INVESTIGATION OF U.S. CREDIT CARD MARKET USING ORIGINAL SURVEY DATA

DISSERTATION

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By

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ABSTRACT

The credit-card market is complex in nature. It involves a non-collateral revolving credit contract combining the characteristic of loan commitment with no upfront fees and minimum required payments. Previous articles in this area addressed the issues of sticky credit-card interest rates and rationality/irrationality of consumer choices. However, there are still many important unanswered questions. My dissertation covers several theoretical and empirical issues of credit-card contracts, credit-card default and credit-scoring problems. It contains original behavioral analyses of both banks and consumers in the credit card market. A new source of data on credit-card usage is employed in the analyses.

The dissertation consists of four main sections. The first section discusses the credit card default and strategic behavior of high-risk cardholders. I address the issue of credit-card default with an ordered probit regression model. Throughout the statistical and
regression analysis, I find that several new financial variables perform better than the traditional measures of household financial status in predicting credit-card default.

The second and third sections explore the competitive behavior of credit-card banks and the diversity of consumer characteristics and choices in terms of default risk and the purpose of credit-card use. I develop a model of price competition among credit card banks under consumers' asymmetric response to interest differentials among multiple credit-card offers. The regression analysis confirms the theoretical prediction on credit-card interest rates based on credit-card holding purpose and default risk. The intro-rate credit card offers from credit card issuers and the balance-switching behavior are also explored.

Finally, the forth section will explore a multi-period theoretical model to take the special aspects of a credit-card contract into consideration for both credit-card bank lending and consumer borrowing decisions.
Default risk of consumers is exogenously given from outside of the model, and credit-card lenders compete with one-period spot market lenders in each period of the model. The model shows that due to the higher risk involved in credit-card loans, credit-card banks are not able to compete with spot market lenders unless minimum required payments and a predetermined credit line are introduced. This model will form the basis for future research.
TO MY MENTOR, LUCIA F. DUNN
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CHAPTER I

INTRODUCTION

1.1 Background for Credit Card Industry

Consumers in the U.S. have increased their credit card usage and borrowing since the 1980's in spite of the high premium of credit card loans.\(^1\) Default rate for VISA and MasterCard members’ credit card debts are reported consistently higher than that of other types of bank loans, and the credit-card default rate has been increasing over the last two decades.\(^2\) After a lull in credit card defaults in the early 1990's, default and personal bankruptcy also began to increase sharply in 1995; and this phenomenon has become a serious issue for banks and policy makers (Domowitz and Eovaldi, 1993).

The potentially serious impact of credit card default on the general state of the economy has prompted

\(^1\) The number of credit card in circulation and the number of credit card transactions increased 34 percent and 55 percent respectively between 1988 and 1994. (Peter S. Yoo, 1997)

a number of researchers to explore the default issue. My dissertation addresses the issue of the determinants of default on credit card debt focusing on the relationship between default and the outcomes of financial choices consumers make within the constraints of the contract terms set by credit card issuers.

Interest rate competition, on the other hand, has been obvious in the market since the early 1990’s because major elements for non-price enhancements were almost exhausted. Consumers also have been offered intro-rate credit cards with the balance transfer options since mid-1990’s, and the prevalence of intro-rate credit cards contributed to the drop both in average credit card rates and in credit card issuers’ interest income as a percentage of asset in 1997.

The interest rate of credit card loan has been studied by many economic researchers since 1990’s due to the paradoxical outcome of the competitive structure of

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3 Before the 1990’s, waiving annual fees and providing credit card program enhancements were the primary targets of competition among card issuers. See The Profitability of Credit Card Operations of Depository Institutions, Federal Reserve Board (1998).
credit card market (Ausubel, 1991; Canner and Luckett, 1992; Mester, 1994; Brito and Hartley, 1995; Calem and Mester, 1995; Park 1997). In line with the issues of the interest rates in the credit card market, my dissertation study takes the diverse types of cardholders and their cardholding motives into account in the market mechanism to explore the interest rate allocation, the market segmentation, and introductory rate and balance switching behavior of consumers.

Finally, a credit card contract in general has special characteristics for both demand and supply sides of market. The characteristics of the contract are positively introduced in the theoretical model, and the strategic implications of the terms of a credit card contract are closely examined. I also focus on the relationship between a consumer’s risk type and her optimal choice of a borrowing mean when she can choose to either one-period spot market loan or a credit-card loan.
1.2 Research Issues

My dissertation consists of four major parts of the research on credit card market. As introduced in Section 1.1, I will discuss in the later sections (1) credit card default and scoring issue; (2) diverse cardholder types/motives and their interest rates; (3) introductory credit card interest rate and balance switching behavior; and (4) theoretical analysis of a credit card contract.

1.2.1 Empirical Investigation of Credit Card Default

To investigate the determinants of default on credit card debt I used empirical observations on household credit card use from a new monthly survey. This study focuses on the relationship between default and the outcomes of financial choices consumers make within the constraints of the contract terms set by credit card issuers. Our new data set contains the most detailed information yet available on a regular basis on certain behavioral aspects of credit card use.
The three new financial variables which we find to have the most significant impact on default are (1) the ratio of total minimum required payment from all credit cards to household income; (2) the percentage of total credit line which has been used by the consumer; (3) the number of credit cards on which the consumer has reached the borrowing limit. All three of these quantities result from consumers’ charging behavior under the unique arrangements of credit card loans whereby a line of credit is issued which consumers may choose to use to a greater or lesser extent. Once variables constructed from these more detailed data are considered, the debt to income ratio, which has been the focus of most previous research on determinants of default, loses its significance as an explanatory variable.

The first two variables above capture specific institutional arrangements of the credit card contract. The debt to income ratio used in many previous studies acts as a rough proxy for the more detailed behavior that is embodied in these two variables. Since credit cards
have expanded the set of decisions that a consumer must make in the use of a debt instrument, they have also expanded the possibilities for the employment of strategy by consumers. These important strategic aspects of credit card use are not adequately reflected in the debt to income ratio. The third new financial variable introduced in this study - the number of cards on which a consumer has reached the borrowing limit (i.e., “maxed-out” on) - while related to the percentage of credit line used, go beyond this latter variable to capture further characteristics of credit card users. It is found to have significant predictive power in explaining the tendency for default beyond the first two variables discussed above.

Finally, our data suggests that consumers in our sample are engaging in a type of Ponzi scheme behavior, obtaining new credit cards which make them able to pay off existing balances. This idea is tested by analyzing a special data set where information of number of cards and average credit line per card is available.
1.2.2 Bank Price Competition and Asymmetric Consumer Responses to Credit Card Interest Rates

This study analyzes market outcomes in the credit card industry when credit card issuers are competing with interest rates and cardholders have different motives for using credit cards. In our model, consumers react differently to interest rate offers depending on their motive. We consider three different groups of credit card users: (1) low-risk convenience users who have only a transactions motive and do not carry a balance; (2) low-risk users who carry a balance and have no default history; and (3) high-risk users who carry a balance and have some positive default history.\(^4\) Since credit card issuers have access to the credit history of consumers and credit-scoring techniques are in widespread use\(^5\), it is reasonable to assume that banks provide different interest rates to different consumers based on their perception of

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\(^4\) We should note that since banks consider risk to be a characteristic embedded in the card user, there is a fourth category of user who is risky but does not borrow. However, we do not consider that group here.

\(^5\) According to Mester (1997), the Senior Loan Officer Opinion Survey found that 97 percent of banks that use scoring techniques employ them in the card application approval decision.
the consumer's risk.

Since the 1990's, interest rate competition has been growing in the credit card market because avenues of competition with non-interest rate enhancements have been almost exhausted. On the other hand, since consumers generally have different motives for holding cards, they will also have different incentives to incur the time and psychological costs of searching for lower interest rate terms.

I show that high-risk consumers should be offered higher interest rates on average than low-risk consumers. However, our model also shows that in equilibrium, due to differences in search incentive, identically-risked cardholders with a borrowing motive will actually end up using lower interest rates than their counterparts in the same risk pool who have only a transactions motive.

I apply the intuitions of the theoretical model in an empirical analysis using data from a new monthly survey. This survey contains many variables pertaining to credit card use that have previously been unavailable to
researchers. Our empirical analysis focuses on the consumer’s credit card balance and default history. It shows that, when the interactions of banks and cardholders are properly controlled, these two variables strongly affect the interest rates of cardholders. This interdependence of the interest rate and default is explored with a two-stage least squares model. We find that default experience has a strong effect on the interest rate of a credit-card holder, but the interest rate does not have a direct impact on credit card default.

1.2.3 Introductory Credit Card Rates and Balance Switching Behavior

In this study I explore the decision process of introductory rate credit card selection and balance transfer to the intro-rate card. The purpose of this study is to address the issue that how the diverse choices of cardholders facing intro-rate credit card solicitations could be explained in the context of rational consumer behaviors. This study shows that a consumer’s choice among three alternatives depends on the two major factors: (1)
the difference between current credit card rate and an offered intro-rate (APRDIFF) and (2) the level of credit card balance (BALANCE).

A nested multinomial logit (NML) model was used to analyze the sequential decision process of cardholders related with intro-rate credit card and balance transfer choices. The result of FIML estimation of the NML regression model shows that for the choice of intro-rate and balance switch, APRDIFF has a positive coefficient and is significant at 1% level. Because intro-rate selection and balance switch activities should involve some time and psychological costs, the interest rate difference between non-intro rate and intro-rate card should be high enough for a household to take the sequence of a new application and balance transfer.

BALANCE was also found to be an important variable for the choice of intro-rate and balance switch in the regression model. The coefficient of the variable is positive and significant at 5% level. Diverse credit card balances give different degrees of incentive to make
balance transfers controlling for APRDIFF. Higher balance gives rise to higher savings on financial charges on balance if APRDIFF is held constant. The coefficients of EDUCAT and CHILDNUM are both positive and highly significant in the choice of intro-rate and balance switch.

1.2.4 Theoretical Analysis of Credit Card Contract

I also discuss a three-period model to introduce credit line and minimum required payments into the consideration of both credit card banks lending policy and consumers' borrowing decisions. We explore a consumer's optimal choice of a borrowing mean between one-period spot market loan and credit-card loan as long-term revolving and committed credit depending on his/her risk type.

It is found that low-risk consumers have no incentive to use credit card as long-term credit and that only high-risk consumers continue to borrow on their credit cards. If credit card banks have enough
information of their customers' default risk, they may optimally select to exclude high-risk group from the credit card market using minimum required payments. Fixed credit line, on the other hand, sets a ceiling on borrowing ability of a credit card borrower, therefore, credit card banks, knowing the optimal borrowing amounts of different risk-types, can avoid lending more to high-risk customers.

Finally, our model shows that credit card banks are not able to compete with spot-market lenders without using minimum required payments and credit line due to the fixed nature of the credit card contract and higher risk imbedded in the long-term loans.
CHAPTER II

LITERATURE REVIEW

Much of the early work on consumer debt focused on traditional loans which are unlike credit card loans in several key respects. Whereas traditional loans involve predetermined loan amounts and fixed payment schedules, with credit card loans, the actual borrowing decision is at the consumer's discretion after receiving a fixed line of credit. Debt repayment on credit cards is flexible, with the minimum monthly repayment being a fixed percentage of the total balance. Finally, unlike many traditional loans, credit card borrowing does not require consumers to post collateral, and this may place a greater risk on the lender. Jaffee and Russell (1976) and Stiglitz and Weiss (1981), as well as others, studied the tradition loan market theoretically using the tools of asymmetric information and adverse selection.

However, with the growth of credit card debt in the U.S. economy in the last decade, researchers have increasingly turned their attention to various aspects of
this unique credit instrument. Pozdena (1991) studied the functions of credit card – payment and credit device – and risk involved in unsecured nature of credit card debt to understand high and sticky credit card rate. Ausubel (1991), who was one of the first to carry out an empirical study of this market, found that abnormally high profits and high and sticky interest rates exist in the industry in spite of its seemingly competitive structure with over 6,000 card issuers. He speculated that search/switching costs and a type of irrational consumer behavior might be involved in these paradoxical market outcomes. Responding to Ausubel’s argument, Brito and Hartley (1995) introduced the aspect of the liquidity service of credit cards which saves consumers the opportunity cost of holding money for payment. They argue therefore that it is rational for consumers to hold positive credit card balances even in the face of the high interest rates. Mester (1994) also pointed that high and sticky interest rates could exist without irrationality on the part of consumers because

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of information problems for the credit card banks. Park (1997) explains the situation by referring to the open-ended nature of the credit card loan and the high risk involved with this for banks; while Stavins (1996) found that defaulters had higher interest elasticities, and this could induce banks to keep their interest rates high. Park (1997b) also tested the effect of change in interest rate on banks’ profits and default rate, and found that lower rate decreased profitability and increased default rate of customers for credit card banks. He argued that the adverse selection problem faced by banks is the potential reason for the result of the test.

Calem and Mester (1995) empirically tested the adverse selection problems in the market, and they suggested that cardholders with high balances tended to have higher search/switching cost due to banks’ inability of identifying the risk of those applicants. For the argument of Calem and Mester, we will discuss more of the relationship between credit card balance and search/switching costs in the later sections. But,
theoretically, a cardholder with a higher balance has a stronger incentive to search (or to switch) for lower interest rates because the financial charge on his balance is proportional to interest rate. Ausubel (1999) applied auction theory model to the problem of banks’ credit card solicitations and the relatively worse quality of the pool of the respondents accepting the pre-approved card to the quality of non-respondents’ pool.

After a lull in credit card defaults in the early 1990’s, default and personal bankruptcy began to increase sharply in 1995; and this phenomenon has become a serious issue for banks and policy makers (Domowitz and Eovaldi, 1993). Work by Ausubel (1997) and Domowitz and Sartain (1999) both find a strong positive correlation between credit card debt and personal bankruptcy filings. The potentially serious impact of credit card default on the general state of the economy has prompted a number of researchers to explore the default issue. Calem and Mester (1995) also examine default in this market and find that cardholders with higher balances have a higher
probability of default. Laderman (1996) concludes that although cyclical factors in the economy affect charge-offs by banks, the aggressive marketing of card issuers since the mid-1980's has deteriorated the quality of the cardholders' pool and contributed to the high rate of charge-offs seen in the 1990's. Morgan and Toll (1997), using a permanent income/life-cycle approach, and Black and Morgan (1998) also attribute rising default to socioeconomic and demographic characteristics of cardholders.

Although Broecker (1990) and Bizer and DeMarzo (1992) are not the studies on credit card market, it is worth to mention the contents and intuitions of those articles because their models can be applied in understanding the current phenomena of credit card market.

Broecker described the market equilibrium process among banks, which are endowed with independent and imperfect tests of customer qualities. In his model, banks, without having self-selection devices, use the credit worthiness test to identify risk types of loan applicants.
Under the given population of customers, as the number of banks in the market increases, the customer pool facing each bank is aggravated because the high risk type’s probability of passing the test is also increased with the number of operating banks. Therefore, as more banks enter the loan market, overall risk in the market becomes higher. As discussed by many researchers, the default and charge-off problems\(^7\) of credit card market has been worse along the trends of increased number of banks and higher degree of competition.

Bizer and DeMarzo modeled a situation in which a loan applicant can make multiple loan contracts sequentially with different banks. If banks cannot offer a fully state-contingent contract, additional loan contract with an independent bank raises an externality on the quality of the previous loans, in that increased risk of default from addition borrowing could not be reflected in the previous contracts. It is also shown that the default risk and the

\(^7\) Credit card charge-off rate was near 6% in 1997, and the rate has been consistently increased over the 25 years. For more details, see Black and Morgan (1998).
interest rate with sequential banking are higher than those under a single loan contract are.

While the research to date on credit card default has provided valuable information about trends in this market, lack of detailed data has hindered progress in understanding consumer behavior and motivation in the use of cards and subsequently in a more complete understanding of default. The Survey of Consumer Finances (SCF) – administered at 3-year intervals – has provided previous researchers the most comprehensive view of consumer debt (Jappelli, 1990; Callem and Mester, 1995; Yoo, 1997, 1998; Black and Morgan, 1998). However, some critical features of the consumer situation are not available in the SCF. The survey utilized here was specifically designed to capture certain complex characteristics which are unique to this market and will be explained in the next section.
CHAPTER III

BACKGROUND OF THE SURVEY DATA

The data on credit card usage come from a monthly random household telephone survey conducted by the Center for Survey Research Center at the Ohio State University in each of the 12 months per year. All data used in the present study are taken for the household level. The data used here come from the period February, 1998 through November, 1999. The sample each month consists of at least 500 households throughout the state of Ohio and ranges as high as 1,200 in some months. For some survey periods special data sets are available covering additional information, and I used the subsets of the survey data relevant to (1) Ponzi behavior (September 1999), (2) credit card interest rate (December 1998 through April 1999), and (3) introductory credit card interest rates and balance switching options (September 1999 through November 1999) based on the study purposes. Ohio is close to national averages in terms of socioeconomic and demographic variables and provides a
representative setting for tracking consumer debt condition.
CHAPTER IV

EMPIRICAL INVESTIGATION OF CREDIT CARD DEFAULT

This chapter uses empirical observations on household credit card use from the telephone survey conducted by the Center for Survey Research to investigate the determinants of default on credit card debt. It focuses on the relationship between default and the outcomes of financial choices consumers make within the constraints of the contract terms set by credit card issuers. Our data set contains the most detailed information yet available on a regular basis on certain behavioral aspects of credit card use.

The three new financial variables which we find to have the most significant impact on default are (1) the ratio of total minimum required payment from all credit cards to household income; (2) the percentage of total credit line which has been used by the consumer; (3) the number of credit cards on which the consumer has reached the borrowing limit. All three of these quantities result from consumers' charging behavior under the unique
arrangements of credit card loans whereby a line of credit is issued which consumers may choose to use to a greater or lesser extent. Once variables constructed from these more detailed data are considered, the debt to income ratio, which has been the focus of most previous research on determinants of default, loses its significance as an explanatory variable.

4.1 Theoretical Aspects of Credit Card Default

With the availability of the data used here, a new and more complex picture of cardholders' behavior has emerged. First, while the debt to income ratio undoubtedly has long-run significance as an indicator or a consumer's overall debt condition, the total minimum required payment to income ratio is more relevant to a consumer's immediate month-to-month ability to avoid default. Credit counselors report that many consumers are more likely to make debt decisions based on the resulting minimum required payment than on the overall cost of the
item purchased on credit. The widespread availability of revolving credit has apparently impacted the nature of budget constraint for many consumers who now maximize utility subject to a minimum required monthly payment constraint rather than an overall income constraint. Therefore it is not surprising that the minimum required payment to income variable was more powerful in predicting default behavior than the debt to income variable.

A second variable which is found to influence default behavior is the percentage of the total credit line which the consumer has used. In our work this variable is computed from the responses to two separate survey questions: the total credit card balances carried forward and total credit line. The ratio of these two quantities forms the critical variable for our empirical model. We should point out that in most previous work, the data used for credit card balances includes both convenience-use balances which will be paid off, as well as carried balances which actually form true revolving

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*Private communication, Susan Murray, Columbus, Ohio.*

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credit (Stavins, 1996; Ausubel, 1999). Our data for balances comes from a survey question which determines balances after most recent monthly payoff, and hence they more accurately reflect actual debt. A high debt balance to credit line ratio should increase the probability of default for a card user. A strategic factor exists for consumers in this variable. A consumer facing default may try to obtain more credit line in order to avoid this situation. Which consumers can actually obtain additional credit is, however, also dependent on bank’s assessment of their riskiness. Hence the balance to credit line ratio works to lower the probability of default in two ways. First it provides the consumer an additional opportunity to move their current repayment obligation to a future period. Secondly, the balance to credit line variable reflects information that banks have about the credit-worthiness of the consumer and this works to lower the denominator (i.e., raise the value of the ratio) for consumers who are known to be high risk.
Another unique aspect of credit card behavior is captured by the number of cards on which a consumer has charged to the credit limit. In our study, we refer to this variable as “maxedcards”. It reflects the way in which consumers manage their credit card purchases. It is an indication of the consumer’s willingness to take on debt beyond the bank’s assessment of their ability to handle that level of debt. Previous researchers have pointed out that independent behavior among many banks (Bizer and DeMarzo, 1992) makes this situation possible. If there were only one card-issuing bank in the economy, then presumably the credit line issued to any consumer should accurately reflect that consumer’s ability to manage that level of credit (given the consumer’s income, obligations, education and earning ability which should all be known to the bank). However, “sequential banking” (Bizer and DeMarzo, 1992) has made it possible for consumers to max-out on more than one card, and this

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9 In fact, as has been pointed out (Broecker, 1990), credit-worthiness tests may not be perfect indicators of the ability to manage credit.
influences their default probability.

Ponzi Behavior

Ponzi scheme behavior in the credit card market is a strategy used by many high-risk cardholders to avoid default by increasing the total credit line available to them via acquisition of new cards. In essence, these consumers would be getting new credit cards in order to pay off old credit card debt in a fashion reminiscent of typical pyramid, or Ponzi, behavior. By contrast, a low-risk cardholder who has been paying off regularly could presumably obtain adequate credit on an existing card and would not need additional cards.

There can be many reasons why a consumer might like to obtain a higher line of credit. For example, richer consumers (who make larger purchases) may desire more credit line than poorer consumers. However, if income and other relevant characteristics are being held constant, then we would expect that a necessary condition for Ponzi behavior to exist would be a positive sign on the partial derivative of the total desired credit line
function with respect to default risk. This is a dynamic process and our data will not allow us to fully identify the motives for obtaining new credit cards. However, members of the credit industry have identified certain key credit card use characteristics which they feel suggest such behavior, and a special data set obtained in September, 1999 provides an opportunity to ascertain if these characteristics are present. To this end, we will identify the riskiness of cardholders in our sample (according to criteria for which data exist) and compare their average credit line per card, total number of credit cards per household, and total lines of credit. We expect that the number of credit cards will be higher and the credit line per card will be lower for the high-risk cardholder who engages in Ponzi behavior. Formally we expect:

\[ \begin{align*}
(1) \quad \text{Number of Credit Cards}_{\text{High Risk}} & > \text{Number of Credit Cards}_{\text{Low Risk}} \\
(2) \quad \text{Credit Line per Card}_{\text{High Risk}} & < \text{Credit Line per Card}_{\text{Low Risk}}
\end{align*} \]
In our empirical analysis below, we will demonstrate that this is the case for our sample.

4.2 The Empirical Model and Results

The data on credit card usage come from a monthly random household telephone survey conducted by the Center for Survey Research Center at the Ohio State University in each of the 12 months per year. All data used in the present study are taken for the household level. The data used here come from the period February 1998 through May 1999. The sample each month consists of at least 500 households throughout the state of Ohio and ranges as high as 1,200 in some months. In addition, a special data set covering information relevant to Ponzi behavior was gathered in September 1999. Ohio is close to national averages in terms of socioeconomic and demographic variables and provides a representative setting for tracking consumer debt condition.
Default and Other Variables

The survey asks respondents how many times in the last six months they have missed making a minimum required payment on a credit card. The response to this question forms the basis of our dependent "default" variable in the ordered probit model below.\textsuperscript{10}

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Percent of Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOTAL SAMPLE OF CARDHOLDERS</td>
<td>5,384</td>
<td>100 %</td>
</tr>
<tr>
<td>NON-DEFAULT GROUP</td>
<td>4,766</td>
<td>88.5</td>
</tr>
<tr>
<td>DEFAULT GROUP</td>
<td>618</td>
<td>11.5</td>
</tr>
</tbody>
</table>

Table 1: Proportion of Defaulters in Sample

In addition to the three important explanatory financial variables which have been discussed earlier, we will use a number of other independent variables to capture other effects and to control for socioeconomic and demographic differences in the sample. Table 2 below lists the variables used in this study as

\textsuperscript{10}By the terms of the credit card contract, a card user is technically in default if a minimum required payment is missed. Practices with regard to collection vary, but banks are officially allowed to write off an unpaid balance after sixty days.
they are taken directly from the survey or as they are computed from these direct variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOPAYMIN</td>
<td>Number of Times of Missing Pay-Off At Least the Minimum Amount Due on Any of Credit Cards In the Past Six Months</td>
</tr>
<tr>
<td>INCOME</td>
<td>Annual Household Before-Tax Income from All Sources</td>
</tr>
<tr>
<td>BALCARRY</td>
<td>Total Amount Owed on All Credit Cards after the Most Recent Payments (i.e., carried over)</td>
</tr>
<tr>
<td>MINPAY</td>
<td>Total Minimum Required Payments</td>
</tr>
<tr>
<td>MPIncRATIO</td>
<td>MINPAY/(INCOME/12)</td>
</tr>
<tr>
<td>CDIncRATIO</td>
<td>BALCARRY / INCOME</td>
</tr>
<tr>
<td>CDLinRATIO</td>
<td>BALCARRY / Total Credit Line from All Credit Cards</td>
</tr>
<tr>
<td>MAXEDCARD</td>
<td>Number of Credit Cards Reached Credit-Limits</td>
</tr>
<tr>
<td>HOMEOWNER</td>
<td>Homeownership: 1 if homeowner, 0 otherwise</td>
</tr>
<tr>
<td>AGE</td>
<td>Respondent’s Age</td>
</tr>
<tr>
<td>EDUCAT</td>
<td>Years of Schooling</td>
</tr>
<tr>
<td>MARRIED</td>
<td>Marital Status: 1 if married, 0 otherwise</td>
</tr>
<tr>
<td>CHILDMUN</td>
<td>Number of Children</td>
</tr>
<tr>
<td>UNEMHUS</td>
<td>Unemployment Status of Husband Among Married Households: 1 if unemployed, 0 otherwise</td>
</tr>
<tr>
<td>UNEMWIFE</td>
<td>Unemployment Status of Wife Among Married Households: 1 if unemployed, 0 otherwise</td>
</tr>
<tr>
<td>UNEMSING</td>
<td>Unemployment Status of Single Among Single Households: 1 if unemployed, 0 otherwise</td>
</tr>
</tbody>
</table>

Table 2: Definition of Variables

Means and standard deviations for the financial and socioeconomic variables used in this research for the total sample as well as for the default and non-default groups are presented in Table 3 below. A t-test on the differences between the means of the two groups has been
performed, and the results of this are also presented in the table. With the simple comparison of those variables it is easily seen that the two groups are different in many aspects. As one might expect, the non-default group appears to be on more solid ground financially: they have higher incomes and greater credit lines, but they carry lower balances on their credit cards. The credit card debt to income ratio is roughly twice as high for the default group as for the non-default group. The defaulters are on average younger, less likely to be married or homeowners, but more likely to have a larger number of children in their households. However, there are no significant differences in the educational levels of the two groups or in the unemployment situations of their households.\textsuperscript{11}

\textsuperscript{11} Age and education refer to the status of the household survey respondent only.
<table>
<thead>
<tr>
<th>Variable</th>
<th>ALL SAMPLE</th>
<th></th>
<th>NON-DEFAULT</th>
<th></th>
<th>DEFAULT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std.Dev.</td>
<td>Mean</td>
<td>Std.Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>INCOME*</td>
<td>$54,140</td>
<td>67564.11</td>
<td>$54,919</td>
<td>70844.75</td>
<td>$49,828</td>
</tr>
<tr>
<td>CREDLINE*</td>
<td>$19,696</td>
<td>30366.46</td>
<td>$20,276</td>
<td>31442.05</td>
<td>$15,817</td>
</tr>
<tr>
<td>BALCARRY*</td>
<td>$2,110</td>
<td>4156.56</td>
<td>$1,967</td>
<td>3879.03</td>
<td>$3,093</td>
</tr>
<tr>
<td>MAXCARDS*</td>
<td>0.23</td>
<td>0.79</td>
<td>0.16</td>
<td>0.62</td>
<td>0.72</td>
</tr>
<tr>
<td>MINPAY*</td>
<td>$109</td>
<td>258.49</td>
<td>$101</td>
<td>245.54</td>
<td>$155</td>
</tr>
<tr>
<td>CDLnratio*</td>
<td>19.2%</td>
<td>0.27</td>
<td>17.1%</td>
<td>0.25</td>
<td>32.9%</td>
</tr>
<tr>
<td>MPIncRATIO*</td>
<td>3.4%</td>
<td>0.08</td>
<td>3.0%</td>
<td>0.07</td>
<td>5.5%</td>
</tr>
<tr>
<td>CDlnRATIO*</td>
<td>5.3%</td>
<td>0.12</td>
<td>4.7%</td>
<td>0.10</td>
<td>9.5%</td>
</tr>
<tr>
<td>HOMEOWN*</td>
<td>81.6%</td>
<td>n.a.</td>
<td>83.0%</td>
<td>n.a.</td>
<td>72.6%</td>
</tr>
<tr>
<td>EDUCAT</td>
<td>14 yrs</td>
<td>1.91</td>
<td>14 yrs</td>
<td>1.93</td>
<td>13 yrs</td>
</tr>
<tr>
<td>MARRIED*</td>
<td>61.8%</td>
<td>n.a.</td>
<td>62.6%</td>
<td>n.a.</td>
<td>54.9%</td>
</tr>
<tr>
<td>AGE*</td>
<td>46 yrs</td>
<td>15.15</td>
<td>47 yrs</td>
<td>15.32</td>
<td>41 yrs</td>
</tr>
<tr>
<td>CHILDNUM*</td>
<td>0.82</td>
<td>1.19</td>
<td>0.79</td>
<td>1.19</td>
<td>1.03</td>
</tr>
<tr>
<td>UNEMPLOY*</td>
<td>0.4%</td>
<td>n.a.</td>
<td>0.5%</td>
<td>n.a.</td>
<td>0.2%</td>
</tr>
<tr>
<td>UNEMWIFE*</td>
<td>0.1%</td>
<td>n.a.</td>
<td>0.1%</td>
<td>n.a.</td>
<td>0.2%</td>
</tr>
<tr>
<td>UNEMISING</td>
<td>0.5%</td>
<td>n.a.</td>
<td>0.5%</td>
<td>n.a.</td>
<td>0.8%</td>
</tr>
</tbody>
</table>

* T-test of difference between default and non-default groups significant at 1% level

**Table 3: Descriptive Statistics for Credit Card Users**

We now present an ordered probit model for analyzing default risk, utilizing the financial variables described above. Here default risk is represented as the number of times in the last 6 months that the respondent has missed making a minimum payment on a credit card. This variable, referred to as NOPAYMIN, takes values from zero to 6 in our data, with zero representing the “no default” group. The financial explanatory variables include: (a) total minimum required payment-to-income ratio; (b)
carried balance to income ratio; (c) percentage of total credit line used; and (d) the number of credit cards on which the consumer has reached the borrowing limit. The socioeconomic and demographic variables presented in Table 3 are also included in this model. We also include the log of income as a control. For this probit regression, the pooled data of 16 survey months is used. We include a dummy variable for each survey month to control for these time differences. The results of the regression are given in Table 4. The marginal probabilities associated with the significant independent variables are presented in Table 5.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTERCP1***</td>
<td>0.9451</td>
<td>0.2765</td>
</tr>
<tr>
<td>INTERCP2***</td>
<td>1.2652</td>
<td>0.277</td>
</tr>
<tr>
<td>INTERCP3***</td>
<td>1.6164</td>
<td>0.2779</td>
</tr>
<tr>
<td>INTERCP4***</td>
<td>1.8741</td>
<td>0.2792</td>
</tr>
<tr>
<td>INTERCP5***</td>
<td>2.0239</td>
<td>0.2804</td>
</tr>
<tr>
<td>INTERCP6***</td>
<td>2.1261</td>
<td>0.2814</td>
</tr>
<tr>
<td>CDLlnRATIO***</td>
<td>0.4798</td>
<td>0.1045</td>
</tr>
<tr>
<td>MPIncRATIO***</td>
<td>1.0156</td>
<td>0.3855</td>
</tr>
<tr>
<td>CDIncRATIO</td>
<td>-0.3354</td>
<td>0.2268</td>
</tr>
<tr>
<td>MAXEDCARDS***</td>
<td>0.2214</td>
<td>0.0301</td>
</tr>
<tr>
<td>LOG(INCOME)</td>
<td>-0.0505</td>
<td>0.0476</td>
</tr>
<tr>
<td>CHILDNUM**</td>
<td>0.0411</td>
<td>0.0205</td>
</tr>
<tr>
<td>MARRIED*</td>
<td>-0.1113</td>
<td>0.0613</td>
</tr>
<tr>
<td>HOMEOWN</td>
<td>-0.001</td>
<td>0.0711</td>
</tr>
<tr>
<td>AGE***</td>
<td>-0.00618</td>
<td>0.00211</td>
</tr>
<tr>
<td>EDUCAT</td>
<td>0.0097</td>
<td>0.0153</td>
</tr>
<tr>
<td>UNEMHUSB</td>
<td>-0.2073</td>
<td>0.4568</td>
</tr>
<tr>
<td>UNEMWIFE</td>
<td>-4.6654</td>
<td>2713.4</td>
</tr>
<tr>
<td>UNEMSING</td>
<td>0.2679</td>
<td>0.3138</td>
</tr>
</tbody>
</table>

n: 3,794
Score: 300.980 with 28 DF (p=0.0001)

* significant at 10% level.
** significant at 5% level.
*** significant at 1% level.

Table 4: Ordered Probit Regression Results

<table>
<thead>
<tr>
<th>N of Default</th>
<th>CDLlnRATIO</th>
<th>MPIncRATIO</th>
<th>MAXEDCARDS</th>
<th>CHILDNUM</th>
<th>AGE</th>
<th>MARRIED</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CDLlnRATIO</td>
<td>MPIncRATIO</td>
<td>MAXEDCARDS</td>
<td>CHILDNUM</td>
<td>AGE</td>
<td>MARRIED</td>
</tr>
<tr>
<td>y=0</td>
<td>-0.1018</td>
<td>-0.2155</td>
<td>-0.0470</td>
<td>-0.0087</td>
<td>0.0013</td>
<td>0.8695</td>
</tr>
<tr>
<td>y=1</td>
<td>0.0343</td>
<td>0.0726</td>
<td>0.0158</td>
<td>0.0029</td>
<td>-0.0004</td>
<td>0.0562</td>
</tr>
<tr>
<td>y=2</td>
<td>0.0293</td>
<td>0.0620</td>
<td>0.0135</td>
<td>0.0025</td>
<td>-0.0004</td>
<td>0.0381</td>
</tr>
<tr>
<td>y=3</td>
<td>0.0149</td>
<td>0.0316</td>
<td>0.0069</td>
<td>0.0013</td>
<td>-0.0002</td>
<td>0.0163</td>
</tr>
<tr>
<td>y=4</td>
<td>0.0064</td>
<td>0.0134</td>
<td>0.0029</td>
<td>0.0005</td>
<td>-0.0001</td>
<td>0.0062</td>
</tr>
<tr>
<td>y=5</td>
<td>0.0035</td>
<td>0.0074</td>
<td>0.0016</td>
<td>0.0003</td>
<td>0.0000</td>
<td>0.0032</td>
</tr>
<tr>
<td>y=6</td>
<td>0.0134</td>
<td>0.0284</td>
<td>0.0062</td>
<td>0.0012</td>
<td>-0.0002</td>
<td>0.0106</td>
</tr>
</tbody>
</table>

(1) Maximum Number of Default is 6.
(2) MAXEDCARDS, CHILDNUM, and AGE are treated as continuous variables.

Table 5: Marginal Effects on Predicted Probability
As expected, the three key financial variables all have positive signs, and all three are significant at the one percent level. An examination of Table 5 reveals that all signs for the marginal effects are as expected. For example, a one percent decrease in the CDLinRatio (i.e., the percentage of total credit line which has been used) will increase the probability of not missing a minimum payment by ten percent. The largest impact on default probability comes from the minimum required payment to income ratio (MPIncRATIO). From Table 5 we see that when the minimum required payment to income ratio decreases by one percent, the probability of not defaulting increases by approximately 22 percent - roughly twice the size of the impact of the CDLinRatio variable. Also, the debt to income ratio, the most commonly used measure of household financial status, is not significant at the 10 percent level when the other financial variables which are of more immediate relevance for a consumer’s default situation are included in the model. As expected, the probability of missing a minimum payment increases significantly as the
number of cards on which a consumer has maxed-out rises. If a consumer maxes out on one more credit card, his or her probability of being able to avoid default decreases by about 5 percent.

Empirical Results on Ponzi Behavior

In order to support our argument that some credit cardholders are engaging in a type of Ponzi scheme, we now present data on the critical aspects of credit card use that members of the credit industry have suggested is involved with such behavior. We use two different types of information to help identify this effect, as will be seen in Tables 6 and 7 below. Both require that we separately identify default and non-default groups in our sample. For the comparisons in Table 6, we use two measures to proxy the risk of a cardholder: (1) CDLinRatio, which is the percentage of the total credit line used; and (2) MPIncRation, which is the ratio of minimum required payment to monthly income. If Ponzi behavior is present, then we would expect that the correlation between these variables and number of cards
held will be higher for the high-risk default group than for the low-risk non-default group. We see in Table 6 below that this is indeed the case.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>All Sample</th>
<th>Non-Default</th>
<th>Default</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Credit Cards &amp; CDLinRatio</td>
<td>.06</td>
<td>-.06</td>
<td>.48</td>
</tr>
<tr>
<td>Number of Credit Cards &amp; MPIncRatio</td>
<td>.32</td>
<td>.22</td>
<td>.67</td>
</tr>
</tbody>
</table>

Table 6: Correlation Analysis with Default Status

For our second investigation, we consider the credit line per card by risk type. For this, we separate our sample into three risk groups based on data from the survey. The types that we consider are shown below in increasing order of riskiness.

![Figure 1: Risk Measure](Figure 1: Risk Measure)
Table 7 compares the number of credit cards held, average credit line, total balance carried, and total credit line from all credit cards for these three different risk types.

<table>
<thead>
<tr>
<th>Mean</th>
<th>All Sample</th>
<th>Convenience Users</th>
<th>No Default Borrowers</th>
<th>Default Borrowers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Credit Cards</td>
<td>3.4</td>
<td>2.5</td>
<td>3.5</td>
<td>4.6</td>
</tr>
<tr>
<td>Credit Line per Card</td>
<td>$6,807</td>
<td>$10,118</td>
<td>$5,583</td>
<td>$5,104</td>
</tr>
<tr>
<td>Balcarry (i.e., Balance)</td>
<td>$2,356</td>
<td>$0</td>
<td>$2,855</td>
<td>$8,089</td>
</tr>
<tr>
<td>Total Credit Line (All Credit Cards)</td>
<td>$18,576</td>
<td>$21,374</td>
<td>$17,369</td>
<td>$18,305</td>
</tr>
</tbody>
</table>

Table 7: Mean Values of Credit Card Variables with Combined Status

The information in Table 7 also supports our notion of Ponzi behavior as defined in Section III. Since banks will limit the credit line of high-risk cardholders, as risk increases, the number of credit cards held should increase and the total credit line per card should decrease. This is indeed found to be the case in the data presented in Table 7. Furthermore, the total credit line of the group with a default history is on average
$3,000 less than that of convenience users, even though the former group has on average 2 more credit cards than the latter group. While these findings cannot prove conclusively that Ponzi behavior exists among some cardholders, it is consistent with expectations of this behavior that have been expressed by many working within the credit industry.

_Socioeconomic Characteristics_

Turning to the results for socioeconomic and demographic characteristics, default risk is found to be inversely related to the age of the cardholder. Default is somewhat less likely for married cardholders, but its likelihood increases with number of children. The lack of significance of education, income, or home-ownership in directly influencing default is noteworthy since banks traditionally have relied heavily on these three characteristics in assessing the credit-worthiness of loan applicants.\(^\text{12}\)

\(^{12}\) None of these variables (education, income, or homeownership) was correlated with default at a level greater than 0.2.
Finally, it is interesting to see how well our empirical model would predict defaulters versus non-defaulters. Based on our ordered probit analysis, we find that the model would predict the actual division of the sample correctly 83 percent of the time.

4.3 Summary of the Study

This chapter has empirically investigated consumer credit card usage and default with a new set of monthly survey data containing variables on credit card behavior that have not previously been available. Credit cardholder default is examined in an ordered probit analysis where the number of missed minimum payments in the last six months (taken as an indicator of default) is fitted to key financial aspects of credit card use and a variety of socioeconomic variables. The three explanatory financial variables which, to our knowledge, are used for the first time in the current study are (a) the total minimum required payment to income ratio; (b) the percentage of total credit line which the consumer has
used; and (c) the number of credit cards on which the consumer has charged to the credit limit. These variables are found to have a significant positive effect on the probability of credit card default. In the presence of these more detailed financial variables, the variable most commonly used to predict default – the total credit card debt to income ratio – is not statistically significant. This result is reasonable since these detailed variables (especially minimum required payment to income ratio) are more relevant for the consumer’s immediate ability to avoid default.

The variable “percentage of total credit line used” reflects a consumer’s ability to avoid default by relying on further credit to pay off old debt. This is an interesting twist on traditional Ponzi or pyramid scheme behavior. Using a data set specially designed to reflect this effect, we have found characteristics that members of the credit card industry have suggested are consistent with such behavior: a high-risk credit card user will
have a higher number of cards, each with a lower per-card credit line.

Finally, the number of credit cards on which a consumer has "maxed out" is an indication of the consumer's willingness to take on debt beyond the bank's assessment of their ability to handle that level of debt, and this is found to expose the consumer to a greater risk of default.

High default has been a major problem in the credit card market and has been growing in recent years despite the strength of the U.S. economy. Clearly credit card default is a complex phenomenon involving many factors beyond the scope of the present research. The variables which we have examined here capture some key behaviors which have not been studied previously and hopefully shed new light on this default problem.
CHAPTER V

BANK PRICE COMPETITION AND ASYMMETRIC CONSUMER RESPONSES TO CREDIT CARD INTEREST RATES

This chapter discusses a theoretic model of price competition among credit card issuers under consumers’ asymmetric response to interest differentials from multiple credit issuers, and derives the equilibrium level of interest rate corresponding to each type of cardholders. Our model shows that in equilibrium, a risk pool of cardholders using the borrowing feature of credit cards should end up using lower interest rates than their counterparts in the same risk pool using no borrowing function do. It is also shown that high-risk consumers should use higher interest rate than that of low-risk consumers in the same group of using borrowing feature of credit cards.

After reviewing the model’s outcome, we apply the intuitions of the theoretic model to empirical analyses using the telephone survey data collected by the Center for Survey Research, Ohio State University. One advantage of using BSP data for our analysis is that we can provide
the amount of carried-over balance of each cardholder, which is different from the total balance because cardholders pay financial charges only on carried-over balance.

Basic data analysis focusing on credit card balance and defaults shows that those two variables strongly affect APR\textsuperscript{13} levels of cardholders when the interactions of banks and cardholders are properly controlled. The regression analysis derived from the final empirical APR function confirms the effects and directions of variables of interests. In addition, the interdependence of APR and default is explored throughout the two-stage least square model, and it is found that default experience has a strong effect on APR level of credit-card holders, but APR does not have a direct impact on credit card default.

5.1 Model of Bank Price Competition Under Asymmetric Consumer Responses

In this section, we develop a simple model to describe the nature of interest rate competition among

\textsuperscript{13} Annual percentage rate or interest rate.
credit card issuers who are facing diverse types of consumers in the market. The focus of the model is on Bertrand-type competition among credit card issuers, combined with asymmetric consumer responses arising from different card-holding motives.

We consider a competitive economy, in which $n$ risk-neutral banks compete with interest rates. Each bank provides a $\$1$ line of credit to each customer, and it is the cardholder's decision whether the given credit is used or not. The cost of funds for both banks is assumed to be zero, and interest is the only source of revenue for the banks. A cardholder is supposed to pay off the principal with interest rates at the end of the period, and the interest charge is the only cost for cardholders. There are no feasible self-selection devices available to banks such as collateral, but banks have perfect information about consumers' repayment probabilities.

In the model there are two types of consumers in terms of their debt repayment probabilities. The repayment probabilities of consumer type $a$ and $b$ are $p_a$.
and $p_a$ respectively, and it is known to the banks that $0 \leq p_a < p_b \leq 1$. It is also known that the proportion of type $a$ consumer is $l$ and that of type $b$ consumer is $1-l$.

In addition to dividing consumer types by their debt repayment probabilities, our model also distinguishes consumers by their motives for using credit cards. We assume that there are two different motives. One type of consumer has a borrowing motive in using cards, and this type represents $\beta$ proportion of consumers. These consumers borrow $\$1$. The second type of consumer merely has a convenience motive for using credit cards, and they do not borrow. There are $1-\beta$ of these consumers. The type of cardholding motive is unknown to banks, so banks cannot assign different interest rates to cardholders based on their motives. Searching for a lower interest rate is assumed to involve a positive cost for a consumer. The search cost is small enough, however, that the savings from lower financial charges, if any, is assumed to dominate this search costs. On the other hand, the consumer who does not search for a lower interest rate
will randomly select a bank interest rate offer and hence incurs no search cost.

Finally, the repayment probability type of a consumer is independent of the credit card holding motive, and each consumer can hold only one credit card in each period. As mentioned earlier, banks can observe the repayment type of each customer, and they offer interest rates based on this observation of repayment types. Therefore the interest rate the bank charges is a function of the repayment probability of the customer.

**Duopoly Model**

Let \( r'(a) \) and \( r'(b) \) denote bank \( i \)'s interest rates for repayment types \( a \) and \( b \) respectively, where \( i = 1, 2 \). There are three possible competitive market equilibria under the Bertrand one-stage game. We describe the first case of equilibrium (Case I), in which \( r'(a) < r'(a) \) and \( r'(b) < r'(b) \). Since the bank-selection process is random for non-borrowers, the proportion of both high and low-risk non-borrowers \( l(1-\beta)+(1-l)(1-\beta) \) is evenly divided
between the two banks. However, the consumer with a borrowing motive will choose the credit cards of Bank 1 because Bank 1 offers lower interest rates for both type a and b consumers than Bank 2. Therefore, the market shares of the two banks under the Case I are

\[
\text{Bank 1: } \frac{1}{2} \left[ l(1 - \beta) + (1 - l)(1 - \beta) \right] + l\beta + (1 - l)\beta
\]

and

\[
\text{Bank 2: } \frac{1}{2} \left[ l(1 - \beta) + (1 - l)(1 - \beta) \right] .
\]

It is obvious that Bank 2 has zero profits regardless of its interest rates, because none of its customers borrow and pay interest charges. By contrast, Bank 1's profit function under Case I is

\[
\Pi_1 = l\beta \left( p_s r^1(a) - 1 \right) + (1 - l)\beta \left( p_s r^1(b) - 1 \right).
\]

In equilibrium, Bank 1 should make zero profits from its customers, which implies that
\[ r^1(a) = \frac{1}{p_a} \quad \text{and} \quad r^1(b) = \frac{1}{p_b} . \]

Therefore, the equilibrium interest rates for both banks under the Case I are such that Bank 1 takes all borrowing cardholders regardless of their repayment probability, and that

\[ r^1(a) > r^1(b), \quad r^2(a) > \frac{1}{p_a}, \quad \text{and} \quad r^2(b) > \frac{1}{p_b} . \]

One interesting aspect of the Case I equilibrium is that the mean interest rate of each customer subgroup - divided by combined types of repayment probability and borrowing motive - can be easily ranked and compared by risk type and search behavior as follows:

\[ E(r \mid \text{risk type} = a \text{ & borrowing motive}) = \frac{1}{p_a} \]
\[ E(r \mid \text{risk type} = b \text{ & borrowing motive}) = \frac{1}{p_b} \]
\[ E(r \mid \text{risk type } = a \ & \ \text{non-borrowing motive}) = \frac{1}{2} \left( \frac{1}{p_a} + \left( \frac{1}{p_a} + \varepsilon_a \right) \right) \]

\[ E(r \mid \text{risk type } = b \ & \ \text{non-borrowing motive}) = \frac{1}{2} \left( \frac{1}{p_b} + \left( \frac{1}{p_b} + \varepsilon_b \right) \right) \]

where \( \frac{1}{p_a} + \varepsilon_a = r^2(a) \) and \( \frac{1}{p_b} + \varepsilon_b = r^2(b) \).

Next we consider equilibrium in Case II where \( r^1(a) > r^2(a) \) and \( r^1(b) < r^2(b) \). In this case, the market shares of the two banks are

Bank 1: \[ \frac{1}{2} \left[ l(1 - \beta) + (1 - l)(1 - \beta) \right] + (1 - l)\beta \]

and

Bank 2: \[ \frac{1}{2} \left[ l(1 - \beta) + (1 - l)(1 - \beta) \right] + l\beta \]

The profit functions of the banks are denoted as

Bank 1: \[ \Pi^1 = (1 - l)\beta \left( p_br^1(b) - 1 \right) \]

and

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Bank 2: \[ \Pi^2 = \beta \left( \frac{r^2(a)}{p_a} - 1 \right) \].

The competitive equilibrium rates of interest assuming the zero profit condition can be easily derived for both banks as follows:

\[ r^1(b) = \frac{1}{p_b} < r^2(b) \quad \text{and} \quad r^2(a) = \frac{1}{p_a} < r^1(a). \]

As in Case I, the non-borrowing cardholders, will be evenly divided between Bank 1 and Bank 2. The high-risk borrowing subgroup uses the credit cards of Bank 2 rather than Bank 1. However, there are no changes in the level of equilibrium interest rates for the two risk types among the borrowers, and the magnitudes of the mean interest rates for the four subgroups in Case II are the same as in Case I.

We now consider the third case of market equilibrium (Case III) under the condition that \( r^1(a) = r^3(a) \) and \( r^1(b) = r^2(b) \). The equilibrium rates for high and low-risk consumer types with a borrowing motive are equivalent to
those in Case I and II. However, the nature of the Case III equilibrium is somewhat different from that of the Case I and II in that the cardholders without a borrowing motive will be subject to the same low interest rates as the cardholders with a borrowing motive. This is because the two banks provide the same interest rate to each risk type. Therefore the interest rate from the random selection of non-borrowers will be identical to the lower interest rate that results from search for the borrowers. Hence the mean interest rates for the high and low-risk types with a non-borrowing motive are identical to rates for their borrowing counterparts.

Finally, as the number of banks in the market increases, the likelihood of Case III equilibrium should decrease. Therefore we do not consider Case III equilibrium in the derivation of theoretical properties for the \( n \)-bank model which follows.
**N Bank Model**

When we consider *n* banks rather than the duopoly case, the properties of the market equilibrium are maintained except for the mean interest rates for two risk subgroups with a non-borrowing motive. Suppose there are *n* banks operating in the credit card market, and they compete with interest rates under the same assumptions as in the duopoly model. Again, there are multiple possible equilibria, but we consider only the equilibrium of Case I because the nature of each equilibrium is basically the same as in the duopoly model.\(^\text{14}\)

Now, consider the case in which \(r'(a) < r'(a)\) and \(r'(b) < r'(b)\), where \(i \neq j\), and \(j=1, 2, i-1, i+1, \ldots, n\). The market shares of banks *i* and *j* are now

\[
\text{Bank i: } \quad \frac{1}{n} [(1-\beta) + (1-n)(1-\beta)] + \beta + (1-\beta)
\]

and

\(^{14}\) Case III equilibrium is not considered in the *n* bank model, and Properties I and II in this section are derived under Case I and II equilibria.
Bank $j$: 
\[ \frac{1}{n} \left[ \beta (1 - \beta) + (1 - \beta) (1 - \beta) \right] \]

The profit function for bank $i$ is the same as the one for bank 1 under the condition that $r^i(a) < r^2(a)$ and $r^i(b) < r^2(b)$. The competitive equilibrium interest rates for $n$ banks under Case I are

Bank $i$: 
\[ r^i(a) = \frac{1}{p_a} \quad \text{and} \quad r^i(b) = \frac{1}{p_b} \]

Bank $j$: 
\[ r^j(a) > \frac{1}{p_a} \quad \text{and} \quad r^j(b) > \frac{1}{p_b} \]

where $j=1, 2, i-1, i+1, n$.

Finally, the mean interest rates for the two risk types within the borrowing motive group are kept unchanged; and the mean interest rates for the two risk types with a non-borrowing motive are such that

\[
E(r \mid \text{risk type} = a \ & \text{non-borrowing motive}) = \frac{1}{n} \left( \frac{1}{p_a} + \sum_{j \neq i} \left( \frac{1}{p_a} + \epsilon_j \right) \right)
\]
\[ E(r \mid \text{risk type} = b \, \& \, \text{non-borrowing motive}) = \frac{1}{n} \left( \frac{1}{p_b} + \sum_{i=1}^{n} \left( \frac{1}{p_i} + \epsilon_i' \right) \right), \]

where \( \frac{1}{p_a} + \epsilon_a' = r'(a) \) and \( \frac{1}{p_b} + \epsilon_b' = r'(b) \).

We find that the property of the \( n \) bank equilibrium for Case I is basically equivalent to the Case I counterpart in the duopoly case. It can also be shown that Case II equilibrium with \( n \) banks has the same property as Case II under the duopoly market. Finally, the equilibrium results of the model can be summarized with the following three propositions.

**Proposition 1:** No banks make positive profits in equilibrium, and the interest rate for type a repayment probability is at least as high as \( \frac{1}{p_a} \), while the interest rate for type b repayment probability is at least as high as \( \frac{1}{p_b} \).
Proposition 2: Given the type of repayment probability, the cardholder with a borrowing motive gets a lower interest rate than the cardholder with a non-borrowing motive.

Proof:

\[
\frac{1}{p_a} < \frac{1}{n \left( \frac{1}{p_a} + \sum_{j=1}^{n} \left( \frac{1}{p_a} + \varepsilon'_j \right) \right)}
\]

and

\[
\frac{1}{p_b} < \frac{1}{n \left( \frac{1}{p_b} + \sum_{j=1}^{n} \left( \frac{1}{p_b} + \varepsilon'_b \right) \right)}
\] .

Proposition 3: Given the motive for credit card-holding, a cardholder with a higher repayment probability gets a lower interest rate than a cardholder with a lower repayment probability, if \( \frac{1}{p_a} - \frac{1}{p_b} > \varepsilon'_b - \varepsilon'_a \) for \( j=1, 2, i-1, i+1, n \) .
Proof:

\[ r'(a) = \frac{1}{p_a} > r'(b) = \frac{1}{p_b} \]

and

\[ \frac{1}{n} \left( \frac{1}{p_a} + \sum_{j \neq i} \left( \frac{1}{p_a} + \varepsilon'_j \right) \right) > \frac{1}{n} \left( \frac{1}{p_b} + \sum_{j \neq i} \left( \frac{1}{p_b} + \varepsilon'_b \right) \right) \]

5.2 Empirical Modeling of Credit Card Interest Rates Determinants

We now develop an empirical model to test the intuitions of the theoretic model discussed in the previous section. We consider consumers’ APR search and banks’ risk perceptions independently before merging those two sides into one functional form for regression analysis. In addition to the regression analysis on APR determination, this study discusses a potential causality problem between APR level and default experience with the two-stage least squares model.

5.2.1 Consumer Search

Consumers’ search for lower APR’s is a function of credit card balance and other socio-economic
characteristics, which affect the incentive of and the economic and psychological costs of APR search. Search for a lower credit card APR is costly for cardholders in terms of time and financial cost of the activities as well as psychological alertness of collecting information on APR offers from multiple credit card banks (CCBs). A consumer’s incentive to search for a lower APR comes from financial charges on their credit card balance, which is proportional to APR level, and, therefore, the incentive for APR search should be higher as the amount of credit card balance is also higher.

However, the search behavior involves various sources of costs, and the costs are diverse across cardholders depending on their economic and social status. Consumer search for a lower APR is a function of credit card balance (BALANCE)\textsuperscript{15}, and social status variables (SOCIO). More

\textsuperscript{15} Credit card balance is also considered in banks’ risk perception. Calem and Mester (1995) empirically test the search/switch cost of cardholders based on credit card balance, and conclude that cardholders with higher balances have higher probability of credit rejection from CCB’s.
formally,

\[ \text{Consumer Search} = CS(BALANCE, SOCIO). \]

5.2.2 Banks' Risk Perception

Credit card banks evaluate consumers' credit risk when they offer contracts to new applicants and current cardholders, and reflect their evaluations in the terms of credit card contracts. One of the representative terms of a credit card contract is APR. In reality, credit card banks can access to credit history and other types of information on consumers, and, therefore, profit maximizing credit card banks should provide individualized (or at least categorized) contracts to consumers based on their perceived credit risks.

The formation of risk perception by CCBs depends on the availability of information on consumers such as default history (NOPAYMIN) \(^{16}\), credit card balance

\(^{16}\) Number of times of missing minimum amount due on any of credit cards in the past six months.
(BALANCE)\(^{17}\), number of credit cards charged on credit maximum (MAXCARDS), and other social status variables (SOCIO).\(^{18}\) Therefore, the functional form of CCBs risk perception is

\[
\text{Bank Risk Perception} = BRP(\text{NOPAYMIN}, \text{BALANCE}, \ldots, \text{SOCIO}).
\]

5.2.3 Empirical Modeling of Credit Card Interest Rates

Credit card APR is determined by the interaction between banks' profit maximizing strategy subject to information availability and consumers' search for lower APR driven by the financial incentive of saving interest cost on credit card balance. Now, we consider the two sides of a credit card contract – banks and consumers – in one function to reflect the interaction of two agents as the major determinant of APR level. The formal function of APR is

\(^{17}\) The total amount of carried-over balance, which is subject to financial charge by credit card APR contract.

\(^{18}\) Correct information of income is known to be unavailable to credit card banks. CCBs usually depend on the report from credit card applicants to collect the information.
\[ APR = APR \left[ \frac{CS(BALANCE, SOCIO),}{BRP(NOPAYMIN, BALANCE, \ldots, SOCIO)} \right] \]

The above formal function is transformed to a more simplified empirical function as follows.

\[ APR = f(NOPAYMIN, BALANCE, \ldots, SOCIO).^{19} \]

### 5.2.4 Interpretation of Basic Data

Table 8 shows that credit card APR has moved between 14.0% and 14.8% for the survey period from December 1998 to April 1999. According to the FRB report (August 1997), credit card interest rates has been decreased since 1991 through 1994 due to the wide use of introductory rate.\(^{20}\)

---

\(^{19}\) The final empirical model includes BALANCE as one of the explanatory variable. Without knowing the functional structure of either consumer search or banks' risk perception, we take the way of putting BALANCE in the empirical function to test the model. The sign and size of the coefficient of BALANCE is ex ante ambiguous because the effects of BALANCE in consumer search and banks' risk perception may take the opposite directions.

\(^{20}\) Credit card APR consistently stayed around 18% level until early 1990's. FRB report (August 1997) says that credit card APR moved in the range between 15.25% and 16.25% for the period of 1994 and 1996.
The credit card APR is shown to be more decreased from the 1996 level from the BSP monthly survey data.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dec-98</td>
<td>326</td>
<td>14.8</td>
<td>5.0</td>
<td>0.9</td>
<td>28.0</td>
</tr>
<tr>
<td>Jan-99</td>
<td>310</td>
<td>14.2</td>
<td>5.2</td>
<td>2.9</td>
<td>30.0</td>
</tr>
<tr>
<td>Feb-99</td>
<td>316</td>
<td>14.3</td>
<td>4.8</td>
<td>2.0</td>
<td>25.0</td>
</tr>
<tr>
<td>Mar-99</td>
<td>307</td>
<td>14.5</td>
<td>5.0</td>
<td>0.9</td>
<td>29.0</td>
</tr>
<tr>
<td>Apr-99</td>
<td>307</td>
<td>14.0</td>
<td>4.9</td>
<td>1.8</td>
<td>22.0</td>
</tr>
<tr>
<td>All Sample</td>
<td>1566</td>
<td>14.4</td>
<td>5.0</td>
<td>0.9</td>
<td>30.0</td>
</tr>
</tbody>
</table>

**Table 8: Trend of Credit Card Interest Rates**

As discussed in the previous section, banks have access to credit history and other types of information on consumers, and the risk perception involved in a credit card contract with a consumer is reflected in the terms of the contract. To see whether cardholders’ default experience affects the APR levels, the mean APR level for default cardholders’ sub-samples are compared to the one for non-defaulters in the Table 9. The difference in APR between the two groups is 1.1% on average, and the difference is statistically significant at 1% level.
<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEFAULT</td>
<td>192</td>
<td>15.3</td>
<td>5.2</td>
<td>1.9</td>
<td>20.0</td>
</tr>
<tr>
<td>NON-DEFAULT</td>
<td>1351</td>
<td>14.2</td>
<td>4.9</td>
<td>0.9</td>
<td>30.0</td>
</tr>
</tbody>
</table>

| TTEST          | T | DF | Prob>|T| |
|----------------|---|----|-----|-----|
|                | 2.7| 1541.0 | 0.0061 |

**Table 9: Repayment Performance and Credit Card Rates**

The implication of credit card balance needs to be considered both in consumer search and CCBs APR decision. Cardholders who carry some balance on their credit cards have stronger incentive to search for lower APR to save financial charges than convenience cardholders do. It is thought that APR level for the group of carrying balance is lower than that of convenience group on the average, if the risk perception of CCBs on various types of cardholders are properly controlled. On the other hand, CCBs may reflect the balance status of cardholders in APR levels, and, therefore, the mean APR difference of the two groups should be interpreted as the result of the interaction between cardholders and CCB's.
Table 10 compares the mean APR's of balance-carry group and convenience user group, and the difference in APR is shown to be 0.8% and statistically significant at 1% level.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONVENIENCE USERS</td>
<td>411</td>
<td>15.0</td>
<td>4.3</td>
<td>1.5</td>
<td>26.0</td>
</tr>
<tr>
<td>BALANCE CARRIERS</td>
<td>1013</td>
<td>14.2</td>
<td>5.2</td>
<td>0.9</td>
<td>30.0</td>
</tr>
<tr>
<td>TTEST</td>
<td></td>
<td>2.9</td>
<td>1422</td>
<td>0.0042</td>
<td></td>
</tr>
</tbody>
</table>

Table 10: Balance Status and Credit Card Rates

Even though we have statistically significant differences in APR levels from the sample dichotomization based either on default history or on balance status in Table 9 and 10, there are some more aspects to be considered related with the interactions between CCBs and the various types of cardholders in the market.

As in Table 9, default and non-default criterion cannot control for the incentive to search for lower APR because non-default group includes two subgroups based on
balance status. Although CCBs tend to offer relatively lower APRs to non-default group, APR levels for convenience users may not be as low as the cardholders with positive balance within the non-default group on average.

The balance criterion in Table 10 has a problem in controlling for the asymmetric APR structure within balance-carry group, because some cardholders in balance-carry group may fail to acquire a lower APR. Therefore, a better way of dividing sample to understand the effect of balance and default on APR levels is to use a combined criterion, which considers both balance status and default experience to divide sample at the same time.

We have three sub-samples to compare APR levels by the combined criterion. In Figure 2, three groups of credit cardholders based on the combined status are compared. The mean APR difference between no-balance and some-balance groups is now 1.2% after controlling for

\[21 \text{ With using combined criterion, the sample is divided to four sub-samples. But, the number of sample for "default and no-balance" group is 19, and we do not include this group in our analysis.} \]
default experience, which is increased by 0.2% from the mean APR difference without default control. On the other hand, the mean APR difference is 2.0% for default and non-default group with control for balance, which is 0.9% higher than the mean APR difference without controlling for balance status.

![Mean APR and Combined Status](image)

**Figure 2: Mean APR and Combined Status**

It is obvious that default experience of cardholders takes adverse effect on acquiring a low APR due to the CCBs higher risk perception and the reflection of the
perception in APR decisions. Meanwhile, the incentive to search for lower APR is also an important determinant of cardholders APR levels. Convenience card-users defined as no-balance and non-default cardholders have no reason to be offered higher APR from CCBs if APR decision of CCBs is based on their risk perceptions. It is, however, shown that convenience users end up with higher APR than the carry and non-defaulters do on the average, which implies that the incentive of search has a strong effect on APR levels of cardholders.

Further support for APR segmentation by default risk is given in Table 11 below. The mean APR of each sub-sample tends to increase with the frequency of default. The data show that missing more than one minimum payment triggers a dramatic hike in the APR level. This can be understood in terms of the CCBs risk perception adjustment mechanism whereby a first default on payment is "tolerated"; but beyond that, further default causes a change in risk perception (see Table 11 below).
<table>
<thead>
<tr>
<th>Number of Missed Payments</th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1351</td>
<td>14.2</td>
<td>4.9</td>
<td>0.9</td>
<td>30.0</td>
</tr>
<tr>
<td>1</td>
<td>77</td>
<td>14.4</td>
<td>5.4</td>
<td>1.9</td>
<td>24.0</td>
</tr>
<tr>
<td>2 or more</td>
<td>115</td>
<td>15.9</td>
<td>5.0</td>
<td>2.9</td>
<td>28.0</td>
</tr>
<tr>
<td>All Sample</td>
<td>1566</td>
<td>14.4</td>
<td>5.0</td>
<td>0.9</td>
<td>30.0</td>
</tr>
</tbody>
</table>

Table 11: Missing Payments and Credit Card Rates

Finally, the correlation between credit card balance and APR should have a negative value if banks’ risk perception is constant across cardholders because APR search incentive is positively related with the level of balance. As we already discussed in Section 5.1, Proposition 2 predicts negative relationship between APR and balance for cardholders within a same risk pool under the Bertrand competition model.

We now consider the implication of Proposition 3 in Section 5.1 regarding the APR differences based on default experience of cardholders. It is predicted that the cardholders having some default experience may be less successful in getting lower APR’s than their non-default counterparts due to the adverse effect of default experience on CCBs risk perception, even if the current
level of credit card balance is the same across all cardholders.

We take a different approach of testing these views throughout comparing the correlation coefficients of APR and balance between default and non-default groups. In Table 12, the correlation between APR and credit card balance for non-defaulters has a negative value (-0.13) in contrast to the positive correlation (0.46) for defaulters. Overall, the relationship between APR and balance is negative, but not for default group, which implies that cardholders with higher balance tend to search more for lower APR, but their default history sets some barriers to lower APR market segments.

CCBs seem to apply higher APR’s to the cardholders of higher credit card balances if they turn out to be defaulters, which is implied from the correlation analysis together with previous statistical discussions. This is strong evidence that it may not be always true for CCBs to treat the level of credit card balance as a signal of
credit risk. Rather, CCBs take the signal of high balance completely different ways depending on credit history of cardholders.

In reality CCBs are known to use wide variety of information on cardholders, and it is their best strategy to draw customers who have high balances and no-default history. On the contrary, the high balance of cardholders with bad credit history is naturally considered very risky due both to high balance and to high probability of next defaults.

22 It has been traditionally accepted that credit card banks take high balance as a signal of high credit risk. Calem and Mester (1995) argue adverse selection problem should exist in the credit card market because cardholders with high balances face high search/switch cost due to the inability of CCBs to distinguish cardholders’ risk types combined with favorable offers of terms such as credit limits from their current card issuers. They also argue that cardholders seeking a lower APR are easily rejected from new issuers because of the high balances, and cardholders’ search incentive is further discouraged with relatively favorable conditions of current credit cards. However, CCBs credit decisions are derived from considerable amount of information on consumers, which means that CCBs can distinguish the types of cardholders at some degree. If we accept CCBs ability of credit risk evaluation, high balance customers are supposed to be treated very different ways based on the credit scores on each customer - very profitable or very unprofitable.
<table>
<thead>
<tr>
<th></th>
<th>Mean APR</th>
<th>Mean Balance</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL SAMPLE</td>
<td>14.35%</td>
<td>$2,255</td>
<td>-0.09</td>
</tr>
<tr>
<td>DEFAULT GROUP</td>
<td>15.23%</td>
<td>$3,004</td>
<td>0.46</td>
</tr>
<tr>
<td>NON-DEFAULT GROUP</td>
<td>14.23%</td>
<td>$2,139</td>
<td>-0.13</td>
</tr>
</tbody>
</table>

Table 12: Correlations of Credit Card Rates and Balance

5.2.5 Regression Results for Credit Card Interest Rate

Here we empirically estimate the regression model discussed in Section 5.2.4. Our theoretical expectation based on the model of Section 5.2 leads to the prediction that credit card balance (BALANCE) will have a negative effect on the APR level, controlling for default risk of cardholders and socioeconomic factors affecting the search cost. To reiterate, a higher balance gives a higher incentive to search for a lower APR, given banks’ risk perception and the opportunity cost of search. The frequency of missing a payment (NOPAYMIN) is expected to have a positive coefficient in the regression since this is the major signal affecting banks’ risk perception.

Socioeconomic variables affect financial and psychological cost of search for consumers. Banks may refer to these same variables in forming their risk
perception of consumers. We have therefore included other financial and demographic variables in the regression model to control for these effects.

| Variable     | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > |T| |
|--------------|--------------------|----------------|------------------------|--------|---|
| INTERCEP     | 19.292             | 1.581          | 12.205                 | 0.0001 |
| NOPAYMIN     | 0.404              | 0.143          | 2.826                  | 0.0048 |
| BALANCE      | -0.015             | 0.003          | -4.932                 | 0.0001 |
| MAXCARDS     | 0.911              | 0.190          | 4.806                  | 0.0001 |
| LOG(INCOME)  | -0.538             | 0.222          | -2.423                 | 0.0156 |
| AGE          | 0.028              | 0.011          | 2.671                  | 0.0076 |
| EDUCAT       | -0.213             | 0.078          | -2.728                 | 0.0065 |
| MARRIED      | -0.116             | 0.318          | -0.363                 | 0.7165 |
| KIDSNUM      | 0.217              | 0.128          | 1.696                  | 0.0901 |

Table 13: OLS Regression to Explain Credit Card Interest Rates

The regression result in Table 13 shows that the frequency of missing payments strongly increases APR level. The coefficient of NOPAYMIN implies 0.4% increase in APR per one missing payment and it is statistically significant at 1% level. This confirms the prediction of Proposition 3 in Section 5.2 that controlling for the credit card balance (which amounts to controlling for the intensity of search), the higher risk signal associated
with the higher number of missed payments leads banks to offer a higher APR. BALANCE is found to have a significant negative effect on APR as predicted by Proposition 2 in Section 5.2, since a higher balance gives a stronger incentive to search for a lower APR. Our final financial variable of interest, MAXCARDS, has a significant positive effect on the APR in this regression. However, the MAXCARDS result is problematic, as we discuss in the next section.

Earlier studies, focusing on the risk signal inherent in a high balance, did not separately distinguish the effect of default from that of balance. The analysis of our data shows that the correlation between credit card balance and the number of missing payments is positive but not strong (0.08). Therefore, high balance does not have to be interpreted high risk signal to CCBs. As seen in the regression results of Table 13, when high balance and default are considered separately as explanatory variables, they show strong and opposite effects on credit card APR determinations, indicating that the search-incentive of a
high balance dominates the risk effect of a high balance in the eyes of the CCBs.

5.3 Addressing Credit Card Default

We should now address the issue that the actions of credit card banks can also affect the probability of default through a higher APR, which directly increases the financial burden on the cardholder. Hence if CCBs increase the APR after observing default from a cardholder, then the CCBs strategy itself increases the probability of another default from that cardholder. We therefore consider the potential interdependency between default and APR by putting the two functional relationships in one system of equations using two-stage least square estimation (2SLS). We include APR as an explanatory variable in addition to household’s financial status variables in the default function. Following our previous findings on credit card default discussed in Chapter 4, we will introduce a variable for the percentage of total credit line which has been exhausted (CDLInRatio) and
another variable for the ratio of total minimum required payment to monthly income (MPlncRatio) as indicators of household financial status. With new availability of APR data in the survey beginning December 1998, the credit card default model can be extended to include APR as a new explanatory variable for default.

\[ \text{NOPAYMIN} = g(\text{CDLRatio}, \text{MPlncRatio}, \text{APR}, \ldots, \text{SOCIO}). \]

Table 14 shows the OLS regression result of the default function. Both CDLinRatio and MPlncRatio again are strong predictors of default.

<table>
<thead>
<tr>
<th>Dependent Variable: NOPAYMIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>INTERCEP</td>
</tr>
<tr>
<td>CDLRATIO</td>
</tr>
<tr>
<td>MPlncRatio</td>
</tr>
<tr>
<td>BALANCE</td>
</tr>
<tr>
<td>APR</td>
</tr>
<tr>
<td>MAXCARDS</td>
</tr>
<tr>
<td>INCOME</td>
</tr>
<tr>
<td>AGE</td>
</tr>
</tbody>
</table>

Table 14: OLS Regression Result of Credit Card Default
Table 14 shows that APR has a positive and significant impact on default. However, we shall see in the next section that when the interdependence between NOPAYMIN and APR is taken into account with a system of equations, APR loses significance as an explanatory variable in NOPAYMIN function. Before moving to the next section, we discuss the problem of truncated response in NOPAYMIN. The technical maximum value of NOPAYMIN is set to 6.\textsuperscript{23} To check the impact of truncated response problem in NOPAYMIN, Tobit regression result is provided in Table 15.

<table>
<thead>
<tr>
<th>Dependent Variable: NOPAYMIN</th>
<th>Variable</th>
<th>Estimate</th>
<th>Std Err</th>
<th>ChiSquare</th>
<th>Pr&gt;Chi</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>INTERCEPT</td>
<td>0.059</td>
<td>0.146</td>
<td>0.166</td>
<td>0.6838</td>
</tr>
<tr>
<td></td>
<td>CDLRATIO</td>
<td>0.298</td>
<td>0.124</td>
<td>5.803</td>
<td>0.0160</td>
</tr>
<tr>
<td></td>
<td>MPRATIO</td>
<td>2.976</td>
<td>0.672</td>
<td>19.590</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>BALANCE</td>
<td>-0.003</td>
<td>0.001</td>
<td>19.522</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>APR</td>
<td>0.011</td>
<td>0.006</td>
<td>3.320</td>
<td>0.0684</td>
</tr>
<tr>
<td></td>
<td>MAXCARDS</td>
<td>0.245</td>
<td>0.042</td>
<td>34.611</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>INCOME</td>
<td>0.0002</td>
<td>0.0001</td>
<td>5.867</td>
<td>0.0154</td>
</tr>
<tr>
<td></td>
<td>AGE</td>
<td>-0.003</td>
<td>0.002</td>
<td>2.476</td>
<td>0.1156</td>
</tr>
</tbody>
</table>

\textsuperscript{23} In the survey the question of NOPAYMIN is “In the past six months, how many times did you not pay off at least the minimum amount due on any of your credit cards?”.
The Tobit regression result is shown in Table 15. Both the sign and the significance of each explanatory variable remains almost the same as the OLS regression counterpart. The response truncation in NOPAYMIN seems to cause no major impact on the estimators in the model, so we continue to keep the linearity assumption for the regression model of NOPAYMIN function.

5.4 Interdependence of Interest Rate and Default

In this section, we address the causality issue of APR and default. In Sections 5.2 and 5.3, the determinants of APR and missed payments were examined independently. Both APR and NOPAYMIN are significant explanatory variables for each other. Therefore, the OLS regressions are biased. The causality problem can be resolved with 2SLS regression, taking each equation in a larger system of APR and NOPAYMIN functions. The 2SLS regression results are provided in Table 16 and 17 below.
| Parameter  | Estimate | Std Err | T for H0: Parameter=0 | Prob>|T| |
|------------|----------|---------|------------------------|-------|
| INTERCEP  | 18.280   | 2.044   | 8.95                   | 0.0001|
| NOPAYMIN  | 2.570    | 1.138   | 2.26                   | 0.0242|
| BALANCE   | -0.011   | 0.004   | -2.76                  | 0.0058|
| MAXCARDS  | 0.161    | 0.424   | 0.38                   | 0.7038|
| LOG(INCOME)| -0.516  | 0.283   | -1.83                  | 0.0682|
| AGE       | 0.028    | 0.014   | 2.07                   | 0.0390|
| EDUCAT    | -0.201   | 0.095   | -2.11                  | 0.0353|
| MARRIED   | -0.108   | 0.383   | -0.28                  | 0.7785|
| KIDSNUM   | 0.179    | 0.155   | 1.16                   | 0.2483|

Table 16: 2SLS Regression Result of Credit Card Interest

In Table 16 we see that the coefficient for NOPAYMIN is approximately six times its OLS coefficient (Table 13), and it also has a higher significance. It is obvious therefore that using the APR function in the system of equations with NOPAYMIN reinforces the importance of NOPAYMIN as a determinant of APR. CHILDNUM and MAXCARDS lose significance in the 2SLS regression. Otherwise, there are no significant changes in the explanatory variables.
| Parameter   | Estimate | Std Err | T for H0: Parameter=0 | Prob>|T| |
|-------------|----------|---------|------------------------|-------|
| INTERCEP    | -0.006   | 0.998   | -0.01                  | 0.9949|
| CDLRATIO    | 0.285    | 0.191   | 1.50                   | 0.1352|
| MPIRATIO    | 2.813    | 0.723   | 3.89                   | 0.0001|
| BALANCE     | -0.003   | 0.002   | -1.88                  | 0.0607|
| APR         | 0.016    | 0.073   | 0.22                   | 0.8227|
| MAXCARDS    | 0.234    | 0.068   | 3.43                   | 0.0006|
| INCOME      | 0.0002   | 0.0001  | 1.71                   | 0.0882|
| AGE         | -0.004   | 0.003   | -1.35                  | 0.1774|

**Table 17: 2SLS Regression Result of Credit Card Default**

Turning to NOPAYMIN regression in Table 17, we find that APR loses its significance in 2SLS model. The APR had been a significant explanatory variable in the OLS/Tobit regressions. However, we see here that APR itself is not the direct cause of credit card default. Rather the risk of credit card default leads CCBs to raise the interest rate to a cardholder. Therefore the proper direction of causality in the relationship between APR and default has been captured in the 2SLS model. For the other independent variables, we find no major change either in significance or size of coefficient.
5.5 Summary of the Study

We have presented a simple model of Bertrand-type competition among credit card issuers under consumers’ asymmetric response to interest differentials from multiple credit issuers. We derived the equilibrium level of interest rate corresponding to each type of cardholder.

We find in any of the possible equilibria, the risk pool of cardholders who have a borrowing motive will end up with a lower interest rates than their counterparts in using their cards (i.e., who do not borrow). This is the result of the greater search incentive of the borrowers. We also show that high-risk borrowers will have a higher interest rate than low-risk borrowers.

The regression analysis confirms the effects and directions of variables of interests. There is an inherent causality issue involving the credit card interest rate and default history since: card issuers are more likely to assign higher interest rates to defaulters, and a higher interest rate could possibly contribute to a
cardholder’s default. The interdependence of the interest rate and default was explored throughout a two-stage least square model, and it was found that default experience has a strong effect on the interest rate level of cardholders, but the interest rate does not have a direct impact on credit card default.
CHAPTER VI

INTRODUCTORY CREDIT CARD INTEREST RATES AND BALANCE SWITCHING BEHAVIOR OF CARDHOLDERS

Due to aggressive marketing and competition among credit card issuers during the 1990’s, the average number of credit cards per cardholder has increased and overall credit card interest rates have decreased during the same period. Consumers in the U.S. have also been offered introductory-rate credit cards with a balance transfer option with increasing frequency. The spread of introductory-rate (intro-rate) credit card offers has contributed to the drop in average credit card interest rates and in credit card issuers’ interest income as a percentage of assets.

In this paper we discuss the process involved in a consumer’s decision to select an introductory rate (intro-rate) credit card and to transfer a balance to the intro-rate card. This decision is a sequential process. A

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24 The Profitability of Credit Card Operations of Depository Institutions, Federal Reserve Board, August 1997.
nested multinomial logit (NML) model is used to analyze the sequential decision process of cardholders related to these choices.

6.1 Empirical Model of Introductory Credit Card Interest Rates and Balance Switching Behavior

A typical intro-rate credit card solicitation from a card issuer includes a low interest rate for some fixed period of time and balance transfer option that allows a consumer to consolidate all (or part) of credit card balance on other credit cards to the new low intro-rate card. Hence, a consumer who is offered an intro-rate credit card can choose the intro-rate card with or without balance transfer option. Because intro-rate card selection is a prerequisite for balance transfer option for a solicited consumer, it is necessary for the consumer to approve the new intro-rate card throughout filling out the form and returning it to transfer previous credit card debts to the intro-rate card. Therefore, the decision making on an intro-rate card and transferring balance is a nested process, which is described in Figure 3.
When a consumer is offered an intro-rate card with a balance transfer option, the consumer should decide whether she accepts the new intro-rate card or not. If she decides to accept the terms of the new card, she is supposed to fill out the form and to return it to the card-issuing bank. The decision nodes A and B at the branch level in Figure 3 indicate that a solicited consumer may choose between applying an intro-rate card.
and keeping a non-intro rate cards. Once she decides to apply for the intro-rate card, then balance transfer is her option accompanied by the intro-rate card application. The choice nodes 1 and 2 below the branch A are related with the balance transfer option for a solicited consumer who chooses to apply for an intro-rate card. The branch node B - a dummy node - and Choice 3 are practically the same decision level, but for the estimation purpose we separate them in Figure 3.

Here we define three utility functions for the three choices: (1) intro-rate card with balance transfer; (2) intro-rate card without balance transfer; and (3) no application. It is assumed that the three choices give different levels of utilities to each consumer. Consumers are rational in the sense that they make choices that maximize their perceived utility subject to various constraints on their choices. However, there may exist random errors in this maximization because of imperfect information and/or optimization.
Therefore, we assume that a consumer’s choice among three alternatives depends on the difference between current non-intro card rate and an intro-rate from a new card, the level of credit card balance, other socioeconomic status, and random errors. The indirect utility functions defined below are consisted of the non-stochastic utility elements and the random errors.

\[ U(1) = V_1'(\beta_1, x_1') + \epsilon_1'(\beta_1, x_1') \]
\[ U(2) = V_2'(\beta_2, x_2') + \epsilon_2'(\beta_2, x_2') \]
\[ U(3) = V_3'(\beta_3, x_3') + \epsilon_3'(\beta_3, x_3') \]

where \( V_1', V_2', \) and \( V_3' \) are non-stochastic utility functions for the \( i \)th household and they are assumed to take linear functional forms. We define the functional forms of the non-stochastic utility elements as follows.

\[ V_1'(\beta_1, x_1') = \beta_1 \cdot x_1' \]
\[ V_2'(\beta_2, x_2') = \beta_2 \cdot x_2' \]
\[ V_i^j (\beta, x_i^j) = \beta \cdot x_i^j \]

where, \( \beta \) is coefficient vector and \( x_i^j \) is characteristics vector of the household \( i \) with choice \( k=1,2, or 3 \). For the normalization purpose, we set

\[ \beta_2 = [0 \ 0 \ \ldots \ 0] \]

A nested multinomial logit (NML) model can be derived from the assumption that the random errors \( (\epsilon_i^1, \epsilon_i^2, \text{ and } \epsilon_i^3) \) are independently and identically distributed with the generalized extreme-value distribution. Then the conditional and unconditional probabilities of the choices are expressed as the following four probability functions.

\[
P(A) = \frac{e^{\rho \nu_i}}{e^{\rho \nu_i} + e^{\nu_3}} = \frac{(1 + e^{\rho / \rho})^\rho}{e^{\rho / \rho} + e^{\nu_3}}
\]

\[
P(B) = \frac{e^{\nu_3}}{e^{\rho \nu_i} + e^{\nu_3}} = \frac{e^{\nu_3}}{(1 + e^{\rho / \rho})^\rho + e^{\nu_3}} = P(3|B) = P(3)
\]
\[ P(1|A) = \frac{e^{\nu_i}}{1 + e^{\nu_i}} \]
\[ P(2|A) = \frac{1}{1 + e^{\nu_i}} \]

where \( V_i = \log(e^{\nu_i}) + 1 \) and \( \rho \) is an endogenous weighting factor\(^{26}\) between \( e^{\nu_i} \) and \( e^{\nu_i} \), which takes value between 0 and 1. The final log-likelihood function to be estimated is

\[
\log L = \sum_{i=1}^{n} \left\{ \begin{array}{c}
1(y = 1) \log P(1|\beta_1, x'_1, \rho) + 1(y = 2) \log P(2|\beta_2, x'_2, \rho) \\
1(y = 3) \log P(3|\beta_3, x'_3)
\end{array} \right\}.
\]

6.2 Interpretation of Basic Data

We use the data from a telephone survey conducted by the Center for Survey Research at the Ohio State University. As introduced in the pervious chapters, our data were collected from a monthly random household telephone survey covering various aspects of households’

\(^{26}\) For more detail discussion about endogenous weighting factor, see Trudy Ann Cameron (1985).
consumption behaviors, their economic perceptions/expectations, credit card spending/repayment patterns, and detailed demographic characteristics. For the survey period between September 1999 and November 1999, the survey asked selected households the levels of their representative credit card rates and whether they are intro rates. If a household turns out to use an intro rate, then the survey also asked whether the household made balance transfer to the introductory rate credit card.

The number of sample for this study is 781 for the three-month survey period, and 13.7% of total sampled households use some types of intro-rate credit card as shown in Table 18.

\[27\text{ A representative credit card rate is defined to be the interest rate of a credit card on which a household charged most if the household carries some balance. Alternatively, if a household does not carry any balance, its representative credit card rate is defined to be the rate of the credit card that is used most frequently.}\]
<table>
<thead>
<tr>
<th>Total Sample</th>
<th>Defaulters</th>
<th>Non-Defaulters</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Percentage of Intro APR Card Users</td>
<td>N</td>
</tr>
<tr>
<td>781</td>
<td>13.7%</td>
<td>104</td>
</tr>
</tbody>
</table>

Table 18: Introductory Rate Credit Card User Proportions

The proportion of intro-rate card users among defaulters\(^{28}\) is 18.3% in contrast to 13.0% among non-defaulters. As discuss in Kim and Dunn (1999b), credit card users with higher balance tend to have higher search incentive for lower rates to save financial charges on their credit card debts. The success of lower rate search, meanwhile, also depends on a cardholder’s credit risk perceived by card issuers. Ausubel (1999) reported that the response rate of high-risk cardholders to intro-rate solicitation letters is higher than that of low-risk cardholders.

Table 18 shows a different aspect of intro-rate availability to diverse risk types of credit card users.

\(^{28}\) Defaulter are the credit card users who missed at least one minimum required payment for the past six months.
Because defaulters' usage of intro-rate is 5.3% higher than their non-default counterparts on average, it seems that the availability of intro-rate itself does not matter much for high-risk cardholders. What really matters for a certain type of a consumer is how much the offered intro-rate is different from the current non-intro credit card rate and how much balance the consumer is carrying on her credit cards. Because the intro-rates are diverse\textsuperscript{29}, the intro-rate card selection of a consumer and balance transfer decision should be based on the two major factors: (1) the difference between current credit card rate and an offered intro-rate and (2) the level of credit card balance.\textsuperscript{30}

We also discuss other aspects of credit card usage and socioeconomic variables that are believed to affect the decision making on intro-rate and balance switching choices.

\textsuperscript{29} According to our survey data analysis, intro-rates distribute between 2.9% and 32% during the same survey period. The mean introductory rate for all samples is 10.2%.

\textsuperscript{30} Duration of introductory interest rate may also affect the decision of a cardholder on intro-rate card selection. For more details on this issue see Ausubel (1999).
We now compare the sample means of variables of interest among subgroups making different choices. Table 19 compares the characteristics of intro-rate cardholders with those of the non-intro rate cardholders.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total Sample</th>
<th>Non-Intro Rate Users</th>
<th>Intro Rate Users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=781 (100%)</td>
<td>N=674 (86.3%)</td>
<td>N=107 (13.7%)</td>
</tr>
<tr>
<td>APRDIFF</td>
<td>5.78</td>
<td>5.6%</td>
<td>6.2%</td>
</tr>
<tr>
<td>BALANCE</td>
<td>$2,652</td>
<td>$2,689</td>
<td>$2,413</td>
</tr>
<tr>
<td>TOTLCARD</td>
<td>3.8</td>
<td>3.7</td>
<td>4.4</td>
</tr>
<tr>
<td>MAXCARDS</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>EDUCAT</td>
<td>13.5</td>
<td>13.6</td>
<td>13.2</td>
</tr>
<tr>
<td>CHILDNUM</td>
<td>0.8</td>
<td>0.8</td>
<td>0.9</td>
</tr>
<tr>
<td>LOGINC</td>
<td>10.7</td>
<td>10.7</td>
<td>10.6</td>
</tr>
<tr>
<td>AGE</td>
<td>45.0 years</td>
<td>45.3 years</td>
<td>43.0 years</td>
</tr>
</tbody>
</table>

Table 19: Comparison between Intro & Non-Intro Rate Card Users

The interest rate difference between non-intro card rate and intro card rate (APRDFF) is 5.7% on average for all samples. The rate difference is higher for the intro-rate card users (6.2%) than that for the non-intro rate card users (5.6%). Average credit card balance (BALANCE) for all samples is $2,652, and there is no statistically
significant difference in credit card balance between intro-rate and non-intro rate cardholders. Overall, each household has 3.8 credit cards on average, and the number of credit cards that an intro-rate cardholder has is 4.4 that is 0.7 more than a non-intro rate cardholder has. The average number of credit cards charged maximum (MAXCARDS) per cardholder is 0.2 for both intro and non-intro card users. For other socioeconomic characteristics — education level (EDUCAT), number of children (CHILDNUM), log of income (LOGINC), and age (AGE) – there are no significant differences between intro and non-intro rate cardholders.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Intro APR Users</th>
<th>Balance Switchers</th>
<th>Non-Switchers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=107 (100%)</td>
<td>N=41 (38.3%)</td>
<td>N=66 (61.7%)</td>
</tr>
<tr>
<td>APRDIFF</td>
<td>6.2%</td>
<td>9.0%</td>
<td>4.5%</td>
</tr>
<tr>
<td>BALANCE</td>
<td>$2,413</td>
<td>$3,592</td>
<td>$1,680</td>
</tr>
<tr>
<td>TOTLCARD</td>
<td>4.4</td>
<td>5.4</td>
<td>3.8</td>
</tr>
<tr>
<td>MAXCARDS</td>
<td>0.2</td>
<td>0.05</td>
<td>0.2</td>
</tr>
<tr>
<td>EDUCAT</td>
<td>13.2</td>
<td>14.2</td>
<td>12.5</td>
</tr>
<tr>
<td>CHILDNUM</td>
<td>0.9</td>
<td>1.2</td>
<td>0.7</td>
</tr>
<tr>
<td>LOGINC</td>
<td>10.6</td>
<td>10.8</td>
<td>10.5</td>
</tr>
<tr>
<td>AGE</td>
<td>43.0 years</td>
<td>40.2 years</td>
<td>44.6 years</td>
</tr>
</tbody>
</table>

**Table 20: Comparison between Balance Switchers & Non Switchers**

Table 20 compares the same variables in Table 19 between balance switchers and non-switchers among intro-rate card users. The rate difference between normal and intro-rate (APRDIFF) is 9.0% for balance switchers and 4.5% for non-switchers on average. By contrast, APRDIFF difference between intro and non-intro rate cardholders is only 0.6%. Average credit card balance for balance switchers is $3,592, which is more than twice the average balance of non-switchers. The balance switchers in our sample also have higher total number of credit cards and more children, and they are younger people than average.
cardholders in total sample. In the next section, the results of nested multinomial logit regression are discussed in line with those explanatory variables examined in Tables 19 and 20.

6.3 Estimation of Nested Multinomial Logit Model

The result of FIML estimation of log-likelihood function defined in Section 6.1 is shown in Table 21. The coefficient vector \( \beta_1 \) corresponds to the utility function for the choice \( \odot \) - intro-rate card selection and balance switch, and the vector \( \beta_3 \) is for the choice \( \heartsuit \) - no selection for intro-rate card. The choice \( \heartsuit \) is normalized for the identification purpose, so the vector \( \beta_2 \) does not appear in Table 21.

First, we discuss the intro-rate card and balance switch choice (Choice \( \heartsuit \)) in Table 4. For the choice of intro-rate and balance switch (\( \beta_1 \), APRDIFF has a positive coefficient and is significant at 1% level. In other words, for the households who did intro-rate card
selection and balance switch, APRDIFF has a positive effect on making the choice \( \hat{0} \).

| Variable | Coefficient | Standard Error | \( P(|Z|>z) \) |
|----------|-------------|----------------|----------------|
| Intercept** | -10.28861 | 4.855666 | 0.0341 |
| APRDIFF** | 0.210971 | 6.93E-02 | 0.0023 |
| BALANCE** | 1.69E-04 | 8.07E-05 | 0.0361 |
| TOTLCARD | 8.88E-02 | 7.72E-02 | 0.2500 |
| MAXCARDS | -1.210058 | 1.282591 | 0.3455 |
| EDUCAT*** | 0.486610 | 0.148745 | 0.0011 |
| CHILDMNUM** | 0.405402 | 0.186352 | 0.0296 |
| LOGINC | 0.161838 | 0.415552 | 0.6969 |
| AGE | -2.26E-02 | 2.31E-02 | 0.3295 |

| Variable | Coefficient | Standard Error | \( P(|Z|>z) \) |
|----------|-------------|----------------|----------------|
| Intercept** | -4.768704 | 2.125646 | 0.0249 |
| APRDIFF | 1.96E-02 | 3.36E-02 | 0.5605 |
| BALANCE | 7.52E-05 | 4.76E-05 | 0.1138 |
| TOTLCARD* | -8.81E-02 | 4.67E-02 | 0.0595 |
| MAXCARDS | 4.57E-02 | 0.199379 | 0.8189 |
| EDUCAT*** | 0.288152 | 9.20E-02 | 0.0017 |
| CHILDMNUM | 1.25E-02 | 0.111087 | 0.9102 |
| LOGINC | 0.240976 | 0.167781 | 0.1509 |
| AGE* | 1.51E-02 | 9.10E-03 | 0.0962 |

Inclusive Value Param.* 0.640571 0.305235 0.0359

Table 21: Nested Multinomial Logit Regression

Log likelihood function -342.1167
Restricted log likelihood -615.5147
Chi-squared 546.7960
Degrees of freedom 19
Significance level 0.0000

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This result makes sense in that intro-rate selection and balance switch activities should involve some time and psychological costs. Hence, the interest rate difference between non-intro rate card and intro-rate card should be high enough for a household to make Choice 0. BALANCE is also an important variable for Choice 0. The coefficient of the variable is positive and significant at 5% level. Diverse credit card balances give different degrees of incentive to make balance transfers controlling for APRDIFF. Higher balance, of course, gives rise to higher saving on financial charges on balance given APRDIFF constant. The coefficients of EDUCAT and CHILDNUM are both positive and highly significant in Choice 0.

We now discuss non-intro card rate and no-balance switch (Choice 3) in Table 21. For the Choice 3 ($\beta_3$), neither APRDIFF nor BALANCE is significant variable in explaining rejecting intro-rate cards. Rather TOTLCARD is negative and significant variable, which means that a consumer with less number of credit cards more tends to
reject a new credit card with an intro-rate. This finding explains the behavioral pattern of credit card users related with the number of credit cards they hold. Some previous researches already examined the relationship between number of credit cards and default risk of cardholders, and the general conclusion is that riskier cardholders tend to have higher number of credit cards. EDUCAT and AGE are also positive and significant variables in Choice ©.

Table 22 shows elasticity values of the significant variables in Choice © ($\beta_1$). Because a change in a variable in one of the three choices can affect both branch level (A and B) and choice level (©, @, and @) probabilities, Table 5 shows total elasticity of each variable separated with branch and choice level elasticities.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Branch</th>
<th>CHOICE</th>
<th>Branch</th>
<th>Choice</th>
<th>Total Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>APRDIFF</td>
<td>INTRO</td>
<td>SWITCH</td>
<td>.332</td>
<td>.587</td>
<td>.920</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NO SWITCH</td>
<td>.332</td>
<td>-.618</td>
<td>-.286</td>
</tr>
<tr>
<td></td>
<td>NON-INTRO</td>
<td>NON-INTRO APR</td>
<td>-.063</td>
<td>--</td>
<td>-.063</td>
</tr>
<tr>
<td>BALANCE</td>
<td>INTRO</td>
<td>SWITCH</td>
<td>.129</td>
<td>.216</td>
<td>.345</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NO SWITCH</td>
<td>.129</td>
<td>-.233</td>
<td>-.104</td>
</tr>
<tr>
<td></td>
<td>NON-INTRO</td>
<td>NON-INTRO APR</td>
<td>-.020</td>
<td>--</td>
<td>-.020</td>
</tr>
<tr>
<td>EDUCAT</td>
<td>INTRO</td>
<td>SWITCH</td>
<td>1.372</td>
<td>4.046</td>
<td>5.418</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NO SWITCH</td>
<td>1.372</td>
<td>-2.500</td>
<td>-1.128</td>
</tr>
<tr>
<td></td>
<td>NON-INTRO</td>
<td>NON-INTRO APR</td>
<td>-.229</td>
<td>--</td>
<td>-.229</td>
</tr>
<tr>
<td>CHILDNUM</td>
<td>INTRO</td>
<td>SWITCH</td>
<td>.082</td>
<td>.177</td>
<td>.258</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NO SWITCH</td>
<td>.082</td>
<td>-.153</td>
<td>-.071</td>
</tr>
<tr>
<td></td>
<td>NON-INTRO</td>
<td>NON-INTRO APR</td>
<td>-.016</td>
<td>--</td>
<td>-.016</td>
</tr>
</tbody>
</table>

**Table 22: Elasticities of Variables in SWITCH (Choice ①)**

When APRDIFF increases by 1% in intro-rate/switch choice node (Choice ①), then the probability of choosing intro-rate credit card (Branch A) is increased by 0.33% and the probability of choosing balance switch under Branch A (Choice ① conditional on A) is also increased by 0.59%. Therefore, the total effect of 1% increase in APRDIFF increases in the probability of choosing intro-rate/switch by 0.92%. The increase in APRDIFF is shown to decrease the probabilities any other choices (② and ③). BALANCE in Choice ① has the same effects as APRDIFF on the three choices in terms of directions of probability.
changes, but the effects on all choices are less responsive than APRDIFF. EDUCAT in intro-rate/switch choice has also the same directional effect on three choices, but EDUCAT is the most elastic among four variables considered in Table 22. The effect of CHILDNUM is similar to other variables.

Using the estimated NML regression, we predicted the cardholders' choices with the explanatory variables in NML model. The result of the choice prediction against actual choices is shown in Table 23. The estimated NML model has 77% of accuracy of predicting the choices of all households in the sample.

<table>
<thead>
<tr>
<th></th>
<th>SWITCH</th>
<th>NO SWITCH</th>
<th>NON INTRO APR</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>SWITCH</td>
<td>5</td>
<td>2</td>
<td>34</td>
<td>41</td>
</tr>
<tr>
<td>NO SWITCH</td>
<td>2</td>
<td>8</td>
<td>55</td>
<td>66</td>
</tr>
<tr>
<td>NON INTRO APR</td>
<td>33</td>
<td>56</td>
<td>585</td>
<td>674</td>
</tr>
<tr>
<td>Total</td>
<td>41</td>
<td>66</td>
<td>674</td>
<td>781</td>
</tr>
</tbody>
</table>

*Row indicator is actual and column is predicted.

Table 23: NML Model Prediction against Actual Choices
6.4 Summary of the Study

I discussed in this chapter the decision process of introductory rate credit card selection and balance transfer to the intro-rate card. The purpose of this study is to address the issue that how the diverse choices of cardholders facing intro-rate credit card solicitations could be explained in the context of rational consumer behaviors. This study shows that a consumer’s choice among three alternatives depends on the two major factors: (1) the difference between current credit card rate and an offered intro-rate (APRDIFF) and (2) the level of credit card balance (BALANCE).

A nested multinomial logit (NML) model was used to analyze the sequential decision process of cardholders related with intro-rate credit card and balance transfer choices. The result of FIML estimation of the NML model shows that for the choice of intro-rate and balance switch, APRDIFF has a positive coefficient and is significant at 1% level. Because intro-rate selection and balance switch activities should involve some time and
psychological costs, the interest rate difference between non-intro rate and intro-rate card should be high enough for a household to take the sequence of a new application and balance transfer.

BALANCE was also found to be an important variable for the choice of intro-rate and balance switch in the regression model. The coefficient of the variable is positive and significant at 5% level. Diverse credit card balances give different degrees of incentive to make balance transfers controlling for APRDIFF. Higher balance gives rise to higher savings on financial charges on balance if APRDIFF is held constant. The coefficients of EDUCAT and CHILDMNUM are both positive and highly significant in the choice of intro-rate and balance switch.
CHAPTER VII

THEORETICAL ANALYSIS OF CREDIT CARD CONTRACT

A typical credit card provides itself a long-term revolving account, and recently CCBs tend to waive annual fees to their cardholders. We develop a highly stylized model describing the characteristics of the credit card market for both CCBs & consumers. Even though the previous articles addressed many issues such as non-responsive credit-card rates, abnormal profits of the industry, and rationality/irrationality of consumer choices in the credit-card market, the nature of the risk involved in credit card loan and the implications of credit card contracts are still remained unanswered yet. In this study we try a new approach to credit card market in term of understanding of consumers' financial choices in credit card market with a highly stylized model describing the characteristics of the market for both CCBs & consumers.

The characteristics of a credit card contract are positively introduced in this model, and the strategic implications for the terms of a credit card contract are
closely examined. We also focus on the relationship between a consumer’s risk type and his/her optimal choice of a borrowing mean between one-period spot market loan and credit-card loan as a long-term revolving and committed credit.

7.1 Basic Structure of the Model

We consider a three-period economy, in which all consumers in the 1st period are identical in terms of their uncertain income of the 2nd and 3rd periods. Consumers have no income at $t_1$, and earn stochastic income later two periods $t_2$ and $t_3$ depending on their income distribution in each period. Utility is concave and time-separable and is assumed to have following functional form.

Utility function: $V(c_1,c_2,c_3) = u(c_1) + u(c_2) + u(c_3)$

$u'(c) > 0$, $u''(c) < 0$, $u(0) = 0$, and $u'(0) < \infty$.

Both consumers and lending institutions including credit-card banks and spot-market lenders are assumed to
know the distribution of the 2\textsuperscript{nd} and 3\textsuperscript{rd} periods' income of consumers, but neither of them have any information of individual borrowers' risk type at $t_1$, as described in Figure 4. We also make the following five assumptions of the probabilities of income realization in the 2\textsuperscript{nd} and 3\textsuperscript{rd} periods.

**Assumptions:**

1. $p(H) + p(L) = 1$. 
2. $p(H \mid H) + p(L \mid H) = 1$. 
3. $p(H \mid L) + p(L \mid L) = 1$. 
4. $p(H \mid H) > p(H) \Leftrightarrow p(L \mid L) > p(L)$. 
5. $p(H \mid H) > p(H \mid L) \Leftrightarrow p(L \mid L) > p(L \mid H)$. 

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One-period spot market loan is available to consumers at $t_1$ and $t_2$ with competitive loan rate, but credit-card contract should be made only at $t_1$ with a fixed interest rate ($r_c$), minimum required payments (MRP) and credit line (L) for the two periods because of the long-term nature of the credit card loan. In other words, consumers can charge on credit cards at $t_2$ only if they accept the terms of
credit-card contract and use it at $t_1$. Due to the nature of the credit-card contract, all three terms of credit card remains constant at $t_1$ as long as a consumer pays MRP at $t_1$. If a consumer fails to pay MRP, CCB can update any of three terms of credit-card contract including canceling the contract with him. In addition, to make our model simple, funding cost of all lending institutions is set to zero, which also implies that saving rate for consumers is zero. Finally, lending institutions can observe their customers’ realized income and collect debt in each period from customers before they can spend it if necessary. For each period, consumers are required to pay their MRPs before they can borrow in the next period. For simplicity of calculation, we normalize

$$H = 1 \quad \text{and} \quad L = 0.$$  

Therefore, 2nd period expected income at $t_1$ is

$$E(Y_{t_1} | t_1) = p(H).$$
The 3rd period expected income at $t_2$ depends on the realization of 2nd period income. If a consumer takes $H$ at $t_2$, his/her expected income for 3rd period at $t_2$ is

$$E(Y_{t_3} | Y_{t_2} = H, t_2) = p(H | H).$$

Otherwise, the consumers ending up with $L$ at $t_2$ has the 3rd period expected income

$$E(Y_{t_3} | Y_{t_2} = L, t_2) = p(H | L).$$

### 7.2 Spot Market Loan

Spot-market loan rate is competitive, which means spot lenders get zero profits at the end of each period. At $t_1$, all consumers are identical in terms of their expected income and default risk. Therefore, spot market lenders can apply only one loan rate to every consumer, which make sure zero profits at $t_2$. Because it is one-period lending, spot-market loan can not be collected two periods later from the point of lending. Therefore, spot
market lenders should reflect this default risk in their lending rate when lending decision is made. The spot market loan rates at \( t_1 \) satisfying the zero profit condition should be

\[
(1+r_1^*) = \frac{1}{1-p(L)}.
\]

Spot market lenders can observe consumers' realization of income at \( t_1 \), and adjust 2\(^{nd}\) period loan rate with their observation together with the conditional probability of 3\(^{rd}\) period income. With two possible income realizations (H or L), spot-market loan rates become two different rates applied to each customer depending on his/her 2\(^{nd}\) period income. For the consumers whose income turns out to be H, the spot loan rate at \( t_2 \) is

\[
(1+r_2^{H}) = \frac{1}{1-p(L|H)}, \text{ and}
\]

if a consumer has an income of L at \( t_1 \), the spot loan rate will be
\[
(1 + r_t^{IL}) = \frac{1}{1 - p(L|L)}.
\]

By the assumptions of (4) and (5), we know that the relative size of spot-market loan rates is

\[r_t^{III} < r_t^{I} < r_t^{IL}.
\]

Under the term structure of spot market loan, consumers decide borrowing (lending) amount in \(t_1\) and \(t_2\) to maximize the expected lifetime utility taking the nature of stochastic income into consideration. Using the logic of backward induction, we can derive two optimal borrowing (\(B_t^{III}\) and \(B_t^{IL}\)) depending on realization of income at \(t_2\). Because those optimal borrowings are function of 1\(^{st}\) period borrowing (or consumption at \(t_1\)), consumers' utility maximization problem is reduced to choose 1\(^{st}\) period borrowing which makes the expected utility maximized. Suppose that a consumer has \(H\) at \(t_2\) with 1\(^{st}\)
period borrowing (or consumption) of $c_i$. Because the borrowing at $t_1$ is from the one-period spot, the consumer is required to pay off the 1st period with the current period income. The following figure indicates the income distribution of $t_1$ and $t_2$ for the consumer whose realized 2nd period income is $H$.

7.2.1 High Income In the 2nd Period with Spot-Market Loan

If this consumer chooses to borrow on spot-market at $t_2$, the distribution of consumption for this person for $t_2$ and $t_3$ is as follows.

\[
1 - (1 + r_{iH}^s) B_{t_2}^{iH} \\
[1 - (1 + r_i^s) C_i] + B_{t_2}^{iH} \\
0
\]

Therefore, the expected utility function for $H$ at $t_2$ with spot-market borrowing in the 2nd period is
\[ EV_{t_1}^{s|H}() = u_{t_1} \left( \left[ 1 - (1 + r_{t_1}^s)C_t \right] + B_{t_2}^{s|H} \right) + p(H | H) u_{t_2} \left( \left[ 1 - (1 + r_{t_2}^{s|H})B_{t_2}^{s|H} \right] \right). \]

The only choice variable in the expected utility function is the 2nd period borrowing, which means that \( H \) adjust \( B_{t_2}^{s|H} \) to maximize his/her expected utility at the point of \( t_2 \). The first-order condition from this maximization problem is

\[ u_{t_1}' \left[ 1 - (1 + r_{t_1}^s)C_t \right] + B_{t_2}^{s|H} \right) = p(H | H)(1 + r_{t_2}^{s|H})u_{t_2}' \left( \left[ 1 - (1 + r_{t_2}^{s|H})B_{t_2}^{s|H} \right] \right) \]

or

\[ \frac{u_{t_2}' \left[ 1 - (1 + r_{t_1}^s)C_t \right] + B_{t_2}^{s|H} \right)}{u_{t_2}' \left( \left[ 1 - (1 + r_{t_2}^{s|H})B_{t_2}^{s|H} \right] \right)} = p(H | H)(1 + r_{t_2}^{s|H}). \]

However, \( p(H | H)(1 + r_{t_2}^{s|H}) = 1 \) because

\[ (1 + r_{t_2}^{s|H}) = \frac{1}{1 - p(L | H)} = \frac{1}{p(H | H)} \]

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by zero-profit condition. Now, the first-order condition simply reduces to

\[ 1 - (1 + r_t^H)C_1 + B_{t_2}^{H} = 1 - (1 + r_t^{H\prime})B_{t_2}^{H\prime}. \]

Finally, the optimal borrowing function for $H$ at $t_2$ derived from the first-order condition is

\[ B_{t_2}^{H} = \left( \frac{1 + r_t^H}{1 + r_t^{H\prime}} \right) C_1. \]

We consider another situation in which $H$ at $t_2$ chooses to be a net-saver. As mentioned earlier, saving rate for the consumer is set to zero due to the fact of zero opportunity cost of fund in this economy. In this case, the expected utility function for $H$ at $t_2$ as a net-saver is

\[ EV_{t_2}^{NetSaver \mid H}(\cdot) = u_{t_2} \left( [1 - (1 + r_t^H)C_1] - S_{t_2} \right) + p(H \mid H)u_{t_2} \left( [1 + S_{t_2}] \right) + p(L \mid H)u_{t_2} \left( S_{t_2} \right). \]
The first-order condition derived from maximizing the expected utility subject to $S_h$ is

$$ u_{t_1}' \left(1 - (1 + r_h^*)C_1 - S_h \right) = p(H | H) u_{t_1}' (1 + S_h) + p(L | H) u_{t_1}' (S_h), $$

which implies that marginal utility of 2nd period consumption for $H$ should be equal to the expected value of marginal utility of 3rd period consumption. Note that $S_h$ can take either positive or negative value in the first-order condition. To find out the condition for $H$ at $t_2$ to be a net-borrower rather than a net-saver, now suppose

$$ u_{t_1}' \left(1 - (1 + r_h^*)C_1 \right) > p(H | H) u_{t_1}' (1) + p(L | H) u_{t_1}' (0) $$

with $S_h = 0$. If the condition holds, then $H$ needs to borrow, which means that optimal $S_h$ is negative, to maximize his/her expected two-period utility. After deriving the
optimal \( C_1 \), we can calculate \( 1-(1+r_i^1)C_i \) as a function of interest rate, which is reduced to

\[
\frac{1}{(2+r_i^{ii'})-(1+r_i^1)(1+r_i^{ii'})}.
\]

7.2.2 Low Income In the 2\textsuperscript{nd} Period with Spot-Market Loan

For the consumers with low-income realization, there is no option for borrowing or saving at the 2\textsuperscript{nd} period. They default on the 1\textsuperscript{st} period borrowing, and face higher interest rate for the 2\textsuperscript{nd} period borrowing in the spot market. With the positive expected income at \( t_3 \) for L, they want to borrow for the 2\textsuperscript{nd} period consumption, and pay off the 2\textsuperscript{nd} period spot-market borrowing with the interest rate \( r_i^{ii'} \) if they get H income at the final period, and otherwise they default again. The following figure depicts the distribution of consumption for L at \( t_1 \) for the 2\textsuperscript{nd} and 3\textsuperscript{rd} periods with availability of spot-market loan.
The expected utility function for L at \( t_2 \) is

\[
EV_{t_2}^L(\cdot) = u_{t_2}(B_{t_2}^{sL}) + p(H \mid L) u_{t_3}(1 - (1 + r_{t_2}^{sL})B_{t_2}^{sL})
\]

The first-order condition from this utility maximization problem is shown to be

\[
u'_{t_2}(B_{t_2}^{sL}) = p(H \mid L)(1 + r_{t_2}^{sL}) u'_{t_3}(1 - (1 + r_{t_2}^{sL})B_{t_2}^{sL})
\]

or

\[
\frac{u'_{t_2}(B_{t_2}^{sL})}{u'_{t_2}(1 - (1 + r_{t_2}^{sL})B_{t_2}^{sL})} = p(H \mid L)(1 + r_{t_2}^{sL})
\]
Applied the same procedure as \( H \) at \( t_2 \) to this case,

\[
p(H \mid L) (1 + r_{t_2}^{RL}) = 1 \quad \text{because} \quad (1 + r_{t_2}^{RL}) = \frac{1}{1 - p(L \mid L)} = \frac{1}{p(H \mid L)}.
\]

Therefore, the first-order condition is again simplified to become

\[
B_{t_2}^{RL} = 1 - (1 + r_{t_2}^{RL}) B_{t_2}^{RL},
\]

from which the borrowing function for \( L \) at \( t_2 \) can be derived as follows.

\[
B_{t_2}^{RL} = \frac{1}{2 + r_{t_2}^{RL}}.
\]

Note that the optimal borrowing for \( L \) is only a function of interest rate, and the first-period borrowing for \( L \) is not considered because spot market lenders are assumed to charge-off the default loan of \( L \) at \( t_2 \).

7.2.3 Equilibrium Borrowing and Consumption with Spot Market Loan

With given term structure of spot market loan, distribution of income, and the assumption of
\[ p(H \mid H) < \left( \frac{u''_{t^i}(1-(1+r_t^i))C_t}{u''_{t^i}(1)} \right), \]
we derived two borrowing functions for H and L at \( t_i \). The expected lifetime utility for a consumer at \( t_i \) is now only a function of first period borrowing (\( C_t \)), so we can derive optimal \( C_t \) as a function of interest rate and distribution of income. The expected lifetime utility function at the point of \( t_i \) is

\[
EV_{t_i} = u_{t_i}(C_t) + p(H) u_{t_i}(1-(1+r_t^i)C_t + B_{t_i}^{elH}) + p(L) u_{t_i}(B_{t_i}^{elL}) + p(H)p(H \mid H) u_{t_i}(1-(1+r_t^{slH})B_{t_i}^{slH}) + p(L)p(H \mid L) u_{t_i}(1-(1+r_t^{slL})B_{t_i}^{slL}).
\]

We plug two borrowing functions derived above into the expected lifetime utility function, then we have

\[
EV_{t_i}(C_t) = u_{t_i}(C_t) + p(H) u_{t_i}\left(1 - \frac{(1+r_t^i)(1+r_t^{slH})}{2+r_t^{slH}}C_t \right) + p(L) u_{t_i}\left(\frac{1}{2+r_t^{slL}}\right) + p(H)p(H \mid H) u_{t_i}\left(1 - \frac{(1+r_t^i)(1+r_t^{slH})}{2+r_t^{slH}}C_t \right) + p(L)p(H \mid L) u_{t_i}\left(\frac{1}{2+r_t^{slL}}\right).
\]
Maximizing the expected utility function with respect to $C_1$ derives the first-order condition as follows.

$$u'_{i_1}(C_1) - p(H) \left( \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} \right) u'_{t_2} \left( 1 - \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} C_1 \right) -$$

$$p(H)p(H \mid H) \left( \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} \right) u'_{t_2} \left( 1 - \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} C_1 \right) = 0.$$ 

The first-order condition is simplified to be

$$u'_{i_1}(C_1) = u'_{t_2(\text{or } t_3)} \left( 1 - \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} C_1 \right),$$

because

$$p(H) \left( \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} \right) = \frac{(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})},$$

$$p(H)p(H \mid H) \left( \frac{(1 + r^i_{t_1})(1 + r^{slH}_{t_2})}{(2 + r^{slH}_{t_2})} \right) = \frac{1}{(2 + r^{slH}_{t_2})},$$

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and the functional form of utility for each period is the same over the three periods. And, the first-order condition implies that

\[ C_1^* = 1 - \frac{(1 + r_1^*) (1 + r_1^{iii})}{(2 + r_1^{iii})} C_1. \]

Therefore, optimal \( t_1 \) consumption/borrowing \((C_1)\) is

\[ C_1 = \frac{(2 + r_1^{iii})}{(2 + r_1^{iii}) + (1 + r_1^*)(1 + r_1^{iii})}. \]

We calculate optimal consumption at \( t_2 \) for \( H \) using the result derived above. It is known that

\[ C_2^H = 1 - (1 + r_1^*) C_1 + B_2^{iii} \] and \( B_2^{iii} = \left( \frac{1 + r_1^*}{2 + r_1^{iii}} \right) C_1 \). After substituting \( C_1 \) derived above in \( C_2 \), it turns out that

\[ C_2^H = \frac{(2 + r_1^{iii})}{(2 + r_1^{iii}) + (1 + r_1^*)(1 + r_1^{iii})}, \]

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which is exactly the same as $C_1$. Let's calculate the consumption of H income at $t_3$ conditional on H at $t_2$. In this case, we indicated earlier that $C_{3^{H|H}} = 1 - \left(1 + r_{t_2}^{n|H}\right)B_{t_2}^{n|H}$, and with substitution of $C_1$, we get

$$C_{2^{H|H}} = \frac{(2 + r_{t_2}^{n|H})}{(2 + r_{t_2}^{n|H}) + (1 + r_{t_1}^n)(1 + r_{t_2}^{n|H})}.$$  

Therefore, it is found that $C_1 = C_{2^n} = C_{3^{H|H}}$, which means along the H income realization from $t_2$ and $t_3$, a consumer chooses the same consumption amount for three periods. Finally, due to the borrowing choice at $t_2$ for this consumer, $C_{3^{L|H}} = 0$.

Let's turn to the L income realization at $t_2$ and consumption choice in this case. For this consumer, the first-period borrowing (and consumption) is the same as H income because at $t_1$, everyone is identical in term of distribution of future income. However, once L is realized at $t_2$, this type of consumers default on their debt and with zero income at $t_2$ and positive final period income,
they want to borrow new debt on spot market. Because $t_2$ period borrowing (and consumption) does not depend on $t_1$ period borrowing and zero income at $t_1$,

$$C^L_2 = B^L_{t_2} = \frac{1}{(2 + r^L_{t_2})}.$$ 

If they receive $L$ at $t_3$, their debt with interest should be paid off. So, Final period consumption in the event $H$ conditional on $L$ at $t_3$ is

$$C^{H|L}_3 = 1 - (1 + r^L_{t_2})B^L_{t_2}$$

$$= \frac{1}{(2 + r^L_{t_2})},$$

which is the same as $C^L_2$. If this consumers has zero income at the final period, his/her consumption is of course zero, or $C^{L|L}_3 = 0$. Now, we summarize the optimal borrowing in each case.
\[ B_{t_1} = \frac{(2 + r^{s%H}_{t_1})}{(2 + r^{s%H}_{t_2}) + (1 + r^s_1)(1 + r^{s%H}_{t_1})}, \]

\[ B^{s%H}_{t_2} = \frac{(1 + r^{s%H}_{t_2})}{(2 + r^{s%H}_{t_2}) + (1 + r^s_1)(1 + r^{s%H}_{t_1})}, \] and

\[ B^{s%H}_{t_2} = \frac{1}{(2 + r^{s%H}_{t_2})}. \]

7.3 Credit Card Loan

The contract for credit card loan is made only at \( t_1 \), because it is a long-term contract (two-period loan in this model) in its nature. This time constraint on the availability of credit card loan implies that a consumer at \( t_1 \) should consider the 2\(^{nd}\) period borrowing condition when he/she chooses between one-period spot market loan and credit card loan. In other words, if the consumer selects the spot-market loan at \( t_1 \), then the person cannot use credit card loan even if spot market rate is higher than fixed credit-card rate. Therefore, the timing
constraint on credit-card contract gives a borrower at \( t \), an incentive to choose credit-card loan in that it provides a guaranteed fixed interest rate at \( t \), for all consumers. Depending on the amount of minimum required payments (MRP) at \( t_2 \), the equilibrium zero-profit credit card rate can be higher than or equal to the 1st period spot-market loan rate defined in the previous section. To understand this aspect of credit card loan, we start with zero MRP and compare the result from it with a positive MRP case. It will be shown that without a positive MRP at \( t_3 \), 1st period spot-market loan rate can not be an equilibrium zero-profit credit card rate due to the higher risk involved in long-term and fixed contract. However, with a positive MRP, credit-card lenders can offer as a competitive interest rate as spot-market lenders.

7.3.1 Fixed Credit-Card Rate with Zero MRP

Suppose that credit-card lenders offer a contract in which the terms are given as follows.
(1) \( (1 + r^c) = \frac{1}{1 - p(L)} = (1 + r^i) \)

(2) \( MRP^c_t = 0 \)

(3) No Constraint on Credit Line

With the terms (1), (2), and (3) in credit-card contract, there's no change in consumers' borrowing decision with credit-card use at \( t_1 \) because they can borrow their desired amount using credit-cards with same rate, and further more, there's no interest rate risk involved in income realization at \( t_2 \) under zero MRP. Once the 2\textsuperscript{nd} period income is realized, consumers can choose anyone between credit-card loan and spot-market loan at \( t_2 \) depending on the interest rates offered from those two lending institutions. Credit-card users' optimal 1\textsuperscript{st} period borrowing is exactly the same as that of spot-market borrowers because the term structure of each period borrowing for consumers remains the same as that under which only spot-market loan is available except for one additional possibility for \( L \) at \( t_2 \). For more detail,
consider H at $t_2$ who used credit card loan at the 1st period. Because $r_{h}^{\text{int}} < r_{h}^{t} = r_{h}^{s}$, H does not have any incentive to use credit card at $t_2$ to borrow. The person rather chooses the spot-market loan after paying off the balance made at $t_1$, so interest rates in each period for H is the same under availability of both credit-card loan and spot-market loan. Two alternatives exist for L at $t_2$ because (1) this type may choose to default on credit-card debt and uses spot-market loan at $t_2$, or (2) the type may want to charge more on credit card without repayment at all at $t_2$. The option between those two alternatives is determined by the relative size of benefits and cost - in terms of utility - from carrying 1st period balance (or default on it) and interest rate differential. If the utility loss from incurring 1st period balance is higher than utility gain from using guaranteed fixed interest rate of credit card, then L at $t_2$ will default on credit card loan, and give up credit-card borrowing to use spot-market. Note that with zero MRP, it is borrower's decision to make default on
credit-card balance. If (1) is chosen by L at $t_2$, then equilibrium consumption, borrowing, and zero-profit interest rates for both credit-card lenders and spot-market lenders remain the same as the case for only spot-market lenders in the market. Now, consider (2) option for L. If the option (2) is better than (1) in terms of expected utility for L, the 2\textsuperscript{nd} period borrowing decision is a function of $C_1$, which should be paid off together with the 2\textsuperscript{nd} period borrowing on credit card and interest rate payments at $t_3$ it the person can. And, in this case, $r^c = r^s$ is not a zero-profit equilibrium credit card rate. To find out sufficient conditions, under which the option (2) is chosen, we compare utility levels from those two choices.

First, let's consider the option (1) and utility level from the choice. As mentioned above, option (1) does not change anything in borrowing and consumption decision for L. Therefore, borrowing function for L is
\[ B_{t_2}^{\text{nl}} = \frac{1}{(2 + r_{t_2}^{\text{nl}})}, \quad \text{and} \]

the expected utility at \( t_2 \) for this choice for \( L \) is

\[ EV_{t_2}^{\text{nl}}(B_{t_2}^{\text{nl}}) = u_{t_2} \left( \frac{1}{2 + r_{t_2}^{\text{nl}}} \right) + p(H \mid L) \cdot u_{t_2} \left( \frac{1}{2 + r_{t_2}^{\text{nl}}} \right). \]

And, the expression inside utility function can be replace by a ratio of probabilities defined in the model description, which is

\[ EV_{t_2}^{\text{nl}}(B_{t_2}^{\text{nl}}) = u_{t_2} \left( \frac{p(H \mid L)}{1 + p(H \mid L)} \right) + p(H \mid L) \cdot u_{t_2} \left( \frac{p(H \mid L)}{1 + p(H \mid L)} \right). \]

because \( 1/(2 + r_{t_2}^{\text{nl}}) = p(H \mid L)/(1 + p(H \mid L)) \). Credit card lenders get zero profit from the first period loan because they charge a loan rate at spot market level with the same default rate as first period spot market loan. Note that the expected utility function with option \((1)\) does not depend
on the first period borrowing (consumption) decision. In contrast, option (2) takes the first period borrowing into consideration because the borrowers are required to pay off the first period balance and interest on it together with the second period borrowing. Therefore, borrowing and consumption allocation for the 2nd and 3rd periods is as follows.

\[ 1 - (1 + r^c) \left( B^{c|L}_{t_2} + (1 + r^c)C_1 \right) \]

The option (2) gives the expected utility function with optimal choice of borrowing \( B^{c|L}_{t_2} \), which is

\[ EV^{c|L}_{t_2}(B^{c|L}_{t_2}) = u_{x_2}(B^{c|L}_{t_2}) + p(H|L) u_{x_2} \left[ 1 - (1 + r^c) \left( B^{c|L}_{t_2} + (1 + r^c)C_1 \right) \right] \]
Because the probability of the 3rd period income realization and the credit card rate are given, the 2nd period credit card borrowing $B_{t_2}^{\text{IL}}$ is only the function of the 1st period borrowing $C_1$. Now, the 2nd period borrowing function for $L$ is not independent from $C_1$, and the optimal choice of $C_1$ may be different from it under spot market or option (1).

The first order condition of the expected utility function with respect to $B_{t_2}^{\text{IL}}$ is

$$
\frac{u'_2(B_{t_2}^{\text{IL}})}{u'_2(1-(1+r^C)B_{t_2}^{\text{IL}}-(1+r^C)^2C_1)} = p(H|L)(1+r^C) < 1,
$$

because $p(H|L)(1+r_{t_2}^{\text{IL}})=1$ and $r^C < r_{t_2}^{\text{IL}}$. Suppose $B_{t_2}^{\text{IL}}(C_1)$ satisfies the first order condition, and derive the 1st period borrowing decision to maximize lifetime utility function, which is
\[ EV_{t_1}^{\text{option}(2)} = u_t(C_t) + p(H) u_t(1 - (1 + r^c)C_t + B_{t_1}^H) + p(L) u_t(B_{t_1}^{\text{LL}}(C_t)) \]
\[ + p(H)p(H \mid H) u_t(1 - (1 + r^H)B_{t_1}^H) \]
\[ + p(L)p(H \mid L) u_t(1 - (1 + r^L)B_{t_1}^{\text{LL}}(C_t) - (1 + r^L)^2 C_t) \]

The expected lifetime utility function with the option (i) is exactly the same as under no availability of credit card loan. Therefore,

\[ EV_{t_1}^{\text{option}(1)} = u_t(C_t) + p(H) u_t(1 - (1 + r^c)C_t + B_{t_1}^H) + p(L) u_t(B_{t_1}^{\text{LL}}) \]
\[ + p(H)p(H \mid H) u_t(1 - (1 + r^H)B_{t_1}^H) \]
\[ + p(L)p(H \mid L) u_t(1 - (1 + r^L)B_{t_1}^{\text{LL}}). \]

Suppose \( EV_{t_1}^{\text{option}(1)} > EV_{t_1}^{\text{option}(2)} \) and \( EV_{t_1}^{\text{LL}} > EV_{t_1}^{\text{HH}} \). In other words, a consumer plans to use spot market loan at \( t_1 \), before their 2nd period income is realized, but, once low income is realized at \( t_2 \), credit card loan is more attractive due to the fixed interest rate of credit card loan. With the condition of \( EV_{t_1}^{\text{option}(1)} > EV_{t_1}^{\text{option}(2)} \), the optimal 1st period borrowing is the same as the spot market equilibrium level derived earlier. This amount of the 1st
period borrowing is ex-post optimal debt for H at \( t_2 \) because for H the term structure of each period is not changed with the addition of credit card availability to this model. However, \( EV_{t_2}^{cl} > EV_{t_2}^{sl} \) condition makes the type L at \( t_2 \) changes the source of borrowing from spot market to credit card, which means L at \( t_2 \) choose the option (2). More specifically, sufficient conditions for L at \( t_2 \) to choose (2) can be derived from the inequality of expected utility functions. We rewrite the inequality \( EV_{t_2}^{cl} > EV_{t_2}^{sl} \) as

\[
u_i \left( B_{t_2}^{cl} \right) + p(H \mid L) \left( 1 - (1 + r^c) \left( B_{t_2}^{cl} + (1 + r^c)C_i \right) \right) > \\
\nu_i \left( \frac{p(H \mid L)}{1 + p(H \mid L)} \right) + p(H \mid L) \nu_i \left( \frac{p(H \mid L)}{1 + p(H \mid L)} \right).
\]

Two sufficient conditions to make this inequality hold are

\[
B_{t_2}^{cl} > \frac{p(H)}{1 + p(H \mid L)} \quad : (1)
\]

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\[1 - (1 + r^c) \left[ B_i^{aL} + (1 + r^c)C_i \right] > \frac{p(H)}{1 + p(H|L)}. \quad : (2)\]

With the two sufficient conditions held, \( L \) at \( t \), chooses the option (2), and he may end up with higher zero-profit equilibrium credit-card rate. If it is the fact, credit-card lenders cannot compete with spot-lenders due to higher interest rate at the 1st period.

### 7.3.2 Fixed Credit-Card Rate with a Positive MRP

Suppose now that credit-card lenders offer a different contract in which minimum required payment is an arbitrary positive number. Otherwise it is the same contract as in Section 7.3.1.

1. \((1 + r^c) = \frac{1}{1 - p(L)} = (1 + r^*_L)\)

2. \(M_{1n} > 0\)

3. No Constraint in Credit Line
We assume that \( EV_{i_1}^{\text{option}(1)} > EV_{i_1}^{\text{option}(2)} \) and \( EV_{i_2}^{r_i} > EV_{i_2}^{r_i} \), are held in the subsection. And, credit card lenders are supposed to continue to offer \( r^c = r_i^c \) but now it is assumed that they require a positive MRP at \( i_2 \) to credit card holders. H at \( i_2 \) are not affected by this change in the terms of credit-card contract because this type wants to pay off all credit-card balance and leave credit card market. But, with a positive MRP, the option (2) is not available to L at \( i_2 \) because L cannot make payment for MRP at \( i_2 \) with zero income realization. Consumers at \( i_1 \) now have only the option (1) when the realized income at \( i_2 \) is L, which leaves the expected lifetime utility with the availability of both spot market and credit card loan the same as without credit card availability. A positive MRP prevents L at \( i_1 \) from choosing (2) even if the option (2) is his/her best interest under the two sufficient conditions derived earlier, and the equilibrium borrowing and consumption levels are not changed from spot market loan. Note that the credit card loan is not used for only one period.
because high-income people at \( t_1 \) voluntarily choose spot market and low income people are prevented from borrowing further on their credit cards.

### 7.3.3 Fixed Credit-Card Rate with Credit Line Constraint

Finally we suppose that credit-card lenders offer another contract in which the lender sets a line of credit at the level of the optimal first period borrowing while maintaining other terms of contract at the levels as in Section 7.3.1.

1. \( (1 + r^f) = \frac{1}{1 - p(L)} = (1 + r^*_{H}) \)

2. \( MRP_{i_2} = 0 \)

3. \( CL_{i_1} = \frac{(2 + r^{iH}_{i_2})}{(2 + r^{iH}_{i_2}) + (1 + r^f_i)(1 + r^{iH}_{i_2})} \)

Credit line is a fixed amount, and it is equivalent to the optimal first period borrowing. Without a positive MRP at \( t_2 \), credit card lenders can offer a competitive interest rate to the borrowers at \( t_1 \) because low-income
people at \( t \) cannot charge more on their credit card. The fixed credit line is used up after the consumer charges the first period consumption on the credit card, and it is impossible to borrow more on credit card without some repayment on the credit card balance made at \( t \). Therefore, fixed credit line and positive MRP have the same effect on equilibrium interest rate, consumption, and borrowing, which are equivalent to the spot market levels.

7.4 Summary of the Study

We introduced a three-period model to consider credit card loan as long-term and revolving credit contract, in which minimum required payments and credit line are two stylized terms of a credit card contract. Default risk is given from outside of the model, and credit card banks compete with one-period spot market lenders in general credit market.

Under the assumption of zero income in the 1st period and a concave utility function, identical consumers want to borrow their 1st period consumption either from credit
card lenders or from spot-market lenders. However, the availability of credit card contract only at the first period and fixed terms - interest rate, minimum required payment, and credit line - give consumers incentive to use credit card loan rather than spot-market loan because of the uncertainty of their future income realization. In the 2nd period, spot-market lenders can take the risk types of borrowers into account when they apply an interest rate to each borrowing applicant throughout observing their 2nd period income realization.

In contrast, credit card lenders providing fixed lending contracts are unable to adjust the interest rate of credit card loan in the 2nd period to reflect the higher default risk of the low-income borrowers. As we saw in the previous sections, the low-risk (or high-income) consumers have no incentive to use credit card as long-term credit in the 2nd period. And, under certain conditions, only high-risk consumers continue to borrow on their credit cards. For those high-risk consumers, credit cards are valuable as a long-term borrowing mean, because
the spot-market borrowing condition for them becomes aggravated when the state of nature reveals in the 2nd period.

Credit card lenders understanding this aspect of credit card contract can use credit line and minimum required payments as predetermined terms of the contract both to detect the financial status of their customers and to prevent the risky action of the bad customers. On the other hand, the fixed credit line has a similar implication in terms of reducing default risk involved in lending unidentified customers with a predetermined limit of credit card borrowing. The fixed credit line naturally sets a ceiling on borrowing ability of credit card borrowers; therefore, credit card lenders, knowing the optimal borrowing amounts of different types of consumers, can avoid lending more to high-risk customers. Finally, credit card lenders can offer a competitive loan premium to borrowers only if minimum required payments and/or credit lines are included in the terms of credit card contracts.
CHAPTER VIII

CONCLUSION AND FUTURE RESEARCH

My dissertation covers several theoretical and empirical issues of credit-card contracts, credit-card default and credit-scoring problems. It contains original behavioral analyses of both banks and consumers in the credit card market. A new source of data on credit-card usage is employed in the analyses.

In Section 4, I used empirical observations on household credit card use from a new monthly survey to investigate the determinants of default on credit card. Using an ordered probit model where number of missed minimum payments represents default, the influence of variables which capture key aspects of credit card use is tested. The most significant determinants of default are found to be (a) the total minimum required payment to income ratio; (b) the percentage of a consumer's total credit line which has been used; and (c) the number of credit cards on which the consumer has reached the charging limit. In the presence of these more detailed
variables, the most commonly used explanatory variable -
total credit card debt to income ratio - is not
statistically significant. New aspects of consumer
behavior with regard to credit cards are revealed in these
investigations. The data suggest that the suspicions
within the credit industry that credit card users are
engaging in a type of Ponzi scheme (or pyramid) behavior
whereby they obtain new credit cards to manage existing
debts and avoid default may indeed be well founded.
Socioeconomic influences are also examined.

In Section 5, I presented a theoretical model of
price competition among credit card issuers under
consumers' asymmetric responses to interest differentials
from multiple credit card issuers. It derives the
equilibrium level of interest rate corresponding to the
risk type and motive (i.e., borrowing versus
convenience/transactions) of cardholders. Using a new
survey data set, it takes bank risk perception and
cardholder search incentive into account in empirically
estimating the determinants of the credit card interest
rate. Focusing on credit card balance and default, it finds that these two variables strongly affect the interest rate levels of cardholders when the interactions of banks and cardholders are properly controlled. The interdependence of the credit card interest rate and default is explored with a two-stage least squares model, and it is found that default experience has a strong effect on interest rate level, but the interest rate does not have a direct impact on credit card default.

I also discussed the decision process of introductory rate credit card selection and balance transfer to the intro-rate card in Section 6. The purpose of this study is to address the issue that how the diverse choices of cardholders facing intro-rate credit card solicitations could be explained in the context of rational consumer behaviors. A nested multinomial logit (NML) model was used to analyze the sequential decision process of cardholders related with intro-rate credit card and balance transfer choices. The result of FIML estimation
of the NML regression model shows that a consumer's choice among three alternatives depends on the two major factors: (1) the difference between current credit card rate and an offered intro-rate and (2) the level of credit card balance.

In Section 7, I discussed a three-period model to introduce credit line and minimum required payments into the consideration of both credit card banks lending policy and consumers' borrowing decisions. We explore a consumer's optimal choice of a borrowing mean between one-period spot market loan and credit-card loan as long-term revolving and committed credit depending on his/her risk type. It is found out that low-risk consumers have no incentive to use credit card as long-term credit, and that only high-risk consumers continue to borrow on their credit cards. If credit card banks have enough information of their customers' default risk, they may optimally select to exclude high-risk group from the credit card market using minimum required payments. Fixed credit line, on the other hand, sets a ceiling on
borrowing ability of a credit card borrower, therefore, credit card banks, knowing the optimal borrowing amounts of different risk-types, can avoid lending more to high-risk customers. Finally, our model shows that credit card banks are not able to compete with spot-market lenders without using minimum required payments and credit line due to the fixed nature of the credit-card contract and higher risk imbedded in the long-term loans.

There are several research issues in the credit card market that are remained to be done in the future. First, we need closer examinations on special consumer groups such as college students and the households with recent bankruptcy experience. As competition in the credit card market grows, more card issuers tend to extend their credit to such high-risk portions of the market. Second, a comparative study of credit card market and the market of home equity lines of credit should be a valuable research for the better empirical understanding of the role of a collateral in a consumer loan contract. Finally, the relationship between credit card balance and
the profits of a bank needs to be both theoretically and empirically examined under diverse information availability.
APPENDIX

A. ORDERED PROBIT REGRESSION - TECHNICAL NOTE

\[ Y* = BX + E \]

where \( B = [\beta_1 \beta_2 \ldots \beta_K]_{1 \times K} \) \( X = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1M} \\ x_{21} & x_{22} & \ldots & x_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{K1} & x_{K2} & \ldots & x_{KM} \end{bmatrix}_{K \times M} \)

\[ E = [e_1 \ e_2 \ \ldots \ e_M]_{1 \times M}. \]

It is assumed that \( y^* \) is a latent dependent variable and \( e_i \sim N(0,1) \) & iid and \( y \) is an ordered categorical variable. In the CSR survey data (February 1998 - May 1999), there are seven ordered categories in NOPAYMIN variable (0 through 6). The percentage frequency of each category is shown in the following table.
Since the error term $\varepsilon_i \sim N(0,1)$, the dependent variable $y_i \sim N(BX,1)$, where $X$ is a $(K \times 1)$ vector.
\[ \Pr(y=0) = \Pr(y^* \leq \mu_1) = \Phi(\mu_1 - BX) \]
\[ \Pr(y=1) = \Pr(\mu_1 < y^* \leq \mu_2) = \Phi(\mu_2 - BX) - \Phi(\mu_1 - BX) \]
\[ \vdots \]
\[ \vdots \]
\[ \Pr(y=6) = \Pr(y^* \leq \mu_1) = 1 - \Phi(\mu_6 - BX) \]

Therefore, the log-likelihood function for the ordered probit regression is

\[ \log L = N_0 \log(\Phi(\mu_1 - BX)) + N_1 \log(\Phi(\mu_2 - BX)) \]
\[ - \Phi(\mu_1 - BX)) + \cdots + N_6 \log(1 - \Phi(\mu_6 - BX)), \]

where \( N_i \) = number of observation for the \( i \)th category.

Finally, the marginal probability of each category with respect to an explanatory variable \( X \) is

\[ \frac{\partial \Pr(y=0)}{\partial X} = \frac{\partial \Phi(-\mu_1 + \beta X)}{\partial X} = -\phi(\mu_1 - BX) \beta \]
\[ \frac{\partial \Pr(y=1)}{\partial X} = (\phi(\mu_1 - BX) - \phi(\mu_2 - BX)) \beta \]
\[
\frac{\partial \Pr(y = 6)}{\partial X} = \phi(\mu_0 - \beta X) \beta.
\]
REFERENCES


