to intro-rates 3.99% or less. Fifty-two percent of them switched a balance to a zero intro-rate. Seventy-five percent of non-switchers received intro-rates 6.99% or less from mail offers and 46% of them received a zero intro-rate.

As shown in Figure 2, half of switchers switched to the intro-rates good for 12 months or longer. In non-switchers mail offers, the 6 month period and 12 month period occur most frequently. Half of them received mail offers with intro-period 6 months or longer.

So, in general, the offers accepted by switchers are on average superior to the mail offers received by non-switchers, both in the aspect of intro-rates and intro-periods. This raises the red flag for checking the "adverse selection" in Ausubel (1999) which states that higher introductory rate leads to inferior respondents.
2.2.3 Acceptance Rate of Different Offers

We always consider non-switchers as potential balance switchers in the future. With access to the non-switchers’ desired offers, we could answer the problem about the acceptance rate, or namely, the percentage of current non-switchers who will be won over by a specific new offer. For non-switchers who already received a zero intro-rate, on average their desired intro-period is 9 months longer than what they got and 5 months longer than the actual intro-period of the rate switchers switched to. To see what the offers need to be for different types of mail-offer receivers, we separate non-switchers who got a zero intro-rate into three groups, according to their intro-periods: zero to three months, three to six months and six to twelve months.

Let \( d \) be the intro-period of a new offer. let \( d^D_i \) be the desired one for non-switcher \( i \). The acceptance rate that an offer with intro-period \( d \) can achieve is \( 0.4 \sum_{i=1}^{N} I(d \geq d^D_i) \), where \( N \) is the sample size of each group and \( I(d \geq d^D_i) \) is an indicator. \( I \) is equal to 1 when the event in the parenthesis is true and 0 otherwise. The multiplier 0.4 comes from the fact that among all the non-switchers who got a zero intro-rate offer, only forty percent of them are willing to switch a balance if the intro-period of this rate is prolonged. We consider the range for the intro-period received is \((0, 3] \), \((3, 6] \) and \((6, 12] \) respectively in each group.

As shown in the Figure 3, an offer with 6-month-intro-period will begin to attract non-switchers in the first group. Any intro-period longer than 12 months does not make further significant effect on raising the acceptance rate and should be considered unnecessary. To attract non-switchers who are in the second group, an offer will not take a substantial effect until the intro-period is prolonged to 12 months. Any period longer than that does not make any significant changes. For non-switchers
who already got relatively good offers: zero intro-rate and an intro-period between
6 and 12 months, an offer with intro-period 12 months will only attract seventeen
percent of them. Limited by the ceiling rate 40%, the profit of attracting the rest
handful of potential non-switchers by prolonging the intro-period barely compensates
the cost of doing so. The information that is useful for card issuers here is that a 12
month offer is the most effective one. Any period longer seems a waste of effort.

For the non-switchers who got positive rates, on average they desire an intro-rate
4.6% points lower and intro-period 6 months longer. Let \((r, d)\) be the a new offer and
\((r^D_i, d^D_i)\) be the desired one. The acceptance rate that this new offer will achieve is
\[
\frac{\sum_{i=1}^{N} I(r^D_i \geq r) I(d \geq d^D_i)}{N}.
\]
As shown in Figure 4, the five curves represent the acceptance rate as a function of intro-period, given five levels of intro-rates at 0%, 3%, 5%, 6%, 10%, and 12%. At \((r, d_i) = (6\%, 12)\), 19% of these non-switchers will switch. At
the offer \((r, d_i) = (0\%, 12)\), 70% of these non-switchers would switch. Given at zero
rates, increasing the intro-period \(d\) from 12 months to 24 months will only boost the
acceptance rate from 70% to 75%. While given intro-period at 12 months, decreasing
the rate from 6% to zero will enhance the acceptance rate remarkably from 19% to
70%. Figure 4 is a piece of evidence of the third finding in Ausubel (1999) which
was referred to "underestimation hypothesis": consumers tend to over respond to
the intro-rate rather than to the intro-period. To grab an overall view, similar figures
could be drawn for the pool of switchers and non-switchers. In that case, the obtained
acceptance rate would be slightly downward biased because the offers already accepted
by switchers are at least as good as their reservation offers.

The real acceptance rate should be smaller than the predicted one. There should
be a fair amount of non-switchers who would never switch at any offer. The ambiguity
of willingness of those who did not report limits us on non-switchers who report their desired offers. As a result, the predicted rate is inflated to some extent.

2.2.4 Test of Significance of Spread between New Card Rate and Old Card Rate

As the major result of Kim (2000) and Ekici, Dunn and Kim (2007), the spread between the new card rate and the old card rate is the key factor of consumers’ balance switching decision. We test the significance of this difference in this section. This question could also be addressed as whether consumers make decisions based on the spread in rates or they only focus on the new rates printed in bold letters on their mail offers.

This test is not immediate to carry through because the spread in rates is only observed for switchers. For non-switchers, this spread is defined as the difference between their current card rate and lowest rate available in the mails. We asked for interest rates on three representative cards in the old survey. We find that non-switchers’ accumulative credit card debt spread evenly on all the current cards in use. They pile up their outstanding balance more intensively on the most recently opened card, which has the lowest interest rate. Since switching away from a higher rate card would bring larger savings, we believe that non-switchers would take their highest rate card as the potential card once they decide to switch. So, the old card rate is assumed to be the highest rate among three cards. We do not use the rate of the unique card from new survey because it is the rate on the most used card and is significantly lower than the rate of other cards.

As Table 4 suggests, although non-switchers’ new rate (the lowest mail rate) is much higher than switchers’ actual new rate they switched a balance to, their old rate
is also significantly higher than switchers’ old rate. As a result, their spreads between old card rate and new card rate are comparable. The fact that we see no difference in their spreads implies that when card holders make decisions about balance switching, they may only focus on the visual and explicit terms in the mail offers, such as intro-rate and intro-period. It also supports our belief that switchers are more active low-rate hunters and users.

2.2.5 Looking Forward on $MMPTI/CCDTI$

We would like to distinguish switchers and non-switchers by looking both forward and backward on their credit risk. The projection of future default risk is primarily based on historical data such as past default frequencies. But since we want to examine the impact of balance switching on debt situation, we look at the credit card debt burden, in the relatively short term and long term. Dunn and Kim (2002) suggests that the ratio of monthly minimum credit card payment-to-income ($MMPTI$), the balance utilization rate and the number of "maxed-out" cards have significant predictive power for households’ default risk. $MMPTI$ reflects the payment pressure of the immediate following month. We treat it as the index of short-term credit card debt burden because it directly discloses card holders’ capability of staying away from missing payments for next month.

The ratio of credit card debt-to-income ($CCDTI$) is commonly used as a predictor of long-term default risk. If we partition these two ratios into several categories in an ascending order, the switching proportion in these categories shows a picture of switchers’ possible default situation in the near and relatively far future. Basically, the switching proportion is bigger when $MMPTI$ and $CCDTI$ are higher. This fact
can be seen in Table 5: when we look forward, both in the short run and the long run, switchers still bear a significantly heavier debt burden. We have reasons to believe that they are more likely to default in the future.

### 2.2.6 Looking Backward on Default History

After we label switchers as riskier borrowers in the future, we assume that they were borrowers that had higher frequency of delinquencies in the past too, given there is no external impact. We further investigate switchers’ default situation after they switched by looking at the link between their default history and credit card debt burdens.

As shown in Table 6, we did not find a strong correlation between cardholders’ switching activity and their default history. Switching behavior happened in the same window when default information was collected. Instead of saying that the switchers and non-switchers had similar default history, we would rather say that switching did reshuffle good borrowers and bad borrowers in a temporary fashion. As a result, we can not distinguish bad borrowers from good ones under the short-lived impact of balance switching. We propose it as our first hypothesis: right after switching, switchers’ default situation had been improved, which is exactly the primary goal of balance switching.

### 2.2.7 Link between Default History and $MMPTI/CCDTI$

It makes perfect sense that borrowers’ risk types are consistent over time. In a time order, those who had debt-paying problems in the past should have heavier debt burden now, and higher default propensity in the future. This consistency could break if some external impact occurs. Switching behavior is one of those activities
that produce such an impact. Without jumping too far from default history to future default, which has not historically grounded, we link cardholders’ past default indicators to their current $MMPTI/CCDTI$ ratios.

Taking non-switchers’ side as the benchmark, we should observe a tight link between their past default activities and their credit card debt burden $MMPTI/CCDTI$. As expected, Table 7 reveals a strong relationship between non-switchers’ past risk types and their debt burdens, in the short run and in the long run.

If the story changes on switchers’ side, we take it as evidence that switching activity does take effect on debt problems. As shown in Table 8, for switchers, the link between $MMPTI$ and default history is weakened. We still observe some strong correlation between $MMPTI$ and past default situation since $MMPTI$ itself represents the debt-paying situation up-front. When it comes to the long-term debt burden $CCDTI$, this link vanishes thoroughly.

Comparing non-switchers’ side with switchers’ side, we found evidence that switchers might have alleviated their debt problem right after switching a balance to a lower rate. Nevertheless, they still confront with a heavier debt burden and higher future default risk than non-switchers, in spite of the temporary improvement in their default situation. This reminds us the existence of "adverse selection" in the balance switching, which will be discussed in the section 2.2.9.

2.2.8 Dependence of the Quality of Mail Offers on Default History

Now we investigate the dependence of quality of mail offers on receivers’ default history. If the quality depends on receivers’ past default situation, the offers go to households according to some preliminary sorting implemented by card issuers;
otherwise, the offers are just sent out arbitrarily. The non-switchers can be divided into three pools based on their past default occurrence (credit card late payment): low risk pool, middle risk pool and high risk pool. Other covariates also work as complementary indicators of default history such as the number of late payment to credit card balance, whether having account collected by collection agencies, and bankruptcy. Table 9\textsuperscript{6} suggests a strong correlation between non-switchers’ lowest rates from mail and their default histories.

Although we still observe some correlation between the default history and intro-rates on switchers’ side, this dependence is weakened to a great extent due to two possible reasons. First is the hypothesis we proposed in section 2.2.6. We notice that for switchers, the word "history" does not precisely refer to a period prior to their switching behavior. Their default information was collected in the same window when their switching activity took place. We believe that their default situation temporarily changed after they switched a balance. Put differently, this default information could differ from the real one that card issuers had collected and based on which they sent out mail offers. Non-switchers are considered as future switchers. Their default history has not yet been affected by their possible future switching behavior. Therefore, the dependence of mail rates on the default histories revealed on non-switchers’ side should be believed true for all the card holders, at day one before switchers actually accepted the offers and the switching effect took place. We propose the second reason as our second hypothesis: the rates actually chosen by switchers do not reflect the average quality of their rate being offered. No matter what rates they already got, they are waiting for a rate that is sufficiently low. When we compare switchers’

\textsuperscript{6}Through out this paper, *** denotes significance at 1% or better.** denotes significance at 5% or better.* denotes significance at 10% or better.
current rates with non-switchers’ current rates, we find that switchers generally hold cards with a lower rate. This means that switchers are more sensitive to a low rate and thus they might not switch until they finally got it. If we regard good offers are the ones with zero intro-rates, we can use Kruskal-Wallis test\(^7\) to detect any dependence of the likelihood of getting a zero rate offer on default histories. Table 10 suggests a more clear-cut line between switchers and non-switchers than Table 9: a crucial dependence of the likelihood of getting a zero-rate offer on default history on non-switchers’ side and an entire independence on switchers’ side. This confirms our believe that switchers’ accepted rates do not show the pattern of their received rates. We will further test these two hypotheses later in our econometric model analysis.

The above discussion leads to our third hypothesis: consumers who experienced bad default histories and are less likely to receive a low rate offer in each month. They have to wait for a longer time to switch. We are going to test it in the duration models in chapter 5.

In contrast to the intro-rate, intro-period has less influence on the profit that card issuers could make. This fact is consistent with our findings that the intro-period lacks a dependence on receivers’ default history. Only intro-rate is what the issuers mainly concern about. The dependence of the quality of mail offers on default history is represented by the decreasing proportions of getting good offers in each risk pool during six months respectively: 0.47, 0.38, and 0.22, taking non-switchers’ side as benchmark.

\(^7\)The Kruskal-Wallis test is a non-parametric test used to compare more than two samples. It is used to test the null hypothesis that all populations have identical distribution functions against the alternative hypothesis that at least two of the samples differ only with respect to location (median), if at all. It is a logical extension of the Wilcoxon-Mann-Whitney Test. Since our default history indicators are mostly categorical and some of them take more than two ordinal values, the Kruskal-Wallis test has more detecting power than regular two sample t test.
2.2.9 Adverse Selection in Balance Switching of Credit Card Market

For non-switchers, their default history is strongly correlated with their current debt burden. Those with worse default history still have higher default risk in the future. But for switchers, the link between their "past" default situation and their current debt burden is almost broken. The best explanation is that their default situation had been improved right after they switched a balance. So we have reasons to believe that switchers' default history before they switched a balance or their default history that would have been if they hadn’t switched a balance was worse than their counterpart. In general, switchers bear a heavier debt burden than non-switchers. As stated above, balance switching is only a short run remedial solution to their default problem. With the previous result that switchers on average accepted superior offers than non-switchers, we claim that the "winners curse" and "adverse selection" exist in the balance switching section.

Among the literature of credit card market, three versions of "adverse selection" appeared in succession. They basically have a reverse effect on each other. In Stiglitz & Weiss (1981): the credit cards rate is upward sticky because if all banks currently charge the same rate, no banks will deviate to a higher rate because the only borrowers who are willing to take this high rate are riskier consumers. In Ausubel (1991): the credit card rate is downward sticky because banks hesitate to decrease the card rate, otherwise they only draw the bad consumers who are sensitive to the rates. Ausubel (1999) puts forward a new version of "adverse selection" against his old one: consumers who take the higher rate offers are higher risk borrowers. In our paper, we proved the "winner's curse" in balance switching mail solicitation as the one proved in
credit card market in Ausubel (1999). The "adverse selection" in balance switching, however, supports the earlier version in Ausubel (1991) and is against Ausubel (1999).

As shown in Table 9 and Table 10, card issuers send out mail solicitations based on the signals of consumers' default history. If the lowest rate from mails hit the bottom line of their expectation, consumers then decide to be a switcher. Following Ausubel (1999), this procedure works as a sealed-bidding auction: issuer \(j\) offers rate \(r^j(s^j)\) based on the signal \(s^j\) of receiver's default risk \(\delta\). The bidder offering the lowest rate wins the auction. Then "winners’ curse" occurs since \(s^j\) is lower than average and \(E(\delta|r^j(s^j)) > E(\delta)\).

But in the other finding of Ausubel (1999), the respondents with worse default risk get relatively inferior offers. More accurately speaking, these respondents with worse default risk were not voluntarily choosing the inferior offers, but were chosen by them. Since his result was based on a large scale of experiments in pre-approved card solicitations, we are more willing to believe the fact in the real world. Nowadays banks distribute credit cards aggressively. If consumers are persevering in searching, it is still promising for them to get a low rate offer, despite of their default risk. Support could be found in Crook (2002) that households with poor payment history do not appear to search more or less than those with better payment histories. Kerr & Dunn (forthcoming 2008 in JBES) further pushes the result by claiming that high likelihood rejection for the high-balance consumers actually spurs their search behaviors.

In our data, switchers are found to have more credit cards in use. Their current card rates are on average lower than those of the current cards that non-switchers hold, no matter for the newest account card, the charged most card or the card carrying the highest balance. Due to their debt situation, switchers obviously exhibit
more sensitivity to the card rates and they search more or wait for a longer time to obtain such a low interest rate. This finding is exactly the characteristic that Ausubel (1991) endow with bad consumers. This kind of consumers is more likely to be switchers in our context of balance switching.

### 2.2.10 Income and Asset Information Categories

We now compare the finance status of switchers and non-switchers. Besides all the covariates we talked about, variables about finance situation are believed to have tight relation with balance switching, either ex-ante or ex-post. We explore interaction between the asset holding and balance switching by looking at the switching proportion in different income, asset, and net worth cohorts.

Income turns out to be insignificant correlated with balance switching behavior, while net worth and asset have negative effect. The switching proportion in each cohort of income, asset and net worth is displayed in Figure 5, Figure 6, and Figure 7.

### 2.2.11 Balance-Carrying History

The survey also tracks the balance-carrying history and records the number of times that balance was carried during the past twelve months. To see if a balance carrier with higher frequency would be more likely to switch, the relationship between frequencies of balance-carrying and switching is checked.

In Table 11, everything looks straightforward except that 5% of the non-balance carriers switched during the past 6 months. Equivalently, 7% of the balance switchers did not carry any balance during the past twelve months. This finding suggests that besides the primary goal of cutting down monthly credit card debt payment, minority
of consumers switch to new cards because of perks or other speculation reasons. In reality, some of them labeled as transactors are found creating credit debt on zero intro-rate cards during the intro-rate period and putting the money borrowed into a saving account with positive interest rate or even to a high yield bearing investment such as stock markets. An alternative possibility is that up till the latest month of survey, some of these transactors switched their payment during the grace period and never got caught as a balance carrier. This is the reason why we keep cardholders rather than revolvers as our target sample. The new survey changed the question from carrying behaviors in the past twelve months to the most recent month. It is not surprising that the 76% of switchers carried balance from last month, while only 35% of non-switchers did so.

In each of the two categories for switchers and non-switchers, the number of months involved carrying balance is evenly distributed, through 0 to 12. There is no strong evidence that those who switched during the last six months carried a balance more times than those who did not. If we separate carriers into 13 groups, according their balance-carrying times (0 – 12) during the past twelve months, we found that the proportion of switching in the past 6 months is not a monotone function of the balance-carrying frequencies. As a result, once carried a balance, almost half of balance carriers did so in each month and the number of times they carried a balance does not affect their switching possibility. A conjecture about this irrelevance could be: the number of times of carrying balances is a piece of detailed information that is not available to banks. Hereby it causes no impact on the card rate, which is the primary determinant of switching.
2.2.12 Socioeconomic Characteristics

Balance switching is an economic behavior affiliated with the complex of social economic characteristics. It is always involved with the effort like careful filing out forms, dealing with both new and old card companies, closely reading the fine print of terms and deciphering the tricky strategies which might lead to pitfalls. All these hand and brain work make it necessary to test whether education background could be a factor that affects consumers’ switching decision.

In Table 12, significant correlations are found between balance switching and socioeconomic characteristics, such as age, gender, marriage status and the number of children in a family. The statistics suggest that the senior is less likely to switch a balance, while women are more likely to switch a balance. A family with more children is more likely to switch a balance. The education background is not significant, however, against the result in Kim (2000) that education is an important factor for switching decision and the most elastic one among all the four variables studied. All these significant covariates will be tested in the duration model in next section.

We also want to investigate that whether balance switching is a regional activity. The Chi-square test shows no significant difference in the four geographic regions, although south area oversees a higher switching proportion than other areas, as shown in Figure 8.
CHAPTER 3

Theoretical Model Analysis of Balance Switching Behavior

3.1 A Simple Theoretical Model

Before we go to empirical analysis, we attempt to rationalize cardholders’ switching decision by using a simple theoretical model.

3.1.1 Model Setting

In practice, card holders usually receive card offers with various APR each month by mail. Banks send out offers based on consumers’ default history. As shown in Table 10, those with higher past default risk are less likely to receive a zero-rate offer. Let $P^D$ be the probability of receiving a zero-rate offer in each month. $D$ denotes three default risk type: low, medium and high. We classify cardholders who never missed credit card payment as of low risk, cardholders who missed once but less than 60 days as of medium risk and cardholders who missed payment for 60 days or longer as of high risk.

$$D = \begin{cases} L & \text{if never missed credit card payment} \\ M & \text{if missed once for less than 60 days} \\ H & \text{if missed for more than 60 days} \end{cases}$$

(3.1)

The theoretical model contains variables described in Table 13.
Since the primary goal of balance switching is to mitigate the debt problem, we only model revolvers’ optimal choice of minimizing their debt payment, putting aside the minor motivation of speculation. We assume that a cardholder carries an outstanding balance with amount equal to $D^c$ at the beginning of the first month. Like paying for an amortized loan, she plans to pay a fixed amount of payment $M$ each month until time $T$. The pay down schedule is set in the way that at time $T$, after she pays the last amount $M$, the total debt will be paid off. Since it is hard to track the consumption propensity of each consumer, we simply assume that she will not add new purchase each month to the original outstanding balances on this card. If this balance carrier does not switch her balance to another lower-rate card, she needs $T = T_n$ months to pay off her original credit card debt. If she plans to launch her first switching at the $s^{th}$ month, the total time length she needs is $T = T_s$ months. So far, the theoretical model focuses on the first move of switching and rules out the repeated activities on lower rates afterwards. The duration spell with old cards shows a pattern of multiples of 6 months. Together with the fact that most of the low transfer rate offers are good for 6 or 12 months, we assume that consumers tend to switch again only when the intro-period expires. In other words, consumers do not continuously keep switching to any lower rate they come across. This fact also explains the absence of intro-period in this model, since we agree that after the first move, switchers always can renew their offer by switching to another card. The practical reason for the conservative behavior of not keeping jumping to any low rate is that switching does cost time and money. Besides the switching fee (usually $50$ to $75$), the application process that applicants need to go through is far from pleasant: they have to be very careful about the tricky terms that are hidden as fine prints in
the offer specifications; they might also need to deal with the old card companies on
the phones. What else matters is the intangible jeopardy that the record of keeping
applying for new cards in a short time might cause on consumers’ credit scores.
All these cost make the frequent switching less worthy. Another explanation is the
intrinsic characteristic of inertia. Once settled down, consumers hesitate to act again
for an interest rate that is only slightly lower.

Let $Y$ be the number of zero-rate offers in $n$ months. $Y$ is assumed to be subject
to a Binomial distribution $\text{Bin}(n, P^D)$. Data tells us that in the past six months,
the proportion of zero-rate receivers among all card holders for each risk type is 0.47,
0.38 and 0.22 respectively. Then $P^D$ is derived as follows.

$$1 - \Pr(\text{ob}(Y = 0|n = 6) = 1 - (1 - P^D)^6 = \begin{cases} 0.47 & \text{if } D = L \\ 0.38 & \text{if } D = M \\ 0.22 & \text{if } D = H \end{cases}$$ (3.2)

Immediately we have:

$$P^D = \begin{cases} P^L \\ P^M \\ P^H \end{cases} = \begin{cases} 10.04\% \\ 7.66\% \\ 4.06\% \end{cases}$$

So the average run length for each risk type to get a zero-rate offer is:

$$ARL^D = \begin{cases} ARL^L \\ ARL^M \\ ARL^H \end{cases} = \begin{cases} \frac{1}{\hat{P}^L} \\ \frac{1}{\hat{P}^M} \\ \frac{1}{\hat{P}^H} \end{cases} \approx \begin{cases} 10 \text{ Months} \\ 13 \text{ Months} \\ 24 \text{ Months} \end{cases}$$ (3.3)

Obviously, those with worse default histories stand on a lower chance to get a
zero-rate offer each month. In other words, to receive a zero-rate offer, their average
run length (the inverse of $P^D$ ) will be longer, compared to those with better default
histories. Switchers are well aware of their own risk types and they know banks are
less likely to offer a zero-rate if their risk is higher. We assume revolvers have their
own expectation that on average how many months they have to wait to receive their
first zero-rate offer. Let \( r_1(t) \) denote the expected best rate offered up until time \( t \), which is based on card holders’ type of default risk \( D \) and \( t \). \( t \) takes discrete values of 1, 2, 3 and so on. For simplicity, we only consider the default risk type as the major factor that affects banks’ rate offers and ignore other minor determinants of consumer-specific characteristics like income and age. So \( r_1(t) \) takes a straightforward linear form as follows:

\[
 r_1(t, APL^D) = \begin{cases} 
  -\frac{r_0}{ARL^D} (t - 1) + r_0 & \text{if } s \leq ARL^D \\
  0 & \text{if } s > ARL^D 
\end{cases}
\]  

(3.4)

Where \( r_0 \) is the current rate at beginning.

In reality, the interest rate comes out randomly subjected to \( P^D \) each month. An offer usually expires after one to two months if not activated. We need to emphasize here that \( r_1(t) \) is not the interest rates cardholders really receive. It only reveals potential switchers’ expectations of the best rate they could get over time. Switchers are well aware of their own risk types and they know banks are less likely to offer a zero-rate if their risk is higher. So they could make their own forecast for the coming zero-rate. We assume that they take the average run length as on average the number of months they have to wait to receive their first zero-rate offer. As for the rate between zero and \( r_0 \), similar expectation could be made. So we assume a downward sloping straight line for the rate function. As a result, our theoretical model only provides a snapshot of revolvers’ decision at beginning about their switching timing based on their expectation of the intro-rate.

At the beginning time \( t = 1 \), the best interest rate balance carriers face is the current rate \( r_0 \). As time goes by, they could come across lower rates and decide whether to switch to it or not. So on average or in expectation, the longer time they
wait, the lower rate they could get. When time equals to $ARLD$, they expect to receive a zero-rate offer. After that, the rate is set at zero.

### 3.1.2 Revolvers’ Optimization Problem

We first consider the non-switching case. At the beginning of the first month, she holds balance $D^c$ and she will pay $M$ in this month. The revolved debt at the beginning of the second month would then be $(1 + r_0)(D^c - M)$. Consequently, the debt at the end of each month $t$ after the fixed amount $M$ is paid would be $(1 + r_0)^{t-1} D^c - M \left( \frac{r_0^{-1}}{r_0} \right)$. So at the beginning of the last month $T$, her remaining debt would be $(1 + r_0)^{T-1} D^c - M (1 + r_0) \left( \frac{r_0^{-1}}{r_0} \right)$. Her debt would be cleared after the last time payment, which means the total time length $T$ is a function of $r_0$, $D^c$ and $M$, expressed as:

$$T_n = \frac{\log(M) - \log(M - \frac{D^c r_0}{1 + r_0})}{\log(1 + r_0)} \quad (3.5)$$

The above equation constrains the fixed amount of payment each month $M > \frac{D^c r_0}{1 + r_0}$. This condition is easily satisfied as long as the original APR is less than 50%, since the monthly minimum payment is max ($10, \alpha D^c$). $\alpha$ is the minimum payment rate. It is 2% in most cases. But now due to pressure from federal regulators, it has been recently increased to 4% by some major credit card issuers.

If this balance carrier does not switch during $T_n$, she pays $M$ each month. The opportunity cost in month $i$ is then $MR^{T_n-i}$, in the perspective at time $T_n$. So the discounted total payment ($DTP^n$) at the day when paying off all credit card debt is:

$$DTP^n = \sum_{i=1}^{T_n} MR^{T_n-i} = M \left( \frac{R^{T_n} - 1}{R - 1} \right) \quad (3.6)$$

$^8$It is equivalent to that $M$ should be larger than 0.99% of the original debt, given the current APR is 12%. 35
Then we consider the balance-switching case.

Suppose this balance carrier switches to $r_1(s)$ at time $s$. Before she can enjoy the lower rate, she usually needs to apply a month in advance and pay the transaction cost $k^9$ at the end of period $s - 1$. Her revolved debt after paying $M$ at the end of time $s - 1$ is denoted as $D(s)$:

$$D(s) = (1 + r_0)^{s-2} D^c - M \left[ \frac{(1 + r_0)^{s-1} - 1}{r_0} \right]$$

(3.7)

At the beginning of time $s$, she holds credit card debt $(1 + r_1(s)) D^c$. From then on, her revolved debt is charged at the new interest rate $r_1(s)$.

Let $s_1$ be the time periods for her to pay off the remaining debt from time $s$. If $r_1(s) > 0$, similarly, we have:

$$(1 + r_1(s))^{s_1} D(s) - (1 + r_1(s))^{s_1-1} M - \cdots - (1 + r_1(s)) M = M$$

(3.8)

If she switches to a zero-rate card at time $s$, she simply needs $s_1 = \frac{D(s)}{M}$ months to clear her debt. So,

$$s_1(r_1(s), D(s)) = \begin{cases} 
\frac{\log(M) - \log(M - r_1 D^c)}{\log(1 + r_1)} & \text{if } s \leq ARL^D \\
\frac{D}{M} & \text{if } s > ARL^D
\end{cases}$$

(3.9)

The total time length given switching is the sum of the time of staying with the old card and the time after switching until the remaining debt is paid off, i.e.:

$$T_s = s - 1 + s_1(s)$$

(3.10)

The discounted total payment for switchers ($DTP^s$) with the discounted transaction cost is expressed as:

$$DTP^s = \sum_{i=1}^{T_s} M R^{i-1} + k R^{s_1(s)} = M \left( \frac{R^{T_s} - 1}{R - 1} \right) + k R^{s_1(s)}$$

(3.11)

$^9$Switching cost includes switching fee, time and effort of applying for new cards and the potential jeopardy to credit scores
Given their expectation of arrival of lower rates, at the very beginning, balance carriers chooses the time point $s$ to switch balances in order to maximize the benefit of switching. This benefit is expressed as the difference between $DTP^n$ and $DTP^s$. On one hand, the earlier they switch, they benefit from a rate lower than $r_0$ for a longer time and save more on discounted total payment. On the other hand, the later they switch, they could enjoy a lower new rate and in turn save more on the rest of their debt payment. What’s more, later switching brings about a lower level of discounted transaction cost. Their optimization problem is specified as follows:

$$\max_s (DTP^n - DTP^s) = \frac{M}{R-1} (R^{T_n} - R^{T_s}) - kR^{s_1(s)}$$

$$\text{s.t. (3.5) - (3.11)}$$

(3.12)

### 3.1.3 Predictions from the Theoretical Model

The optimal switching timing is $s^*\left(D^c, r_0, M, ARL^D, k, R\right)$, based on all the expectations of future rates. Instead of solving for the explicit form of optimal $s^*$, we calibrate our model using the statistical result and some common sense. Then we draw the benefit of balance switching as a function of switching time point $s$. The optimal timing $s^*$ might not be an exact math for the actual one due to the assumption of the expectation of lower rates. But the findings here could fill the lacking of theoretical explanation for switchers’ motivation until now. We will test the theoretical predictions in duration models in chapter 5.

Figure 9 shows nine pictures of benefit of balance switching for revolvers. Three columns represent the three risk types. The average run length takes value of $ARL^L=10$; $ARL^M=13$; $ARL^H=24$ respectively for each column. Three rows represent the three levels of original card balance. Data tells us that the medium of the amount switched
is $4,000. We also want to compare it with a lower level $1,000 and a higher level $10,000. Other parameters are calibrated as: $R=1.04$, $r_0=\frac{APR_0}{12}=1\%$, $M=0.04 \times Dc$.

Figure 9 displays two striking findings: first, in each row, the optimal balance switching time point is the $10^{th}$ month for low default risk type and the $13^{th}$ month for the middle default risk type. Both of these switching timings are exactly the time points when they expect to receive the zero intro-rate. For high risk type, however, their optimal switching time point is around the $21^{th}$ month, 3 months ahead of the arrivals of their zero intro-rate. This is probably because they can not afford to wait that long, so they choose a desirable rate which is slightly above zero to make the discounted total payment as small as possible. According to simple linear form of the expected best intro-rate, the rate in $21^{th}$ month is almost zero. In a nutshell, the revolvers choose an intro-rate that is sufficiently low (either zero or close to zero) to switch to, despite their past risk types. This is in favor of the homogeneity of the accepted rates by switchers, as observed in our data. The underlying intuition lends support to the third hypothesis in section 2.2.7 that revolvers with bad default history have to wait longer to switch because their desirable rate arrives later. In the duration models, we then expect a negative effect of the past default risk on switching hazard rate, or equivalently, a positive effect on the duration spells.

Second, in each column, the benefit curves show uniform pattern for three levels of card balance, indicating that the amount of credit card debt itself seems not a powerful momentum for balance switching. This finding might be frowned upon since we tend to think that larger amount of credit card debt should push revolvers to switch more quickly. Kim (2000) did find it as a key driver of balance switching. The theoretical model, however, does not take into account of other variables that predict the degree
of urgency more powerfully. Neither does it consider the interaction effect of original credit card debt and other crucial variables. A more formal test of significance will be conducted systematically in the duration analysis in chapter 5.

This theoretical model has some flaws. We simply assume that revolvers could finally pay off their debt and avoid the possibility that they might run into any debt problem during the course. A person who has difficulty of affording the minimum monthly payment could rush into switching to elude serious debt problem, rather than choosing the optimal time point to minimize his lifetime payments. In our data, we do find some switchers switched to a rate that is higher than zero. While the model does not fit the changing priorities for particular individual, it does a good job on revealing switchers’ choice of timing, given they are forward looking. The linear rate function could also be improved to track the arrival of good rate better, if endowed with more information on offer receiving.

3.2 Exercise of Recursive Dynamic Optimization

Previous theoretical analysis is based on static mode. Revolvers choose their switching timing at the very beginning. While in practice, balance switching is a dynamic decision and could be carried based on different reservation rates over time. The following section will do an exercise of recursive dynamic optimization, aiming to pointing out how switchers’ reservation rates change over time and how they differ between risk types.

3.2.1 Notations and Assumptions

Some notations are same as the ones we used before. We assume that time takes discrete values. Initial month is \( t = 1 \) and \( t = 1, 2, 3, \ldots \). Current credit card debt
is $D^c$ (default at 4,000). Old rate is $r_0$ (set as 0.01). $r(t)$ is the rate offered in month $t$ and it is subject to distribution $F(\cdot)$, with corresponding pdf $f(\cdot)$.

For risk type $D$, $r^D(t) = \{0, 0.0008, 0.0017, \ldots, 0.02\}$ with probability $p^D = \{p_0^D, p_1^D, \ldots, p_{24}^D\}$. At each month $t$, a revolver holds a reservation rate $r_t^*$. He will switch a balance if and only if $r_t \leq r_t^*$. $k$ is the transaction cost. $d_t$ is the debt at the beginning of month $t$. $m_t$ is the minimum monthly payment, set as $\max(\alpha \cdot d_t, 25)$ with $\alpha = 4\%$. For any pair $\{d, r\}$, given no balance switching, a revolver takes $T$ months to pay off debt $d$ at rate $r$. For every pair of $\{d, r\}$, the total number of months needed to pay off the debt could be obtained. Also we can calculate the revolved debt $\{d_t\}_{t=1}^T$ and monthly payment $\{m_t\}_{t=1}^T$ at each time. The total payment from then on is defined as $P(d, r) = \sum_{t=1}^T m_t$. $\pi_t$ is the total expected payment from month $t$ to the date of paying down, given no balance switching until month $t$. For now, we only consider switching once.

### 3.2.2 Recursive Equilibrium Strategy

The reservation rate $\{r_t^*\}_{t=1}^T$ at each time $t$ can be solved by recursive dynamic optimization.

In the last month $T$:

\[ \pi_T = d_T = m_T \]  
\[ r_T^* = -1 \times 10^{-3} \]  

In month $T - 1$:

\[ \pi_{T-1} = m_{T-1} + m_T \]  
\[ r_{T-1}^* = \begin{cases} 
-1 \times 10^{-3} & \text{if } P(d_{T-1}, 0) + k > \pi_{T-1} \\
r & \text{otherwise}
\end{cases} \]

where $r$ satisfies: $P(d_{T-1}, r) + k = \pi_{T-1}$.
In month $T - 2$:
\[
\pi_{T-2} = m_{T-2} + \int_0^{r_{T-1}^*} \left[ P(d_{T-1}, s) + k \right] f(s) ds + \pi_{T-1} \cdot [1 - F(r_{T-1}^*)] \tag{3.17}
\]
\[
r_{T-2}^* = \begin{cases} 
-1 \times 10^{-3} & \text{if } P(d_{T-2}, 0) + k > \pi_{T-2} \\
r & \text{otherwise}
\end{cases} \tag{3.18}
\]

where $r$ satisfies: $P(d_{T-2}, r) + k = \pi_{T-2}$.

In month $T - t$:
\[
\pi_{T-t} = m_{T-t} + \int_0^{r_{T-t+1}^*} \left[ P(d_{T-t+1}, s) + k \right] f(s) ds + \pi_{T-t+1} \cdot [1 - F(r_{T-t+1}^*)] \tag{3.19}
\]
\[
r_{T-t}^* = \begin{cases} 
-1 \times 10^{-3} & \text{if } P(d_{T-t}, 0) + k > \pi_{T-t} \\
r & \text{otherwise}
\end{cases} \tag{3.20}
\]

where $r$ satisfies $P(d_{T-t}, r) + k = \pi_{T-t}$ for $t = 1, \cdots, T - 1$. Then we solve $\{r_t^*\}_{t=1}^T$ and thus the equilibrium probability of switching in each month $\{F(r_t^*)\}_{t=1}^T$.

### 3.2.3 Characterization of Main Variables in Numerical Examples

The comparison of different types of card holders in default risk and original balance level is shown in the following numerical examples.

The conclusion we can make from the Figure 10- Figure 14 are: high risk card holders have higher reservation rates than low risk card holders; revolvers with higher debt level have higher reservation rates. $\pi_t$ is the expected total payment from current month $t$, conditional on not switch until $t$ and could switch in future. $\sum_{s=t}^T m_s$ is the total payment from current month $t$, conditional on never switch. $\pi_t$ decreases faster at $D^c = $10,000 than at $D^c = $4,000 and $D^c = $2,000, suggesting that higher level of debt leads to lower reservation rate. High risk type revolvers have lower probability of switching at each time $t$. So we should expect the positive effect of default history on duration spells.
3.2.4 Predicted Duration Spell before Switching

\( \tilde{T} \) is a random variable, denoting the duration time switchers stay with old cards. \( \tilde{T} = 1, 2, \cdots, (T + 1) \). Since we already have the reservation rate at each time \( t \), we can obtain the probability of switch at each time.

\[
\text{Prob}(\tilde{T} = t) = (1 - F(r_1^*)) (1 - F(r_2^*)) \cdots (1 - F(r_t^*)) F(r_{t+1}^*)
\]

(3.21)

\[ E(\tilde{T}) \text{ (std) } = 2.7 \ (2.1) \text{ for low risk type revolver and } 4.2 \ (3.6) \text{ for high risk type revolvers. High risk type revolvers on average wait for a longer time. This estimated duration time is similar for all the three levels of debt, implying that the amount of credit debt itself is insignificant factor on duration spells. In later empirical work, we will compare this estimated duration with the one obtained from data.} \]
CHAPTER 4

Econometric Models and Empirical Investigations

4.1 Theoretical Foundation for Econometric Models

To proceed the empirical analysis in the following section, we build the economic theory foundations based on which we set up our econometric models. The utility function is defined as \( U(x) \), where \( x \) is the vector of various consumption goods. A representative household maximizes their utility by choosing the quantity of consumption goods at given price vector \( p \) under the budget constraint \( px = Y \). Here we assume that \( Y \) is the discretionary income, defined as the residual of household income subtracted by the discounted debt payment and the cost of raising the children, i.e.,

\[
Y = y - DTP \times I(balance \ carrying) - c \times childnum
\]

In the above equation, \( y \) is the household income; \( DTP \) is the discounted credit card payment; \( c \) is the average cost of raising a child (according to the 2005 report from the Department of Agriculture, the cost of raising a child to the age of 17 will be approximately $500,000); \( childnum \) is the number of children raised by this household; and \( I(balance \ carrying) \) is an indicator, which is 1 when the event of balance carrying is true and 0 otherwise. Given the consumption goods price vector
$p$ and the child-raising cost $c$ as constant parameters, the indirect utility is $V (y, DTP, balance\ carrying, childnum)$. When facing the binary choice of switching, this representative household chooses to switch a balance if $V^s - V^n > 0$, not to switch if $V^s - V^n \leq 0$, where $V^s$ and $V^n$ denote the indirect utility given switching or not switching respectively.

Recall that our simple theoretical model in chapter 3 already demonstrated that for a balance carrier, $DTP$ is a function of the $T^n/T^s$, the time paying off the debt. For non-switchers, $T^n$ is $T^n(D^c, r_0)$; for switchers, $T^s$ is $T^s(D^c, r_0, r_1, d)$, given minimum payment rate $\alpha$, switching traction cost $k$, and the market rate $R$ as constant parameters\(^{10}\).

We define the latent variable as $I^*$, expressed as:

$$I^* = X_0\beta_0 + \varepsilon$$

where $X_0 = (D^c, r_0, r_1, d, y, balance\ carrying, childnum )$.

We only observe whether a card holder switched a balance or not. There are two types of sample members:

- **Type I** $I = 1$ if $I^* = V^s - V^n > 0$
- **Type II** $I = 0$ if $I^* = V^s - V^n \leq 0$

Among these explanatory variables, the interest rate $r_1$ is a principal factor that determines card holders’ balance switching decision. For non-switchers, this rate is observed as the best intro-rate offered in the past 6 months, denoted as $r^n$. For switchers, this rate is the one they actually switched a balance to, which is equal to or lower than their reservation rate, denoted as $r^s$.

\(^{10}\)To simplify our theoretical model, we omitted the intro-period of the switching offer as one of the determinants of the balance switching decision. In reality, the factor also plays a role when cardholders decide to switch or not. So we add it in our empirical analysis.
\[ r = \begin{cases} r^s & \text{if } I^* > 0 \\ r^n & \text{if } I^* \leq 0 \end{cases} \]

In a common sense, banks screen consumers’ creditworthiness largely based on their past default behaviors before they set rates and send the offers to specific consumers. As a result, \( r^n \) is determined by receivers’ default history \( H^D \), and other characteristics such as age \( a \), income \( y \), net worth \( w \) and home ownership \( houseown \). \( r^s \) is not only determined by card issuers but also selected by switchers. Here we treat \( r \) as a function of \( r \) \( (H^D, houseown, y, w, age, yeardummy) \). The year dummy is added to capture the effect of macroeconomic climate on rate setting over a time horizon. We plug in the interest rate function and get the reduced form of the probit equation as below:

\[ I^* = W\delta + \varepsilon \quad (4.1) \]

where \( W = (D^c d, balancecarrying, childnum, H^D, houseown, y, w, age, yeardummy) \).

All the variable notations used in the econometric models could be found in Table 14.

### 4.2 Endogenous Switching Regression Models

Non-switchers have not yet adopted a switching action and their debts or default situations develop naturally. As shown in the previous statistical analysis, on non-switchers’ side, past default risk is tightly linked to the debt burden \( CCDTI \). The historical default information also has direct influence on quality of their switching offers. As a result, we see a clear-cut relationship between default indicators and the lowest intro-rates in the mails.
While the story on switchers’ side is more complex. Because of the switching activity, the surface relationship between their past default risk, and the chosen intro-rate, and $CCDTI$ does not reveal the similar pattern as we see from non-switchers’ side. Taken as a benchmark, the pictures of non-switchers today describe what the switchers’ world looked like before they switched. Comparing the stories on both non-switchers’ side and switchers’ side gives us probing insight on when switchers make their move and how it influences their debt-paying on credit cards. The first two hypotheses put forward in section 2.2.6 ~ 2.2.7 are further inspected in this section.

The balance switching decision might create interaction effects with observed or unobserved individual characteristics (Maddala & Nelson (1975)). If the switching decision is based on individual self-selection, it is likely that switchers have systematically different characteristics from non-switchers. This sub-sample heterogeneity is econometrically problematic when unobserved characteristics are distributed differently across these two types of card holders. Thus, unobserved variables may influence both balance switching decision, the interest rate and $CCDTI$, resulting in inconsistent estimates of the effect of balance switching on interest rate or $CCDTI$. An endogenous switching regression model avoids these problems by taking into account of the interaction between self-selection and individual characteristics (Gould and Lin (1994)).

We first want to test whether the link between default history and $CCDTI$ is broken on switchers’ side. Based on the theoretical foundations in the previous section, the endogenous switching regression model is the structural form $(I)$ which contains two stages with three equations $(4.2)-(4.4)$. Equation $(4.2)$ represents card holders’ choice of balance switching and the latent variable is $I_t^*$. Card holders choose
to switch a balance if $I_i^* > 0$ and not to if otherwise. So the probit regression consists of indicator and the latent equation.

\[
I_i = \begin{cases} 
1 & \text{if } I_i^* > 0 \\
0 & \text{if } I_i^* \leq 0
\end{cases}
\]

\[
I_i^* = W_i \delta + \varepsilon_i = \alpha z_i + X_i \beta + Y_i \mu + \varepsilon_i
\]  \hspace{1cm} (4.2)

$W_i$ in equation (4.2) breaks down to three parts. $z_i$ is the key indicator of card holders’ default history, which is used by banks as the primarily interest rate driver, i.e.,

\[
z_i = \text{late payment to credit card} = \begin{cases} 
-1 & \text{if never missed payment} \\
0 & \text{if missed payment for less than 60 days} \\
1 & \text{if missed payment for more than 60 days}
\end{cases}
\]

\[
X_i = (\text{bankruptcy, houseown, y, w, age, yeardummy})
\]

$X_i$ is a vector of the individual-specific characteristics that affect card holders balance switching decision and also used by banks as complementary factors when setting interest rates, including age, net worth, income, home ownership, and whether reported bankruptcy in the past six months.

\[
Y_i = (D^c, d, balancecarrying, childnum)
\]

$Y_i$ is a vector contains some variables, which are either the features of the card offer, such as the intro-period, or household’s characteristics that affect their balance switching decision, but not used by banks when setting interest rates, such as balance carrying history and credit card debt.

We regress $CCDTI$ on the past default history $z$ and other characteristic variables $X$. For non-switchers, $CCDTI$ is the relative longer term debt burden and is mainly determined by card holders debt paying history along with other characteristics. For
switchers, \( CCDTI \) is resulted in the mixture effect of the past default situation and the switching impact.

\[
CCDTI = \begin{cases} 
  CCDTI^s \text{ if } I^* > 0 \\
  CCDTI^n \text{ if } I^* \leq 0 
\end{cases}
\]

\[
CCDTI_i^s = \pi_{01}z_i + X_i\pi_{11} + \eta_{1i} 
\]

\[
CCDTI_i^n = \pi_{02}z_i + X_i\pi_{12} + \eta_{2i} 
\]

We attempt to test the relationship between \( CCDTI \) and \( z \), with joint effect of \( X \).

Next, we want to test the hypothesis that the new intro-rates are well chosen by switchers. They do not show as much dependence on their past default situation or other individual-specific characteristics as non-switchers. The structural form \((II)\) contains three equations \((4.5)-(4.7)\), which are similar to \((4.2)-(4.4)\), except that the dependent variables in the second stage OLS regressions are interest rates now.

\[
I_i^* = W_i\delta + \varepsilon_i = \alpha z_i + X_i\beta + Y_i\mu + \varepsilon_i 
\]

\[
r_i^s = \gamma_{01}z_i + X_i\gamma_{11} + \varepsilon_{1i} 
\]

\[
r_i^n = \gamma_{02}z_i + X_i\gamma_{12} + \varepsilon_{2i} 
\]

There are several estimation methods that could be conducted. The simplest way is to do the probit and OLS separately on the original data, ignoring the possible selection bias. Other two approaches that take into account the selection bias are method of Heckman two-stage and the method of full information maximum likelihood. We introduce these two methods in next section. After that, we will talk about the how we deal with the missing data problem. At the end of this chapter, empirical results are provided and compared among all the estimation methods used.
4.2.1 Estimation method #1: Heckman Two-stage Estimation

In the structural form (I), the error terms $\varepsilon_i, \eta_{1i}$ and $\eta_{2i}$ are assumed to be jointly normally distributed with zero means and variances $\sigma_{\eta_1}^2, \sigma_{\eta_2}^2,$ and $\sigma_\varepsilon^2$ respectively.

The probit estimation (4.2) gives out $\hat{\delta}$ and the estimated switching probability $\Phi(\hat{\delta}W)$. The inverse mills ratio for equation (4.3) and (4.4) are $\lambda_1 = \frac{\phi(\hat{\delta}W)}{\Phi(\hat{\delta}W)}$ and $\lambda_2 = -\frac{\phi(\hat{\delta}W)}{1-\Phi(\hat{\delta}W)}$. The $\phi$ and $\Phi$ are the standard normal density function and distribution function. The conditioned OLS regression equations are expressed in (4.8) and (4.9).

$$CCDTI^*_i = \pi_{01}z_i + X_i\pi_{11} + \sigma_{\eta_1}\lambda_1 + \omega_{1i}$$

(4.8)

$$CCDTI^*_n = \pi_{02}z_i + X_i\pi_{12} + \sigma_{\eta_2}\lambda_2 + \omega_{2i}$$

(4.9)

The coefficient of inverse mills ratios are the covariance between $\eta_{1i}$ and $\varepsilon_i, \eta_{2i}$ and $\varepsilon_i : \sigma_{\eta_1} = cov(\eta_{1i}, \varepsilon_i)$ and $\sigma_{\eta_2} = cov(\eta_{2i}, \varepsilon_i)$. Significant coefficients verify the existence of self-selection effect.

In the structural form (II), similarly, we have conditioned OLS regression equations (4.10) and (4.11).

$$r_i^a = \gamma_{01}z_i + X_i\gamma_{11} + \sigma_{1\varepsilon}\lambda_1 + \varepsilon_{1i}$$

(4.10)

$$r_i^b = \gamma_{02}z_i + X_i\gamma_{12} + \sigma_{2\varepsilon}\lambda_2 + \varepsilon_{2i}$$

(4.11)

Where $\sigma_{1\varepsilon} = cov(\varepsilon_{1i}, \varepsilon_i)$ and $\sigma_{2\varepsilon} = cov(\varepsilon_{2i}, \varepsilon_i)$.

4.2.2 Estimation method #2: Full information maximum likelihood estimation

FIML method allows us to estimate the parameters in the structural equations simultaneously. Taking the structural form (I) for example, the estimation result gives out $\rho_j$ ($j = 1, 2$), which is the correlation coefficient between $\eta_{ji}$ and $\varepsilon_i$. $\rho_j = \frac{\sigma_{ji}}{\sigma_{\eta_j}\sigma_\varepsilon}$. 
The likelihood function for maximum likelihood estimation is as follows:

\[ L = \prod_{i=1}^{Q} f(CCDTI_i^s) \Pr \left( I_i = 1 \mid CCDTI_i^s \right) \times \prod_{i=0}^{Q} f(CCDTI_i^n) \Pr \left( I_i = 01 \mid CCDTI_i^n \right) \quad (4.12) \]

where

\[ f(CCDTI_i^s) = \left( \frac{1}{\sigma_{1\eta}} \right) \phi \left( \frac{CCDTI_i^s - \pi_{01} z_i + X_i \pi_{11}}{\sigma_{1\eta}} \right) \quad (4.13) \]

\[ f(CCDTI_i^n) = \left( \frac{1}{\sigma_{2\eta}} \right) \phi \left( \frac{CCDTI_i^n - \pi_{02} z_i + X_i \pi_{12}}{\sigma_{2\eta}} \right) \quad (4.14) \]

\[ \Pr \left( I_i = 1 \mid CCDTI_i^s \right) \text{ and } \Pr \left( I_i = 0 \mid CCDTI_i^n \right) \text{ are the selection probabilities,} \]

conditional on the observed debt to income ratio CCDTI_i^s and CCDTI_i^n respectively. They are obtained by:

\[ \Pr \left( I_i = 1 \mid CCDTI_i^s \right) = \Phi \left[ \frac{1}{\sqrt{1 - \rho_1^2}} \left( \alpha z_i + X_i \beta + Y_i \mu + \left( \frac{\rho_1}{\sigma_{1\eta}} \right) \eta_i \right) \right] \quad (4.15) \]

\[ \Pr \left( I_i = 0 \mid CCDTI_i^n \right) = \Phi \left[ \frac{1}{\sqrt{1 - \rho_2^2}} \left( \alpha z_i + X_i \beta + Y_i \mu + \left( \frac{\rho_2}{\sigma_{2\eta}} \right) \eta_i \right) \right] \quad (4.16) \]

Under assumption of \( \sigma^2_\varepsilon = 1 \), \( (\varepsilon_i, \eta_i) \sim N \left( (0,0), \left( \begin{array}{cc} 1 & \rho_j \eta \rho_j \sigma_{nj} \\ \rho_j \sigma_{nj} & \sigma^2_j \end{array} \right) \right) \), \( j = 1, 2 \).

**4.2.3 Empirical Results**

We should first address how we deal with the problem of missing values. Although CFM data provides exclusive information on balance switching behavior in credit card section, it is fresh and raw. The maximum number of observations of our target
sample for some variables is 5660. But there are quite a few others contain a fair amount of missing values. We have large enough data size to look at the statistics of single variable or the correlation between two variables. But when it comes to system analysis as multivariate regressions, the negative effect of missing values is amplified because of the interaction effect. In that case, we would suffer from regression based on the pairwise deletion. Due to this problem, we can not proceed to the second stage OLS regression after adding the inverse mills ratio derived from the first stage of probit regression, neither can we accomplish the FIML estimation successfully. And the real damage from missing values is not so much reduced sample size as it is the possibility that the remaining data set is biased.

There is no perfect way or easy method to solve this problem. The modern approaches include expectation-maximization algorithm and multiple imputation technique. In this dissertation, we adopted the latter together with the RII (Repeated Imputation Inference) because it is convenient on software package and can be simplified by the newly developed approach of Marcov Chain Monte Carol (MCMC).

For the Heckman two-stage method, there are two ways of imputation. We can first estimate the selection equation using the original data set. Then we multi-impute the data combined with the estimated inverse mills ratios. The OLS regressions in second stage are then conducted based on the multi-imputed data. Alternatively, we can impute the original data before both the two steps of estimation. For the FIML estimation, we need to impute the original data first. The RII approach produces
the average point estimates over all the imputations, and their corresponding standard errors, \( t \) statistics and \( p \) values, taking within-imputation variance and between-imputation variance into account. As in \( SCF \) data, the number of imputation is set at 5.

Since our data set contains some dummy variables and some other covariates which are not very close to normally distributed random variables, the multi-imputed data would be distorted more or less. As a result, the estimation results from these two ways of imputation differ from each other to some extent, in addition to their intrinsic differences. Only under the case where we finish the first step and then impute the data, our probit estimation is completely based on our original data set without any input distortion. Table 15 and Table 16 show the probit result based on original data and the estimation of the OLS regressions based on imputed data. Among 5583 card holders, there are 593 switchers and 4990 non-switchers. But the number of observations we could use in probit equation is only 685 due to missing values.

Table 15 shows the estimation result of probit and OLS regression to demonstrate the linkage between default history and \( CC\text{DTI} \). Since the self-selection equation is the reduced form, we do not see the primary effect of intro-rate on the balance switching decisions in the table. What we can see is that besides the intro-rate effect, the switching decision basically depends on the card holders’ balance carrying history and the quality of the offer. Longer intro-period offer attracts more switchers. Card holders with higher level of outstanding balance are more likely to switch. Bankruptcy record works as an obstacle to balance switching perhaps because it is hard for the claimers to receive a decent balance switching offer. In Figure 15, we draw the Lorenz
curve to make a gain chart, showing the predictive power of our switching model. The solid line is the cumulative percentage of switchers among all the switchers in the deciles of the whole sample, by a descendent rank of their predicted probability of switching. The dotted line is the benchmark as the whole sample is ranked randomly. The more the solid line deviates from the dotted line northwest bound, the better predictive power this model has. Approximately, all these significant variables in the third column in Table 15 jointly have 71% prediction power as predicting the switching probability.

OLS estimation of equation (4.3)-(4.4) is shown in the first two columns in Table 15. As expected, for non-switchers, the link between the default history and CCMTI is clear and tight. The severity of late payments to credit card is closely related to a higher level of CCMTI. And it is consistent with the convention wisdom that bankruptcy record is a red flag too. Besides the historical default indicators, household income and net worth could also play an important role in determining the debt burdens. Those with higher level of income are regarded as safer borrowers with sound debt obligations. While for switchers, the bankruptcy is still lightly related to CCMTI. But we do not find any relation between past default on credit cards and their CCMTI. These jointly imply that switching a balance did save credit card debtors from debt problems such as defaulting on cards, but not very effective for those already on the edge of bankruptcy. Still, higher income alleviates debt burdens and dents future default probability. If we control for income, the elderly tend to have heavier debt burdens due to their cumulative credit card debts. The broken link between the default "history" and CCMTI on switchers’ side implies that the default situation in the same window of balance switching did change from what it
would have been if they had not switched. Our first hypothesis so far gains support from the systematic analysis on the data. The covariance between $\varepsilon$ and $\eta_j (j = 1, 2)$ is significant. We are confirmed that this is switching regression with endogenous switching.

Table 16 shows the estimation result of probit and OLS regressions to demonstrate the dependence of interest rates on default history. For non-switchers, bankruptcy and late payments to credit card have negative effect on banks rate offers. House ownership also gains some credit for borrowers when it comes to banks’ credit rating system. Controlling for borrowers’ default history, banks treat those in older age cohorts as riskier borrowers and charge them a higher interest rate. The year dummy variable is significant, consistent with the fact that interest rates have been crawling up from 2005 to 2007. We take non-switchers’ side as the benchmark and believe that banks do set rate based on borrowers’ default history and some other individual-specific characteristics. So switchers’ received intro-rate should show the similar pattern as revealed on the non-switchers’ side. But the fact is that besides the macroeconomic climate effect, we only find one variable that has a very weak effect on the intro-rate for switchers: the late payment to credit card. This result tells two things. First, switchers’ reservation rates do vary slightly, if at all, across their default risk types. Borrowers with worse default records have higher reservation rates. This is consistent with Figure 10 in the theoretical model analysis. Second, the rates switchers actually chose do not have the same pattern as their received rates since we do not see any other relevance. Although switchers receive different rates based on their default history and other factors, they wait for a rate that is sufficiently low. The homogeneity of the rates they chose covers the heterogeneity of the rates they actually received. So our
second hypothesis about switchers’ choice of rates is here supported: $r^*_i$ is well-chosen among all the offers during time $t_i$ and switchers wait until their desired rate appears. As a result, switchers with bad default histories stand less chance to receive a lower rate offer and thus wait for a longer time. This finding leads to the prediction that the default risk has negative effect on the hazard rate of switching. We will test it in our duration models in chapter 5.

The FIML is conducted based on the imputed data. To confirm our findings and avoid imputation distortions, we use the original data set and do OLS estimation directly without correcting the self-selection bias. The quantitative results of direct OLS regression are in Table 17 and 18. The qualitative results of these four methods are tabulated together in Table 19 and 20. Blank denotes insignificance; minus sign denotes significantly negative effect and plus sign denotes significantly positive effect.

Method I: Do probit first, impute data and then do OLS
Method II: Impute data first, then do two step estimation
Method III: Impute data first, then do FIML
Method IV: Directly do OLS based on original data

In Table 19, the estimation results from the four estimation methods are basically consistent. On switchers’ side, the link between their default history and $CCDTI$ is broken. For non-switchers, their $CCDTI$ is strongly bonded with the major indicator of their default history, although its relationship with other complimentary variables is not quite decided. We believe that switching activity does change borrowers’ debt-paying situation temporarily.

As shown in Table 20, the default history is consistently deterministic on non-switchers’ side. We also see some confirmed relationships between rates and net worth and age. The pattern is not repeated for switchers’ accepted rates, which only suggest unique and weak relevance to their major default indicator.
Overall, our quantitative result is fairly robust. The interest rate is a critical factor that determines the switching decision. A low enough rate is the priority concern for card holders who are prone to switch a balance. Although offered a tremendous amount of interest rates by the banks each month, the switchers won’t move until their desirable rates arrive. The homogeneity of their desirable rates covers up the most part of the heterogeneity in their received rates. What’s more, if we look at whether they switched to a zero-rate instead of looking at the specific rate, we find that the preference for zero-rate is prevailing and does not suggest relevance to their default history nor any of their individual characteristics. Another important finding is that switchers did improve their succeeding default situation after switching a balance. But their postponed debt-paying procedure still bring on debt problem in the long run, especially if this pain-killer leads them to faster balance accumulation.
5.1 Duration Model Analysis

To evaluate the effect of default history, outstanding credit card balance, stress over debt and the short debt burden on the time spell before switching, we build duration models to do survival analysis. The observation of duration time spell $t_i$ is the time length that switcher stayed with their old cards before switching. We don’t have $t_i$ for non-switchers, however. The best information we can get is how long they have stayed with their old cards till the survey. Since the proportion of switchers among all the card holders is only 11%, our data contains more right censored observations than complete ones. The card holders open their credit card account at random time point, so, each non-switcher has a specific fixed censoring time, in which case we call the generalized type I censoring. The most appropriate variable in our data that could be used as the right censored time spell for non-switchers is their time length of opening credit card account till the survey date.

Figure 16 and 17 draw the hazard rate and the survival probability as functions of time $t$. The most notable feature of our hazard rate function is the multi-modes with most fluctuation happening in the first two year. The hazard rate has spikes on the
6 month, 12 month and 24 month time point. It is consistent with the typical intro-
periods. Some switchers switch a balance to a low intro-rate for 6, 12 months. After
the intro-period expires, they switch again. After two years, the hazard probability
converges towards zero. This implies that those who need to switch a balance to
save them from debt problem would do so no later than the first twenty-four months.
Consumers who haven’t done that after twenty-four months are more likely to be
revolvers without too much trouble of paying debt. The survival function has a dent
on the 12 month time point. As time goes by, it converges to 90% as only 10% of
card holders are switchers.

Before we set up our duration model, we need to find out candidate variables we
use as observed heterogeneity. The variables of interest are tested individually using
the tests by SAS. Those with a significance level higher than 0.25 are kept as potential
candidates for our duration model. The test result suggests that the variables that
might have effect on duration spell or hazard rate include gender, age, past default
risk, level of debt stress, dummy for zero rate offer, number of children in family, rank
of MMPTI and year dummy variable. The dummy variables for late payment and
bankruptcy, amount of net worth and asset, the new interest rate are ruled out in
this first round. So the predictors kept in the duration model are specified in vector
X.

\[ X = (\text{credit card late payment, stress over debt, } \log(\text{credit card debt}), \text{ rank of MMPTI, gender, age, year dummy}) \]

The following two subsections discuss two ways to build the duration model, the
Cox-proportional hazard rate model and accelerated lifetime model.
5.1.1 Invalidation of Cox-proportional Hazard Rate Model

Cox-proportional hazard rate model is widely used in survival analysis. It is also called the semi-parametric method since we do not need to specify a distribution to represent the survival time. The primary assumption of Cox-proportional hazard rate model is proportionality, i.e., the hazard rates of two cardholders with different covariates value are proportional. The hazard rate function takes a form as:

\[
h(t|X, \theta) = h_0(t) \phi(X) \eta(\theta) = h_0(t) \exp(X\beta + \theta)
\]

(5.1)

Where \(X\) represents a vector of observed covariates which is listed above, \(\theta\) represents unobserved heterogeneity with distribution \(f(\theta)\). For simplicity, we do not consider about \(\theta\) so far.

Test of Proportionality

\(X\) include both time-invariant covariates, such as gender, year dummy, and time-variant covariates such as default history, age, accumulated credit card debt, level of stress over debt, etc. Since most of them are time-variant covariates, it is necessary to test the assumption of proportionality before we run the regression.

There are several alternative ways to verify that whether a model satisfies the assumption of proportionality. The most visual way is to look at the Kaplan-Meier curves for categorical predictors. An alternative way is to generate the Cox-Snell residual or Schoenfeld residuals and see if the plot of the estimated cumulative hazard rate against the residual is close to a straight line. More certain conclusion can be made by the numeric test: we create interactions of time and each predictor and then test the significance of these newly generated time-dependent variables in the model. The lack of parallelism of Kaplan-Meier curves and the result of the numerical test
show that age and year dummy violate the proportionality assumption. We then seek
the other type of duration model to fit our data.

5.1.2 Accelerated Lifetime Model

Different from the Cox-proportional hazard model which starts from the hazard
rate, the accelerated lifetime model starts from a linear regression of the log of time
spell on the covariates.

\[
\ln(T) = X\beta + \sigma w
\]

(5.2)

Where \(T\) is the random variable of time spell which takes observed value \(t\). \(w\) is
a random variable with zero mean and unit variance. Three common choices for
the distribution of \(w\) are extreme-value, normal and logistic distributions, which lead
to Weibull, Log-normal and Log-logistic distributions for \(T\) respectively. Two more
distributions for \(T\) are also considered in this dissertation: Exponential distribution
and Gamma distribution. The fitness of the model will be compared by the AIC and
BIC model selection criterion.

The survival function could be derived as:

\[
S(t|X) = \Pr(T > t | X) = \Pr(X\beta + \sigma w > \ln(t) | X) = \Pr(e^{\sigma w} > te^{-X\beta} | X) = S_0(te^{-X\beta})
\]

(5.3)

Where \(S_0\) is the survival function of the baseline failure time \(e^{\sigma w}\). Immediately, we
have the hazard function:

\[
h(t|X) = h_0(te^{-X\beta}) e^{-X\beta}
\]

(5.4)

The likelihood function is:

\[
L(\delta | t_i, X_i) = \prod_{i=1}^{n} f(t_i, \delta | X_i)^{y_i} \prod_{i=1}^{n} S(t_i, \delta | X_i)^{1-y_i}
\]

(5.5)
Where $f(t_i, \delta | X_i)$ is the density function for $t_i$ and $S(t_i, \delta | X_i)$ is the survival function for $t_i$. $\delta = (\beta, \sigma)$ is the parameter vector to be estimated. $y_i$ is the indicator of censoring.

$$y_i = \begin{cases} 1 \text{ if uncensored} \\ 0 \text{ if censored} \end{cases}$$ (5.6)

Usually we maximize the log-likelihood function with respect to parameters:

$$\ln L(\delta | t_i, X_i) = \sum_{i=1}^{n} y_i \ln f(t_i, \delta | X_i) + \sum_{i=1}^{n} (1 - y_i) \ln S(t_i, \delta | X_i)$$

$$= \sum_{i=1}^{n} y_i \ln h(t_i, \delta | X_i) - \sum_{i=1}^{n} (1 - y_i) \ln S(t_i, \delta | X_i)$$

$$= \sum_{i=1}^{n} y_i \ln h(t_i, \delta | X_i) - \sum_{i=1}^{n} \int_{0}^{t_i} h(t_i, \delta | X_i)$$ (5.7)

**Choice of Distribution of Duration Time $T$**

To do the MLE, we need to assume a specific formulation of $h(t_i, \delta | X_i)$. Five distributions of $t$ are commonly adopted and each of them comes from a corresponding distribution assigned to error term $w$. The appropriateness of the choice of distribution of $w$ is not pre-determined and usually depends on the comparison of the estimation results of all of them, supported by the empirical evidence from the data analysis.

Ghilagaber & Gyimah (2004) makes a neat summary of six distributions in common use, based on some previous work of Stacy (1962) and Prentice (1974). This dissertation uses five of these distributions and compares their fitness in the application of our $CFM$ data.

In general, $w$ is assumed to have the density function as follows:

$$f(w | q) = \begin{cases} \frac{|q|}{1(q^2)} (q^2)^{-2} \exp \{q^{-2} [qw - \exp(qw)]\} & \text{if } q \neq 0 \\ (2\pi)^{-\frac{1}{2}} \exp \left( -\frac{w^2}{2} \right) & \text{if } q = 0 \end{cases}$$ (5.8)
Equation (5.8) is called Extended Generalized Gamma (EGG) distribution. \( w \) takes some well-known distributions as the parameter \( q \) (the inverse of \( q \) is called Gamma shape) takes specific values. In the concrete,

\[
f(w|q) = \begin{cases} 
\exp \{ w - \exp (w) \} & \text{if } q = 1 \text{ and } \sigma = 1 \\
\exp \{ w - \exp (w) \} & \text{if } q = 1 \\
(2\pi)^{-\frac{1}{2}} \exp \left( -\frac{w^2}{2} \right) & \text{if } q = 0 \\
\frac{|q|}{\Gamma(q-2)} (q^{-2})^{q-2} \exp \{ q^{-2} [qw - \exp (qw)] \} & \text{if } q > 0
\end{cases}
\] (5.9)

The above four density function with respect to \( w \) are well recognized as extreme-value distribution when \( q = 1 \), normal distribution when \( q = 0 \) and Gamma distribution when \( q > 0 \). Accordingly, \( T \) will take Exponential distribution, Weibull distribution, Log-normal distribution and Gamma distribution. Another distribution of \( T \)-the Log-logistic distribution is also of interest, which can not come from a special case the EGG. If we assume \( w \) is logistic distributed with density function equal to:

\[
f(w) = \frac{e^w}{(1 + e^w)^2}
\] (5.10)

then \( T \) is Log-logistic distributed.\(^{11}\)

As a summary, the density function \( f(t|X) \) for \( T \) and its corresponding hazard rate function \( h(t|X) \) is displayed in Table 21. \( \lambda = \exp [-X\beta] \) is the scale parameter, which is the rescale effect of explanatory variables on time directly. \( \sigma \) is the shape parameter, which captures the time evolution of the hazard. In the case of Weibull distribution, \( \frac{1}{\sigma} \) is called Weibull shape. \( \sigma < 1 \ (> 1) \) implies that the hazard rate is increasing (decreasing) as time goes by. In the case of Log-logistic distribution, \( \sigma < 1 \)

\(^{11}\)Log-logistic model now gains more interest because it considers more flexibility of the baseline and the computation difficulties are lessened by the development of computer skills and software packages. Previous application of log-logistic model could be found in Diekmann (1992), Shoukri & Mian & Tracy (1988) and Kai Li (1999).
means an inverse U-shaped hazard and $\sigma > 1$ means that hazard rate is a decreasing function of time with dramatic drop in the initial periods. When $\frac{1}{\sigma} = 1$, the hazard rate decreases mildly.

The density function of duration for Gamma distribution takes a more complicated form: $f (u|X) = \frac{\left(\frac{q^2}{u^2}\right)^{\frac{1}{2} q^2} \exp\left(-\frac{q^2}{u^2}\right)}{|q|u\Gamma(q^2)}$, for $ln(u) = w$. So for $ln(t) = X\beta + \sigma w$, the density function of $t$ takes a form as:

$$f (t|X) = \left(\lambda^\frac{1}{2} t^\frac{1}{2} - 1\right) f \left((\lambda t)^{\frac{1}{2}} | X\right)$$

The survival function for $t$ takes a form as:

$$S (t|X) = \int_{(\lambda t)^{\frac{1}{2}}}^{\infty} \frac{\left(q^2 x^\frac{1}{2}\right)^{q^2} \exp\left(-\frac{q^2}{x^\frac{1}{2}}\right)}{|q|x\Gamma (q^2)} dx$$

$$= \begin{cases} \int_{q^2 \left((\lambda t)^{\frac{1}{2}}\right)}^{\infty} \frac{q^{q^2 - 1} e^{-y}}{\Gamma(q^2)} dy & \text{if } q > 0 \\ \int_{0}^{q^2 \left((\lambda t)^{\frac{1}{2}}\right)} \frac{q^{q^2 - 1} e^{-\varphi}}{\Gamma(q^2)} d\varphi & \text{if } q < 0 \end{cases}$$

Where $\varphi = q^2 x^\frac{1}{2}$. The hazard function is inverse U-shaped if $q > 1$ and U-shaped if otherwise.

**Kaplan-Meier Curves**

Kaplan-Meier curves help us obtain some preliminary impressions of the effects of major predictors. The Kaplan-Meier estimator is the nonparametric maximum likelihood estimate of survival function. We can also use the advantage of accommodating censored data, which in our case are the large proportion of non-switchers. When there is no truncation or censoring occurs, the Kaplan-Meier curve is equivalent to the empirical distribution.

In Figure 18, the K-M curves representing low default risk and medium default risk are under the one representing high default risk. The hint is that the history of
credit card late payment has a negative effect on hazard rate. On the other hand, the
two curves for low and medium default risk almost overlap, implying that what really
matters is the severity of default. As long as the revolver did not delay their payment
for more than 60 days, their switching timing is quite similar to that of those who never
missed a payment. In Figure 19, the K-M curves representing three levels of stress
over debt depart from each other obviously, suggesting a pattern that the balance
keeper suffering higher debt stress are more likely to switch a balance away quickly.
The K-M curves in Figure 20 represents four categories of credit card debt:($0, $500],
($500, 1500] , ($1500, 5000] and ($5000, ∞). Among these four groups, revolvers with
credit card debt ($500, $1500] rather than ($0, $500] are most likely to stick with old
cards, whereas revolvers with credit card debt ($5000, ∞) are most likely to switch.
Overall, although the credit card debt is an important factor in decision of balance
switching, it does not show a positive driving power of pushing debtors to switch. The
K-M curve based on each of the above categorical variables only gives their marginal
effect. To take into account the joint effect, we next explore their driving power in
the model estimation.

5.1.3 Empirical result
AIC and BIC Model Comparison

The Cox-proportional hazard rate model estimates the parameters without neces-
sary consideration of the base line hazard function. But the pros of capturing the
true baseline better fostered by this feature might be lost due to the violation of
the proportionality assumption. If this assumption does not hold obviously, previous
study shows that the estimate from Cox proportional hazards regression might not be
consistent. But the parametric accelerated lifetime duration models also have flaws
as they might not capture the base line very well. In circumstance that there is no single perfect alternative under all of the conditions examined here, we compare the estimation results of parametric models and five distributions and find out that the significance and the sign of each covariate are consistent under these two approaches.

We adopt the Akaike information criterion (AIC)
\[ AIC = -2 \log (\text{likelihood value}) + 2 \times (\text{number of parameters}) \]
and the Bayesian Information Criterion (BIC)
\[ BIC = -2 \log (\text{likelihood value}) + \text{(log (number of observations))} \times (\text{number of parameters}) \]

12 It is developed by Hirotsugu Akaike in 1971 and proposed in Akaike (1974).
13 It is also known as Schwarz’s Bayesian criterion (SBC).

The AIC, BIC values and the maximum likelihood for each of the five distributions of \( T \) are shown in Table 22. The combined results suggest that the model based on Gamma distribution is relatively most appropriate to fit our data among the five types of parametric duration models.

Estimates of Coefficients and Interpretations.

As shown in Table 23, the coefficient estimates and their significance are very close among all these five models, except that the significance of log of credit card debt is getting weaker in the models with higher goodness of fit. It turns out completely insignificant in Gamma model, which is considered as the best fit to our data best. This result is consistent with our prediction from the theoretical model that the timing of switching does not depend on the amount of debt itself. The more powerful triggers of switching are stress over debt and the rank of \( MMPTI \). Both of them have negative effect on the time card holders stick to their old cards. The former
reflects borrowers’ anxiety of seeking ways to solve their debt problems, based on their own subjective judgment. The latter works as an indicator of near term debt burden and urgent need for mitigating solutions. The default history indicator decelerates the speed of switching because those who have poor payment history would receive relatively higher rates. As a result, they need to wait for a longer time for a desirable low rate offer. Besides, the elderly tend to be more settled down with their cards perhaps because they stand on more stable financial status and they are more conservative. The year dummy is significantly negative, consistent with the fact that the in the several years past, balance switching gains popularity as a channel of debt consolidation. Although the survey year 2005-2007 experienced the peak of the house boom, research suggests that consumers expand their consumption and borrowing simultaneously through collateralized channel - Heloc and noncollaterized channel-credit card. The regression of proportional hazard rate model is also conducted as a reference. In spite of the invalid proportionality assumption, proportional hazard rate model gives out same significance levels for each covariate. And as expected, their signs are exactly opposite to those shown in Table 23. Overall, our estimation result is consistent with our previous statistical description and the theoretical predictions.

To compare the model performance on projecting the hazard rate, we draw the estimated hazard curves based on the five distributions for a representative individual who has the typical attributes among card holders. More specifically, this individual is a 50 years old male, carrying an average level of credit card debt, with medium degree of debt stress and rank of $MMPTI$, in scenario of year 2007. Figure 21 shows the five fitted hazard rate curves based on the five distributions respectively. Exponential curve is flat at 0.0311; Weibull, Log-logistic and Log-normal curves are
downward-sloping with Log-normal curve is at the lowest level. Gamma curve has a unique bell shape. The probability of switching increases in the initial six months and reaches the peak in the window of sixth to twelfth month. After that, it quenches to zero. According to our model comparison, Gamma distribution fits our data best. Recall that the hazard rate fluctuates most in the initial 6 months and 12 months in the real hazard curve in Figure 16. It also can be seen that the estimated hazard rate of Gamma hazard curve provides a relatively better match for the real hazard rate both in volume and trend.

5.2 Structural Duration Model with Unobserved Heterogeneity

5.2.1 Proportional Unobserved Heterogeneity

In our previous analysis, Exponential and Weibull models are still proportional hazard models. The scale parameter $\lambda$ is set as $\exp(-X\beta)$. As a result, the hazard ratio is completely determined by the independent variables, i.e., the individual characteristics. The hazard curve of Weibull distribution is decreasing as time elapses. As we mentioned earlier, this could be the consequence of unobserved heterogeneity. As seen in model estimation result in Table 23 and the fitted hazard functions in Figure 21, we are in similar situation as Blossfeld & Hamerle (1992). Although our five hazard curves consistently exhibit negative time dependence, the Gamma shape and scale parameters are not equal to 1. So we also have good reasons to believe that there is unobserved heterogeneity we neglected in our Weibull model. The generalized Gamma model in previous section could also be considered as a method of detecting the unobserved heterogeneity. We now explore a structural model to accommodate this issue and control for both observed and latent heterogeneity. The duration time
spell before switching is still considered as subjected to a Weibull distribution. But we take into account the unobserved heterogeneity by adding a proportional factor \( v \). The hazard rate \( h(t|X,v) \) is \( \alpha \lambda^\alpha t^{(\alpha-1)} v \) (where \( \alpha = \frac{1}{\sigma} \)). The values of \( v \) are distributed across the population of card holders according to a Gamma distribution with shape \( k \) and scale \( \theta \), i.e. \( v \sim \text{Gamma}(k, \theta) \) with the following density function:

\[
g(k, \theta) = v^{k-1} \frac{\theta^k}{\Gamma(k)} \exp(-v\theta)
\]  

(5.11)

So the duration model is structured with Weibull distribution for duration and Gamma distribution for unobserved heterogeneity.

The corresponding survival function is:

\[
S(t|X,v) = \exp(-\lambda^\alpha t^\alpha v)
\]  

(5.12)

Then the density function of duration is the product of hazard and survival functions:

\[
f(t|X,v) = h(t|X,v) S(t|X,v) = \alpha \lambda^\alpha t^{(\alpha-1)} v \exp(-\lambda^\alpha t^\alpha v)
\]  

(5.13)

Integrating over all possible values of \( v \) gives the density of Weibull-Gamma duration model, which we call the structural model.

\[
f(t|X) = \int_0^\infty f(t|X,v) \cdot g(k, \theta) dv
\]

\[
= \alpha \lambda^\alpha t^{(\alpha-1)} \left( \frac{\theta^k}{(\theta + \lambda^\alpha t^\alpha)^k} \right) \int_0^\infty v^{k-1} \frac{\exp(-\left(\theta + \lambda^\alpha t^\alpha\right) v)}{\Gamma(k)} \cdot \left(\theta + \lambda^\alpha t^\alpha\right)^k dv
\]

\[
= \alpha \lambda^\alpha t^{(\alpha-1)} \left( \frac{\theta^k}{(\theta + \lambda^\alpha t^\alpha)^k} \right) E(v|v \sim \text{Gamma}(k, (\theta + \lambda^\alpha t^\alpha)))
\]

\[
= \alpha \lambda^\alpha t^{(\alpha-1)} \left( \frac{\theta^k}{(\theta + \lambda^\alpha t^\alpha)^k (\theta + \lambda^\alpha t^\alpha)} \right)
\]

\[
= \frac{\alpha k \lambda^\alpha t^{(\alpha-1)}}{\theta} \left( \frac{\theta}{\theta + \lambda^\alpha t^\alpha} \right)^{k+1}
\]  

(5.14)
Similarly, we derive the survival function independent on the disturbance:

\[
S(t|X) = \int_{0}^{\infty} S(t|X, v) \cdot g(k, \theta) \, dv \\
= \int_{0}^{\infty} v^{k-1} \exp(- (\theta + \lambda^\alpha t^\alpha) v) \cdot \theta^k \, dv \\
= \frac{\Gamma(k)}{\Gamma(k - 1)} \frac{\theta^k}{(\theta + \lambda^\alpha t^\alpha)^{k-1}} \int_{0}^{\infty} v^{k-1} \exp(- (\theta + \lambda^\alpha t^\alpha) v) \cdot (\theta + \lambda^\alpha t^\alpha)^{k-1} \, dv \\
= \frac{1}{(k - 1)} \frac{\theta^k}{(\theta + \lambda^\alpha t^\alpha)^{k-1}} E(v|v \sim \text{Gamma}((k - 1), (\theta + \lambda^\alpha t^\alpha))) \\
= \frac{1}{(k - 1)} \frac{\theta^k}{(\theta + \lambda^\alpha t^\alpha)^{k-1}} (k - 1) \\
= \left( \frac{\theta}{\theta + \lambda^\alpha t^\alpha} \right)^k
\] (5.15)

Immediately, we have the CDF as:

\[
F(t|X) = 1 - S(t|X) = 1 - \left( \frac{\theta}{\theta + \lambda^\alpha t^\alpha} \right)^k
\] (5.16)

Plugging in equation (5.13) and (5.14) into our log of likelihood function, we derive the objective function, where \( y_i \) is the balance switching indicator.

\[
\ln L(\delta|t_i, X_i) = \sum_{i=1}^{n} y_i \ln f(t_i, \delta|X_i) + \sum_{i=1}^{n} (1 - y_i) \ln S(t_i, \delta|X_i) \\
= \sum_{i=1}^{n} \left\{ y_i \ln \left( \frac{\alpha k \lambda^\alpha t^\alpha_i}{\theta} \right) + (y_i + k) \ln \left( \frac{\theta}{\theta + \lambda^\alpha t^\alpha_i} \right) \right\}
\] (5.17)

where the parameter vector \( \delta = (\alpha, k, \theta, \beta) \), \( \lambda_i = \exp(-X_i \beta) \).

5.2.2 Newton-Raphson Optimizer for Parameter Estimates

We get the maximum likelihood estimates with Newton-Raphson optimization algorithm to hurdle the computation difficulty caused by missing value and the huge iteration requirement for convergence. The initial values for the newly added parameters \( k \) and \( \theta \) are set as \( k_0 = 10 \) and \( \theta_0 = 1 \). We take the estimates for Weibull
distribution in Table 21 as initial values for the remaining parameters. Since our
objective function is completely differentiable, the parameter estimates are almost
independent of initial values (Brusilovsky 2006). The estimates are \( \hat{\alpha} = 1.0750 \)
\( \hat{k} = 0.4325 \) and \( \hat{\theta} = 0.1801 \). The coefficients for the observed heterogeneity are \( \hat{\beta}' = (11.561, 1.4959, -0.5736, -0.2006, 0.1147, -0.2296, 0.0377, -4.5825, 0.0696) \). There
are similar to the estimates in Table 21, except that the rank of \( MMPTI \) and the
interaction of stress and credit card debt turn out to be insignificant.

The fitted hazard rate is a function of time \( t \);

\[
\hat{h}(t|X) = \frac{\hat{\alpha} \hat{k} \exp(-\hat{\alpha}X\hat{\beta}) t^{(\hat{\alpha} - 1)}}{\hat{\theta} + \exp(-\hat{\alpha}X\hat{\beta}) t^{\hat{\alpha}}}
\] (5.18)

As shown in Figure 22, although the fitted hazard rate is much lower when we take
into account the unobserved heterogeneity, it also bell-shaped, with a highest hazard
rate occurring in the window of sixth to twelfth month. Blossfeld & Hamerle (1989)
demonstrated that the structural duration model with Weibull duration and Exponen-
tial unobserved heterogeneity is equivalent to the Log-logistic duration model.
This means that the Log-logistic accelerated lifetime model already automatically ac-
commodated the unobserved heterogeneity, at least partially. It is still outperformed
by the Gamma model in the parallel comparison. In this sense, we believe the Gamma
model is least affected by the negative effect of unobserved heterogeneity.

### 5.3 Conclusions

The previous sections lead us to the conclusions. Credit card issuers send out
mail offers according to a preliminary sorting based on consumers default history.
It is universally recognized that those with a better payment record stand a larger
chance to get low rate offers. Facing the mail solicitations, consumers tend to over
respond to the intro-rate relative to the intro-period due to more obvious marginal benefit on monthly payment. When considering about balance switching, card holders only focus on the new terms instead of the difference between old card rates and new card rates.

Several pieces of information from our data work jointly as evidence that riskier borrowers are more sensitive to the interest rates. Although affected by their worse payment history, they always find ways to take advantage of the teaser rates and seize any low rate that ever occurs. In line with Ausubel (1991), "winners’ curse" and "adverse selection" exist in balance switching. The offers accepted by switchers are on average superior to the mail offers received by non-switchers. While the default history is tightly linked to $CCDTI$ for non-switchers, we found a broken linkage on switchers’ side. So we have good reasons to believe that balance switching could temporarily improve borrowers’ debt situation. But switchers still have heavier debt burden than non-switchers. It reminds us that moving the debt around is not a panacea for debt problems. Seeing the rising credit card debt, the short term relief from the monthly payment in turn brings on loose discipline on spending and borrowing, which is going to the opposite direction of escaping the revolving debt cycle eventually.

When making decisions about the switching time point, consumers who are prone to switch a balance trade off between the benefit of switching earlier to save on monthly payment for a longer time and the benefit of switching later to enjoy a higher amount of saving on the rest of the discounted payment to debt based on a lower rate. The past default record plays an important role in determining their switching time points because it affects the average run length for them to receive a low rate. Labeled as riskier borrowers, switchers exhibit higher sensitivity to low
rates. Although switchers with bad payment history have a reservation rate that is slightly higher, they basically showed some patience in waiting for an intro-rate that is sufficiently low. Women and the elderly are found to be more conservative on switching, implying that balance switching is more like a mid-age male’s game. As a deterministic factor that affects switching decision, the total amount of credit card debt does not have significant driving power to push revolvers to switch sooner. Whereas the higher level of stress over debt hastens consumers’ switching timing. This is an intrinsic characteristic of consumers, however. The card issuers who have no access to this information are recommended to use the ratio of $MMPTI$ as a proxy to track potential switchers’ switching time points. And we are not surprised to find that average duration before switching is shortened in year 2006 since the banks had been aggressive on sending out balance switching offers during this period. Our survival analysis also provides a bell-shaped hazard function for a representative card holder. If he wants to be a switcher, he is most likely to switch in the initial six to twelve months of his debt cycle.
APPENDIX A

Tables
<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-switcher</th>
<th>Switcher</th>
</tr>
</thead>
<tbody>
<tr>
<td>Old interest rate on balance</td>
<td>14.12%</td>
<td>13.30%</td>
</tr>
<tr>
<td>New interest rate offered in the mail</td>
<td>4.43%</td>
<td>3.11%</td>
</tr>
<tr>
<td>Proportion of zero intro-rate in mail offers</td>
<td>(Yes=1, No=0)</td>
<td>45%</td>
</tr>
<tr>
<td>Spread between old card rate and new card rate</td>
<td>9.96%</td>
<td>10.07%</td>
</tr>
<tr>
<td>Intro-period for the new intro-rate</td>
<td>9.08</td>
<td>13.41</td>
</tr>
<tr>
<td>Whether carrying a balance in past 6 months</td>
<td>(Yes=1, No=0)</td>
<td>76%</td>
</tr>
<tr>
<td>Whether missed loan or credit card payment</td>
<td>(Yes=1, No=0)</td>
<td>14%</td>
</tr>
<tr>
<td>Credit card late payment</td>
<td>-0.83</td>
<td>-0.79</td>
</tr>
<tr>
<td>Whether account collected by collection agencies</td>
<td>-0.82</td>
<td>-0.79</td>
</tr>
<tr>
<td>House ownership</td>
<td>83%</td>
<td>86%</td>
</tr>
<tr>
<td>House loan late payment</td>
<td>0.008</td>
<td>0</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>9%</td>
<td>10%</td>
</tr>
<tr>
<td><em>CCDTI</em></td>
<td>0.04</td>
<td>0.15</td>
</tr>
<tr>
<td><em>MMPTI</em></td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Rank of <em>MMPTI</em></td>
<td>3.01</td>
<td>4.92</td>
</tr>
<tr>
<td>Number of months staying with old cards</td>
<td>77</td>
<td>22</td>
</tr>
<tr>
<td>Stress over credit card debt</td>
<td>2.21</td>
<td>2.77</td>
</tr>
<tr>
<td>Log of credit card debt</td>
<td>2.91</td>
<td>6.23</td>
</tr>
<tr>
<td>Log of income</td>
<td>10.16</td>
<td>10.56</td>
</tr>
<tr>
<td>Log of net worth</td>
<td>11.36</td>
<td>10.96</td>
</tr>
<tr>
<td>Age</td>
<td>55</td>
<td>49</td>
</tr>
<tr>
<td>Gender</td>
<td>(Male=1, Female=0)</td>
<td>0.46</td>
</tr>
<tr>
<td>Number of children in the family</td>
<td>0.72</td>
<td>0.96</td>
</tr>
<tr>
<td>Education</td>
<td>4.14</td>
<td>4.33</td>
</tr>
</tbody>
</table>

Table 1: Variable Definitions and Means for Switchers and Non-switchers
<table>
<thead>
<tr>
<th>Number of credit cards in hands</th>
</tr>
</thead>
<tbody>
<tr>
<td>switchers</td>
</tr>
<tr>
<td>4.2</td>
</tr>
</tbody>
</table>

**Wilcoxon Mann-Whitney Test**

<table>
<thead>
<tr>
<th>Normal approximation Z</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.18</td>
<td>&lt; 0.0001</td>
</tr>
</tbody>
</table>

Table 2: Comparison on Number of Credit Cards in Hands

<table>
<thead>
<tr>
<th>Card type</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Newly opened card</td>
<td>9.92</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Charged most card</td>
<td>5.38</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Highest balance card</td>
<td>5.51</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>The unique most used card</td>
<td>9.53</td>
<td>&lt; 0.0001</td>
</tr>
</tbody>
</table>

Table 3: Two Sample t-test on the Interest Rates

<table>
<thead>
<tr>
<th>Non-switchers</th>
<th>Switchers</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Old card rate</td>
<td>14.12</td>
<td>13.30</td>
</tr>
<tr>
<td>New card rate</td>
<td>4.43</td>
<td>3.11</td>
</tr>
<tr>
<td>Spread between old rate and new rate</td>
<td>9.96</td>
<td>10.07</td>
</tr>
</tbody>
</table>

Table 4: Two Sample T-test on New Rate and Old Rate and the Spread

<table>
<thead>
<tr>
<th>Debt burden</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCDTI</td>
<td>0.185***</td>
</tr>
<tr>
<td>MMP TI</td>
<td>0.133***</td>
</tr>
</tbody>
</table>

Table 5: Correlation between Debt Burden and Balance Switching

<table>
<thead>
<tr>
<th>Default history indicators</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit card late payment</td>
<td>0.035**</td>
</tr>
<tr>
<td>Number of payment missed</td>
<td>0.014</td>
</tr>
<tr>
<td>Account collected</td>
<td>0.018</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Table 6: Correlation between Default History and Balance Switching
<table>
<thead>
<tr>
<th>Default history indicators</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit card late payment</td>
<td>0.110*** 0.109***</td>
</tr>
<tr>
<td>Number of payment missed</td>
<td>0.048*** 0.074***</td>
</tr>
<tr>
<td>Account collected</td>
<td>0.104*** 0.094***</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>0.043*** 0.002</td>
</tr>
</tbody>
</table>

Table 7: Correlation between Default History and Debt Burden for Non-Switchers

<table>
<thead>
<tr>
<th>Default history indicators</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit card late payment</td>
<td>0.030 0.187***</td>
</tr>
<tr>
<td>Number of payment missed</td>
<td>0.066 0.209***</td>
</tr>
<tr>
<td>Account collected</td>
<td>0.018 0.158***</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>-0.035 -0.059</td>
</tr>
</tbody>
</table>

Table 8: Correlation between Default History and Debt Burden for Switchers

<table>
<thead>
<tr>
<th>Default history indicators</th>
<th>Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit card late payment</td>
<td>0.147*** 0.099**</td>
</tr>
<tr>
<td>Number of payment missed</td>
<td>0.068*** 0.058</td>
</tr>
<tr>
<td>Account collected</td>
<td>0.138*** 0.106**</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>0.109*** 0.063</td>
</tr>
</tbody>
</table>

Table 9: Correlation between Default History and Intro-rate

<table>
<thead>
<tr>
<th>Default history indicators</th>
<th>Chi-square statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit card late payment</td>
<td>17.71*** 1.72</td>
</tr>
<tr>
<td>Number of payment missed</td>
<td>22.50** 4.90</td>
</tr>
<tr>
<td>Account collected</td>
<td>13.60*** 2.00</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>2.78** 1.19</td>
</tr>
</tbody>
</table>

Table 10: Kruskal-Wallis Test on Dependence of Zero Rate on Default History
<table>
<thead>
<tr>
<th>Group</th>
<th>Total-sample</th>
<th>Sub-sample</th>
<th>Sub-sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>switched</td>
<td>not switched</td>
</tr>
<tr>
<td>Balance carriers</td>
<td>1130</td>
<td>219(19%)</td>
<td>911(81%)</td>
</tr>
<tr>
<td>Non-balance carriers</td>
<td>337</td>
<td>16(5%)</td>
<td>321(95%)</td>
</tr>
<tr>
<td>Switchers</td>
<td>235</td>
<td>219(93%)</td>
<td>16(7%)</td>
</tr>
<tr>
<td>Non-switchers</td>
<td>1232</td>
<td>911(74%)</td>
<td>321(26%)</td>
</tr>
</tbody>
</table>

Table 11: Balance Switching and Balance Carrying History

<table>
<thead>
<tr>
<th>Socioeconomic Characteristics</th>
<th>Correlation with switching</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.1194***</td>
</tr>
<tr>
<td>Number of children</td>
<td>0.0697 ***</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.0424***</td>
</tr>
<tr>
<td>Marriage status</td>
<td>0.0257*</td>
</tr>
<tr>
<td>Education</td>
<td>0.0214</td>
</tr>
<tr>
<td>Race</td>
<td>-0.0154</td>
</tr>
</tbody>
</table>

Table 12: Correlation between Switching and Socioeconomic Characteristics

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D^c$</td>
<td>The original credit card outstanding balance</td>
</tr>
<tr>
<td>$ARL_D$</td>
<td>Average run length for the first zero-rate offer to occur for a cardholder of default risk type $D$</td>
</tr>
<tr>
<td>$r_0$</td>
<td>The original monthly interest rate on balances ($r_0 &gt; 0$)</td>
</tr>
<tr>
<td>$r_1$</td>
<td>The intro-rate that the representative revolver switches to</td>
</tr>
<tr>
<td>$M$</td>
<td>A fixed amount of monthly payment (more than or equal to the minimum monthly payment)</td>
</tr>
<tr>
<td>$R$</td>
<td>Market interest rate</td>
</tr>
<tr>
<td>$T$</td>
<td>Time length of paying off the outstanding balance</td>
</tr>
<tr>
<td>$t$</td>
<td>The $t^{th}$ month; ($t = 1, 2, \ldots, T$)</td>
</tr>
<tr>
<td>$s$</td>
<td>Time point the representative revolver decides to switch away from her old card;</td>
</tr>
<tr>
<td>$k$</td>
<td>Switching cost</td>
</tr>
</tbody>
</table>

Table 13: Notation Definition in the Theoretical Model
<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CCDTI$</td>
<td>Debt burden in the long run=$\frac{credit\ card\ debt}{income}$</td>
</tr>
<tr>
<td>$T (T^s/T^n)$</td>
<td>Time needed to pay off credit card debt</td>
</tr>
<tr>
<td>$r$</td>
<td>intro-rate</td>
</tr>
<tr>
<td>$d$</td>
<td>Intro-period</td>
</tr>
<tr>
<td>$k$</td>
<td>Switching cost</td>
</tr>
<tr>
<td>$s$</td>
<td>Time point to switch</td>
</tr>
<tr>
<td>$D^c$</td>
<td>Total amount of credit card debt</td>
</tr>
<tr>
<td>$y$</td>
<td>Income</td>
</tr>
<tr>
<td>$w$</td>
<td>Net worth</td>
</tr>
<tr>
<td>$a$</td>
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<td>Balance carry history</td>
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</tr>
<tr>
<td>$HD^{z (bankruptcy)}$</td>
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</tr>
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<td>Year dummy</td>
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Table 14: Notation Definition in Econometric Models
<table>
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<th>Selection</th>
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<tr>
<td>Est.</td>
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<td>Est.</td>
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<tr>
<td></td>
<td>(Se.)</td>
<td>(Se.)</td>
<td>(Se.)</td>
</tr>
<tr>
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<td>0.7458***</td>
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<tr>
<td></td>
<td>(0.1370)</td>
<td>(0.0572)</td>
<td>(0.4627)</td>
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<td>-0.0162*</td>
<td>0.4167**</td>
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<tr>
<td></td>
<td>(0.0481)</td>
<td>(0.0081)</td>
<td>(0.1777)</td>
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<tr>
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<td>-0.0091</td>
<td>0.0151**</td>
<td>0.0750</td>
</tr>
<tr>
<td></td>
<td>(0.0335)</td>
<td>(0.0064)</td>
<td>(0.1227)</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>0.1047*</td>
<td>0.0437***</td>
<td>-0.9849***</td>
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<tr>
<td></td>
<td>(0.0598)</td>
<td>(0.0103)</td>
<td>(0.3017)</td>
</tr>
<tr>
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<td>(0.0074)</td>
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<td>(0.0179)</td>
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<td>(0.0002)</td>
<td>(0.0053)</td>
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<td>-0.0152***</td>
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<td>(0.0051)</td>
<td>(0.2019)</td>
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<td>0.0254***</td>
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<td>(0.0051)</td>
</tr>
<tr>
<td>Balance carrying history</td>
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<td>0.7983***</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>(0.2471)</td>
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<tr>
<td>Log of credit card debt</td>
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<td></td>
<td>0.0639***</td>
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<td></td>
<td></td>
<td>(0.0186)</td>
</tr>
<tr>
<td>Number of children in family</td>
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<td>0.0247</td>
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<td>(0.0153)</td>
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</tr>
<tr>
<td>Sample size</td>
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</table>

Table 15: Heckman Two-stage Estimates of Endogenous Switching Model I

The Link between Default History and \(CCDTI\)

79
<table>
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<th>Variable</th>
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<th>Selection</th>
</tr>
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<td>Constant</td>
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<td>(0.4627)</td>
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<tr>
<td>(0.6540)</td>
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<tr>
<td>(0.4642)</td>
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<tr>
<td>Bankruptcy</td>
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<td>-0.9849***</td>
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<td>(0.3017)</td>
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<td>-0.0316</td>
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<tr>
<td>(0.0601)</td>
<td>(0.0264)</td>
<td>(0.0179)</td>
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<tr>
<td>(0.0524)</td>
<td>(0.0299)</td>
<td>(0.0173)</td>
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<td>-0.0063</td>
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<tr>
<td>(0.0168)</td>
<td>(0.0079)</td>
<td>(0.0053)</td>
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<td>0.5704***</td>
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<td>(0.3462)</td>
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<td>(0.2019)</td>
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</tr>
<tr>
<td>Intro-period for new rate</td>
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<td></td>
<td>0.0254***</td>
</tr>
<tr>
<td>(0)</td>
<td>(0.0051)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Balance carrying history</td>
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<td></td>
<td>0.7983***</td>
</tr>
<tr>
<td>(0)</td>
<td></td>
<td>(0.2471)</td>
<td></td>
</tr>
<tr>
<td>Log of credit card debt</td>
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<td></td>
<td>0.0639***</td>
</tr>
<tr>
<td>(0)</td>
<td></td>
<td>(0.0186)</td>
<td></td>
</tr>
<tr>
<td>Number of children in family</td>
<td></td>
<td></td>
<td>0.0247</td>
</tr>
<tr>
<td>(0)</td>
<td></td>
<td>(0.0571)</td>
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</tr>
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<td>-1.0100</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
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<td>4990</td>
<td>685</td>
</tr>
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</table>

Table 16: Heckman Two-stage Estimates of Endogenous Switching Model II Dependence of Intro-rate on Default History
## Table 17: OLS Regression Based on Original Data
The Link Between Default History and CCDTI

<table>
<thead>
<tr>
<th>Variable</th>
<th>Switcher</th>
<th>Non-switcher</th>
<th>Switcher</th>
<th>Non-switcher</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est.</td>
<td>Est.</td>
<td>(Se.)</td>
<td>(Se.)</td>
</tr>
<tr>
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<td>0.3863***</td>
<td>(0.2598)</td>
<td>(0.0359)</td>
</tr>
<tr>
<td>House ownership</td>
<td>0.1151**</td>
<td>0.0008</td>
<td>(0.0547)</td>
<td>(0.0071)</td>
</tr>
<tr>
<td>Credit card late payment</td>
<td>0.0099</td>
<td>0.0272***</td>
<td>(0.0387)</td>
<td>(0.0061)</td>
</tr>
<tr>
<td>Bankruptcy</td>
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<td>(0.0602)</td>
<td>(0.0088)</td>
</tr>
<tr>
<td>Log of income</td>
<td>-0.1432***</td>
<td>-0.0230***</td>
<td>(0.0226)</td>
<td>(0.0031)</td>
</tr>
<tr>
<td>Log of net worth</td>
<td>0.0036</td>
<td>-0.0037***</td>
<td>(0.0051)</td>
<td>(0.0007)</td>
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<td>Age</td>
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<td>-0.0005***</td>
<td>(0.0014)</td>
<td>(0.0002)</td>
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<td>Year dummy</td>
<td>0.0040</td>
<td>-0.0008</td>
<td>(0.0289)</td>
<td>(0.0043)</td>
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</table>

Number of observation used: 468 3589
\[ \begin{array}{l|rr}
\text{Variable} & \text{Switcher} & \text{Non-switcher} \\
\hline
\text{Constant} & 1.9985 & 6.3448^{***} \\
 & (1.2745) & (0.6310) \\
\text{House ownership} & -0.7731 & -1.2310^{***} \\
 & (0.6645) & (0.3259) \\
\text{Credit card late payment} & 1.0174^{**} & 1.4862^{***} \\
 & (0.4643) & (0.2696) \\
\text{Bankruptcy} & 0.6634 & 1.7699^{***} \\
 & (0.7352) & (0.3814) \\
\text{Log of income} & 0.0292 & -0.0463 \\
 & (0.0591) & (0.0292) \\
\text{Log of net worth} & 0.0312 & -0.0785^{**} \\
 & (0.0573) & (0.0336) \\
\text{Age} & 0.0290^{*} & 0.0179^{**} \\
 & (0.0169) & (0.0085) \\
\text{Year dummy} & 0.6794^{*} & 0.6718^{***} \\
 & (0.3488) & (0.2062) \\
\hline
\text{Number of observation used} & 489 & 2231
\end{array} \]

Table 18: OLS Regression Based on Original Data
Dependence of Rate on Default History
<table>
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<th>Estimation method</th>
<th>Switchers</th>
<th>Non-switchers</th>
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<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>House ownership</td>
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<td>-</td>
</tr>
<tr>
<td>Credit card late payment</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Log of income</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Log of net worth</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Age</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Year dummy</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
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<td>593</td>
</tr>
</tbody>
</table>

Table 19: Qualitative Result of Default Link of Four Estimation Methods

<table>
<thead>
<tr>
<th>Estimation method</th>
<th>Switchers</th>
<th>Non-switchers</th>
</tr>
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<tbody>
<tr>
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<tr>
<td>House ownership</td>
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<td>-</td>
</tr>
<tr>
<td>Credit card late payment</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Bankruptcy</td>
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<td>+</td>
</tr>
<tr>
<td>Log of income</td>
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<td>-</td>
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<tr>
<td>Log of net worth</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Age</td>
<td>+</td>
<td>+</td>
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<tr>
<td>Year dummy</td>
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<td>+</td>
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<tr>
<td>Sample size</td>
<td>593</td>
<td>593</td>
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Table 20: Qualitative Result of Rate Dependence of Four Estimation Methods
\[
\begin{align*}
  f(t \mid X) & = \lambda \exp(-\lambda t) \\
  h(t \mid X) & = \lambda \\
  \text{Weibull} & = \frac{1}{\sigma} \lambda^{1/\sigma} t^{1/\sigma - 1} \exp \left[ - \left( \frac{1}{\sigma} t \right)^{1/\sigma} \right] \\
  & = \frac{1}{\sigma} \lambda^{1/\sigma} t^{1/\sigma - 1} \exp \left[ - \left( \frac{1}{\sigma} t \right)^{1/\sigma} \right] \\
  \text{Log-logistic} & = \frac{1}{\lambda + \lambda t^{1/\lambda}} \\
  & = \frac{1}{\lambda + \lambda t^{1/\lambda}} \\
  \text{Log-normal} & = \frac{1}{\sqrt{2\pi}\sigma t} \exp \left[ - \frac{1}{2} \left( \frac{\ln t - X}{\sigma} \right)^2 \right] \\
  & = \frac{1}{\sqrt{2\pi}\sigma t} \exp \left[ - \frac{1}{2} \left( \frac{\ln t - X}{\sigma} \right)^2 \right] \\
  \end{align*}
\]

Table 21: Density Function and Hazard Rate of Five Distributions

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<th>Distribution</th>
<th>Maximum Log of Likelihood</th>
<th>AIC</th>
<th>BIC</th>
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<td>Exponential</td>
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<td>1802.71</td>
<td>3742.81</td>
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<tr>
<td>Weibull</td>
<td>-419.54</td>
<td>1775.09</td>
<td>3717.36</td>
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<tr>
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<td>-406.86</td>
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<td>-403.52</td>
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<tr>
<td>Gamma (Best Fit)</td>
<td>-402.83</td>
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Table 22: Duration Model Comparison
<table>
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<tr>
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<th>Logistic</th>
<th>Log-normal</th>
<th>Gamma</th>
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<td>Est. (Se.)</td>
<td>Est. (Se.)</td>
<td>Est. (Se.)</td>
</tr>
<tr>
<td>Constant</td>
<td>6.6329***</td>
<td>7.4804***</td>
<td>6.7730***</td>
<td>6.9227***</td>
<td>6.8000***</td>
</tr>
<tr>
<td>Credit card late payment</td>
<td>0.4286**</td>
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<td>0.7017***</td>
<td>0.6790***</td>
<td>0.6739***</td>
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<td>Stress over debt</td>
<td>-0.4786***</td>
<td>-0.5461***</td>
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<td>-0.4257***</td>
<td>-0.4002***</td>
</tr>
<tr>
<td>Log(ccdebt)</td>
<td>-0.1238**</td>
<td>-0.1373*</td>
<td>-0.1104*</td>
<td>-0.0963</td>
<td>-0.0859</td>
</tr>
<tr>
<td>Rank of MMPTI</td>
<td>-0.1019***</td>
<td>-0.1327***</td>
<td>-0.133***</td>
<td>-0.1175***</td>
<td>-0.1060***</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.0788</td>
<td>-0.1191</td>
<td>-0.1028</td>
<td>-0.1654</td>
<td>-0.2052</td>
</tr>
<tr>
<td>Age</td>
<td>0.0331***</td>
<td>0.0376***</td>
<td>0.0396***</td>
<td>0.0378***</td>
<td>0.0367***</td>
</tr>
<tr>
<td>Stress*log(ccdebt)</td>
<td>0.0516***</td>
<td>0.0584***</td>
<td>0.0521***</td>
<td>0.0510**</td>
<td>0.0495**</td>
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<tr>
<td>Year dummy</td>
<td>-1.6611***</td>
<td>-2.1625***</td>
<td>-2.5673***</td>
<td>-2.7389***</td>
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<td>1.0000</td>
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<td>-0.3041</td>
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Table 23: Estimation Result of Five Accelerate lifetime Models
APPENDIX B

Figures
Figure 1: Histogram of Intro-rate for Switchers and Non-switchers

Figure 2: Histogram of Intro-period for Switchers and Non-switchers
Figure 3: Acceptance Rate for Non-switchers Who Got Zero Intro-rate
Figure 4: Acceptance Rate for Non-switchers Who Got Positive Intro-rate
Figure 5: Switching Proportion in Income Categories

Figure 6: Switching Proportion in Asset Categories
Figure 7: Switching Proportion in Net Worth Categories

Figure 8: Switching Proportions in Geographic Regions
Figure 9: Switching Benefit for Revolvers with Three Types of Default Risk and Three Debt Levels
Figure 10: Reservation Rates for Card Holders: Low risk vs. High risk

Figure 11: Reservation Rates for Card Holders with Different Credit Card Debt
Figure 12: Comparison of $\pi_t$ and $p_t$.

Figure 13: Expected Payment for Card Holders with Different Credit Card Debt.
Figure 14: Switching Probability at Each Time Point:
Low Risk vs. High Risk
Figure 15: The Predictive Power of Probit Model
Figure 16: Hazard Rate Function

Figure 17: Survival Function
Figure 18: K-M Curves for Three Types of Default Risk

Figure 19: K-M Curves for Three Levels of Stress over Debt
Figure 20: K-M Curves for Four Categories of Credit Card Debt
Figure 21: Fitted Hazard Rates for Five Accelerated Lifetime Models
Figure 22: Fitted Hazard Rate for Structural Duration Model
APPENDIX C

Survey Questions on Balance Switching

1. In the past 6 months, have you switched any balances between cards or to a new card?

2. Did you switch balances between existing cards, to a new card or both?

3. Think about the most recent time you switched a balance in the last 6 months, how long had you been carrying a balance on the card that you switched away from?

4. In the past 6 months, what was the lowest credit card interest rate offer you got in the mail?

5. How many months was that introductory offer good for?

6. What would the introductory offer rate and the length of the offer period have to be to make you interested in switching some balances?

7. Would you have taken the bank’s offer of a zero percent rate if the introductory rate period were longer?

8. How many months would a zero percent rate have to last to get you to take the offer?

9. Please think about the most recent time your household switched balances. What was the interest rate on the card you switched to?

10. How long was this new rate good for?
11. About how much did you switch?

12. What was the old interest rate on the card you switched away from?

13. Was there a fee for switching balances?

14. About how much?

15. Are there any attractive perks on the card you switched balances to, such as cash back bonus awards, frequent flyer miles, discounts, or something else?
BIBLIOGRAPHY


[20] Kerr, Sougata and Stephen Cosslett and Lucia Dunn (2004), "Do Banks Use Private Information from Consumer Accounts Evidence of Relationship Lending in Credit Card Interest Rate Heterogeneity", working paper, the Ohio State University, Columbus, OH.


