Two Essays on Credit Markets

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Abstract of the Dissertation

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With the brisk growth of credit card usage and debt over the past decade, the credit card market attracted more academic attention than ever before. The dissertation studies two important issues in this market, having to do with personal bankruptcy and consumers' debt, estimating credit card demand by using the RD design method.

The first chapter examined the relationship between personal bankruptcy law and consumer' debt. I approach this issue by developing a two-period consumption model and empirically analyzing the relationship between leniency of personal bankruptcy laws and consumer' debt. The theoretical model and empirical work show that there is non-monotonic relationship between the bankruptcy laws and consumer's total debt. As the law becomes more lenient, total consumer debt increases at the beginning and then decreases. I also find that there exists a discontinuous jump in consumers' total debt as bankruptcy exemptions increase. Furthermore, personal bankruptcy laws have different impacts on the debt of rich and poor consumers. The leniency of the personal bankruptcy law increases high-income consumers' debt while decreasing low-income consumers' debt. Finally, this study contributes to the literature by specifically focusing on the credit card debt, which is considered as the type of unsecured debt that is most affected by bankruptcy law. Consumers who live in states with unlimited bankruptcy exemptions have significantly lower total debt, but significantly higher credit card debt. This finding suggests that bankruptcy laws have different impacts on consumers' total debt and credit card debt.

The second chapter estimates the demand for credit card by using a regression discontinuity approach. Using the credit card application data provided by a major credit card issuer, this study is the first to apply the method to estimate the demand for credit cards. The method exploits a unique feature of the credit card solicitation campaign design. The credit issuer gives consumers different interest rate offers based on the consumers' credit score. We find that demand for credit cards is near unit elasticity. The demand elasticity is estimated at -1.07. In addition, consumers with better credit rating are more responsive to interest rates than consumers with lower credit rating. The results also show that without controlling for the endogeneity of contracts, a regression model would give biased estimates.

To my loving family

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1 Does Lenient Personal Bankruptcy Law Cause More Debt

1.1 Introduction

Personal bankruptcy filings in the U.S. increased from 1.2 per 1,000 people in 1980 to 5.4 per 1,000 in 2004, and individual total debt rose from 20% to 40% of total non-real-estate consumer debt from 1985 to 2000 (Federal Reserve Statistics). In 2007, the credit card debt market showed signs of strain. American Express (AXP) reported forecasting "signs of stress" and boosted its loss reserves in its core U.S. card unit by 44%. Capital One (COF), Bank of America (BAC), and Washington Mutual (WM) all said they are bracing for a 20% or higher increase in credit card losses over the near and medium term. As personal bankruptcy is becoming a common social issue, researchers pay more attention on personal bankruptcy. Personal bankruptcy filings are highly correlated with consumers' debt. Figure 1.2 shows, high consumer' debt is closely associated with higher personal bankruptcy filings.

Does the leniency of personal bankruptcy law cause more consumer' debt and bankruptcy filings? To answer this question, researchers study the impact of personal bankruptcy law on consumer's debt, by analyzing the credit market (Alosio and Bruno(2006), Livshits et al. (2006), Jose-Victor Rio-Rull (2007)) and consumer' and lender' behavior (Gropp, Scholz and White (1999), Hynes and Berkowitz (1998), Lin and White (2001)).

This chapter approaches this issue by developing a two-period consumption model and empirically analyzing the relationship between the leniency of personal bankruptcy law and consumers' credit card debt. The model and empirical work show that there is a non-monotonic relationship between bankruptcy law and consumer's debt. As personal bankruptcy law becomes more lenient, consumers' total debt first increases and then decreases. This chapter also indicates that there might exist a discontinuous jump in total debt as the bankruptcy exemption increases. Furthermore, it shows that personal bankruptcy laws have different impacts on rich and poor consumers. Lenient personal bankruptcy laws increase high-income consumers' debt while decrease low-income consumers' debt. Finally, this chapter extends study to credit card debt, which is considered as typical unsecured and mostly affected by bankruptcy law.

This chapter contributes to previous studies in the following ways. First, it confirms and extends the Aliosio and Bruno (2006) study. They use population and time-series macro variables in U.S. to show there is a non-monotonic relationship between the debtors' default punishment and the size of the credit market. Comparing to their paper, this study builds a theoretical model to compare the effect of bankruptcy law on rich and poor consumers showing why there exist different bankruptcy impacts for rich and poor consumers. Second, individual level credit bureau scores are included in the analysis[1]. Third, this study implies there might exist a discontinuous jump in consumers' total debt as bankruptcy exemptions increase from zero to unlimited. Jose-Cictor Rios-Rull, Chatterjee and Corbae (2007) discussed the importance of credit bureau scores. In effect, debtors signal their risk status to creditors through using credit scores. Thus, to ignore credit scores in the analysis will induce bias in estimates of bankruptcy law on

[1] Three independent institutions provide credit scores as a standard for assessing individual's

consumer's debt. Unlike the previous literature (Chomsisengphet and Elul (2004), Ross and Ying (2002)), this study finds that bankruptcy law itself has a significant influence on credit card debt even of controlling for credit bureau scores. Third, previous studies address the relationship between leniency of personal bankruptcy law and consumers' debt by focusing on total debt (Gropp, Scholz and White (1999)) and home mortgage debt (Lin and White (2001))) Hynes and Berkowitz (1998)). This paper contributes to the literature by specifically analyzing the credit card market using a unique dataset provided by a commercial bank. Commonly, credit card debt is considered as the major form of unsecured debt, which is not tied to any asset, and consumers can discharge most of their unsecured debt after filing for bankruptcy. Therefore, credit card debt ought to be affected by bankruptcy provisions and laws.

A two-periods consumption model is developed to explore how bankruptcy law affects credit demand and supply. On the one hand, bankruptcy law can be viewed as insurance against negative unexpected shocks such as job loss, divorce, or illness. In this way, lenient bankruptcy law could motivate consumers to amass more debt; further have more incentive to file bankruptcy. On the other hand, the more lenient is the personal bankruptcy law, the higher the risk credit lenders face, since lenders may not be repaid after consumers file for bankruptcy. Therefore, a lenient personal bankruptcy law encourages credit lenders to implement stricter lending standards (e.g, lower credit limits, higher interest rates) to compensate for higher default risk.

The model shows that there exists an optimal level of bankruptcy law. At this level, consumers can obtain optimal welfare. If the leniency of bankruptcy law is lower than

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creditworthiness, the scores are related to previous payment behavior, especially unsecured debt.

this optimal level, the supply is greater than demand and consumer debt is the same as credit demand. Therefore, more lenient bankruptcy exemption increases credit demand, further increasing debt. However, if the lenient magnitude of bankruptcy is higher than this optimal level, the supply is less than demand and consumer's debt is equal to credit supply. Thus, more lenient bankruptcy exemption decreases consumer's debt. If all types of consumers face the same level of bankruptcy law, poor consumers have incentive to have more debt and are more likely to file bankruptcy than rich consumers, therefore, face stricter lending standards.

The dataset used in this study is provided by an anonymous commercial bank. The dataset consists of individual level credit and debt information, such as total debt, mortgage debt, and credit card debt. It also includes individual-level risk indicators, such as credit bureau scores and bankcard utilizations. Furthermore, this dataset includes demographic information, including income and age.

U.S. states have their own bankruptcy provisions and laws and those vary over states. This property can be used to study the impacts of personal bankruptcy laws by comparing states. Bankruptcy exemptions are defined as the lists of the kinds and values of property that is legally beyond the reach of creditors. The debtor in bankruptcy keeps the property if the value of property is lower than the exemption value. For example, consider a consumer who lives in a state with exemption amount of $50,000. She has $40,000 in property asset and $30,000 in debt. By filing for bankruptcy, this consumer can keep $40,000 asset and get rid of $30,000 debt since her asset amount is below the exemption amount. Therefore, a high bankruptcy exemption is generally viewed as a lenient bankruptcy law, which benefits bankruptcy filers. What value and properties may be exempted is determined by state and varies from state to state. I supplement the dataset by states bankruptcy exemptions. Furthermore, personal debt can be divided into unsecured debt and secured debt. Secured debts usually are tied to an asset, like a car for a car loan, or a house for a mortgage. Lenders can repossess cars and foreclose on houses. Unsecured debts are not tied to any asset, and include credit card debt, bills for medical care, signature loans, and debts for other types of services such as education loans. Intuitively, it would seem that unsecured debt is more likely to be affected by the level of bankruptcy exemption than secured debt. For example, if consumers with limited wealth borrow both unsecured debt and secured debt at the same interest rate, they have incentive to pay back the secured debt first if they live in a state with high bankruptcy exemptions.

This chapter first presents background information and summarizes previous literature. In second part, I develop a two-period consumption model in which consumer' and lender' behavior jointly determines consumer' debt, I draw out three testable propositions. In the third part, I describe the unique data provided by the credit card company and show descriptive evidence. Finally this chapter examines the effect of bankruptcy law on total debt and credit card debt. Finally, I discuss results and their implications for future work.

1.2 Background Literature

1.2.1 Legal and Institutional Background

BRA-78 introduced federal exemptions while nowadays 16 states allow residents to use either the federal or the state exemptions, which mostly benefit to individuals. The particular types of assets that may be exempt and the dollar values of exemptions vary widely over states.

Before 1978, bankruptcy exemptions were specified by the states and were low. The Bankruptcy Reform Act of 1978 (BRA -78) was the first national overhaul where the main purpose was to give people a "fresh start" after bankruptcy. Personal bankruptcy generally is considered the last resort when facing financial ruin because the results are long-lasting and far-reaching. Bankruptcy information (both the date of filing and the later date of discharge) remain on a credit report for 10 years, and can make it difficult to obtain credit, buy a home, get life insurance, or sometimes get a job. However, bankruptcy is still an attractive option for individuals to get rid themselves of their financial difficulty. There are two primary types of personal bankruptcy: Chapter 13 and Chapter 7. Each must be filed in federal bankruptcy court. As of April 2006, the filing fees run about $274 for Chapter 13 and $299 for Chapter 7.

Chapter 7 is known as straight bankruptcy, and involves liquidation of all assets that are not exempt. The exemptions consist of a home and property exemption. Property exemption may include automobiles, work-related tools, and basic items. By filing under Chapter 7 of the law, a debtor keeps the value of the assets designated as exempt under the law and may waive most of unsecured debt payments. To qualify for Chapter 7, debtors are required to undergo mean testing, since the law prohibits people from filing for Chapter 7 if their incomes are above certain thresholds and they could repay a minimum percentage or amount of their non-priority unsecured debt over a five year period. Chapter 13 helps debtors avoid liquidation of their assets by requiring them to repay their debt out of future income for the next three to five years. At the end of the payment plan, any remaining unsecured debt is discharged. To qualify for a Chapter 13 discharge, people must have a regular income and their total unsecured and secured debt must be less than $269,250 and $807,750, respectively. Filers must wait 8 years after receiving a discharge in Chapter 7 before they can file again under that chapter. The Chapter 13 waiting period is much shorter and can be as little as two years between filings. Both types of bankruptcy may get rid of unsecured debts and stop foreclosures, repossessions, garnishments and utility shut-offs, and debt collection activities. Both also provide exemptions that allow people to keep certain assets, although exemption amounts vary by state. According to a survey of bankruptcy filers, the majority of personal bankruptcies are to low income individuals —about 85% have income levels below the 40th percentile and the median income is $24,108, which is about half of the U.S. median household income. About 70% debtors file for bankruptcy under Chapter 7. Debtors tend to prefer Chapter 7 to Chapter 13 if their assets are less than the bankruptcy exemption because doing so allows them to avoid repayment from either assets or future income. Chapter 7 and Chapter 13 are highly correlated. Suppose, for example, that a person with assets of $30,000 lives in a state whose exemption level is $20,000. By filing under Chapter 7, this individual would lose $10,000 in assets; therefore, he/she would not pay more than $10,000 from future income by filing under Chapter 13. As a result, this paper will not distinguish Chapter 7 from Chapter 13.

1.2.2 Literature Review

Many authors have proposed theories to explain how bankruptcy exemptions affect supply and demand for secured and unsecured credit. Several empirical studies have been conducted to examine those effects.

Stiglitz and Weiss (1981) addressed the question of why lenders would impose constraints in the first place. Jappelli (1990) found that 19% of household face credit constraint and low-income, low-wealth and younger households are more likely to be rationed in the credit market. Cox and Jappelli (1993) and Duca and Rosenthal (1993) found that households who were discouraged from borrowing are constrained by credit supply. Rosenthal (2002) also provides a review of the literature on the impact of borrowing constraints on homeownership. Feldman (2001) provides empirical evidence about the impact of mortgage interest rates on homeownership outcomes. These and subsequent studies stratify empirical samples into constrained and unconstrained households and examine the impact of a wide range of different credit supply terms on individual' borrowing decisions. Rosenthal notes an important finding of these studies: the wealth constraint appears to restrict access to homeownership with far greater frequency than do income constraints. But none of these studies discusses how bankruptcy laws affect credit rationing.

Potential explanations for higher bankruptcy filings and higher personal debt can be grouped into two categories: Warren and Warren Tyagi (2003), Luckett (2002) address that negative shocks (job loss, divorce, illness) leads to financial trouble, and Shepard(1984), Marcus(1998), Gross and Souleles(1998) point out that bankruptcy law is more lenient and cost of filing is relatively low. However, Livshits, MacGee and Tertilt (2007) find that negative shock as well as legal changes in bankruptcy law cannot quantitatively account for the rise in bankruptcies. Instead, they find that credit market innovations are the major reason. Chatterjee, Corbae and Nakajima (2006) developed a theory of personal default that is consistent with U.S. bankruptcy law and proved the existence of a steady-state competitive equilibrium in the credit market. Furthermore, Alosio and Bruno (2006) developed a two-period consumption model to show how individual credit is the equilibrium point of credit supply and demand. By using aggregate data, they show there is a non-monotonic relationship between the bankruptcy exemptions and the amount of credit to individuals. Their paper implies that majority of the states in U.S. do not reach the optimal homestead exemption level, which should be neither too high nor too low. However, this paper did not discuss how bankruptcy exemption combined with income affects credit constraints.

Several empirical efforts have been to study how bankruptcy law affects consumers' debt. Gropp, Scholz and White (1997) examine how exemptions affect aggregate household credit by using a Survey of Consumer Finance 1983 single cross section dataset. They assume that debtors can shift assets between secured debt and unsecured debt to maximize their bankruptcy benefits. Therefore, they argue that there is no need to separate secured from unsecured debt. The results showed: 1) higher exemptions lead to higher turn down rate for access to credit; 2) total debt is positively related to exemptions for high-asset people and negatively related for low-asset households. 3) Higher exemptions lead to higher interest rates on automobile loans for low-asset households. These results are what might be expected: for low asset households, credit constraints will dominate while for high asset household, credit demand dominates. They further point out that exemptions may redistribute credit to households with more assets. The main shortcoming of the paper is that they do not separate secured debt from unsecured debt. In reality, it is not easy for individuals to optimize benefits by reallocating secured and unsecured debt. Usually unsecured debt is a short-run debt while secured debt is a long-run debt. (For example, people do not use a credit card to buy a house.) Second, unsecured creditors are more likely to be affected by personal bankruptcy than secured creditors since debtors discharge most unsecured debt while secured debt has collateral. Therefore, many researchers concerned that homestead exemption should have different effect on the supply of secured and unsecured credit.

Many efforts have been made to focus on home mortgages since researchers believe that households cannot easily arbitrage assets and debts over secured and unsecured debts. Hynes and Berkowitz (1998) suggested that homestead exemptions could actually benefit the mortgage lender since the mortgage lender is senior to claim the asset with respect to its collateral. Besides, individuals are intended to pay more secured debt as well as keeping higher unsecured debt if their assets are less than bankruptcy exemption. In particular, by using the Home Mortgage Discrimination Act (HMDA) from 1990 to 1995 they showed that higher homestead exemptions have tended to reduce by using the Home Mortgage Discrimination Act (HMDA) from 1990 to 1995 and mortgage rates. By contrast, Lin and White (2001) develop a model that show that higher exemptions should lead to a tightening of the terms of credit and they found empirical support using HMDA data from 1992 through 1997 because bankruptcy process and foreclosure itself may delay the payment time and costly for mortgage lender.

Studies of home mortgage debt have ignored credit bureau scores (used as a industry standard for individual credit quality). Ross and Ying (2002) stress the importance of controlling for creditworthiness in studies of mortgage credit supply. Barakova in 2003 shows that wealth and credit quality constraints significantly reduce the likelihood owning a house. Chomsisengphet and Elul (2004) first found that exemptions have no effect on the probability of being turned down in a mortgage application after controlling for credit bureau scores by using merged data from a major credit bureau with HMDA dataset. The result indicates that there exists a relationship between homestead exemption and credit scores. High homestead exemption lower the score only for those who actually have a mortgage recorded while non-homeowners do not care about homestead exemptions.

Existing research into bankruptcy property exemptions usually found significant adverse consequences for consumer unsecured credit markets, raising interest rates and credit rationing. Charles Grant (2002) used a simple Tobit model to find that increasing the exemption level causes less unsecured debt held, using Consumer Expenditure Survey data. This analysis indicated that credit constraints are important.

1.3 Theory

Bankruptcy may be viewed as a form of insurance for individuals facing financial difficulties. Lenient bankruptcy law can motivate individuals to acquire more debt, lso cause them to be credit-constrained. A rational lender may limit how much debt any borrowers are allowed to hold. An actual or an expected personal bankruptcy will encourage lenders to employ some combination of stricter lending standards and terms. In theory, bankruptcy law can affect the supply and cost of credit, particularly unsecured credit such as credit card lending. This paper develops a two-period individual model following the paper given by Aloisio and Bruno (2007).

1.3.1 Individual's Problem

Consider a consumer who lives for two periods and maximizes utility over consumption *c*. At the beginning of the first period, the consumer has durable goods with value *D* (i.e., a house or a car) that she consumes in both periods, but it depreciates at rate $(1-\delta)$. First period income w_1 is observed but the second period income is uncertain with S states $w_{2s} \in [w_{21}, \cdots w_{2s}]$. The probability of each state is $p_s = p[s \mid w_1]$, with probability of the state of second period income depending on first period income. For example, low-income consumers are more likely to stay in low-income status in the second period, while high-income consumers are more likely to stay in high-income status.

There are a large number of agents divided into two groups: potential borrowers and lenders. Financial institutions are the lenders who provide debt via a contract (B, r). B is the debt amount and r is the interest rate. Borrowers can borrow or save at a risk free saving rate r_f. Each lender is assumed have enough money to lend. If a borrower files for bankruptcy, part of her debt will be discharged, and some of her assets, including durable goods (*D*) and present income will be exempted up to the amount *E*. The bankruptcy law determines the level of bankruptcy exemption *E* exogenously.

Consumption in the first period determines the level of individual debt *B* at the beginning of period 2:

$$B = c_1 - D - w_1 \tag{1.1}$$

If B is greater than 0, this indicates that the consumer spent more than the sum of his/her wage and durable goods. In the second period, borrowers face the decision of whether to file for bankruptcy. If consumer does not file, she needs to pay back $(1+r)B$ debt; if she files for bankruptcy in the second period, she needs to pay back $Min[\max(w_{2s}+D-E,0),(1+r)B)]$, which is amount that over exemptions.

If individual do not file for bankruptcy, wealth is shown in Equation (1.2):

$$\max(w_{2s}+\delta D-(1+r)B,0) \tag{1.2}$$

If individual files for bankruptcy, wealth is given by

$$\min(w_{2s}+\delta D,E)+\max(w_{2s}+\delta D-E-(1+r)B,0) \tag{1.3}$$

It is optimal to file for bankruptcy if and only if the wealth in bankruptcy is more than wealth in non-bankruptcy. That is,

$$\min(w_{2s}+\delta D,E)+\max(w_{2s}+\delta D-E-(1+r)B,0)>\max(w_{2s}+\delta D-(1+r)B,0) \tag{1.4}$$

$$\text{Given} \quad E>0, r\geq 0, B\geq 0$$

In conclusion, if $(1+r)B>\max(w_{2s}+\delta D-E,0)$, the optimal choice for individuals is to file for bankruptcy, else will not file bankruptcy. In other words,

The optimal choice is not to file for bankruptcy:

$$(1+r)B \leq \max(w_{2s}+\delta D-E,0)$$

The optimal choice is to file for bankruptcy:

$$(1+r)B > \max(w_{2s}+\delta D-E,0),$$

Let l_s represent the bankruptcy decision.

$$l_s=\begin{cases}1 & (1+r)B>\max(w_{2s}+\delta D-E,0)\\ 0 & (1+r)B\leq \max(w_{2s}+\delta D-E,0)\end{cases} \tag{1.5}$$

The probability of non-bankruptcy $\sum_s p_s(1-l_s)$ and then probability of bankruptcy is $\sum_s p_s l_s$.

The second period wealth for the borrowers is given as follows, given the optimal choice is made

(1.6) $$W_{2,s} = \begin{cases} w_{2s} + \delta D - (1+r)B & if\ nobankruptcy \\ \min(w_{2s} + \delta D, E) & if\ bankruptcy \end{cases}$$

Individual problem can be summarized as follows

$$\underset{(r,B)}{Max}[Eu(c)] = u(c_1) + \beta\left[\sum_{s=1}^{S} p_s u(c_{2s})\right]$$

$$c_1 = w_1 + D + B$$
$$W_{2s} = w_{2s} + \delta D - Min[(1+r)B, Max(w_{2s} + \delta D - E, 0)]$$

Individual faces a set of contracts with interest rates and debt amount offered by lenders, and then chooses an optimal one that can maximize her expected utility. Since this model is a two-period model, second period consumption c_{2s} equals to second period wealth W_{2s}.

1.3.2 Lenders' Participation

For the lenders, the expected return on lending must be no less than the risk-free return assuming that lenders are risk-neutral. Therefore, the lender's participation constraint is:

(1.7) $$(1+r_f)B \le \sum_s p_s(1-l_d)(1+r)B + \sum_s p_s l_d[\max(w_{2s} + \delta D - E, 0)]$$

The first part of the right hand side of equation (1.7) is the expected return given that the consumer does not file for bankruptcy in the second period, while the second part is the expected return under bankruptcy. The interest rate difference $(r - r_f)$ is a risk premium that could offset the lender if the consumer defaults. If Equation (1.7) is satisfied, for each fixed *E*, a set of contracts (B, r) is available for individuals.

Observe that the lenders' expected return, described by their participation constraint, determines the set of contracts available in the economy. Available contracts depend on the bankruptcy exemption level *E*. If *E* equals zero, the insurance from bankruptcy is zero, this decreases the possibility of borrower's bankruptcy and consequently diminishes the cost of credit—the interest rate r. The higher bankruptcy exemption is, the lower the possibility that the income plus goods value overcomes the exemption level, increasing the possibility of bankruptcy. Then, interest rate charged to the loan increases and the supply of credit goes to zero.

1.3.3 Propositions

Proposition 1: For all types of consumers, as the bankruptcy exemption rises, the individuals have incentive to have more debt.

Proposition 2: For all types of consumers, as the bankruptcy exemption increases, lenders provide stricter contracts (B, r).

Proposition 3: If there are two types of consumers (poor, rich), poor consumers may face stricter lending contracts than rich consumers for the same bankruptcy exemptions.

Therefore, there are two distinct forces acting in the proposed problem in terms of bankruptcy exemptions. If *E* decreases, since the benefit from bankruptcy is lower and consumers may choose lower B and avoid bankruptcy to optimize their utility. For lenders, lower E indicates that lender's participation constraint, equation (1.7), is more easily satisfied. Therefore, lenders will like to provide contract with higher B and lower r. Contrarily, with an increase in the bankruptcy exemption E, consumers are tempted to take on more debt, but they will face stricter contracts with lower B and higher r.

1.3.4 Baseline Calculations

In the calculation, I show how debt amount B and interest rate r change as the bankruptcy exemption and consumer's income varies. For convenience, the model is simplified. In the second period, there are only two states of income uncertainty (High Income/Low Income), i.e. (s = h; l). The lenders are risk-neutral and the consumers are risk-averse with logarithm utility function.

The borrower problem is as follows:

$$
\begin{aligned}
&\max_{r,B} = \ln(c_1) + \beta[p_l \ln(c_{2l}) + P_h \ln(c_{2h})] \\
&s.t. \\
&(1+r_f)B \le \sum_s P_s(1-l_{d,s})(1+r)B + \sum_s P_s l_{d,s}[\max(w_{2s} + \delta D - E, 0)] \\
&c_1 = w_1 + D + B \\
&c_{2l} = w_{2l} + \delta D - \min[(1+r)B, \max(w_{2l} + \delta D - E, 0)] \\
&c_{2h} = w_{2h} + \delta D - \min[(1+r)B, \max(w_{2h} + \delta D - E, 0)] \\
&l_s = \begin{cases} 1 & (1+r)B > \max(w_{2s} + \delta D - E, 0) \\ 0 & (1+r)B \le \max(w_{2s} + \delta D - E, 0) \end{cases}
\end{aligned}
$$

The definition and value of parameters are specified in Table 1.1. Both consumers and lenders can observe first period income. Individuals have some value of durable goods based on their first period income. There are two uncertain states for individuals' second period income (high income state and low income state); the probability of each state is one half. Bankruptcy exemption E varies from 0 to 2. The depreciation rate $(1-\delta)$ on durable good is 0.1. Time discount rate β is 0.98. Risk-free interest rate is 1.05. Debt amount B ranges from 0 to 2 (boundary is big enough for equilibrium point). Borrowing cost $(1+r)$ ranges from 1.05 to 3(boundary is big enough for equilibrium point).

Figure 1.4 shows the lenders' participation constraint equation (1.7) for different bankruptcy exemptions. As the bankruptcy exemption increases from 0.2 to 0.55, there are fewer contracts lenders are willing to provide. For the same interest rate r, higher bankruptcy exemption E leads to lower lending amount B. For the same lending amount B, higher E leads to higher lending cost r.

In the second period, consumers make decision on whether they will file for bankruptcy. There are three possible scenarios for bankruptcy decisions in the second period.

Scenario A: Do not file for bankruptcy in either the low-income or high-income state. Individual's problem can be presented as following equation,

$$
\begin{cases}
\text{Expected Utility:} \\
\ln(w_1+D+B)+\beta(p_l * \ln(w_{2l}+\delta D-(1+r)B)+p_h * \ln(w_{2h}+\delta D-(1+r)B)) \\
\text{Budget Constraint:} \quad \begin{aligned} c_1 &= w_1+D+B \\ c_{2l} &= w_{2l}+\delta D-(1+r)B \\ c_{2h} &= w_{2h}+\delta D-(1+r)B \end{aligned} \\
\text{Bankruptcy Decision} \quad l_l=0 \quad l_h=0
\end{cases}
$$

Lenders' Participation Constraint: $(1+r_f)B \le (1+r)B$

Scenario B: File for bankruptcy for low-income state but not for high-income state. Individual's problem can be presented as

$$\begin{cases} \text{Expected Utility:} \\ \ln(w_1+D+B)+\beta(p_l*\ln(w_{2l}+\delta D-\max(w_{2l}+\delta D-E,0))+p_h*\ln(w_{2h}+\delta D-(1+r)B)) \\ \text{Budget Constraint:} \quad \begin{array}{l} c_1 = w_1+D+B \\ c_{2l} = w_{2l}+\delta D-\max(w_{2l}+\delta D-E,0) \\ c_{2h} = w_{2h}+\delta D-(1+r)B \end{array} \\ \text{Bankruptcy Choice} \quad l_l = 1 \qquad l_h = 0 \end{cases}$$

Lenders' Participation Constraint: $(1+r_f)B \le p_h*(1+r)B+p_l[\max(w_{2l}+\delta D-E,0)]$

Scenario C: File for bankruptcy in both the low-income and high-income states, Individual's problem is,

$$\begin{cases} \text{Expected Utility} \\ \ln(w_1+D+B)+ \\ \beta(p_l*\ln(w_{2l}+\delta D-\max(w_{2l}+\delta D-E,0))+p_h*\ln(w_{2h}+\delta D-\max(w_{2h}+\delta D-E,0)) \\ \text{Budget Constraint:} \quad \begin{array}{l} c_1 = w_1+D+B \\ c_{2l} = w_{2l}+\delta D-\max(w_{2l}+\delta D-E,0) \\ c_{2h} = w_{2h}+\delta D-\max(w_{2h}+\delta D-E,0) \end{array} \\ \text{Bankruptcy Choice} \quad l_l = l_h = 1 \end{cases}$$

Lenders' Participation Constraint:

$$(1+r_f)B \le p_h*[\max(w_{2h}+\delta D-E,0)]+p_l[\max(w_{2l}+\delta D-E,0)]$$

If an individual is in the low-income state and gets greater benefit from non-bankruptcy than bankruptcy, the optimal decision for consumer is not for bankruptcy. Under this condition, scenario A is the optimal choice. If an individual gets more benefit from bankruptcy in the low-income state while obtains more benefit from non-bankruptcy in the high-income state, the optimal decision for individual is to file for bankruptcy in the low-income state and not file for bankruptcy in high-income state. Scenario B is optimal choice. If an individual is in the high-income state and obtains more benefit from bankruptcy, Scenario C is the optimal choice. To summarize,

$$\begin{cases} \text{Scenario A is optimal choice if } (1+r)B \le \max(w_{2l}+\delta D-E,0) \\ \text{Scenario B is optimal choice if} \max(w_{2h}+\delta D-E,0) >= (1+r)B > \max(w_{2l}+\delta D-E,0) \\ \text{Scenario C is optimal choice if } (1+r)B > \max(w_{2h}+\delta D-E,0) \end{cases}$$

Figure 1.5, Figure 1.6 and Figure 1.7 show how consumers' optimal choice changes from Scenario A to Scenario C as bankruptcy exemption increases. As the exemption increases, lender's participation constraint becomes to stricter and individuals' indifference curve changes, therefore, individual's optimal choice of contract (B,r) and optimal decision for bankruptcy changes.

Figure 1.5 shows that Scenario A is the optimal choice if bankruptcy exemptions equal 0.4. Two curves (1 and 2) divide the area into three parts. In area I, individuals will not file for bankruptcy in either low or high-income states (Scenario A). In area II, consumers will file for bankruptcy for low-income state but not bankruptcy in the high-income state (Scenario B). In area III, consumers will file for bankruptcy in both low-income and high-income states (Scenario C). Curve 3 is lender's participation constraint and Curve 4 indifference curve. Figure 1.5 displays the optimal choice for individual is to take low debt amount in the first period and not file for bankruptcy in both low-income and high-income states if bankruptcy exemption is low enough. As the bankruptcy exemption increases, lender's participation and consumers' indifference curve change. Figure 1.6 shows that Scenario B is optimal choice given bankruptcy exemptions equal to 0.6. Scenario C will never be the optimal choice because of lenders' participation constraints. As bankruptcy exemptions increase, individuals will get more benefit from filing for bankruptcy; therefore, they will prefer taking more debt in the first period and filing for bankruptcy in the second period. Lenders also can expect higher risk in the second period by lending more debt under generous bankruptcy exemption. Therefore lenders will restrict lending amounts and increase interest rate. Figure 1.7 indicates that that both scenario A and scenario B can be optimal choices for individuals at some given bankruptcy exemptions. That is, individuals can obtain the same expected utility by taking lower debt amount B and making bankruptcy decision as scenario A, or taking higher debt amount B and making decision as scenario B. We can observe from Figure 1.7 that both contracts A and B are optimal choices for consumers to maximize their expected utility. Therefore, the optimal choice changing from Scenario A to Scenario B generates a discontinuous jump in total consumers' debt and interest rate by continuously increase bankruptcy exemptions. The optimal bankruptcy choice changes from scenario A to scenario B generate a discontinuous jump in total debt amount B and borrowing cost r.

Figure 1.8 displays calculated results for relationship between optimal debt amount B and bankruptcy exemptions in base scenario. It shows that there is a non-monotonic relationship between bankruptcy exemptions and consumers' total debt. And there might exist some discontinuous point for total debt amount as bankruptcy exemptions increase from 0.4 to 0.7. Figure 1.9 displays results on the relationship between optimal interest rate r and bankruptcy exemptions in base scenario. As bankruptcy exemptions increase, optimal interest rate firstly is flat at the risk-free level and then increases until some critical value. There is a discontinuous jump in the optimal interest rate. Figure 1.10 displays relationship between individual's expected utility and bankruptcy exemptions. It shows that individuals' expected utility has a non-monotonic relationship with the bankruptcy exemption. Individuals obtain highest expected utility when bankruptcy exemptions are in the middle range. Expected utility is a continuous function of bankruptcy exemptions even though the optimal choice of contract can be discontinuous.

1.3.5 Simulations

A normal distribution is used to simulate first-period income for high-income and low-income consumers. High-income consumers will have probability of 0.7 to stay in high-income status for the second period while low-income consumers will have probability of 0.7 to stay in low-income status. Figure 1.11 simulates total borrowing debt for low-income individuals and high-income individuals. As the figure shows, in area I, as bankruptcy exemptions increase, debt increases for both low-income and high-income consumers, and low-income consumers may have more debt than high-income consumers. In area II, as bankruptcy exemptions increase total debt increases for high-income consumers but decreases for low-income consumers. This indicates that low-income consumers are more likely to face credit constraints and stricter contracts. In area III, as bankruptcy exemptions increase; debt decreases for both high-income and low-income consumers. And high-income consumers will have higher debt than low-income consumers. Figure 1.12 shows simulated result of interest rate for low-income and high-income individuals. Low-income individuals always face higher interest rate than high-income individuals.

1.4 Data, Identification, and Descriptive Evidence

A large credit card issuer provided the dataset used in this paper. This sample consists of 200,000 individuals in the company's 2005 campaign. Information includes extensive coverage of financial issues for accounts such as FICO credit score, total bankcard credit limit, loans and debts, and interest rates for the new offer. Total bankcard credit limit is accumulative credit limit over all credit cards. Debt information includes total revolving debt and separate information on secured debt (mortgage) and unsecured debt (total credit card debt). The dataset also provides limited demographic information, which includes state of residence, age, gender and income. (Education and race are not available for this dataset.) I supplement this dataset with information on states' bankruptcy exemptions.

Most states have separate homestead exemptions and property exemptions. The exemption values vary widely across states. Table 1.2 shows the homestead and non-homestead bankruptcy exemptions for each state. Observations are in 1,000-dollar units. The homestead exemption amount refers to the maximum amount of home asset that debtors are allowed to keep in bankruptcy and the value is 999 for unlimited exemption. Five states have unlimited homestead exemption. Homestead exemption is the main concern in personal bankruptcy. Property exemptions include personal property, tools of the trade, the cash value of life insurance and pensions, household goods and clothing, and a miscellaneous ("wild card") category. The variable "Use Federal Exemption?" indicates whether residents can choose between the state's bankruptcy exemption and the Federal bankruptcy exemption. For each state, I also compute the total exemption, which is the sum of homestead and property exemptions. The overall exemption is assumed to be unlimited if the homestead exemption is unlimited. Sixteen states allow filers to choose between the state exemption and Federal exemption while the rest require use of the state's exemption. Table 1.3 displays the distribution of bankruptcy exemptions. I group the states into 5 categories according to their bankruptcy exemptions amounts. Figure 1.3 shows there exists variation within each group. For example, both Maryland and Wyoming have low bankruptcy exemptions, and the characteristics of these two states may be different.

Table 1.4 presents a summary of the main financial and demographic variables. In this sample, Credit Bureau scores of consumers exceed 670 with an average of 744. Since Freddie Mac considered a score below 620 as the "borrower's credit reputation is probably not acceptable", the consumers in this sample have a very good credit history. Therefore, this paper only can focus on customers with relatively high credit quality. Financial information on debt includes secured debt (i.e. total mortgage balance) and unsecured debt (i.e. total credit card balance), as well as total debt. Furthermore, the bureau credit score, total bankcard number and utilization of bankcards are shown in this table. The median of total credit card debt is \$8,242 and the mean for this variable is \$10,448. The median and mean of individual's total mortgage balance are \$53,083 and \$81,873 separately. The big difference of mean and median of the mortgage balance indicates that the distribution is highly skewed. The variable "Mortgage Total Number Open" shows how many mortgage accounts the consumers have, with the mean of 0.69 and median of 1 imply that most consumers either own one house or have no house. In the U.S. about 70% of households own houses. Therefore, this number indicates that this dataset may represent the population. Bankcard utilization is the ratio of total credit card balances to total credit card limit, with the average being about 15%. "Total inquiry Number in two years" represents how many inquiries from banks or other credit providers were made for the consumer in the past two years and the average is 5. Several Dummy variables are used to represent demographic variables, which consist of income, age, home region, and gender. The average age is 47 years. Income range of the consumer is estimated according to the zip code of the place the consumer lives and how long have they been there. About 45% of individual' incomes lie in the range \$50,000 to \$100,000. I define dummy variables for the quartiles of bankruptcy exemptions. Only 16 of consumers live in states with unlimited homestead exemptions. Macro variables include education, unemployment rate, homeownership rate, and bankruptcy rate. All macro variables are measured at the state level. The variable "Education" represents percentage of population with a Bachelor's degree or more in 2004 in the state.

I divide the states into four groups according to bankruptcy exemption levels from lowest to unlimited. The breakpoints for the bankruptcy exemption are \$10,000, \$20,000, \$45,000, \$500,000 and unlimited. Quartile breakpoints for income are \$30,000, \$50,000, and \$100,000. Table 1.5 compares the mean of key variables by bankruptcy exemption groups. (Bankruptcy exemptions are the sum of homestead and property exemption in dollars units.) Using the statistics in Table 1.5, Figure 1.13 compares total debt across four exemption groups of states and shows that there might exist a non-monotonic relationship between bankruptcy exemptions and total debt. Figure 1.14 shows average credit card debt across four bankruptcy exemptions groups. It suggests that higher bankruptcy exemptions may increase credit card debt. Consumers who live in the states with unlimited bankruptcy exemptions have much higher credit card debt than consumers who live in the states with limited exemptions.

1.5 Specifications and Regression Analysis

I use the natural log of debt as the dependent variable since the distribution of debt is highly skewed. In the baseline regression, interaction effects of income and bankruptcy are not considered. I treat bankruptcy exemption as continuous variable[2]. Independent variables include credit bureau score, total bankcard numbers, bankcard utilization as well as bankruptcy exemptions. Table 1.6 gives estimates of the effect of total bankruptcy exemptions amount on total debt. In both control and non-control regressions, the coefficient for variable "bankruptcy exemption" is significantly positive and the coefficient for variable "Exemption Squared" is significantly negative. This indicates that there is a non-monotonic relationship between bankruptcy exemption and total debt. Furthermore, as credit bureau score increases (i.e., better creditworthiness), total debt decreases. Men have more debt than women. Consumers who have more credit cards or have higher bankcard utilization will have more debt. Rich consumers have more debt than poor consumers. The total debt first increases then decreases with age.

Figure 1.15 plots the residuals of total debt regression on bankruptcy exemptions. It roughly shows residuals' variation turns larger after exemptions are over $110,000. To test whether there exists a structural change in the total debt regression, I separate sample into two sub-samples. One sub-sample includes observations with bankruptcy exemptions

[2] For states with unlimited bankruptcy exemption, I use $1,000,000 as value.

less than \$110,000 and the other sample includes observations with bankruptcy exemptions greater than \$110,000. A Chow structural change test is highly significant at a break point exemption of \$110,000.

Table 1.8 accounts for potential combined effects of bankruptcy exemption and income on total debt. I treat the bankruptcy exemption as a continuous variable for states whose exemptions are not unlimited and use a dummy variable for states with unlimited exemptions. The first set of four variables is the interactions of limited continuous exemption with income quartile dummies, leading to four income-exemption interaction variables (where states with unlimited exemptions are coded as zeros). A second set of four variables is interactions of the dummy variable for states with unlimited exemptions with the four income quartile dummies. I also include Credit Bureau Score, age, total bankcard number, as well as dummy variables for geographic variation, gender. The results show that total debt level is positively and significantly correlated with the bankruptcy exemption for households in the top half of the income distribution, and the estimated coefficient on the total exemption for households in the bottom quartile of the income distribution is negative and significant if bankruptcy exemption is limited. However, comparing states with limited bankruptcy exemption to those with unlimited exemption, consumers who live in the state with unlimited exemptions have significantly lower total debt. The interpretation of coefficients for bankruptcy exemptions is shown in table 1.8; As bankruptcy exemptions increase from 0 to \$50,000, total debt will decrease by 2% for individuals in the bottom if the income distribution, increase by 3.6% for individuals in the third quartile of this distribution, and increase by 2% in the top quartile. If bankruptcy exemptions increase from \$50,000 to unlimited, total debt will decrease more by 14% for individuals in the bottom income distribution, and decrease by 8% for individuals in the third quartile income distribution and 10% for individuals in the top income distribution.

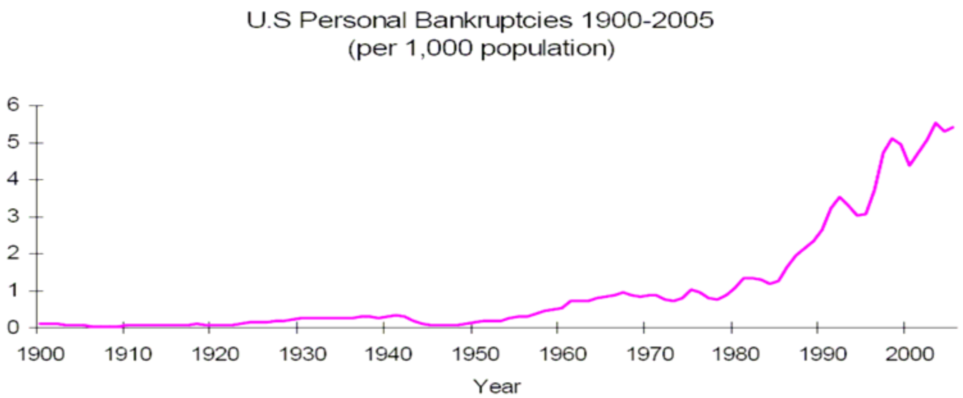
Table 1.10 gives estimates for total credit card debt. In this regression, I use total mortgage amount as a proxy for wealth. The table shows that bankruptcy exemptions have little impact on consumers' credit card debt if individuals live in the states with limited bankruptcy exemptions. However, comparing the states with limited exemptions and unlimited exemptions, consumers who live in the states with unlimited bankruptcy exemptions have higher credit card debt even controlling for income effects. Age is negatively related to total credit card debt, and not surprisingly, there is a negative relationship between credit bureau score and total credit card debt. The result further shows that the higher unemployment rate is the higher total credit card debt. Total credit card debt is positively related to total home mortgage debt. Low education consumers have more credit card debt than high education consumers.

1.6 Conclusion

To sum up, this study develops a theoretical model to capture two forces in credit market in terms of bankruptcy exemptions. Higher bankruptcy exemptions motivate consumers to acquire more debt, but cause lenders to implement stricter lending standards. These two forces together make the relationship between bankruptcy exemption and consumers' debt non-monotonic. For all types of consumers, when the bankruptcy exemption is less than some critical value, consumers' demand is dominant, consumers' debt increase as bankruptcy exemptions rise; but when bankruptcy exemption is greater than this critical value, lender's supply is dominant and consumers face credit constraint, consumers' debt decrease as bankruptcy exemptions rise. The critical bankruptcy exemption value is different for different types of consumers. For the same bankruptcy exemption value, poor individuals already face credit constraint while rich individuals do not have constraint. As a result, poor consumers' debt decreases while rich consumers' debt increase as bankruptcy exemptions rise in some range. Besides, there might exist a discontinuous jump in consumers' total debt as bankruptcy exemption increases.

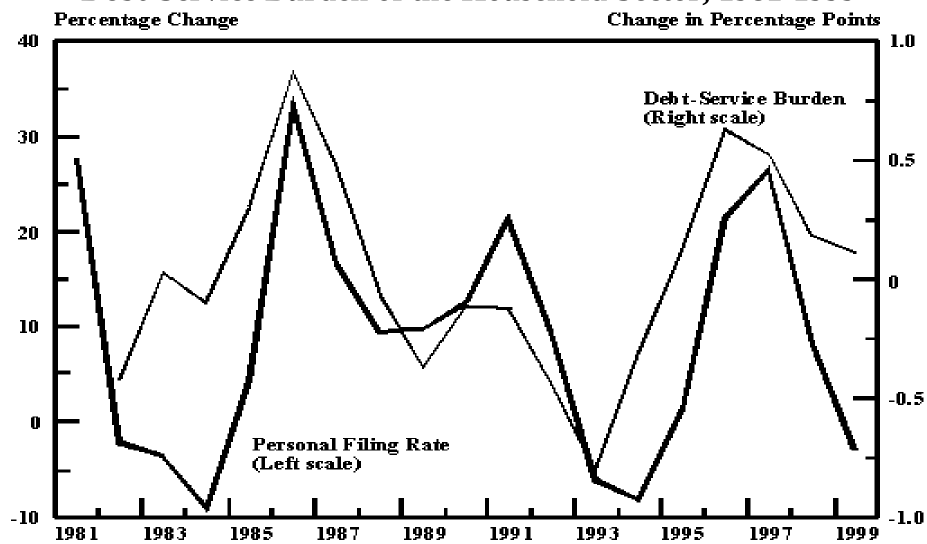
Furthermore, this study conducts several empirical analyses on both total debt and credit card debt. In the baseline regression for total debt, in the states with limited bankruptcy exemptions, rich consumers have more total debt while poor consumers have less total debt as bankruptcy exemption increases. Comparing the states with limited bankruptcy exemptions and unlimited bankruptcy exemptions, consumers have less total debt if they live in unlimited bankruptcy exemptions. In the regression for credit card debt, I find consumers have more credit card debt in the states with unlimited exemptions comparing to the similar consumers who live in the states with limited bankruptcy exemptions. There exist different impacts of unlimited bankruptcy exemptions on total debt and credit card debt. It may imply two future explorations. 1) Consumers' behaviors might be heterogeneous in the states with limited and unlimited bankruptcy exemptions. 2) How bankruptcy exemptions affect mortgage market.

Figure 1.1 U.S. Personal Bankruptcies Filing



Source: Thomas A. Garrett, Federal Reserve Bank of St. Louis

Figure 1.2 Growth in the Personal Filing Rate &
Debt-Service Burden of the Household Sector, 1981-1999



Source: Congressional Budget Office; Department of Commerce, Bureau of the Census; Federal Reserve Board.
Note: The debt-service burden, which is plotted with a one-year lag, is the ratio of the household sector's debt-service payments to disposable (after-tax) income.

Figure 1.3 Bankruptcy Exemptions Distribution Over States

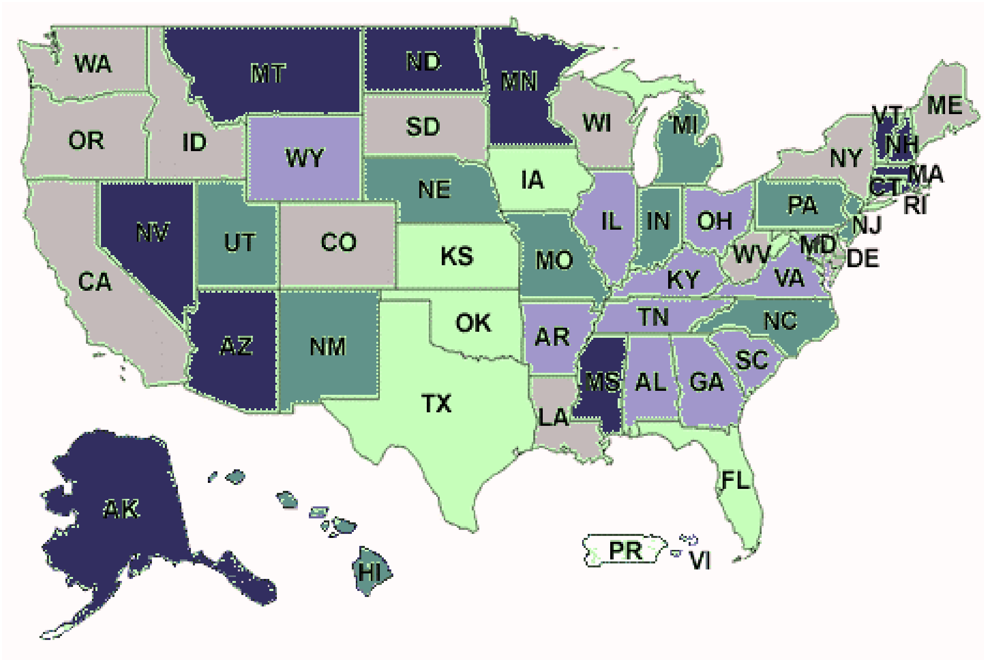


Figure 1.4 Lenders' Participation Constraints

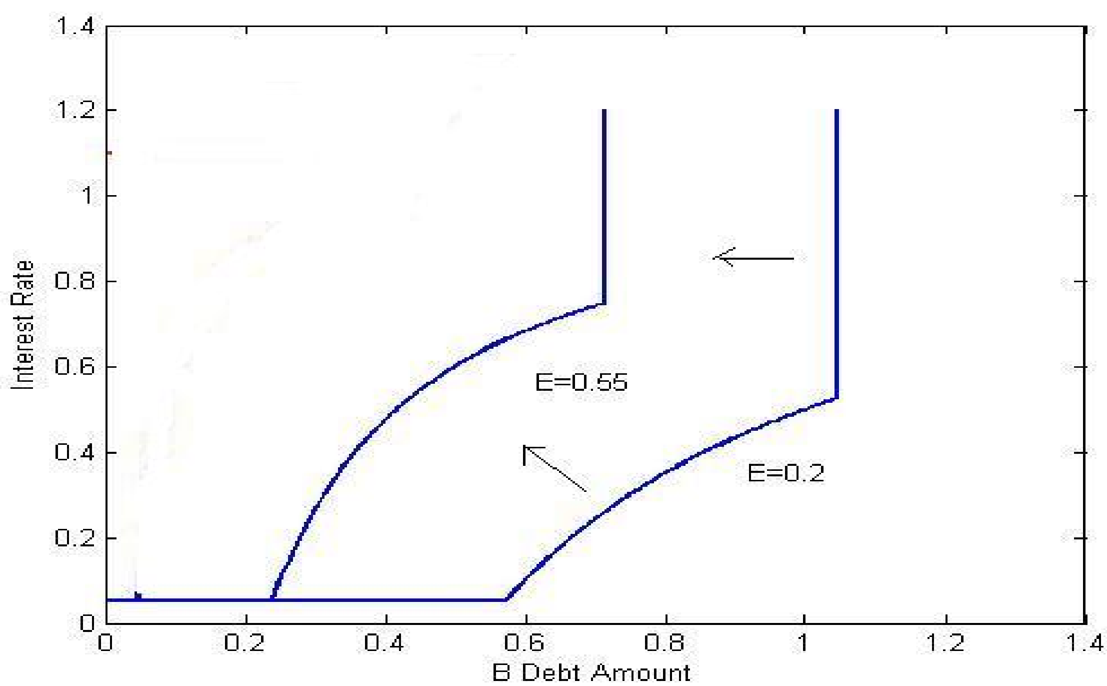


Figure 1.5 Consumers' Optimal Choice for Bankruptcy Exemption E=0.4

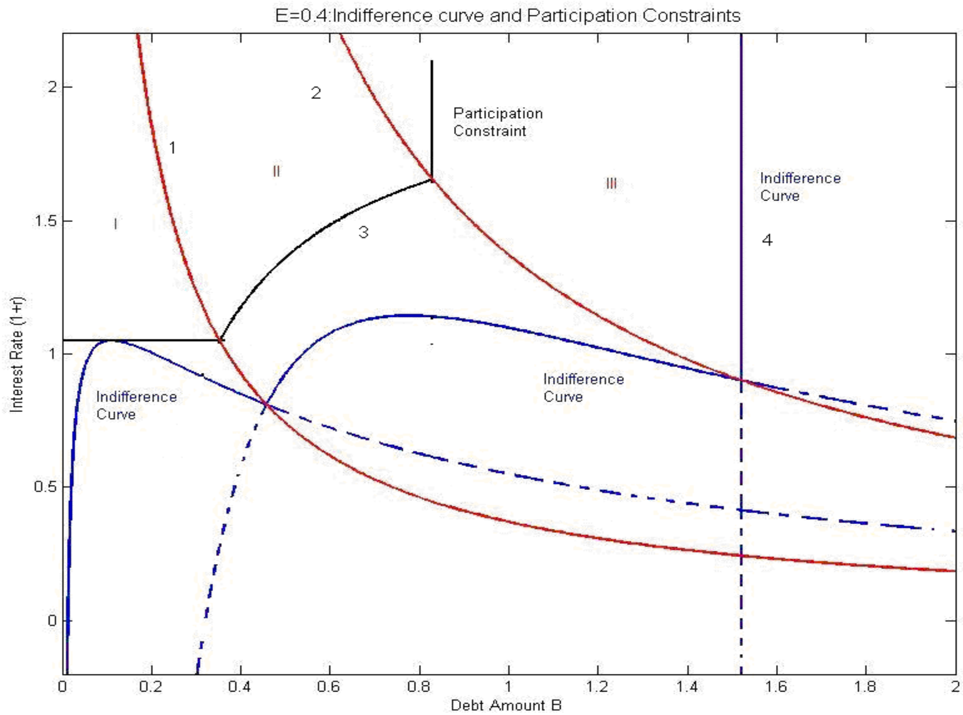


Figure 1.6 Consumers' Optimal Choice for Bankruptcy Exemption E=0.6

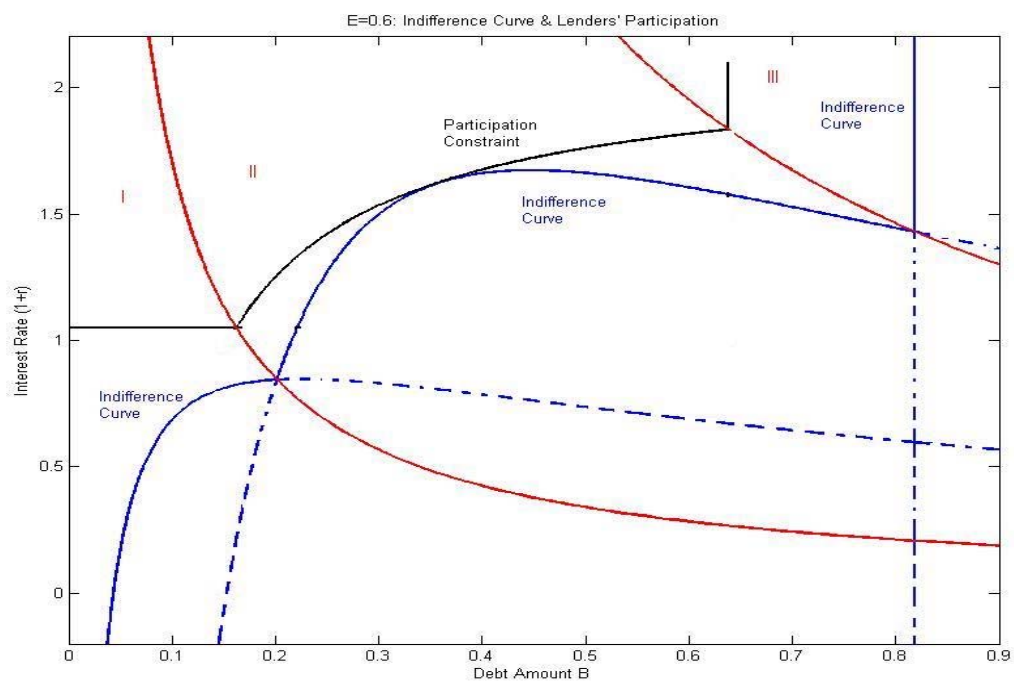


Figure 1.7 Consumers' Optimal Choice for Bankruptcy Exemption E=0.53

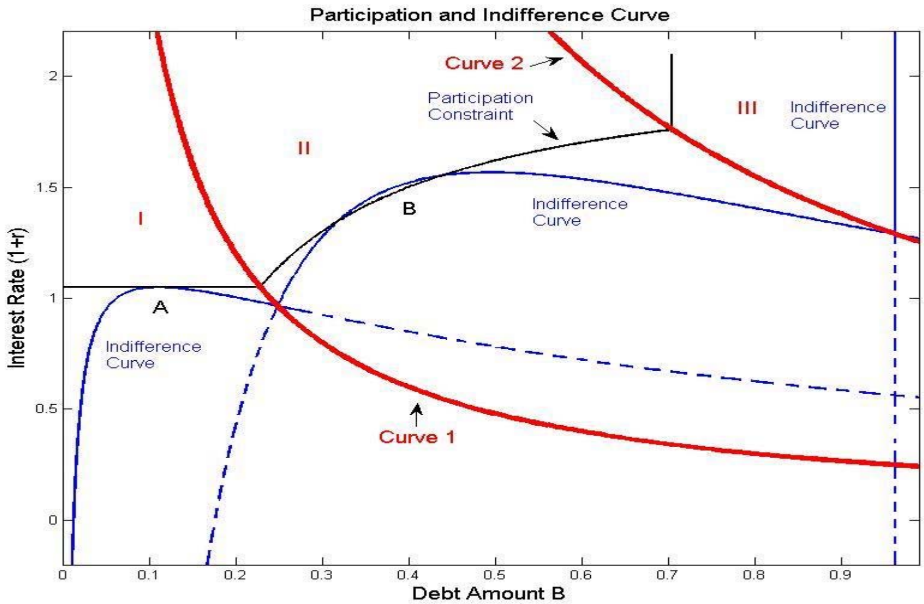


Figure 1.8 Debt Amount Calculation for baseline scenario

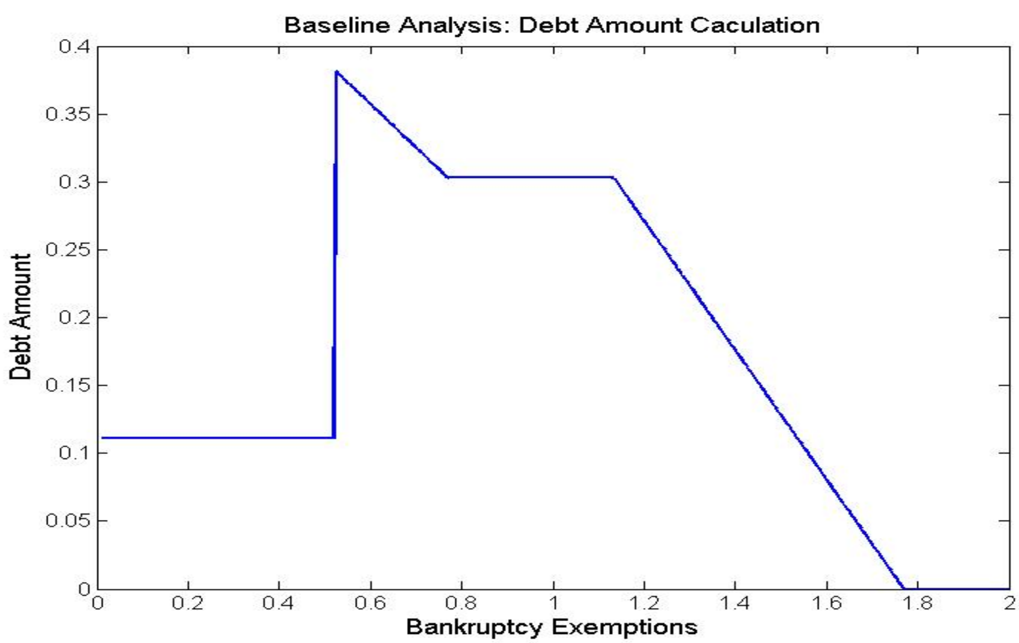


Figure 1.9 Interest Rate Calculation for baseline scenario

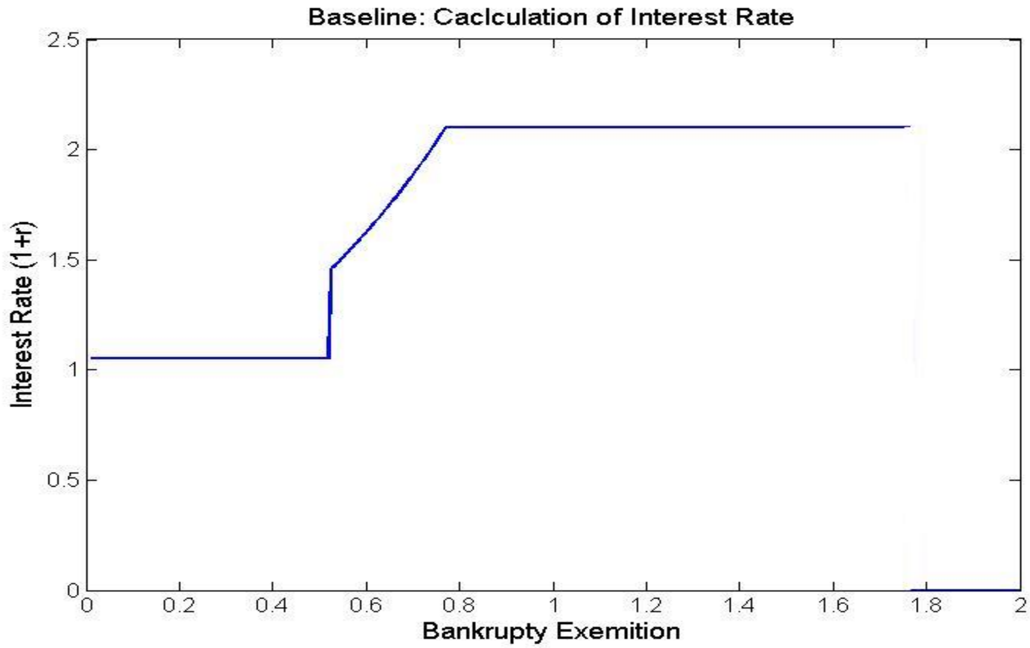


Figure 1.10 Calculation of Expectation Utility for baseline scenario

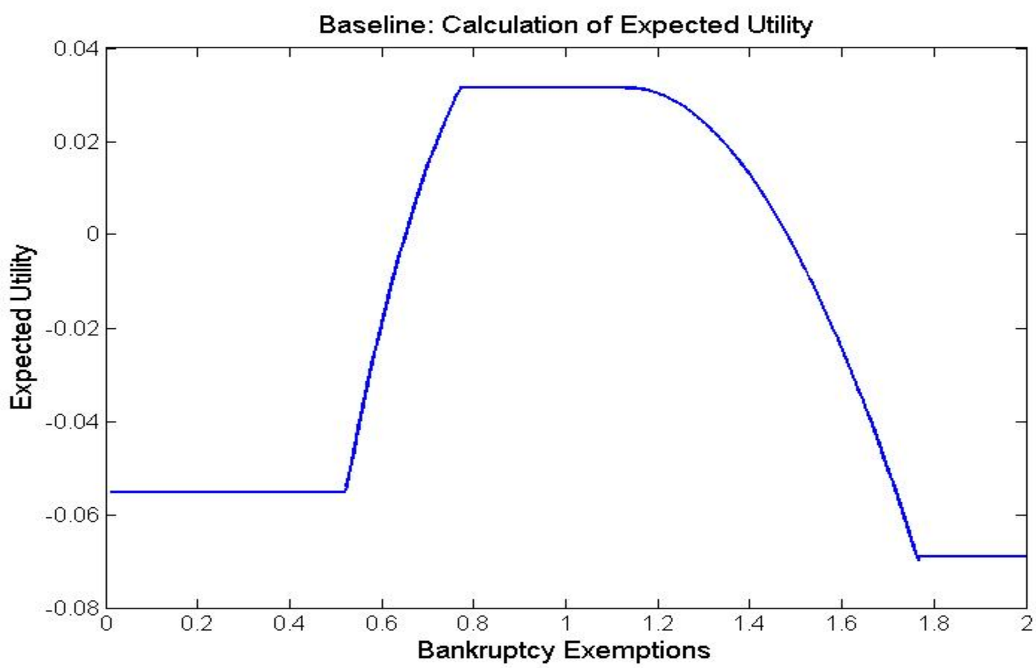


Figure 1.11 Simulated results: Comparison of consumers' total debt: Low Income vs. High Income

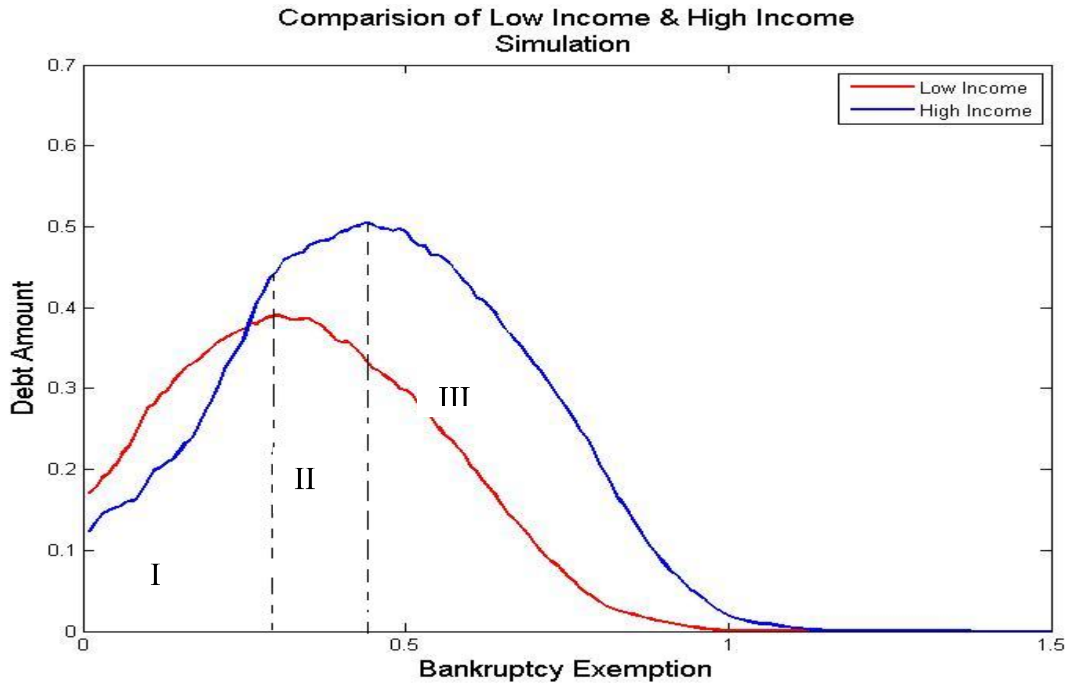


Figure 1.12 Simulated results: Comparison of interest rate: Low Income vs. High Income

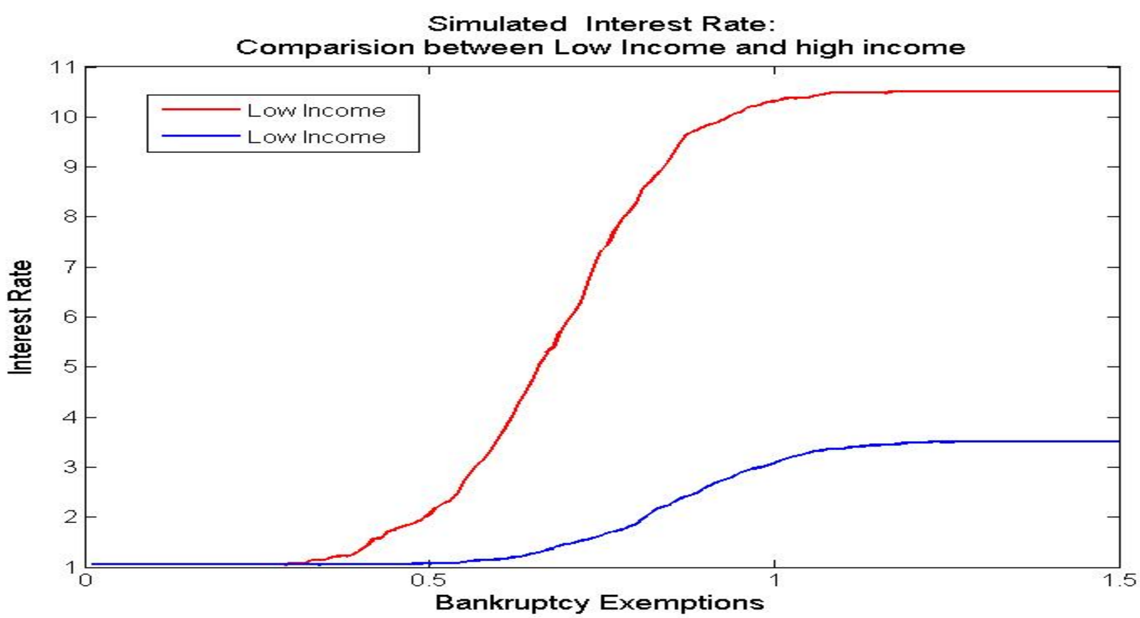


Figure 1.13 Median of Total Debt in Exemptions Groups

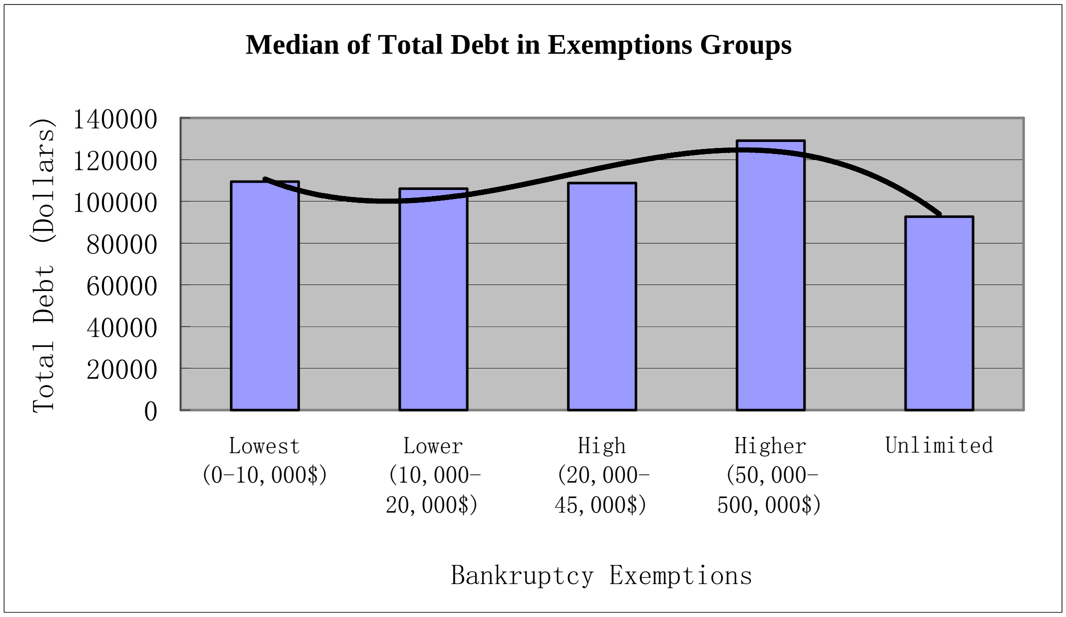


Figure 1.14 Median of Total Credit Card Debt in Exemption Groups

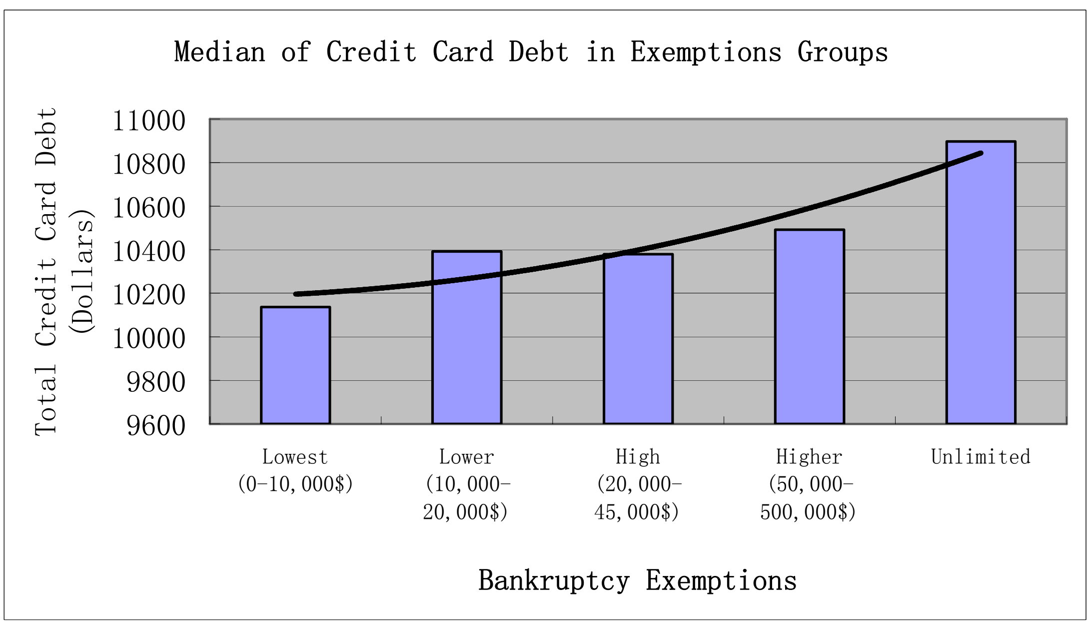


Table 1.1 Variable Definition for two-periods consumption model

Variable	**Definition**	**Value**
w_1	Income in the first period	Baseline: 0.5
E	Bankruptcy Exemption Amount	0-3
w_{2h}	Income in the second period if Good Status	$1.5w_1$
w_{2l}	Income in the second period if Bad Status	w_1
D	Durable Good (Consumed in both periods)	$0.6w_1$
1-δ	Depreciation Rate for Durable Good	0.1
p_l p_h	Probability of Good Status in the second Period Probability of Bad Status in the second period	0.5 0.5
β	Time Discount Rate	0.98
r_f	Risk-free interest Rate	1.05
t	Credit Constraint parameter	0.3
Control Variable	**Definition**	**Value**
r	Borrowing Interest Rate	0.05-2
B	Debt Amount	0-3
l_s	Decision for Bankruptcy	0,1

Table 1.2 State Bankruptcy Exemptions

State	State Home Stead	State Non-Homestead	Use FederalExemption
Alabama	5	10.5	No
Alaska	67.5	3	No
Arizona	150	12.5	No
Arkansas	2.5	3	Yes
California	50	10.675	No
Colorado	45	17	No
Connecticut	75	2.5	Yes
DC	0	4.75	Yes
Delaware	50	55.5	No
Florida	999	1	No
Georgia	10	5.5	No
Hawaii	20	3.575	Yes
Idaho	50	11.3	No
Illinois	7.5	1.95	No
Indiana	15	4	No
Iowa	999	27	No
Kansas	999	28.5	No
Kentuky	5	4.5	No
Louisiana	25	12.5	No
Maine	35	10.75	No
Maryland	0	17	No
Massachusetts	500	4.7	Yes
Michigan	3.5	9	Yes
Minnesota	200	21.8	Yes
Mississippi	75	10	No
Missouri	15	9	No
Montana	100	10	No
Nebraska	12.5	4	No
Nevada	350	37	No
New Hampshire	100	12.5	Yes
New Jersey	0	1	Yes
New Mexico	30	6	Yes
New York	50	12.4	No
North Carolina	18.5	10.5	No
North Dakota	80	1.2	No
Ohio	5	2.55	No
Oklahoma	999	12.5	No
Oregon	25	7.7	No
Pennsylvania	0	0	Yes
Rhode Island	200	16.6	Yes
South Carolina	5	5.45	No
South Dakota	30	8	No
Tennessee	5	5.9	No
Texas	999	30	Yes
Utah	20	2.5	No
Vermont	75	12.5	Yes
Virginia	5	17	No
Washington	40	12.3	Yes
West virginia	25	13.9	No
Wisconsin	40	14.7	Yes
Wyoming	10	4.4	No
Federal	18.45	16.77	n.a

Source:http://www.bankruptcyaction.com/

Table 1.3 Homestead Bankruptcy Exemptions Distribution

Homestead Exemptions	Value ($1,000)			States	
1st Quartile	[0,10]	Maryland	Arkansas	Alabama	Kentuky
		Ohio	South Carc	Tennessee	
		Virginia	Illinois	Georgia	Wyoming
2nd Quartile	[10,20]	Nebraska	Indiana	Missouri	Hawaii
		Michigan	New Jersey	New Mexic	Pennsylvania
		North Caro	Utah		
3rd Quartile	[20,45]	Louisiana	Oregon	West virgin	South Dakota
		Maine	Washingtoı	Wisconsin	Colorado
		California	Delaware	Idaho	New York
4th Quartile	[50,500]	Alaska	Connecticu	Mississippi	Vermont
		North Dakc	Montana	New Hamp	Arizona
		Minnesota	Rhode Isla	Nevada	Massachusetts
Unlimited	unlimited	Florida	Iowa Texa	Kansas	Oklahoma

Table 1.4 Summary Statistics

Variable	Mean	Median	Std Dev	Minimum
Observations	207112			
Financial Variables				
Bureau Credit Score	744	746	33	670
Credit Card Total Balance	10448	8242	8859	0
Credit Card Total Limit	62493	54149	41534	0
Total Card Numbers	13	12	5	0
Bank Card Utilization (%)	15	13	11	0
Total Mortgage Balance	81873	53083	109529	0
Mortgage Total Number Open	0.69	1	0.7	0
Auto Total Balance	7846	0	12362	0
Auto Number Open	0.6	0	0.74	0
All Total Balance	112051	84232	117587	0
Total Inquiry Num in two years	5	4	3	1
Demographic Variables				
Income (under $15,000)	0.05	0	0.23	0
Income ($15,000-19,999)	0.03	0	0.16	0
Income ($20,000-29,999)	0.06	0	0.24	0
Income ($30,000-39,999)	0.08	0	0.27	0
Income ($40,000-49,999)	0.1	0	0.3	0
Income ($50,000-74,999)	0.25	0	0.43	0
Income ($75,000-99,999)	0.18	0	0.38	0
Income ($100,000-124,999)	0.1	0	0.29	0
Income ($125,000-$149,000)	0.06	0	0.23	0
Income (more than $150,000)	0.1	0	0.3	0
Age	46.51	46	13.37	17
Age (under 24)	0.04	0	0.2	0
Age (25-34)	0.16	0	0.37	0
Age (35-44)	0.26	0	0.44	0
Age (45-54)	0.27	0	0.44	0
Age (55-64)	0.17	0	0.38	0
Age (over 65)	0.1	0	0.3	0
Northwest dummy	0.22	0	0.41	0
Midwest dummy	0.24	0	0.42	0
South dummy	0.33	0	0.47	0
West dummy	0.21	0	0.41	0
Male	0.51	1	0.5	0

Variable	Mean	Median	Std Dev	Minimum
Exemptions				
First Quartile for Homestead	0.21			
Second Quartile for Homestead	0.23			
Third Quartile for Homestead	0.1			
Forth Quartile for Homestead	0.31			
Unlimited homestead	0.16			
Offer Factors				
Interest rate	9.20%	9%	1.71%	5%
Macro Factors		Population Median		
Education	28	27	27.7	
Unemployment rate (%)	8	7	5	
Homeownership Rate (%)	69	71	69	
Bankruptcy Rate (per 100,000 Population)	579	530	586	

Note: "Education" Variable: Percent of Population with a Bachelor's Degree or More in 2004

Table 1.5 Statistics by Bankruptcy Exemptions Groups

	Bankruptcy Exemptions				
Variable	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	Unlimited
Bureau Credit Score	744.26	745.36	745.6	744.34	742.32
Credit Card Total Balance	10136.23	10391.7	10379.2	10491.5	10897
Credit Card Total Limit	61224.02	61815.6	60801.3	63150.6	64960.6
Total Credit Card Numbers	12.74	13.06	12.62	13.12	13.03
Bank Card Utilization	14.74	14.96	15.19	14.65	14.66
Total Mortgage Balance	80562.34	74865.4	79554.8	97970.2	63571.1
Mortgage Total Number	0.73	0.7	0.72	0.66	0.69
Auto Total Balance	7986.18	7645.57	7469.67	7313.81	9252.5
Auto Number	0.62	0.63	0.57	0.55	0.67
All Total Balance	109505.67	106118	108783	129051	92649.4
Total Inquiry Number in two years	5.33	4.26	4.44	4.46	5.54
First Quartile Income (<$19,999)	0.07	0.07	0.08	0.09	0.09
Second Quartile Income (<$49,999)	0.23	0.24	0.26	0.23	0.27
Third Quartile Income (<$124,999)	0.54	0.53	0.5	0.53	0.5
Fourth Quartile Income (>$124,999)	0.16	0.16	0.16	0.15	0.14
Education	27.48	26.34	26.36	31.11	25.35
Unemployment Rate (%)	5.06	5.12	5.19	4.94	4.25
Observation	42526	47105	21253	63845	32383

Table 1.6 Baseline Regression for log(Total Debt)

	Control Regression			Non Control Regression		
	Estimate	T-Value		Estimate	T-Value	
Intercept	7.321	79.03	***	10.470	122.7	***
Beacon Score	-0.002	-18.72	***	-0.005	-54.0	***
Log(total Bank card Number)	0.604	89.76	***			
Bank Card Utilization	0.018	58.05	***			
Total Exemption($1,000)	0.0005	8.05	***	0.0005	7.3	***
Total Exemption Sqaure	-6.24E-07	-9.2	***	-5.77E-07	-8.3	***
Income1(<$15000)	-1.061	-66.31	***	-1.0887	-66.5	***
Income2(<$19999)	-0.983	-48.13	***	-0.997	-47.7	***
Income3(<$29999)	-0.826	-54.79	***	-0.820	-53.2	***
Income4(<$39999)	-0.668	-47.76	***	-0.646	-45.1	***
Income5(<$49999)	-0.514	-38.45	***	-0.491	-36.0	***
Income6(<$74999)	-0.308	-27.7	***	-0.286	-25.2	***
Income7(<$99999)	-0.149	-12.73	***	-0.128	-10.7	***
Income8(<$124999)	-0.063	-4.73	***	-0.046	-3.4	***
Income9(<$149999)	0.015	0.96	***	0.027	1.7	***
Age	0.144	108.05	***	0.177	133.7	***
Age Sqaure	-0.001	-110.1	***	-0.002	-130.2	***
Gender	0.167	28.38	***	0.173	28.6	***
Midwest dummy	0.173	17.76	***	0.165	16.6	***
South dummy	0.145	14.05	***	0.109	10.3	***
West dummy	0.207	22.06	***	0.209	21.8	***
Education	0.009	10.07	***	0.009	10.0	***
Unemployment Rate	-0.025	-7.11	***	-0.023	-6.3	***
Adjusted R square		0.1988			0.1619	

Figure 1.15 Plots Residual for baseline regression of total debt

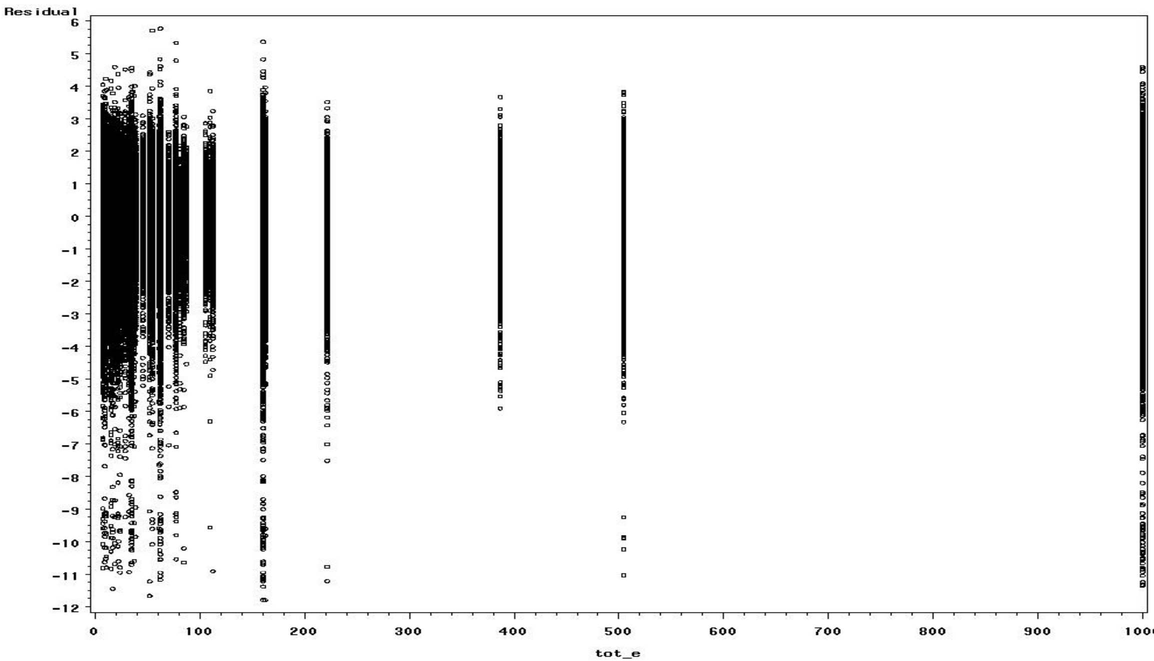


Table 1.7 Structural Change Test

	Total Exemption <=$110,000				Total Exemption>$110,000			
	Non Controlled		Controlled		Non Controlled		Controlled	
Variable	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Intercept	10.9841	885.33	7.4693	20.91	10.8811	469.37	7.3134	12.82
Credit Bureau Score			-0.0020	-4.11			-0.0014	-2.05
Log (bank card Number)			0.4570	30.68			0.5364	25.53
Bank Card Utilization			0.0143	27.43			0.0150	19.84
Total Exemption($1,000)	-0.0022	-3.16	-0.0053	-4.09	0.0011	8.55	0.0005	1.64
Total Exemption Sqaure	0.0000	0.33	0.0000	3.1	0.0000	-10.87	0.0000	-2.42
income			0.1339	47.77			0.1435	36.88
age			0.1126	37.65			0.1232	30.73
ageage			-0.0012	-38.08			-0.0012	-30.55
Male			0.1556	12.23			0.1471	8.16
Midwest dummy			0.0948	4.19			-0.1484	-2.32
South dummy			0.0718	3.32			-0.1854	-1.81
West dummy			0.2621	11.36			-0.1219	-1.74
Education			0.0084	4.82			-0.0141	-2.22
unemploy_rate			-0.0132	-1.79			-0.0224	-1.6
N observations				32770				18608
R Square				0.1836				0.2015

Structural Change Test

Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	110	3	207106	2.78	0.0397

Table 1.8 Regression for total debt by income quartiles

Variable	Control Regression Estimate	Control Regression t Value	Non Control Regression Estimate	Non Control Regression t Value
Intercept	6.2089	67.52 ***	9.3558	110.8 ***
Credit Bureau Score	-0.0019	-18.65 ***	-0.0050	-53.88 ***
Log (bank card Number)	0.6080	90.27 ***		
Bank Card Utilization	0.0180	58.05 ***		
Exemption (in $1,000)*1st income quartile dummy	-0.0004	-4.38 ***	-0.0005	-5.27 ***
Exemption*2nd income quartile dummy	0.0001	1.43 *	0.0001	1.08
Exemption*3rd income quartile dummy	0.0007	15.36 ***	0.0007	15.89 ***
Exemption*4th income quartile dummy	0.0003	4.64 ***	-0.0001	-1.21
Unlimited exemption*1st income quartile dummy	-0.1679	-8 ***	-0.1922	-6.88 ***
Unlimited exemption*2nd income quartile dummy	-0.1217	-6.61 ***	-0.1058	-6.33 ***
Unlimited exemption*3rd income quartile dummy	-0.0539	-3.95 ***	-0.0335	-2.58 ***
Unlimited exemption*4th income quartile dummy	-0.1059	-6.04 ***	-0.1768	-7.95 ***
Income	0.1234	71.91 ***	0.1274	72.82 ***
Age	0.1449	108.38 ***	0.1776	134.22 ***
Age Square	-0.0015	-110.65 ***	-0.0018	-130.9 ***
Male	0.1691	28.64 ***	0.1743	28.88 ***
Midwest dummy	0.1764	18.14 ***	0.1692	17.02 ***
South dummy	0.1493	14.53 ***	0.1134	10.79 ***
West dummy	0.2171	23.87 ***	0.2180	23.43 ***
Education	0.0089	9.96 ***	0.0090	9.81 ***
Unemployment Rate	-0.0262	-7.32 ***	-0.0239	-6.54 ***
Adjusted R square		0.198		0.16

Table 1.9 Case Analyses

Bankruptcy Exemption Increases from 0 to $50,000	**Total Debt**	
Combined bankruptcy exemption (in $1,000)*dummy variable for the first quartile of the total income distribution	-0.0004	↓ 2%
Bankruptcy exemption*2nd income quartile dummy	0.0001	
Bankruptcy exemption*3rd income quartile dummy	0.0007	↑ 3.6%
Bankruptcy exemption*4th income quartile dummy	0.0003	↑ 1.5%
Bankruptcy Exemption change from $50,000 to unlimited		
Unlimited bankruptcy exemption*1st income quartile dummy	-0.1679	↓ 14%
Unlimited bankruptcy exemption*2nd income quartile dummy	-0.1217	
Unlimited bankruptcy exemption*3rd income quartile dummy	-0.0539	↓ 8%
Unlimited bankruptcy exemption*4th income quartile dummy	-0.1059	↓ 10%

Table 1.10 Regression for total credit card debt

	Control Regression			Non Control Regression		
Variable	Estimate	t Value		Estimate	t Value	
Intercept	6.9101	89.87	***	15.0788	192.98	***
Credit Bureau Score	-0.0045	-53.79	***	-0.0135	-159.09	***
Log(Total Mortgage Amount)	0.0590	227.44	***	0.0138	26.92	***
Log (bank card Number)	0.7426	131.74	***			
Bank Card Utilization	0.0113	24.9	***			
Exemption (in $1,000)*1st income quartile dummy	-0.0001	-1.17		-0.0002	-1.83	**
Exemption*2nd income quartile dummy	-0.0001	-1.68	*	-0.0001	-0.91	
Exemption*3rd income quartile dummy	0.0001	1.98	**	0.0001	2.24	**
Exemption*4th income quartile dummy	0.0001	1.57		-0.0001	-1.9	
Unlimited exemption*1st income quartile dummy	0.0298	1.7	*	-0.0404	-1.57	
Unlimited exemption*2nd income quartile dummy	0.0545	3.54	***	0.0737	4.77	***
Unlimited exemption*3rd income quartile dummy	0.1077	9.46	***	0.1220	10.16	***
Unlimited exemption*4th income quartile dummy	0.0971	6.64	***	0.0452	2.2	***
Income	0.0489	33.87	***	0.0472	28.93	***
Age	0.0813	71.24	***	0.1301	103.65	***
Age Square	-0.0007	-60.8	***	-0.0011	-86.95	***
Male	-0.0203	-4.12	***	-0.0355	-6.36	***
Midwest dummy	-0.0667	-8.2	***	-0.0737	-8	***
South dummy	-0.0748	-8.7	***	-0.1428	-14.68	***
West dummy	-0.0563	-7.4	***	-0.0572	-6.64	***
Education	-0.0001	-0.16		-0.0028	-3.27	***
Unemployment Rate	0.0057	1.92	**	0.0110	3.26	***
Adjusted R square		0.37			0.19	

2. Estimating the Demand for Credit Cards: A Regression Discontinuity Approach

2.1 Introduction

This study focuses on estimating the effects of the interest rate on the demand for credit card. Among the available financing tools, credit cards are the most commonly used. The visa USA Research reveals that credit card accounted for 49% of spending in 2005, up from 25% in 1995. Moreover, credit cards, in particular bankcards (i.e., Visa, MasterCard, Discover, and American Express), represent the leading source of unsecured credit for most households. According to the latest information gathered by the US Census Bureau, there were 164 million credit card holders in the United States in 2003 and that number is projected to grow to 176 million by 2008. These same Americans own approximately 1.5 billion cards, an average of nearly nine credit cards issued per credit card holder. According to Federal Reserve Statistical Release G.19 on consumer credit in 2007, the size of the total consumer debt grew nearly 1.5 times in size from 2001 ($1.7 trillion) to 2006 ($2.4 trillion). The average household in 2005 carried nearly $8,000 in credit card debt, up almost 2 times from the $4,400 level of 2001. Therefore, credit cards are not only important to personal finance but also to the aggregate economy.

In studying the credit card market, the effects of interest rates on demand for credit plays a crucial role. However, the actual evaluation of the demand for credit card has been a complicated problem. A consumer's decision on whether to apply for a new credit card or borrow from an existing credit card is influenced by a number of factors, a significant number of which are not observed by the credit card company. The most important missing information has to do with the consumers' other options, such as the contract offers from other competing credit card companies and availability of other source of financing.

It is impossible for a credit card company to know whether these competing companies will offer credit to a particular consumer and what the terms and conditions of those offers are. Firstly, firms may have different information on the same consumer. Even though all firms obtain the same information, such as credit score and credit report variables from credit bureaus, firms also use private information, such as the consumers' previous transaction records with the firm. Secondly, even if firms have the same information about a consumer, firms may give different offers because they have different solicitation strategies according to their target profit and risk levels. Firms usually rely on proprietary consumer behavior models to determine contract offers to consumers in addition to the standard credit score. Thus the contract offers will be various for the same consumer.

Moreover, consumers outside offers are likely to be highly correlated with the contract offer that a firm plans to make. The high correlations of contracts between firms are due to several reasons. Firstly, firms rely on the same information source. The three major credit bureaus, Equifax, Experian, and Trans Union, collect detailed information. Firms usually obtain the credit bureau report before deciding upon the contract offer. Hence, firms share much common information about consumers. Secondly, even though firms use different proprietary models to decide contracts, those models have similar objectives. For example, a consumer with good credit history is likely to be identified by all competing firms. As a result, a consumer who receives an attractive contract offer from one firm is also likely to receive attractive offers from competing firms.

The lack of information about consumers' outside options and the possible correlation of contracts from competing firms makes the evaluation problem hard. It is very difficult to separate the effects of the interest rate from consumers' unobserved outside options. For instance, it is very likely that biased estimates of the effect of interest rate on credit demand would be obtained by simple comparisons of consumers who receive different interest rate. Consumers who receive low interest rate offers are likely to be "good" customers who may receive similar offers or even better offers from other competing credit card companies.

This chapter proposes an alternative method to estimate the demand for credit card controlling for the endogeneity of contracts. The main idea of our method is to exploit a unique feature of the credit card solicitation campaign design to obtain a reliable estimate of the effect of the interest rate on demand. The recent advance in information technology allows credit card companies to develop sophisticated consumers credit-scoring models. Using a propriety customer score for each consumer, the credit card company divides consumers into several marketing groups. Within a group, consumers are offered the same contract, while across groups the contract parameters are different. As a result, consumers whose scores lie on the opposite side of the cutoff point are assigned to different contracts (i.e., different interest rate). This practice creates a discontinuity in the contract that a consumer receives at the cutoff points. For consumers who are on the opposite sides of these cutoff points, their underlining demand should be very similar. Yet they receive different contract offers. Thus the difference in response rate should be driven mainly by the difference in contract rates. In addition, as the cutoff points are propriety information, neither consumers nor competitors can change their behaviors around cutoff points. The difference in interest rate at the cut off points can be viewed as exogenous.

This method is in essence a regression discontinuity design method (RD). The RD method has recently become a standard evaluation framework for estimating causal effects with non-experimental data. The program evaluation literature shows that the RD method can be used to obtain reliable estimates of causal effects (Hann, Todd and Van Der Klaauw (2001), Imbens and Lemieux (2007)). The key feature of RD method is that the "treatment" is given to individuals if and only if an observed covariate crosses a known threshold. Thus, under weak smoothness conditions, the probability of receiving treatment near the cut-off behaves as if individuals were randomly assigned. An advantage of the RD method is that it can identify causal effects under much weaker assumptions, while standard methods of dealing with endogeneity usually rely on exclusion restrictions (IV method), the distribution of error terms, or conditional independence assumptions (Matching Method). In practice, the RD design method has been used in a number of empirical applications to successfully estimate the causal effect using non-randomized data, such as the effects of class size on student' performance (Angrist and Lavy 1999), the effects of financial aid on college enrollment (Van der Klauuw 2003), the impact of universal insurance coverage on health care utilization (Card, Dobkin and Maestas 2004), willingness to pay for clean air by exploring housing markets (Chay and Greenstone 2005), and the benefits of delayed primary school enrollment (McEwan and Shaprio 2007). In addition, Lee (2003), Lemieux and Milligan

(2004), and Chen and van der Klauuw (2004) exploit randomized variation near the point of discontinuity to solve the problem of selection bias.

Using data provided by a major credit card issuer, this study estimates the demand for credit card using the control function method proposed by Van Der Klaauw (2003). This study finds that consumers' demand for new credit cards has near unit elasticity, estimated at -1.14. In addition, consumers with better credit rating are more responsive to interest rates. The demand elasticity for consumers with higher credit rating is -1.4 while that for consumers with lower credit rating is insignificant. Moreover, the results suggest that the control function needs to be very flexible. A restrictive parametric control function, such as linear or quadratic control function, may produce biased results. This study also finds that without controls for the endogeneity of contracts, the interest rate and response rate are positively correlated. Thus the existing estimates of demand for credit card will be biased estimates.

This study contributes to the existing literature in the following ways. First, it provides a first estimate of the demand for credit cards in the US explicitly controlling for the endogeneity of contract offers. Empirical estimation of the demand for credit card is very limited not only because the aforementioned endogeneity problems but also because of the lack of micro-level data. Several recent studies examine the credit demand using proprietary data from developing countries. Dehejia, Montgomery and Morduch (2005) estimate the demand for credit in Bangladesh using data from credit cooperation in the slums of Dhaka, Bangladesh. Their results show that borrowers are highly sensitive to interest rate changes; with he implied interest rate elasticity falling in the range from –0.73 to –1.04. Furthermore, they find that less wealthy households are more sensitive to the loan price comparing to the wealthier household. Karlan and Zinman (2005) estimates the demand elasticties for consumer credit using randomized data provided by a South African lender. They find downward-sloping demand to price. The elasticity is much lower (less than –0.5) over a wide range of prices. In addition, price sensitivity increases at higher-than-normal rates. This result is opposite to the paper from Gross and Souleles (2002). Gross and Souleles also find that price sensitivity increases with income, opposite to the previous paper. Alessie, Hochguertel and Weber (2005) examine unique data on credit applications received by the leading provider of consumer credit in Italy and find that demand is elastic to interest rate and more elastic for competitive market.

Second, our study shows that the regression discontinuity method could be very useful in estimating demand functions. Empirical estimation of demand functions has attracted tremendous interest in many fields of economics, such as industrial organization and marketing. The standard method of dealing with endogeneity problem in demand estimation, such as the BLP method (Berry Levinsohn and Pakes 1995), usually relies on instrumental variables (IV) methods. A good instrumental variable needs to satisfy both the exclusion restriction and rank conditions. In many applications, it is difficult to find good instruments. This study shows that the regression discontinuity method could provide an alternative solution to the endogeneity problem, which could be used in a number of applications. In practice, firms' pricing and advertising decisions usually exhibit discrete changes.

The rest of the chapter is organized as follows: Section 2 provides background information about the US credit card market. Section 3 introduces a simple model of competition in this. Section 4 describes the data and Section 5 presents the empirical model and discusses the identification conditions. Section 6 provides the major findings and sensitivity analysis. Finally, Section 7 concludes.

2.2 US Credit Card Market

The credit card is one of the most commonly used short-term financing tools in the US. The use of direct solicitation mail to acquire new card users, commonly referred to as new account acquisition, is one of main methods by which credit card issuers attract new consumers. A typical new account acquisition campaign works as follows. Before the start of the campaign, credit card issuers obtain credit bureau reports on a large number of consumers from the three main credit bureaus: Equifax, Experian and Trans Union. Credit card issuers then analyze the credit report information of those consumers, and decide whether to extend an offer to a particular consumer. The contract terms are usually based on the consumer' credit history. Afterward, credit card companies send out offer letters to pre-approved consumers with information about the contract parameters, such as various interest rate and relevant fees. Sometimes the offers also include lower interest rates for balance transfers and purchases for promotional purpose. Upon receipt of the offer letters, consumers then decide whether to apply for new credit card. The credit issuer then makes the final decision on whether to offer the credit card and sets the credit limit for those applicants.

Several feature of this application process are worth mentioning. First, the interest rate is stated in the offer letter but the credit limit is determined after consumers apply for the card. Second, credit issuers could reject a credit card application even though the consumer is pre-approved. The typical reason for doing so is that the applicants profile worsens over acquisition period. Another common reason for rejecting the application is failure to provide the necessary documents (i.e., bill statements, employee statement).

Recent developments in information technology have significantly changed the way credit card companies conduct their accounts acquisitions. Their companies increasingly rely on sophisticated scoring algorithms to estimate consumers risk and profitability. Companies use those credit models to determine the terms of the contracts to consumers. In addition, companies realize that their profitability critically depends on the performance of credit scoring models. Companies therefore invest heavily on the development of credit scoring models and the details of these models are usually kept secret because firms differ in risk tolerance and may have different targeted rates of return, the credit scoring models may differ significantly across firms.

It is also worth mentioning the role of large data vendors such as Equifax, Experian and Trans Union in this market. They collect detailed information on consumers' personal financial records. Because all firms in the credit card industry rely on the data provided by these three credit bureaus, firms share a lot of information about consumers underlining credit risk and payment history. Firms also have many sources of private information on their own customers that is not shared with competitors. For example, detailed information on the type of spending by consumers is usually not reported to the credit bureaus. A firm may know how much a given customer spends on gas stations, and retail stores etc, while its competitors only observe the total credit balance. In addition, many consumers also use other financial services provided by the credit card issuing bank, such as checking, investment, and mortgage. This information is usually not shared among competing firms.

2.3 A model of competition in the credit card market

This section models the competition in the credit card market. The credit card company observes incomplete information about a consumer's profitability. Based on the information, the credit card company offers a consumer a contract with a specific interest rate. Upon receiving all the contracts, consumers decide which credit card to choose.

A consumer will choose the best contract among all available choices. The indirect utility of choosing the contract from credit card company is

(2.1) $$U_i = \alpha + \beta R_i + \varepsilon_i$$

where R_i is the interest rate offered by the company to the *i*th consumer.

In addition, consumers can choose not to apply for any credit card or choose the credit card from other competing companies. The indirect utility of choosing these other options is

(2.2) $$U_i^c = \alpha^c + \beta R_i^c + \varepsilon_i^c$$

where R_i^c is the interest rate from other competing credit card companies.

Consumers will choose to take the contract from company X if and only if $U_i > U_i^c$. For individual i, the difference in utility is

(2.3) $$D_i^* = \alpha - \alpha^c + \beta(R_i - R_i^c) + (\varepsilon_i - \varepsilon_i^c)$$

Therefore, the consumer's application decision depends on the interest rate offered by company X as well as the rate offered by *i*th competitors. Let D_i=1 if consumers choose to apply for the credit card from company X, while D_i=0 otherwise. Thus, D_i=1 if D_i^*>0. The probability of that consumer choose contract from company X is given by

$$\text{(2.4)} \qquad \begin{aligned} \Pr(D_i = 1) &= \Pr(D_i^* > 0) \\ &= \Pr(\alpha - \alpha^c + \beta(R_i - R_i^c) + (\varepsilon_i - \varepsilon_i^c) > 0) \end{aligned}$$

However, in most cases, the credit card company X does not observe the interest rate R_i^c from other competing companies. The utility difference D_i^* can be written as

$$\text{(2.5)} \qquad D_i^* = \overline{\alpha} + \beta R_i + \mu_i \quad \text{Where } \overline{\alpha} = \alpha - \alpha^c \text{ and } \mu_i = -\beta R_i^c + (\varepsilon_i - \varepsilon_i^c).$$

If interest rate from competing companies R_i^c is correlated with interest rate R_i from company X, then μ_i is correlated with R_i. An OLS regression of equation (2.5) will give a biased estimate of β.

2.4 Data

A large credit card issuer provided the dataset used in this paper. The data include a list of around 22,500 consumers. (The exact number is not reported due to confidentiality reason). For each consumer, detailed information is available on their financial status from the credit bureau report. The most important variables include bureau credit score, total bankcard limit (the sum of the credit limits of all credit cards in a consumer's possession), the total bank card balance (the sum of credit card debt of all credit cards), as well as demographic information such as age and gender. The bankcard utilization ratio is a measure of credit constraint, computed by dividing the total credit card balance by the total credit limit. If the utilization ratio is 1, the consumer is credit constrained. For each consumer, the dataset includes the contract parameters and whether the offer is acceptable.

Table 2.1 reports the summary statistics. Consumers in this sample have fairly high credit scores. The range of credit bureau score in the U.S. is from 300 to 850, while the credit bureau scores in the sample range from 670 to 830. The average bureau score in the sample is around 750, while the average score is 640 in U.S. The average total bankcard limit is around $30,400, with a maximum of $315,900 and a minimum of zero, while the average total bankcard debt is $5,200 with a maximum of $50,000 and a minimum of zero. The average credit utilization ratio is 17%. Thus, most of the consumers in the sample are not credit-constrained. Forty eight percent of the sample is male and the average age is 51.

For each consumer on the list, the credit issuer calculates a customer score using a proprietary credit risk model. Thus, the customer score is different from the bureau score and it is information that only this firm knows. The customer score ranges from 212 to 280 with an average of 238. The firm assigns consumers to one of three mailing groups based on their customer scores. Customers will receive different interest rate (backend APR[3]) based on which group they are assigned. Specifically, customer whose score is above 240 will receive a 7.99% backend rate, those whose score is between 230 and 240 will receive a 8.99% rate and those with scores below 230 receive a 9.99% rate. In addition, for promotional purposes, consumers will receive 0% introductory interest rate for first 12 months. As is the common practice in the US credit card industry, the credit issuer does not state the credit limit in the offer letter. Instead, the company determines the credit limit after consumers decide whether to accept the solicitation offer. The corresponding response rate is about 0.069.

This study compares the observed consumer characteristics between respondents and

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[3] Backend APR is the interest rate after introductory promotion periods.

non-respondents. Similar to Auseubel (1999), this study finds clear evidence of adverse selection: Respondents have worse profiles than non-respondents, lower bureau credit scores, higher levels of debt and higher credit utilization ratios. The average bureau credit score among non-respondents is 751 while the average score among respondents is 735. The customer score shows a similar pattern, with average scores for respondents and non-respondents of 234 and 238 respectively. Average credit card debt is about $10,200, for respondents, almost double the debt for non-respondents ($4,900). At the request of credit issuer to preserve confidentiality data, the number for balances is rounded to hundreds. Furthermore, average credit card utilization ratio is 0.21 for respondents and 0.17 for non-respondents. In addition, the respondents are slightly younger and men are more likely to apply.

Table 2.2 compares the summary statistics across offer groups. Group 1 includes consumers whose customer score is below 230 and receive offers with a 9.99% interest rate. Group 2 consumers have scores between 230 and 240, and receive 8.99% rate. Consumers with scores above 240 who receive 7.99% rate, belong to group 3. Comparing across the three groups, consumers in Group 1 have a lower bureau credit scores, higher level of debts, lower credit limits and higher credit utilization ratios. The average customer score, which is unique, and private for the firm increases from 222 in Group 1 to 257 in Group 3. For demographic variables, Group 1 includes more male and younger consumers than Group 2 and 3.

Interestingly, even though Group 1 consumers receive the worst contracts with the highest rates of interest, their response rate are the highest among all three groups. Group 3 consumers have the best contract with the lowest interest rate, but their response rate is the lowest. The average response rate is 8.6%, 6.5% and 5.3% for Group 1, Group 2 and Group 3 respectively. This simple comparison of response rate across three groups suggests that the estimation of the demand for credit cards has to take into account the endogeneity of contracts. Otherwise, the positive correlation of the contract interest rate and the response rate would imply that higher interest rates increase the demand for credit cards.

2.5 Empirical Model

Let Y_i be the outcome variable. This study will focus on consumers' binary decision of whether to accept the solicitation offer as a measure of consumers' demand for credit card. Thus Y_i equal 1 if consumers respond to the solicitation offer. Let R_i be the interest rate stated on the offer letter. A common way to estimate the demand for credit card employs the following regression equation

$$Y_i = \beta_1 X_i + \beta_2 R_i + \varepsilon_i \tag{2.6}$$

In which, X_i represents other variables that may affect the consumers' decision to accept the offer, such as the bureau score, the amount of total credit card debt, total credit limit, and demographic variables. β_2 is the parameter attached to the interest rate.

If a credit card company randomly assigns different interest rates to observationally equivalent consumers, then β_2 can be consistently estimated by linear probability or Probit models. However, in practice the interest rate is correlated with a number of factors that are not observed by the econometrician, such as the interest rates offered by competing firms. As a result, unobserved error terms are likely to be correlated with the interest rate variable. The regression estimates will be biased.

Our strategy for estimating the causal relationship between the interest rate and credit card demand uses additional information about how firm chooses the interest rate. A unique feature of the firm's marketing strategy is the formula to determine interest rate offers.

$$R_i(S_i) = 7.9\% + 1\% * 1(S_i \le 240) + 1\% * 1(S_i < 230) \tag{2.7}$$

where S_i is the internal customer score calculated by the firm is proprietary modeling method. Consumers with higher scores will receive lower interest rate. In addition, the assignment of interest rate has the following discrete jump point. Customer whose score is above 240 will receive 7.99% interest rate, customers whose score is between 230 and 240 receive 8.99% interest rate and those with score below 230 receive offers with 9.99% interest rate.

This type of regression discontinuity model is commonly referred to as Sharp Design, as consumers are assigned to different contracts based only on their customer scores. As argued in Kahn, Todd and Van der Klauuw (2001) and Van der Klauuw (2003), under the local continuity assumptions, the local average treatment effect at each cut off point can be identified by

$$\beta_2 = \frac{Lim_{S\downarrow S_0} E[Y \mid S] - Lim_{S\uparrow S_0} E[Y \mid S]}{E_{S\downarrow S_0}(R \mid S) - E_{S\uparrow S_0}(R \mid S)} \tag{2.8}$$

We will illustrate this by two figures. Figure 2.1 and Figure 2.2 illustrate the main idea of the RD method. Figure 2.1 plots interest rate as a function of customer score near 240. Figure 2.2 plots the conditional expectation of response rate Y for the same range of customer score. Notice that we only observe the response rate for 7.99% interest rate offers for consumers whose customer scores are above 240 and the response rate for 8.99% offers for consumers whose customer scores below 240. Figure 2.2 plots observed outcome by solid lines. The two dashed lines in the figures are the unobserved response rate. Figures 2.1 and 2.2 show that the difference in the response rate near the cutoff point can be explained by the difference in the interest rates. Before using RD regression, it is necessary to check other control variables in X_i which also have an effect on response. Figure 2.3 shows bankcard total limit by score, Figure 2.4 shows bankcard total balance by score and Figure 2.5 shows beacon score (which is provided by credit bureau) by score (which is generated by the company). These three figures indicates other control variables are roughly continuous over score.

An advantage of using RD design method is that the effect of interest rate can be identified under much weaker assumptions. The only assumption is the local continuity assumptions. A limitation of RD design method, however, is that only the treatment effect at the cut off point can be identified.

Since *S* is the only determinant of the interest rate, it will capture any correlation between R_i and ε. In this case, a popular way of controlling for selection bias problem is to use the control function approach (Van der Klaauw (2003)). Namely, one can add the correct specification of the control function *K(S)* in the regression equation.

$$(2.9) \qquad Y_i = \beta_1 X_i + \beta_2 R_i + K(S_i) + w_i$$

where $K(S)$ is the conditional mean function $E(\varepsilon \mid S)$ and $w = Y - E[Y \mid E, S]$. If the control function $K(S)$ is correctly specified, the estimate of β_2 gives us the causal effect of the interest rate on the outcome variable.

If the control function is misspecified, the estimates will likely be biased. Therefore, the control function should be as flexible as possible. In practice, most studies use a semi-parametric specification of the control function. For example, Van der Klaauw (2002) uses a power series approximation for $K(S)=\sum_{j=1}^{J}\eta_j S^j$, where the power number of function is estimated by generalized cross-validation method. Our study uses a spline to approximate the control function where the smoothing parameters are determined by generalized cross validation method. The main advantage of using a spline function instead of power series approximation is that the statistical software, SAS, provides a command PROC GAM to easily estimate the linear additive semiparametric regression model using spline functions.

2.6 Estimation Results and Robustness Check

This section presents the main empirical findings. It begins with a simple comparison of the response rate near the cutoff point. Then it presents the baseline results using the regression discontinuity design method. Afterward, a robustness check is conducted. In the end, to assess the potential bias from failing to control for endogeneity of contracts, this section compares an OLS estimator to RD design estimates.

Because the RD design method only identifier the causal effect at the discontinity point, we would like to use the data as close to the cut off point as possible. Using data farther away from the cutoff point may bias the estimates if the control function is misspecified.[4] Unfortunately, using observations close to the cut off point leaves us with

[4] Ludwig and Miller (2005) discuss specific methods for choosing bandwidths for RD Design.

very few observations. Thus, this section will first present results using only observations very close to the cut off point, and will then present results using a wider window around the cutoff point.

An intuitive and simple estimator for these effects is the difference in the response rate between those with internal customer score in a small interval above the cutoff point and below the cutoff point. Given the selected interval width around the cutoff point, the average response rate of those with score just above the cutoff and below the cutoff can be viewed as a nonparametric estimate of $Lim_{S\downarrow S_0} E[Y \mid S]$ and $Lim_{S\uparrow S_0} E[Y \mid S]$.

The top panel of Table 2.3 presents the difference in the response rate for those within 3 points of S (interval customer score) below and above each cutoff points. This table first considers the cutoff point at 240. The average response rate of those 3 points above this cutoff point is 5.39 percent, while the average response rate of those 3 points below is 4.64 percent. The difference in response rate is 0.75 percent. Since the interest rate above 240 is 7.9 percent and the interest rate below is 8.9 percent, the results suggest that a 1% decrease in interest rate leads to an increase in response rate of 0.75 percent. In terms of elasticity, since the interest rate at 240 is 8.9 percent and the average response rate is 5%, the results imply a demand elasticity of 1.36. However, the standard errors are quite large for both estimates. This is because only a small number of consumers are close to this cutoff point.

The result at the lower cutoff point 230 is surprising. The average response rate is 8.66 percent and 8.13 percent respectively for those 3 points below and above the cutoff point. Thus a 1% decrease in interest rate actually reduces the response rate by 0.5 percent. However, since the standard error is large, it is not reasonable to conclude that the difference in response rate is statistically different from zero.

The bottom panel of Table 2.3 presents the difference in the response rate for consumers within a smaller window (2 points) around the cutoff point. The results are similar to the results in the top panel. Around the higher cutoff point (S=240), the difference in response rate is 0.8 percent, while at the lower cutoff point (S=230), the difference in response rate is -0.3 percent.

The control function method uses additional information from observations with customer score farther away from the cutoff point. In addition, the control function method could control for the effects of other factors on the demand for credit card.

Table 2.4 presents the baseline result using the control function method and additional covariates. The first set of covariates measure variables related to consumer's credit risk, such as utilization ratio, utilization Ratio Square, bureau credit score, and bankcard total limit. This information is obtained from consumer's credit report. The second set of variables includes demographic variables such as male, age and age squared. As a robustness check, it also presents the result without controls for these covariates.

The estimated coefficient of the interest rate is -0.8809 and significant. This suggests that the probability of applying for a credit card decreases by 0.88 percent if the interest rate increases by one percent. Given that the average response rate is 6.9% and average interest rate is 8.99%, the demand elasticity is -1.14. The demand for credit is actually fairly elastic. In addition, the estimate without controlling for other covariates is qualitatively similar. The coefficient of interest is estimated at -0.7490 and marginally significant. This suggests that the results are not driven by other covariates.

The estimates of other covariates show some interesting findings. First, the estimate of utilization ratio is significant at 0.0802 indicates that the credit constrained consumers are more likely to apply for a new credit card. The estimate of utilization ratio squared is significant at -0.0898, which suggest that, as utilization ratio increases, the probability of applying for credit card increases but at a slower rate. The coefficient of bureau credit score is significant at -0.0005. Therefore consumers with good credit are less likely to apply for another credit card. Total credit limit has a statistically significant and positive effect on the demand for credit card. Thus, consumers with high credit limit are more likely to apply for additional credit, (A thousand-dollar increase in credit limit increases the probability of applying for credit card by 0.18%). There is no difference in the probability of applying for credit card between male and female customers, while younger consumers are more likely to apply.

Since it is possible that the effects of interest rates differ for consumers with different customer score, table 2.5 presents the results allowing the effects of interest rate to differ at the two cut-off points. This regression uses the same set of control variables and replaces the interest rate variable in the baseline model with two dummy variables for 8.99% interest rate and 7.99% interest rate. The omitted group is the one receiving the 9.99% interest rate. Thus the estimates of 7.99% interest rate dummy is the difference in the response probability between 7.99% and 9.99% interest rate for those consumers at the upper cutoff point (S=240), while the estimates of 8.99% interest rate dummy is the difference in the response probability between 8.99% and 9.99% for those consumers at the lower cutoff points (S=230).

The coefficient of 7.99% interest rate dummy is 0.0189 and significant, while the coefficient of 8.99% dummy is 0.0063 and insignificant. This suggests that the probability of applying for credit card decreases by 1.89% if the interest rate increases from 7.99% to 9.99%. Given that the average response rate when S=240 is 5% and the interest rate is 7.99%, the demand elasticity is -1.51. The results suggest that consumers at the higher cutoff points are more likely to respond to the changes in interest rate than consumer at the lower cutoff point. One possible explanation for this finding is that consumer with high customer score are not credit constrained and do not need to apply for credit unless the offer interest rate is really very attractive. Another possible explanation is that consumers with high customer score may receive more offers, as they are perceived as low risk consumers. As such, they are able to choose among several competing offers.

2.6.1 Robustness Check

The control function approach requires that the control function be correctly specified. Misspecification of control function could lead to biased estimates. The baseline result uses a semiparametric method to estimate the control function as flexible as possible. As a robustness check, Table 2.6 gives the model estimates produced by alternative parametric functional forms. This helps us understand whether misspecification of the control function could lead to seriously biased estimates. Table 2.6 provides the results of using linear, quadratic and cubic functions to approximate the control function. The estimates of the interest rate parameter are 0.332, -0.2492 and -0.1203 for the linear, quadratic, and cubic control function, respectively. In addition, none of the estimated interest rate coefficient is significant. The above results suggest that misspecification of control function could lead to biased estimates. Therefore, it is important to allow the control function to be as flexible as possible.

2.6.2 Comparison with OLS estimates

This study can control for the endogeneity of contract because we have information on not only the internal customer score but also exactly how consumers are selected into different contracts. However, this information is usually not available for most of the existing studies. One could argue that the results may not be far from the true value if regression controls for additional consumer characteristics. To evaluate the potential bias from failing to control for the endogeneity of contract, Table 2.7 estimates the baseline model without using the information on the selection process. Table 2.7 presents the results of a linear probability model without using the customer score variable that determine the contract, while controlling for all other variables in the baseline model reported in Table 2.4. The linear probability model's estimate of interest rate is 0.7357 and significant. The interest rate is positively correlated with the response rate. The OLS estimates would suggest that the demand for credit card actually increases with the interest rate. Clearly, without controlling for endogeneity of contract, the estimates of the effect of interest rate on demand for credit card are biased.

2.6.3 Sensitivity Test

Table 2.8 conducts sensitivity test by using spline function with fixed degree of freedom equal 4, 5 and 6 instead of using generalized cross validation method to determine degree of freedom in Table 2.4. The coefficient for interest rate in the regression (DF=4) is not significant but negative, while the coefficients for interest rate in the regressions (DF=5, DF=6) are significantly negative. Table 2.8 shows that non-parametric RD design regressions are not sensitive for degree of freedom.

2.7 Conclusion

Using the credit card application data provided by a major credit card issuer, this chapter estimates the demand for credit using a regression discontinuity method. The results show that consumers' demand for credit card is near unit elasticity. The demand elasticity is estimated at -1.14. In addition, consumers with better credit rating are more responsive to interest rate than consumer with lower credit rating. Furthermore, the findings show that without controlling for the endogeneity of contracts, the interest rate and demand for credit card are positively correlated.

This chapter shows that the regression discontinuity method could be a very useful tool to estimate the demand function. In many applications in empirical IO and marketing, dealing with the endogeneity problem is usually one of the most important parts of the analysis. Instrumental variable methods are the most commonly used method. However, in many applications, it is very difficult to find good instruments. In this case, regression discontinuity design method could provide an alternative way to solve the endogeneity problem. Compares with the IV method, RD design method has several advantages. First, it relies on much weaker assumptions about the underlining data generating process. The only assumption that RD design method uses is the continuity assumption. In contrast, the IV method usually relies on exclusion restrictions. Second, many applications in empirical IO and marketing could use the RD design method. As in the application of this paper, in many cases firms make decisions based on some cut-off rules. For example, the pharmaceutical companies usually assign physicians to different marketing cells. Physicians in different cells receive different marketing intensities. Firms' pricing decisions are usually discrete as well. As long as the researchers have knowledge of the decision process, this information could be used in RD design application.

Figure 2.1 Discontinuity in Offer

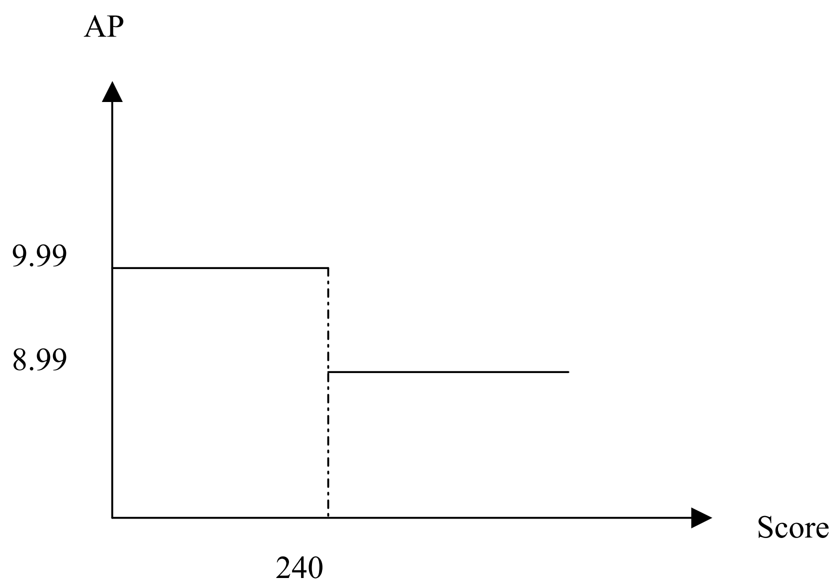

Figure 2.2 Discontinuity in Response Rate

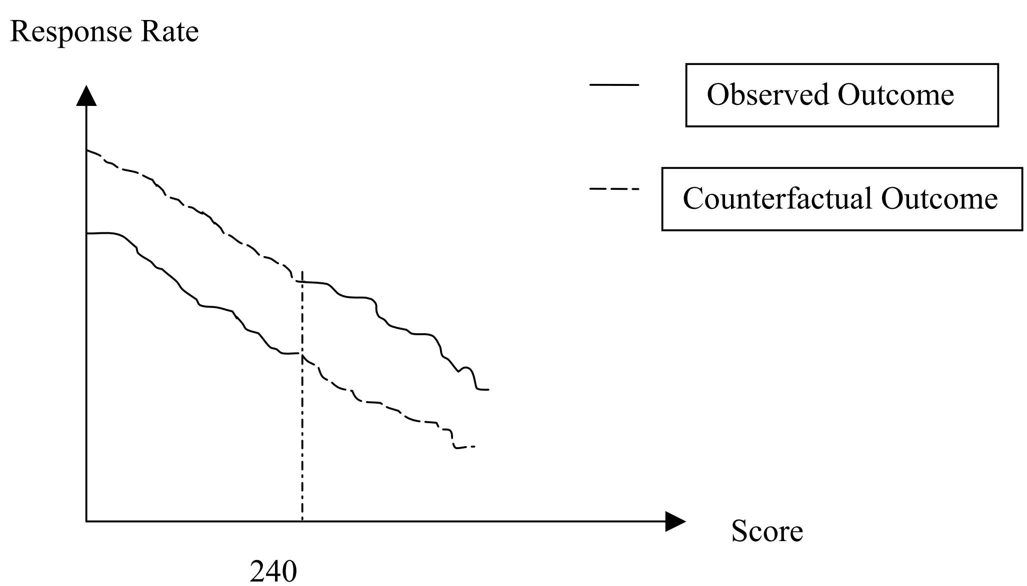

Figure 2.3 Bank Card Total Limit by Score

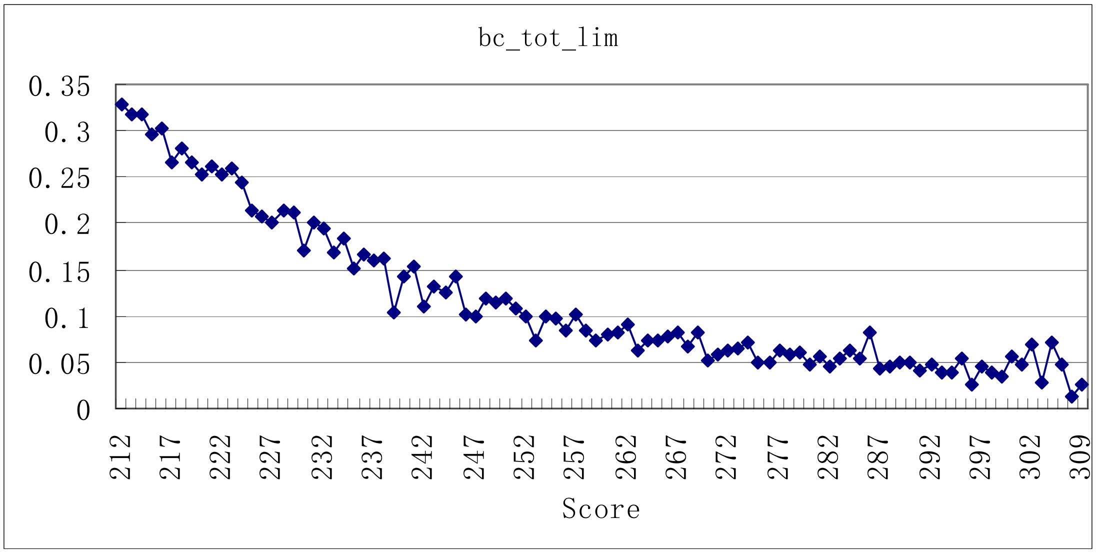

Figure 2.4 Bank Card Total Balance by Score

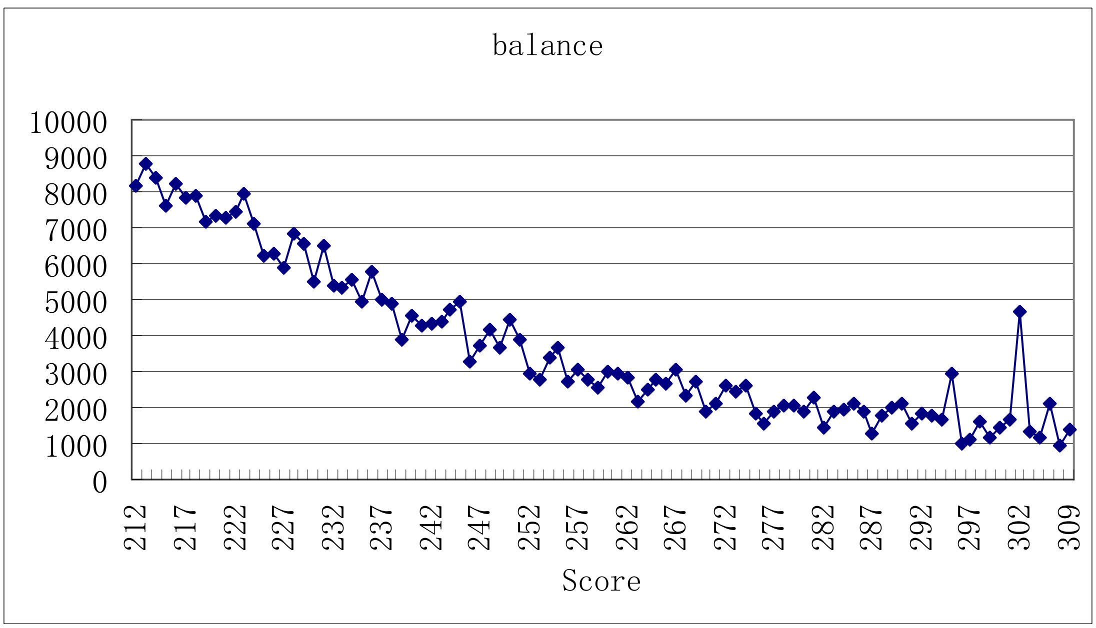

Figure 2.5 Beacon Score by Score

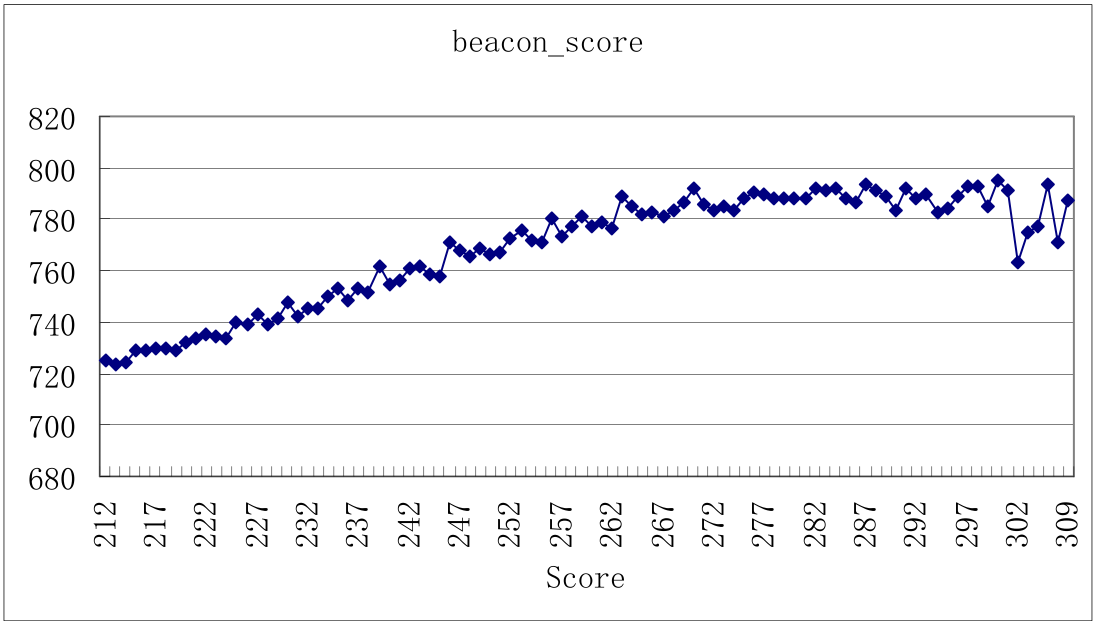

Table 2.1 Summary Statistics

Variable		Total		Resp	Not Resp	% Resp
	Mean	Min	Max	Mean	Mean	
Bureau Score	750	670	830	735	751	
BC total Balance	5200	0	50000	10200	4900	
BC total Limit	30400	0	315900	52000	28800	
BC Utilization	0.17	0.00	1.00	0.21	0.17	
Customer Score	238	212	280	234	238	
Male	0.48	0.00	1.00	0.50	0.47	
Age	51	18	99	49	51	
OBS	22532			1557	20975	0.069

Table 2.2 Summary Statistics by Marketing Groups

Variable	Total	Resp	Not Resp	% Resp
Group1 (score<230 with APR=9.99%)				
Bureau Score	730	720	740	
BC total Balance	7200	12100	6800	
BC total Limit	27700	46300	25900	
BC Utilization	0.25	0.27	0.25	
Customer Score	222	221	222	
Male	0.49	0.51	0.49	
Age	47	46	47	
OBS	9178	793	8385	0.086
Group2 (230<=score<=240 with APR=8.99%)				
Bureau Score	750	730	750	
BC total Balance	5100	10500	4800	
BC total Limit	29800	53300	28100	
BC Utilization	0.16	0.20	0.16	
Customer Score	235	235	235	
Male	0.47	0.48	0.47	
Age	52	49	52	
OBS	4735	308	4427	0.065
Group3 (score>240 with APR=7.99%)				
Bureau Score	780	760	780	
BC total Balance	3200	6700	3000	
BC total Limit	33700	61200	32100	
BC Utilization	0.09	0.11	0.09	
Customer Score	257	257	257	
Male	0.46	0.50	0.46	
Age	55	53	55	
OBS	8619	456	8163	0.053

Table 2.3. A simple comparison of the response rate near the cutoff point

		Mean	St. Error	Obs
3-point intervals				
	score=230,231,232	0.0813	0.2735	1168
S1=230	score=229,228,227	0.0866	0.2813	2044
	Difference	-0.0053		
	score=241,242,243	0.0539	0.2260	779
S2=240	score=240,239,238	0.0464	0.2104	1444
	Difference	0.0075		
	elasticity	1.3643		
2-point intervals				
	score=230,231	0.0783	0.2688	792
S1=230	score=229,228	0.0817	0.2740	1359
	Difference	-0.0034		
	score=241,242	0.0522	0.2227	517
S2=240	score=240,239	0.0442	0.2057	1063
	Difference	0.0080		
	elasticity	1.5221		

Table 2.4 Baseline Estimates: Treat Interest Rate as continuous Variable

	Control			Non Control		
	Estimate	Sd	t-stat	Estimate	Sd	t-stat
Intercept	0.7447	0.0949	7.85	0.4210	0.0872	4.83
Interest Rate	-0.8809	0.4166	-2.11	-0.7490	0.4260	-1.76
utilization	0.0802	0.0222	3.61			
utlization sq.	-0.0898	0.0284	-3.16			
Bureau Score	-0.0005	0.0001	-7.97			
BC total Limit($1000)	0.0018	0.0001	28.10			
male	0.0001	0.0033	0.03			
age	-0.0030	0.0006	-4.60			
age2	0.0000	0.0000	4.42			
Linear(score)	-0.0008	0.0002	-3.73	-0.0012	0.0002	-5.57
Observations	22532					
	DF	Chi-Square	Pr > ChiSq	DF	Chi-Square	Pr > ChiSq
Spline(score)	5.37	15.46	0.01	5.49	18.15	0.00

Table 2.5 Baseline Estimates: Treat Interest Rate as Dummy Variable

	Control			Non Control		
	Estimate	Sd	t-stat	Estimate	Sd	t-stat
Intercept	0.7447	0.0949	7.85	0.4210	0.0872	4.83
Interest Rate	-0.8809	0.4166	-2.11	-0.7490	0.4260	-1.76
utilization	0.0802	0.0222	3.61			
utlization sq.	-0.0898	0.0284	-3.16			
Bureau Score	-0.0005	0.0001	-7.97			
BC total Limit($1000)	0.0018	0.0001	28.10			
male	0.0001	0.0033	0.03			
age	-0.0030	0.0006	-4.60			
age2	0.0000	0.0000	4.42			
Linear(score)	-0.0008	0.0002	-3.73	-0.0012	0.0002	-5.57
Observations	22532					
	DF	Chi-Square	Pr > ChiSq	DF	Chi-Square	Pr > ChiSq
Spline(score)	5.37	15.46	0.01	5.49	18.15	0.00

Table 2.6 Robust Analysis

Specification	Linear		Quadratic		Cubic	
	Estimate	Sd	Estimate	Sd	Estimate	Sd
Intercept	0.5051	0.0949	1.4155	0.4263	3.1825	4.9318
Interest Rate	0.3320	0.4167	-0.2492	0.4940	-0.1203	0.6102
utilization	0.0799	0.0222	0.0808	0.0222	0.0808	0.0222
utilization sq.	-0.0864	0.0284	-0.0902	0.0284	-0.0903	0.0284
Bureau Score	-0.0005	0.0001	-0.0005	0.0001	-0.0005	0.0001
BC total Limit($1000)	0.0018	0.0001	0.0018	0.0001	0.0018	0.0001
Male	0.0001	0.0033	0.0001	0.0033	0.0001	0.0033
age	-0.0030	0.0006	-0.0030	0.0006	-0.0030	0.0006
age2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Linear	-0.0003	0.0002	-0.0071	0.0031	-0.0295	0.0622
Quadratic			0.0000	0.0000	0.0001	0.0003
Cubic					0.0000	0.0000
Adj R-Sq		0.056		0.0561		0.0561

Table 2.7 OLS Estimates

	Estimate	Sd
Intercept	0.4239	0.0646
backend	0.7357	0.2331
utilization	0.0810	0.0222
utilization sq.	-0.0870	0.0284
Bureau Score	-0.0005	0.0001
BC total Limit($1000)	0.0018	0.0001
male	0.0002	0.0033
age	-0.0031	0.0006
age2	0.0000	0.0000
Adj R-Sq		0. 0559

Table 2.8 Sensitivity Analysis

Specification	DF=4		DF=5		DF=6	
	Estimate	Sd	Estimate	Sd	Estimate	Sd
Intercept	0.6686	0.0949	0.7101	0.0949	0.7390	0.0949
backend	-0.0050	0.0042	-0.0071	0.0042	-0.0085	0.0042
utilization	0.0805	0.0222	0.0803	0.0222	0.0803	0.0222
utilization sq.	-0.0899	0.0284	-0.0898	0.0284	-0.0898	0.0284
Bureau Score	-0.0005	0.0001	-0.0005	0.0001	-0.0005	0.0001
BC total Limit($1000)	0.0018	0.0001	0.0018	0.0001	0.0018	0.0001
Male	0.0001	0.0033	0.0001	0.0033	0.0001	0.0033
age	-0.0030	0.0006	-0.0030	0.0006	-0.0030	0.0006
age2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Linear(Score)	-0.0006	0.0002	-0.0007	0.0002	-0.0008	0.0002
Spline(score)	Chi-Square	Pr > ChiSq	Chi-Square	Pr > ChiSq	Chi-Square	Pr > ChiSq
Cubic	9.6550	0.0217	12.7179	0.0127	15.3557	0.0089
Adj R-Sq		0.056		0.0561		0.0561

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