ESSAYS ON CONSUMER LINES OF CREDIT: CREDIT CARDS AND HOME EQUITY LINES OF CREDIT

DISSERTATION

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By

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ABSTRACT

Lines of credit in the consumer credit market are primarily in the forms of credit cards (CCs) and Home Equity Lines of Credit (HELOCs). In the first chapter of the dissertation I focus on the special usage of lines of credit as a hedge against optimally uninsured risks. This framework helps me understand why some consumers hold lines of credit and do not draw on them. Consumers weigh the various non-interest costs of HELOC borrowing against the benefits of low and income tax-deductible interest rates. I show that consumers optimally choose CCs as the preferred risk-financing instrument for sufficiently small amounts of debt. For relatively large amounts of indebtedness, they prefer to use HELOCs exclusively; and for extremely large borrowing needs, the costs of collateralization of credit induce consumers to carry debt on both CCs and HELOCs. The motive to consolidate debt introduces simultaneity in consumers’ choice of holding debt on lines of credit, which is addressed with an appropriate econometric model. In the second chapter of the dissertation I examine the nature of the information asymmetry prevalent between borrowers and lenders in the market for HELOCs and test how collateral helps overcome this asymmetric information. Two distinct paradigms have emerged from the theoretical studies investigating the role of collateral in explaining the risk-spread in the market for collateralized loans. The sorting-by-observed-risk paradigm
predicts a positive association between collateral and borrower risk and hence a positive relationship between the amount of collateral pledged and the rate of interest charged. The sorting-by-private-information paradigm, on the other hand, postulates a negative relationship between collateral and credit price. I find empirical support for the sorting-by-private-information paradigm in the market for HELOCs. In the final chapter of the dissertation I theoretically and empirically identify the determinants of credit card borrowing limits when banks can simultaneously choose the borrowing limit and the interest rate in their loan contracts. I find a positive relationship between borrower quality and the borrowing limit on CCs, correcting for banks’ selection of credit card holders and for the influence of the endogenous variable, the credit card interest rate.
Dedicated to my parents
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CHAPTER 1

CHOICE OF CONSUMER LINES OF CREDIT: SECURED VERSUS UNSECURED

1.1 Introduction

This chapter of my thesis addresses some of the fundamental issues in the market for consumer lines of credit. I focus on two main lines of credit facing the consumers – credit cards (CCs), the unsecured line, and the secured Home Equity Lines of Credit (HELOCs). My research examines three primary questions pertaining to these two lines of credit –

i. Why do consumers borrow on lines of credit, as opposed to taking out traditional loans?

ii. What determines the choice of incurring debt on CCs versus HELOCs?

iii. Why do some consumers hold debt on both CCs and HELOCs?

To answer these questions I develop a theoretical model, implications of which are empirically tested using the Survey of Consumer Finances data, recognizing and correcting for the sample selection and endogeneity bias.

Consumers face risky environments. Risks are typically financed by insurances. Consumers hedge against the risks of “loss” of wealth by purchasing insurance contracts
and by paying insurance premiums. However, there are no traditional insurances for financing many of the risks that consumers face. There exist insurances covering the “loss” due to house fire or natural calamity or theft. However, there is no traditional insurance to hedge against the “loss” of wealth due to some sudden need for home repair. Consumers usually insure themselves through planned savings (i.e. by planned accumulation of liquid wealth) against the permanent fall in income due to retirement and against the need for liquidity for items such as college tuition payments. They are, however, unable to insure themselves against the risk of unforeseen tuition fee increases. Hence, there is a need to investigate the role that lines of credit play in consumers’ risk management in an environment lacking traditional insurances for various risks they face.

So let me first address the question as to why consumers borrow on lines of credit, as opposed to taking out traditional loans. Eisenhauer (1994) argued that consumers use lines of credit as instruments of risk management. He concluded that in an environment of risk together with an imperfect insurance market providing full but unfair insurance policies, consumers will optimally keep some “losses” uninsured and finance the uninsured “losses” by borrowing on their lines of credit. Hence, he argued that even if consumers have the option to fully insure, the presence of lines of credit would optimally induce them to under-insure - for example, to buy only collision insurance for the car and keep the car repair risk uninsured, and to be financed by borrowing on lines of credit. The absence of traditional insurances for several types of consumer risks is therefore likely to be an equilibrium outcome.

However, Eisenhauer failed to incorporate one of the main features of borrowing on lines of credit - the repayment flexibility. Therefore, he had to rely on the restrictive
assumption of imperfect insurance market. I am able to show that even in the presence of full and actuarially fair insurance policies, consumers will optimally keep some “losses” uninsured and borrow on their lines of credit to finance the uninsured “losses” if the repayment schemes in lines of credit make borrowing costs accrue at rates lower than consumers’ rates of discounts. Should a loss occur, the savings from not paying full insurance premiums and paying lines of credit debt overtime will outweigh the interest cost for consumers with sufficiently high discount rates.

The presence of flexible lines of credit may also replace a large part of consumers’ precautionary savings, as they will then not need to accumulate liquid wealth for insuring against the so-called “rainy days”. Since the observed debt on lines of credit depends, among other things, on the occurrence of “losses”, I can provide an explanation, other than the argument of “convenience use”, for the absence of borrowing among holders of lines of credit. Furthermore, my framework explains why some consumers with lines of credit are observed not to use them either for borrowing or for transaction purposes, a phenomenon particularly puzzling in the case of HELOCs, which involve upfront fixed costs.

Consumers face heterogeneous environments of risk (e.g., risks from day-to-day household income-expenditure flows may be small, while the risks of unplanned home repairs may be substantial). Wealth-income profiles dictate the nature and magnitude of the risks consumers face. A question that needs to be addressed in this context is what roles do the two primary lines of credit, namely CCs and HELOCs, play in consumers’ risk management under heterogeneous risk environments. In other words, I want to understand the factors that determine the choice of incurring debt on CCs versus
HELOCs. In order to address this issue, I will analyze the key properties of CCs and HELOCs.

Properties of CCs and HELOCs

Interest costs are the only significant costs associated with CC borrowings. However, in order to obtain HELOCs, consumers have to incur several fixed costs - for example, attorney fees, collateral appraisal costs, points, membership fees etc. Moreover, since HELOC borrowings put consumers’ homes in jeopardy, I postulate some variable costs over and above the interest costs, called the costs of collateralization of credit. Since HELOCs are secured by consumers’ homes and CCs are unsecured, the interest costs on HELOC borrowings are usually lower than those on CC borrowings. Finally, the interest costs on loans taken on HELOCs (and not those on CCs) are income-tax-deductible.

Consumers weigh the various non-interest costs of incurring HELOC debt against the benefits of low and income tax-deductible interest rates. I show that for sufficiently large amounts of desired debt (as determined by consumers’ preferences and wealth-income-risk profiles), consumers will optimally choose HELOCs as the preferred risk-financing instrument, and for smaller amounts of desired indebtedness, they will prefer CCs. Intuitively, if substantial amounts are desired to be held on HELOCs, then the gains in utility due to lower interest rates and income tax advantages must outweigh the losses due to the various non-interest costs of HELOCs. Hence, consumers facing heterogeneous risk environments prefer to use different lines of credit for financing risks of varying magnitude. For consumers who have already undertaken very large amounts
of debt on their HELOCs, the costs of collateralization of credit make the motives to consolidate debt into HELOCs very weak, and hence these consumers can be found to hold debt on both CCs and HELOCs. Therefore, this research gives a rational explanation for the observed puzzling phenomenon of consumers holding both types of debt.

Although HELOCs have been around since the 1980s, the median CC balance for those with positive balances on CCs does not show any clear declining trend. The median CC balance rose almost 40 percent, from $1,100 in 1992 to $1,500 in 1995. However, it remained more or less unchanged between the years 1995 and 2001. By way of modeling the costs (other than the interest costs) of HELOCs along with the benefits, I not only analyze the decision to hold debt on HELOCs, but also gain insight into the factors hindering the transfer of balances away from CCs and into HELOCs. The costs of HELOCs make them unattractive for relatively small amounts of desired indebtedness and the non-interest variable costs make the motives to consolidate debt into HELOCs become weaker with increased HELOC borrowings. Therefore, I am able to provide an explanation for the lack of a pronounced declining trend in the CC indebtedness despite the presence of accessible and apparently cheaper alternate lines of credit, such as the HELOCs.

**Background and Previous Research**

Beginning with Ausubel (1991), researchers began to look into the market for consumer lines of credit, especially into CCs. The bulk of the literature on CCs concentrated on answering the question as to why have the average CC interest rates remained sticky at such a high level. Ausubel (1991) argued that the reason for this
downward-rigid interest rates and the presence of supernormal profits was the failure of competition in the CC market. He partly attributed this failure of competition to the myopic consumers who failed to foresee indebtedness and interest payments on their outstanding balances. Brito and Hartley (1995), virtually in response to Ausubel (1991), argued that the consumers carried high-interest CC debts, not due to myopia but due to the fact that obtaining low-interest bank loans involved transaction costs. Mester (1994) argued that the low-risk borrowers who had access to low interest collateralized loans left the CC market. This made the average client pool of the CC market riskier and thereby preventing the interest rates from going down. Park (1997) explained the credit card interest rate stickiness using the option value nature of lines of credit. A major empirical paper in this literature put forward by Calem and Mester (1995) found evidence for consumers’ reluctance to search for lower rates due to high search costs in this market. A more recent paper by Cargill and Wendel (1996) suggests that due to the high presence of convenience users, even modest search costs could keep the majority of consumers from seeking out lower interest rates. Gross and Souleles (2002) utilize a unique new dataset of credit card accounts to analyze how people respond to changes in credit supply. They find that increases in credit limits generate an immediate and significant rise in debt, consistent with the buffer-stock models of precautionary saving, as cited in Deaton (1991), Carroll (1992), and Ludvigson (1999).

HELOC borrowing grew from virtually nil in 1982 to $40 billion by 1986. By 1993, it was $110 billion (Canner and Luckett 1994); at the end of 1997, the estimated HELOC borrowing was $153 billion (Canner, Durkin, and Luckett 1998) and the most recent estimate of HELOC debt will amount to $180 billion. HELOCs have been seen to
be playing an increasingly important role in household’s ability to influence consumption patterns (Canner and Luckett 1994; DeMong and Lindgren 1990). Chen and Jensen (1985) analyzed the propensities to use HELOCs for consumption purposes within the framework of life cycle hypothesis. Their findings indicated a profile of HELOC users who were relatively young, lived in larger households, and had lower networths yet larger incomes. The results, however, showed no significance with respect to the value of the housing asset. According to Eugeni (1993), recent tax revisions affecting the deductibility of interest paid, advantageous interest rates, and intensive marketing campaign of HELOCs have contributed to the dramatic increase in their use. Delaney (1994) noted that with mortgage payments viewed as a form of ‘forced’ savings, one of the largest assets accumulated by a household during its life cycle is the equity in the home. This accumulated equity was largely untapped as a source of financial flexibility until recently. Several authors have tried to provide some explanation for the growth in HELOC borrowing in US. Salandro and Harrison (1997) used The Survey of Consumer Finances (1989 and 1992) to identify the determinants of demand for HELOCs among households possessing various lines of credit, other than CCs or business lines of credit. They found that the choice of HELOCs was influenced principally by the percentage of equity in home, income, net worth, age of the borrower, and credit price. All this research on CCs and HELOCs did not answer a simple question as to why use lines of credit to borrow when the borrowers have the option of taking out regular loans. For example, why borrow on HELOCs when there are Home Equity Loans (HELs) available. In order to answer that question, one needs to focus on the aspects of lines of credit that are absent in regular loans and in this chapter I plan to do just that.
Since 1986, lenders have heavily promoted HELOCs. In 1986, nearly half of all large financial institutions allocated more advertising funds to home equity accounts than to any other credit products (Canner, Ferguson, and Luckett 1988). One of the most important of all the influences on the growth of HELOCs has been the Tax Reform Act of 1986. While the 1986 Tax Reform Act called for consumer interest deductibility to be phased out by 1991, only the $100,000 cap now limits the interest deductions on equity indebtedness. This means that the interest paid on HELOCs is still partially tax deductible, which is not the case for the interest paid on CCs. Therefore, it was generally expected that HELOCs would arrest the growth of CC debt in the US. Authors like Mester (1994) argued that low-risk borrowers who have access to low interest charging collateralized loans would leave the CC market. Hence for sometime, researchers have been anticipating and arguing about the transfer of balances away from CCs and into HELOCs. However, despite general expectations, the literature on consumer credit has failed to explicitly incorporate the use of HELOCs as instruments of debt consolidation.

In this chapter, I will model and empirically test the effect of debt consolidation into HELOCs on consumers’ CC debt.

1.2 The theoretical model

I will model a typical consumer’s choice of borrowing on lines of credit as a lifetime utility maximization problem in an environment of risk. I consider three different scenarios:

1. The consumer has only CC to borrow on
2. The consumer has only HELOC to borrow on
3. The consumer has access to both CC and HELOC

Let me define the following:

$U$: Utility Function; $U' > 0$, $U'' < 0$

$W_t$: Wealth of the Consumer at time period $t$

$q$: Insurance Coverage

$L$: “Loss”; $L > 0$

$p$: The Probability of Occurrence of the “Loss”

$r_C$: Rate of Interest on CC

$r_H$: Rate of Interest on HELOC; $r_C > r_H$

$t$: Income Tax Rate; $0 < t < 1$

$\tau$: Fixed Cost of Obtaining HELOC; $\tau > 0$

$\delta$: The Discount Factor; $0 < \delta < 1$

$C$: Cost of Collateralization of Credit

$\alpha$: The Required Rate of Repayment; $0 < \alpha < 1$

Before I start with the formal optimization problems under my three different scenarios, I need to clearly explain the environment that the consumer is in and also spell out the assumptions I make in the process.

There are two states of the world - the “loss” state and the “no-loss” state. There are also two time periods – 0 and 1. Since I am trying to explain borrowings on lines of credit, I do not consider the use of lines of credit for transaction purposes. The phenomenon of ‘convenience use’ is, therefore, not modeled in this chapter.
**Assumption 1:** The required rate of repayment, $\alpha$, is the same in HELOCs and CCs.¹

**Assumption 2:** The consumer actually pays back at the rate at which he/she is asked to.²

**Assumption 3:** $C = c(D^H)$, $1 > c > 0$ and $D^H$ is the unpaid debt on HELOC. The *cost of collateralization of credit* ($C$) is a cost in the sense that it is costly to take a collateralized loan as opposed to a non-collateralized loan. Since HELOC is secured by household’s home, carrying debt on HELOC puts his/her home at risk. The variable ‘$C$’ captures the cost that HELOC indebtedness imposes by way of putting household’s home in jeopardy. Moreover, the greater is the amount owed on HELOC, the higher is the risk of losing the home. Hence, the *cost of collateralization of credit* is reasonably assumed to be a positive function of the amount of unpaid debt on HELOC.

**Assumption 4:** Insurance is actuarially fair. Hence, $\text{Premium} = pq$.

**Assumption 5:** Uncertainty about the state of the world is present only in period 0.

**Assumption 6:** Wealth of the consumer ($W_t$) is exogenously determined. The consumer has exogenously chosen the periodic wealth levels in a way that there is no gain in utility from transferring wealth from one period to another.

If the consumer fully insures against all states of the world, then the period 0 expected utility is given by $V^F = U(W_0 - pL)$ and the period 1 expected utility is $U(W_1)$. It can be shown that without any lines of credit to borrow on and under actuarially fair insurance policy, buying full insurance in period 0 is in fact optimal for the consumer. Moreover, it must be emphasized that my typical consumer is a “partially optimizing

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¹ Consumers are often required to repay 2%-3% of their outstanding balances on credit cards, HELOCs or on any other loans.

² This assumption is often true for credit cards and more often for HELOCs and mortgage loans.
consumer”, choosing only the desired level of insurance coverage (q), as opposed to a “fully optimizing consumer”, choosing both the insurance coverage and the levels of wealth (W_i). A borrowing instrument is commonly used by consumers for smoothing out consumption across time periods. Any loan, including a line of credit, can be used by consumers to serve the purpose of consumption smoothing. Since I am trying to isolate a purpose for line of credit borrowing that a standard loan instrument cannot capture, I consider a “partially optimizing consumer” instead of a “fully optimizing consumer”. Another motivation for considering this “partially optimizing consumer” behavior will be the fact that abysmally low market rates of return are inducing almost the entire set of consumers (irrespective of their discount rates) to take out some sort of loans, such as, student loans, car loans or home loans. Therefore, under the environment of extremely low market rates of return, the question as to why consumers borrow is almost trivial. A more interesting question that has not been answered very satisfactorily in the literature is that among all the various borrowing instruments that consumers have access to, what purpose do borrowings on lines of credit specially serve? So my assumption that the consumer has already chosen the periodic wealth levels, W_0 and W_1, in a way that there is no gain in utility from transferring wealth from one period to another, helps me focus on the more interesting aspect of line of credit borrowing, over and above its use as an instrument for smoothing consumption across time periods.
1.2.1 The choice to borrow in the presence of credit card only

Let me suppose that the consumer has only CC to borrow on. The consumer pays a premium ‘pq’ in period 0, irrespective of the state of the world. His/her discounted expected lifetime utility is given by,

\[ V^C = V_0^C + \delta V_1^C \]

where

\[ V_0^C = (1 - p) U(W_0 - pq) + p U(W_0 - pq - \alpha(L - q)) \] and

\[ V_1^C = (1 - p) U(W_1) + p U(W_1 - (1 - \alpha)(L - q)(1 + r_c)) \].

Having only CC to borrow on, the consumer now faces the following optimization problem:

Maximize \( V^C \) w.r.t.\( q \) \( \Rightarrow \)

\[ (1 - p) U'(W_0 - pq^*) = (\alpha - p) U'(W_0 - pq^* - \alpha(L - q^*)) + \delta(1 - \alpha)(1 + r_c) U'(W_1 - (1 - \alpha)(L - q^*)(1 + r_c)) \] \( (1) \)

More compactly I have,

\[ (1 - p) U'(C_{N_o}) = (\alpha - p) U'(C_{L_o}) + \delta(1 - \alpha)(1 + r_c) U'(C_{L_i}) \] \( (2) \)

where the variable ‘\( C_{i_j} \)’ represents consumption, subscripts N and L indicate “no-loss” and “loss” states and subscripts 0 and 1 represent the time periods.

Using equation (2), I have

\[ \frac{U'(C_{N_o})}{U'(C_{L_o})} < 1 \iff \delta < \frac{U'(C_{L_o})}{(1 + r_c)U'(C_{L_i})} = \delta^C. \]

Equation (2) and concavity of the utility function gives me,

\[ \delta < \delta^C \]

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\[ U'(C_{N_0}) < U'(C_{i_0}) \]
\[ W_0 - pq^* > W_0 - pq^* - \alpha(L - q^*) \]
\[ \alpha(L - q^*) > 0 \]
\[ q^* < L \]  \hspace{1cm} (3)

Hence, if \( \delta < \delta_C \), then I have \( q^* < L \). In other words, if the repayment scheme in CC makes the cost of borrowing accrue at a rate lower than consumer’s rate of discount, the consumer will then optimally want to under-insure in period 0 and borrow on CC. Should a loss occur, the savings from not paying full insurance premiums and paying CC debt overtime will outweigh the interest cost for a consumer whose discount factor is lower than \( \delta_C \). The desired “loss” state contingent CC debt, defined as \( D^* \), is \( D^*_0 = (1 - \alpha)(L - q^*) \) in period 0 and is \( D^*_1 = 0 \) in period 1. If \( D^*_0 > 0 \), then the consumer optimally wants to use CC to finance the uninsured “loss”. However, in the absence of a realized “loss”, CC debt will not be observed in period 0 even if \( D^*_0 \) is positive. Therefore, a reason for the unobserved debt among CC holders can be the non-occurrence of the projected “losses”. This can provide an explanation for the observed lack of usage of CCs for borrowing or transaction purposes among CC holders. Let \( D^*_C \) be the optimal unconditional debt on CC (i.e. the desired CC debt, irrespective of the state of the world and the time period that the consumer is in). Therefore, \( D^*_C \) is observed if it is non-negative.

It is possible to find conditions under which the consumer will not purchase any insurance coverage in period 0. For any degree of risk aversion, there exist a critical
value for \( \delta \), say \( \delta^* \), such that if \( \delta \leq \delta^* \), then the consumer does not insure at all in period 0.

From equation (2), I get

\[
\delta^* = \frac{(p - \alpha)U'(C_{Lc}) + (1 - p)U'(C_{Nc})}{(1 - \alpha)(1 + r_c)U'(C_{Lc})}
\]  

(4)

where the marginal utilities in equation (4) are evaluated at \( q^* = 0 \).

1.2.2 The choice to borrow in the presence of HELOC only

Now let me suppose that the consumer now has only HELOC to borrow on. Interest payments associated with HELOC debt are income tax-deductible along with the fact that there are fixed costs \( \tau \) and non-interest variable costs, called the costs of collateralization of credit \( C \). The consumer’s discounted expected lifetime utility is now given by,

\[
V^H = V_0^H + \delta V_1^H
\]

where

\[
V_0^H = (1 - p) U'(W_0 - pq - \tau) + p U'(W_0 - pq - \alpha(L - q) - c(1 - \alpha)(L - q))
\]

and

\[
V_1^H = (1 - p) U'(W_1 - \tau) + p U'(W_1 - \alpha(L - q)(1 + r_H(1 - \tau))).
\]

Having only HELOC to borrow on, the consumer now faces the following optimization problem:

Maximize \( V^H \) w.r.t. \( q \)

\[
(1 - p) U'(W_0 - pq^* - \tau) =
\]

\[
(\alpha + c(1 - \alpha) - p) U'(W_0 - pq^* - \alpha(L - q^*) - c(1 - \alpha)(L - q^*)) +
\]
\[ \delta(1 - \alpha)(1 + r_H(1-t)) U'(W_1 - \tau - (1 - \alpha)(L - q^{**})(1 + r_H(1-t))) \]  

(5)

More compactly I have,

\[
(1 - p) U'(C_{N_0}) = (\alpha + c(1 - \alpha) - p) U'(C_{L_0}) + \delta(1 - \alpha)(1 + r_H(1-t)) U'(C_{L_i})
\]  

(6)

where the variable ‘\(C_{i,j}\)’ represents consumption, subscripts N and L indicate “no-loss” and “loss” states and subscripts 0 and 1 represent the time periods.

Using equation (6), I have

\[
\frac{U'(C_{N_0})}{U'(C_{L_0})} < 1 \iff \delta < \frac{(1-c)U'(C_{L_0})}{(1 + r_H(1-t))U'(C_{L_i})} = \delta^H.
\]

Equation (5) and concavity of the utility function gives me,

\[ \delta < \delta^H \]

\[ \iff U'(C_{N_0}) < U'(C_{L_0}) \]

\[ \iff W_0 - pq^{**} - \tau > W_0 - pq^{**} - \tau - \alpha(L - q^{**}) - c(1 - \alpha)(L - q^{**}) \]

\[ \iff (\alpha + c(1 - \alpha))(L - q^{**}) > 0 \]

\[ \iff q^{**} < L \]  

(7)

Hence, if \(\delta < \delta^H\), then I have \(q^{**} < L\). In other words, if the repayment scheme in HELOC makes the cost of borrowing accrue at a rate lower than consumer’s rate of discount, the consumer will then optimally want to under-insure in period 0 and borrow on HELOC. Should a loss occur, the savings from not paying full insurance premiums and paying HELOC debt overtime will outweigh the interest cost for a consumer whose discount factor is lower than \(\delta^H\). The desired “loss” state contingent HELOC debt, defined as \(D^{**}\),
is $D_0^{**} = (1 - \alpha)(L - q^{**})$ in period 0 and is $D_1^{**} = 0$ in period 1. If $D_0^{**} > 0$, then the consumer optimally wants to use HELOC to finance the uninsured “loss”. However, in the absence of a realized “loss”, HELOC debt will not be observed in period 0 even if $D_0^{**}$ is positive. Hence, a reason for the observed lack of usage among HELOC holders can be the non-occurrence of the projected “losses”. Similarly, let $D_H^{**}$ be the optimal unconditional debt on HELOC (i.e. the desired HELOC debt, irrespective of the state of the world and the time period that the consumer is in). Therefore, $D_H^{**}$ is observed if it is non-negative.

It is again possible to find conditions under which the consumer will not purchase any insurance coverage in period 0. For any degree of risk aversion, there exist a critical value for $\delta$, say $\delta^{**}$, such that if $\delta \leq \delta^{**}$, then the consumer does not insure at all in period 0. From equation (6), I get

$$\delta^{**} = \frac{(p - \alpha - c(1 - \alpha))U'(C_{n_0}) + (1 - p)U'(C_{n_0})}{(1 - \alpha)(1 + r_H(1 - t))U'(C_{L_1})}$$

(8)

where the marginal utilities in equation (8) are evaluated at $q^{**} = 0$.

1.2.3 The choice to borrow in the presence of credit card and HELOC

Let me finally address the choice of incurring debt when the consumer has access to both CCs and HELOCs. The discounted expected lifetime utility from not obtaining a HELOC and potentially borrowing $D_0 = (1 - \alpha)(L - q)$ on CC is given by

$$V^C = V_0^C + \delta V_1^C.$$  

For $D_0 = 0$, I have $V^C = U(W_0 - pL) + \delta U(W_1)$. 

The discounted expected lifetime utility from potentially borrowing $D_0$ on HELOC only is given by

$$V^H = V_0^H + \delta V_1^H.$$  

For $D_0 = 0$, I have $V^H = U(W_0 - pL - \tau) + \delta U(W_1 - \tau)$.

Hence, $\forall \tau > 0$ and for $D_0 = 0$, I have, $V^H - V^C < 0$. Let me draw upon the following condition that realistically represents the situation for a consumer with access to both types of lines of credit:

**Condition 1:** $V^H - V^C$ is a strictly increasing function of $D_0$. This is equivalent to requiring the following:

$$\frac{\alpha}{(1-\alpha)}U'(C^C_0) + \delta(1+r_c)U'(C^C_1) > \frac{\alpha}{(1-\alpha)} + c)U''(C^H_0) + \delta[1 + r_H(1-t)]U'(C^H_1),$$

where

$$C^C_0 = W_0 - pq - \frac{\alpha}{1-\alpha}D_0,$$

$$C^C_1 = W_1 - D_0(1 + r_c),$$

$$C^H_0 = W_0 - pq - \tau - \frac{\alpha}{1-\alpha}D_0 - cD_0,$$

$$C^H_1 = W_1 - \tau - D_0(1 + r_H(1-t)).$$

Now suppose that the consumer has both CC and HELOC at his/her disposal, then the new discounted expected lifetime utility from potentially borrowing $D_0$ is

$$V^B = V_0^B + \delta V_1^B$$

where

$$V_0^B = (1 - p) U(W_0 - pq - \tau) +$$
\[ p \ U(W_0 - pq - \tau - \frac{\alpha}{1-\alpha} D_0^C - \frac{\alpha}{1-\alpha} D_0^H - cD_0^H) \] and

\[ V_1^B = (1 - p) U(W_1 - \tau) + p \ U(W_1 - \tau - D_0^C (1 + r_c) - D_0^H (1 + r_H (1-t))) \]

where \( D_0^C \) is the CC debt, \( D_0^H \) is the HELOC debt and \( D_0^C + D_0^H = D_0 \).

I now consider a typical consumer’s behavior under the scenario where he/she has both CC and HELOC at his/her disposal. Let \( \forall D_0^H \), such that, \( \bar{D} \geq D_0^H \geq 0 \), I have \( \frac{\partial(V^B)}{\partial D_0^H} - \frac{\partial(V^B)}{\partial D_0^C} \geq 0 \). In other words, for a consumer with both CC and HELOC taken out and with relatively small desired HELOC debt, transferring balances away from CC and into HELOC does not reduce utility. Moreover, let \( \forall D_0^H > \bar{D} > D \), I have \( \frac{\partial(V^B)}{\partial D_0^H} - \frac{\partial(V^B)}{\partial D_0^C} < 0 \), which means that for extremely large desired HELOC debt, the risk of losing the home and therefore the cost of collateralization of credit is so high that consumer loses, in terms of utility, by consolidating debt into HELOC. The consumer behavior described in this paragraph can be summarized by the following condition:

**Condition 2:** \( \frac{\partial(V^B)}{\partial D_0^H} - \frac{\partial(V^B)}{\partial D_0^C} \) is a strictly decreasing function of \( D_0^H \) that intersects the \( D_0^H \)-axis at \( \bar{D} \) (\( \bar{D} > D \)). This boils down to requiring the following:

\[ c(\frac{\alpha}{1-\alpha} + c)U^*(C_0) < \delta[r_c - r_H (1-t)][1 + r_H (1-t)]U^*(C_1) \], where

\[ C_0 = W_0 - pq - \tau - \frac{\alpha}{1-\alpha} D_0^C - \frac{\alpha}{1-\alpha} D_0^H - cD_0^H \] and

\[ C_1 = W_1 - \tau - D_0^C (1 + r_c) - D_0^H (1 + r_H (1-t)) \].
From the foregoing analysis of consumer’s choice under the three different scenarios, and given my assumptions and conditions, I have the following results:

a. \( D_0 > 0 \), if \( \delta < \delta^C \),

b. \( \exists \ D > 0 \), such that \( V^H - V^C = 0 \),

c. For \( D_0 < D \), I have \( V^H - V^C < 0 \),

d. For \( D_0 > D \), I have \( V^H - V^C > 0 \) and

e. For \( D_0 > \overline{D} > D \), I have \( V^B \bigg|_{D_0^C=D_0, \overline{D}, D_0^H=\overline{D}} > V^H \).

The consumer desires to under-insure and borrow on lines of credit in the first place, if he/she is sufficiently impatient (i.e. if \( \delta < \delta^C \)). For a consumer with both CC and HELOC at his/her disposal and with relatively small desired debt (i.e. \( \forall D_0 \leq \overline{D} \)), balance transfer away from high-interest CC and into HELOC is beneficial. However, the costs of HELOC prevent the consumer from using HELOC for very small amount of desired debt (i.e. for \( D_0 < \overline{D} \)). Only if the desired debt level exceeds \( \overline{D} \), it makes sense for the consumer to want to borrow on a HELOC. Finally, for extremely large desired debt level (i.e. for \( D_0 > \overline{D} > \overline{D} \)), the risk of losing the home and therefore the cost of collateralization of credit is so high that debt consolidation into HELOC makes the consumer worse off and hence I find the consumer induced to carry debt on both CC and HELOC.
1.3 Data

The data used in this study is a pooled sample of 1995 and 1998 *U.S. Surveys of Consumer Finances* (SCF). SCF is a nationwide survey conducted by National Opinion Research Center (NORC) on behalf of the Board of Governors of the Federal Reserve System of United States. These two recent waves of the SCF provide a large and rich data set on household assets, liabilities, demographic characteristics and a number of variables capturing household attitudes. In 1998, 4,305 families were surveyed, while in 1995 the number was 4,299. Together there were 8,604 families in the pooled sample. The sample had 6,493 households with at least one bank-type CC (which was 75.46% of the total number of households in the sample) and 2,664 households carried outstanding balances on their bank-type CC. There were 669 households with HELOCs (which was 7.78% of the total number of households) and 373 of these households carried outstanding balances on their HELOCs.

To adjust the asset and liability variables to the 1998 dollars, a factor of 1.0622 was applied to the figures for 1995. To adjust the family income variables of 1995, I applied a factor of 1.0904. These are widely used factors devised to compare SCF figures of 1995 and 1998.

Since my main focus in this chapter is to model consumers’ choice of incurring debt when they have access to both CCs and HELOCs, I select a sample of 5,157 households with positive equity in their homes and with at least one bank-type CC in their possession.

As described by Table 1.6, I have four types of sample members:
I. \( D^C = D^H = 0 \), where \( D^C \) is the observed CC debt and \( D^H \) is the observed HELOC debt. According to the theoretical model, I can observe this set of data if the consumers have taken out HELOCs and yet are not carrying any debt on them either because the “losses” have not occurred or because they have repaid their entire HELOC debt. I can also observe this set of observations if the consumers have only CCs to borrow on and they do not carry debt on them either because the “losses” have not occurred or because they have repaid their entire CC debt.

II. \( D^C > 0 \) and \( D^H = 0 \). I can observe this set of observations either if the consumers only have CCs and are carrying debt on them or if they have both HELOCs and CCs and yet they are carrying debt only on their CCs. This second scenario can occur if some consumers have extremely large desired levels of debt, along with the fact that “losses” have only partially realized during the data collection period. Since the consumers are waiting for the big chunk of “losses” to arrive and since at very high levels of desired debt consolidation into HELOCs are utility reducing, I can find some consumers carrying balances on their CCs despite having zero balances on their HELOCs.

III. \( D^C = 0 \) and \( D^H > 0 \). I can observe this set if the consumers are carrying debt only on their preferred line, the HELOCs.

IV. \( D^C > 0 \) and \( D^H > 0 \). This can occur if some consumers have such extremely large levels of debt taken out on their HELOCs that consolidating further debt into HELOCs is not beneficial and hence they are carrying debt on CCs and HELOCs.

Table 1.7 shows that the average CC debt among households with positive levels of CC debt is significantly less than the average HELOC debt (among HELOC debtors), implying that the consumers on average borrow substantial amounts on their HELOCs.
Again according to Table 1.8, an overwhelming majority of HELOC debtors have credit card utilization rates (≡ Debt / Credit Limit) to be strictly less than one, which implies that the substantial borrowings on HELOCs are not due the fact that consumers have reached their CC borrowing limits.

Table 1.9 supports the fact that the average rate of interest on the collateralized HELOCs is less than that on the non-collateralized CCs. Finally, Tables 1.10 and 1.11 compare the average consumer profiles of CC debtors, HELOC debtors and HELOC non-debtors.

1.4 The econometric model

The consumer’s discounted expected lifetime utility from potentially carrying $D_0^*$ amount of CC debt in period 0, is given by

$$V^C = V_0^C + \delta V_1^C$$

where

$$V_0^C = (1 - p) U(W_0 - pq^*) + p U(W_0 - pq^* - \frac{\alpha}{(1-\alpha)} D_0^*)$$

and

$$V_1^C = (1 - p) U(W_1) + p U(W_1 - (1 + r_C^*)D_0^*).$$

Hence, I have the desired period 0 CC debt as, $D_0^* = G (W_0, W_1, r_C, \alpha, p, \delta)$, and also the optimal unconditional CC debt as, $D^C_0 = g (W_0, W_1, r_C, \alpha, p, \delta)$. Let $D_i^C$ denote the optimal unconditional CC debt for household ‘i’. Therefore I have, $D_i^C = g (W_{0i}, W_{1i}, r_{Ci}, \alpha_i, p_i, \delta_i)$.

Again, the consumer’s discounted expected lifetime utility from potentially carrying $D_0^{**}$ amount of HELOC debt in period 0, is given by
\[ V^{H**} = V_0^{H**} + \delta V_1^{H**} \]

where

\[ V_0^{H**} = (1 - p) \ U(W_0 - pq^{**} - \tau) + p \ U(W_0 - pq^{**} - \tau - \frac{\alpha}{1 - \alpha} D_0^{**} - cD_0^{**}) \] and

\[ V_1^{H**} = (1 - p) \ U(W_1 - \tau) + p \ U(W_1 - \tau - (1 + r_H (1 - t))D_0^{**}) \] (1 + 1). Hence, I have the desired HELOC debt to be, \( D_0^{**} = H(\tau, c, t, r_H, W_0, W_1, \alpha, p, \delta) \), and the optimal unconditional HELOC debt for household ‘i’ as, \( D_i^{H*} = h(\tau_i, c_i, t_i, r_{H_i}, W_{0i}, W_{1i}, \alpha_i, p_i, \delta_i) \).

At \( D_0 = D \), I have \( V^H - V^C = 0 \); therefore the cutoff debt level \( D \) is a function of all the variables in the model, i.e. \( D = f(\tau, c, t, r_H, W_0, W_1, \alpha, p, \delta, r_C) \). Similarly, the cutoff level of debt for household ‘i’ is given by \( D_i = f(\tau_i, c_i, t_i, r_{H_i}, W_{0i}, W_{1i}, \alpha_i, p_i, \delta_i, r_{Ci}) \).

**Implications from the Theoretical Model**

1. HELOC debt for household ‘i’ (\( D_i^{H*} \)) is observed if it is greater than the cutoff level of debt \( D_i \).

2. For household ‘i’, the marginal gain from consolidating debt away from credit cards and into HELOCs is non-negative for all debt combined levels less than \( D_i \), that is I have,

\[ \frac{\partial [V^B(D_i^{C*}, D_i^{H*})]}{\partial D_i^{H*}} - \frac{\partial [V^B(D_i^{C*}, D_i^{H*})]}{\partial D_i^{C*}} \geq 0, \forall i \& 0 \leq D_i^{H*} + D_i^{C*} \leq D_i. \]
Since all the households in the sample have at least one bank-type CC, negligible ($\varepsilon$) costs of obtaining CCs will guarantee that for all households in the sample the desired period 0 CC debt, $D_{0i}^* > 0$ and hence the optimal unconditional CC debt, $D_i^{C*} \geq 0$. Hence within my sample, I have the observed CC debt, $D_i^C = D_i^{C*}$. The motive to consolidate debt into HELOCs is likely to make the observed sample of CC debt to be non-random. Following testable Implication 2, I expect the observed CC debt to be negatively influenced by HELOC indebtedness. This observational difference must be captured by two different CC debt equations. The endogenous variable, $D_i^{H*}$, should define which of the two CC debt equations is relevant for household ‘i’. Therefore, debt consolidation motive brings in simultaneity in consumer’s choice of debt. I need to account for this simultaneity in my econometric model. Moreover, following testable Implication 1, I expect the household to decide to borrow on HELOCs if the desired HELOC debt ($D_i^{H*}$) is greater than the threshold level $\bar{D}_i$. Hence, my econometric model has to incorporate this selection process into the estimation as well. Finally, owing to the cross-sectional nature of my data set, I use the period 0 wealth ($W_{0i}$) and the period 1 wealth level ($W_{1i}$) interchangeably for my estimation purposes.

Let me assume that within my model the between household variation in ‘$p_i$’ is purely random. Let me also assume that ‘$\delta_i$’ is captured by variables such as Age, Income, Household Size, Race and Education Level of the household (jointly represented by vector $S_i$). Hence

$$\delta_i = \varphi_i' S_i + \eta_i.$$ 

Among the HELOC debtors, I have the following equation for $D_i^C$
\[ D_i^C = \gamma D_i^H + \beta_1 X_{1i} + u_{1i} \]  \hspace{1cm} (9)

where \( D_i^H \) is the observed HELOC debt and \( X_{1i} \) is a vector of exogenous variables affecting \( D_i^C \).

Among the HELOC non-debtors, I have yet another equation for \( D_i^C \)

\[ D_i^C = \beta_3 X_{1i} + u_{3i} \]  \hspace{1cm} (10)

Let me define the following vectors:

- \( W_{0i} \): Equity in the Home, Liquid Assets, Non-House-Non-Financial Assets and Family Assets (represented by the size of the household);
- \( X_{1i} \): \( W_{0i}, r_{Ci}, \alpha_i, S_i \) and CC Borrowing Limit
- \( F_i \): Incidence of Mortgage Debt, Debt Repayment Frequency and Mortgage Rate of Interest

The *marginal cost of collateralization of credit*, \( c_i \), is considered to be a function of the individual’s risk-type. I have the dummy defining the incidence of delinquency, the dummies capturing household’s attitude towards risk and \( \alpha_i \) (jointly represented by vector Risk\(_i\)) explaining household’s risk-type.

The dummy variable which determines whether household ‘i’ itemizes tax-deductions or not, and household income (jointly represented by vector \( T_i \)) capture the income-tax rates (\( t_i \)). The *fixed* costs of obtaining HELOCs (\( \tau_i \)) have no variation across households, i.e. I have \( \tau_i = \tau \ \forall \ i \). Therefore, the *fixed* costs go into the constant terms of the HELOC and the reservation debt equations. Moreover, equity in the home (HOMEQUITY), the risk-type (captured by vector Risk\(_i\)) and other household characteristics (\( F_i \)) describe \( r_{Hi} \).

Thus I have
\[ c_i = \alpha_0 + \alpha_1 \text{Risk}_i + \varepsilon_{1i}, \]
\[ t_i = \alpha_2 + \alpha_3 T_i + \varepsilon_{2i} \text{ and} \]
\[ r_{Hi} = \alpha_4 + \alpha_5 \text{HOMEQUITY} + \alpha_6 \text{Risk}_i + \alpha_7 F_i + \varepsilon_{3i}. \]

Substituting for \( c_i, t_i, \tau_i, \delta_i \) and \( r_{Hi} \) into \( D_{iH^*} \); using \( W_{0i}, \alpha_i \) and imposing the assumption of randomness on \( p_i \), I have a reduced form equation for \( D_{iH^*} \)
\[ D_{iH^*} = \beta_2 X_{2i} + u_{2i} \quad (11) \]
where \( X_{2i} \) is a vector of exogenous variables influencing \( D_{iH^*} \).

With similar substitutions and assumption of randomness imposed on \( p_i \), I have yet another reduced form equation for \( D_i \)
\[ D_i = \beta_4 X_{4i} + u_{4i} \quad (12) \]
where \( X_{4i} \) is a vector of all the exogenous variables in my model.

The HELOC debt is observed if \( D_{iH^*} > D_i \). Therefore, let me define the choice function for HELOC debt to be,
\[ I_i^* = D_{iH^*} - D_i = \beta_2 X_{2i} - \beta_4 X_{4i} + u_{2i} - u_{4i} \]
\[ = \delta Z_i - u_i. \quad (13) \]

Therefore, my econometric model is given by
\[
\begin{align*}
D_i^C &= \gamma D_i^H + \beta_1' X_{1i} + u_{3i} \\
D_i^H &= D_i^{H^*} = \beta_2' X_{2i} + u_{2i} \\
D_i^H &= 0 \\
D_i^C &= \beta_3' X_{1i} + u_{3i}
\end{align*}
\]
where \( u_{1i}, u_{2i}, u_{3i} \) and \( u_i \) follow Multivariate Normal with means zero, variances \( \sigma_1^2, \sigma_2^2, \sigma_3^2 \) and 1 and correlation coefficients \( \rho_{12}, \rho_{13}, \rho_{1u}, \rho_{23}, \rho_{2u} \) and \( \rho_{3u} \) respectively. If \( X_{2i} \)
contains at least one variable that is not included in \( X_{1i} \), then all the parameters of the model are identified. Since HELOC is a secured borrowing instrument and it has exclusive features such as tax-deductibility of interest rates, the variables capturing these properties, such as \( c_i \) and \( t_i \), provide the necessary variables for identifying the parameters of my model. In order to correct for the endogeneity present in the CC debt equation of HELOC borrowers, I use the estimated HELOC debt \( \hat{D}_i^H \) as an instrument.

The above econometric model is estimated by *probit two-stage method*. Lee et al. (1980) describe the estimation procedure. In my model, \( I_i^* \) is not observed. All I observe is

\[
I_i = 1 \text{ if household ‘i’ carries HELOC debt (i.e. if } I_i^* > 0) = 0 \text{ otherwise.}
\]

Let me assume that there are \( N_1 \) observations for which \( I_i = 1 \) and \( N_2 \) observations for which \( I_i = 0 \), so that the total sample size is \( N = N_1 + N_2 \). Let me define

\[
\phi_i = \phi(\delta'Z_i) \text{ and } \Phi_i = \Phi(\delta'Z_i),
\]

where \( i = 1, 2, \ldots, N \), \( \phi \) is the standard normal density and \( \Phi \) is the cumulative normal.

Since

\[
E(u_{2i} | I_i = 1) = -\sigma_{2u} \frac{\phi_i}{\Phi_i},
\]

I can write equation (11) as

\[
D_i^H = \beta_2 X_{2i} - \sigma_{2u} \frac{\phi_i}{\Phi_i} + \mu_{2i}
\]

where \( E(\mu_{2i}) = 0 \) and \( \sigma_{2u} = \text{Cov}(u_2, u) \).
I first estimate $\delta$ by probit maximum likelihood (i.e. I get $\hat{\delta}$). Then I estimate

$$D_i^H = \beta_2' X_{2i} - \sigma_{2u} \frac{\hat{\phi}_i}{\Phi_i} + \mu_{2i}$$

by ordinary least squares. Here $\hat{\phi}_i$ and $\hat{\Phi}_i$ are $\phi_i$ and $\Phi_i$ with $\hat{\delta}$ substituted for $\delta$.

I can similarly estimate the reduced form parameters in equation (10). I have

$$D_i^C = \beta_3' X_{3i} + \sigma_{3u} \frac{\hat{\phi}_i}{1-\Phi_i} + \mu_{3i}$$

where $\sigma_{3u} = \text{Cov}(u_3, u)$.

The structural equation corresponding to $I_i = 1$ is given by

$$D_i^C = \gamma D_i^H + \beta_1' X_{1i} + u_{1i}.$$  

Since

$$E(u_{1i} \mid I_i = 1) = -\sigma_{1u} \frac{\phi_i}{\Phi_i},$$

I can write equation (9) as

$$D_i^C = \gamma \hat{D}_i^H + \beta_1' X_{1i} - \sigma_{1u} \frac{\hat{\phi}_i}{\Phi_i} + \mu_{1i}$$

where $E(\mu_{1i}) = 0$ and $\sigma_{1u} = \text{Cov}(u_1, u)$.

I estimate,

$$D_i^C = \gamma \hat{D}_i^H + \beta_1' X_{1i} - \sigma_{1u} \frac{\hat{\phi}_i}{\Phi_i} + \mu_{1i}$$

by ordinary least squares, where $\hat{D}_i^H = \hat{\beta}_2' X_{2i} - \hat{\sigma}_{2u} \frac{\hat{\phi}_i}{\Phi_i}$.
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Table 1.1: Variable List. * Household’s risk-tolerance varied within a 1 to 4 scale.
Since all the second stage estimations use some sort of estimated variables as regressors, the asymptotic covariance matrices of the second stage ordinary least squares estimators require some corrections. See Lee et. al. (1980) for the derivations of the asymptotic covariance matrices of probit two-stage estimators.

1.5 Results and discussion

Table 1.1 presents the definitions of the variables used in the econometric analyses.

Table 1.2 shows the results of a probit equation explaining the decision to hold HELOC debt. The Equity in Home (HOMEQUITY) and the Household Size variable (HOUSEHOLDSIZE) positively influence the choice to hold HELOC debt. However, income of the household (INCOME), household’s liquid asset (LIQUIDASSET) and Non-House-Non-Financial Asset (NHNFINASSET) have a negative impact on the HELOC debt holding decision because such households have less need to resort to borrowing in the face of an uninsured loss. I have some support for Mester’s (1994) hypothesis that relatively low-default-risk borrowers self-select themselves as HELOC debtors. The predicted sign for the parameter corresponding to DELINQUENCY is negative. However, the predicted sign for the parameter corresponding to RISK1 variable is positive and that for RISK3 is negative, which implies that HELOC borrowing becomes less attractive as borrowers become more risk averse. Further, the tax-deductibility incentive plays some role as I find that the predicted sign for ITEMIZE to be positive. The credit card borrowing limit (CREDITLIMIT) has a significant positive influence on the choice of holding HELOC debt. The demographic variables such as
<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-3.808***</td>
<td>0.335</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>0.00001</td>
<td>0.00006</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>-0.0002*</td>
<td>0.0001</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>-0.000003</td>
<td>0.000004</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>0.095***</td>
<td>0.024</td>
</tr>
<tr>
<td>RISK1</td>
<td>0.034</td>
<td>0.068</td>
</tr>
<tr>
<td>RISK3</td>
<td>-0.212**</td>
<td>0.096</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>-0.298</td>
<td>0.269</td>
</tr>
<tr>
<td>INCOME</td>
<td>-0.0001**</td>
<td>0.00007</td>
</tr>
<tr>
<td>ITEMIZE</td>
<td>0.105</td>
<td>0.09</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>-0.01</td>
<td>0.135</td>
</tr>
<tr>
<td>MORTGAGERATE</td>
<td>0.005</td>
<td>0.021</td>
</tr>
<tr>
<td>REPAYMENTFREQ</td>
<td>1.747***</td>
<td>0.102</td>
</tr>
<tr>
<td>MORTGAGE</td>
<td>-2.381***</td>
<td>0.256</td>
</tr>
<tr>
<td>RCI</td>
<td>-0.012*</td>
<td>0.007</td>
</tr>
<tr>
<td>AGE</td>
<td>0.01***</td>
<td>0.003</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>-0.009</td>
<td>0.1</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>0.045***</td>
<td>0.015</td>
</tr>
<tr>
<td>CREDITLIMIT</td>
<td>0.001**</td>
<td>0.0005</td>
</tr>
</tbody>
</table>

Table 1.2: Probit equation explaining the decision to carry HELOC debt.\(^3\)

\(^3\) Refer to page 29 for the definitions of the variables used in the table. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level.
<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS Coefficient</th>
<th>S.E.</th>
<th>Probit Two-Stage Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-86.082</td>
<td>76.312</td>
<td>-63.543</td>
<td>328.751</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>0.046***</td>
<td>0.009</td>
<td>0.046**</td>
<td>0.009</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>0.086*</td>
<td>0.045</td>
<td>0.087*</td>
<td>0.047</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>0.011***</td>
<td>0.001</td>
<td>0.011***</td>
<td>0.001</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>7.045</td>
<td>5.307</td>
<td>6.636</td>
<td>7.777</td>
</tr>
<tr>
<td>RISK1</td>
<td>22.787*</td>
<td>13.78</td>
<td>22.587*</td>
<td>13.737</td>
</tr>
<tr>
<td>RISK3</td>
<td>-8.787</td>
<td>20.439</td>
<td>-8.027</td>
<td>22.669</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>15.854</td>
<td>59.43</td>
<td>17.275</td>
<td>61.378</td>
</tr>
<tr>
<td>INCOME</td>
<td>-0.071***</td>
<td>0.022</td>
<td>-0.07***</td>
<td>0.024</td>
</tr>
<tr>
<td>ITEMIZE</td>
<td>23.923</td>
<td>19.046</td>
<td>23.421</td>
<td>19.902</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>-65.629</td>
<td>86.111</td>
<td>-66.298</td>
<td>84.528</td>
</tr>
<tr>
<td>MORTGAGERATE</td>
<td>4.7</td>
<td>5.152</td>
<td>4.742</td>
<td>5.062</td>
</tr>
<tr>
<td>REPAYMENTFREQ</td>
<td>-10.26</td>
<td>22.144</td>
<td>-17.625</td>
<td>106.849</td>
</tr>
<tr>
<td>MORTGAGE</td>
<td>-68.063</td>
<td>46.131</td>
<td>-60.149</td>
<td>121.098</td>
</tr>
<tr>
<td>AGE</td>
<td>1.175*</td>
<td>0.678</td>
<td>1.132</td>
<td>0.907</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>3.37</td>
<td>21.239</td>
<td>3.44</td>
<td>20.737</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>3.234</td>
<td>3.299</td>
<td>3.051</td>
<td>4.132</td>
</tr>
<tr>
<td>LAMBDA⁺</td>
<td>-5.437</td>
<td>77.245</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

|                      | \( \bar{R}^2 = 0.392 \) | F-value =14.88*** | N = 346 |
|                      | \( \bar{R}^2 = 0.39 \)   | F-value =13.97*** | \( \sigma_2 = 113.18 \) | N = 346 |

Table 1.3: OLS and probit two-stage estimates of HELOC debt, DHI (DHI = 0 for 4811 obs.).

---

4 Refer to page 29 for the definitions of the variables used in the table. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level; + LAMBDA = \( \frac{\hat{\phi}_i}{\Phi_i} \).
AGE and SCHOOL also have significantly positive effect on the decision to borrow on HELOC. Finally, the debt repayment frequency (REPAYMENTFREQ) has a significant positive influence, while the existence of mortgage debt (MORTGAGE) and the credit card interest rate (RCI) have a significant negative influence on HELOC debt-holding decision.

Table 1.3 presents the results for OLS and probit two-stage regressions for HELOC debt. The OLS equation is given only for the sake of comparison; it is not the correct procedure to use. The variables capturing household wealth all have positive impact on the volume of HELOC debt carried by the household. Again, among the set of HELOC debtors the relatively risk-loving ones carry more debt. This is supported by the fact that the predicted sign for RISK1 is positive. Household Income (INCOME) has a negative estimated sign in the HELOC debt equation. The estimated value of $\sigma^2_u$ is 5.437. However, since the estimated value of $\sigma^2_u$ is not significantly different from zero, I conclude that there is no empirical evidence of sample selection in the estimates of the HELOC debt equation.

Table 1.4 presents the 2SLS (for comparison) and the probit two-stage estimates for the CC debt equation for individuals with HELOC debt. The household wealth variables have the usual positive predicted signs. The CC rate of interest has an insignificant, but positive estimated influence on the volume of CC debt. An explanation for this unusual sign is that for credit card debtors with HELOC to borrow on, the debt consolidation motive (captured by the HELOC debt) makes the effect of credit card interest rate on household’s credit card debt irrelevant. Household Income (INCOME) has the usual negative coefficient and among the demographic variable only the race
<table>
<thead>
<tr>
<th>Variables</th>
<th>2SLS</th>
<th>Probit Two-Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>S.E.</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>-0.9</td>
<td>6.012</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>0.003*</td>
<td>0.002</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>0.007*</td>
<td>0.004</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>0.0006*</td>
<td>0.0003</td>
</tr>
<tr>
<td>HOUSEHOLD_SIZE</td>
<td>0.944**</td>
<td>0.462</td>
</tr>
<tr>
<td>RCI</td>
<td>0.062</td>
<td>0.121</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>-7.28</td>
<td>6.749</td>
</tr>
<tr>
<td>INCOME</td>
<td>-0.006**</td>
<td>0.003</td>
</tr>
<tr>
<td>AGE</td>
<td>0.032</td>
<td>0.062</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>2.821*</td>
<td>1.681</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>-0.155</td>
<td>0.263</td>
</tr>
<tr>
<td>CREDITLIMIT</td>
<td>0.084***</td>
<td>0.018</td>
</tr>
<tr>
<td>DHI</td>
<td>-0.054*</td>
<td>0.029</td>
</tr>
<tr>
<td>LAMBDA</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

-LogL = -1256.773  
N = 346

-LogL = -1250.766  
σ₁ = 9.177  
N = 346

Table 1.4: 2SLS and probit two-stage estimates of credit card debt equation for households with HELOC debt.⁵

⁵ Refer to page 29 for the definitions of the variables used in the table. I have, ** - Significant at 1% Level; *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level; + LAMBDA = \( \frac{\hat{\phi}_i}{\Phi_i} \).
<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS</th>
<th></th>
<th>Probit Two-Stage</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>S.E.</td>
<td>Coefficient</td>
<td>S.E.</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>2.777***</td>
<td>0.657</td>
<td>2.757***</td>
<td>0.692</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>-0.0002**</td>
<td>0.0001</td>
<td>-0.0001**</td>
<td>0.0001</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>-0.0001***</td>
<td>0.00006</td>
<td>-0.0001*</td>
<td>0.00006</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>-0.000004</td>
<td>0.000004</td>
<td>-0.000003</td>
<td>0.000004</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>0.208***</td>
<td>0.061</td>
<td>0.103</td>
<td>0.066</td>
</tr>
<tr>
<td>RCI</td>
<td>-0.024</td>
<td>0.017</td>
<td>-0.009</td>
<td>0.018</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>-0.121</td>
<td>0.361</td>
<td>-0.188</td>
<td>0.379</td>
</tr>
<tr>
<td>INCOME</td>
<td>-0.00001</td>
<td>0.00002</td>
<td>-0.000006</td>
<td>0.00002</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.03***</td>
<td>0.006</td>
<td>-0.025***</td>
<td>0.006</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>0.272</td>
<td>0.251</td>
<td>0.264</td>
<td>0.263</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>0.014</td>
<td>0.03</td>
<td>0.035</td>
<td>0.033</td>
</tr>
<tr>
<td>CREDITLIMIT</td>
<td>0.0009**</td>
<td>0.0003</td>
<td>0.0007*</td>
<td>0.0004</td>
</tr>
<tr>
<td>LAMBDA+</td>
<td></td>
<td></td>
<td>-4.88***</td>
<td>0.78</td>
</tr>
</tbody>
</table>

\[
\bar{R}^2 = 0.02
\]
\[
\text{F-value} = 9.86***
\]
\[
\text{N} = 4811
\]

\[
\bar{R}^2 = 0.027
\]
\[
\text{F-value} = 12.2***
\]
\[
\sigma_3 = 5.456
\]
\[
\text{N} = 4811
\]

Table 1.5: 2SLS and probit two-stage estimates of credit card debt equation for households with no HELOC debt.\(^6\)

---

\(^6\) Refer to page 29 for the definitions of the variables used in the table. I have, \(***\) - Significant at 1% Level; \\
\(**\) - Significant at 5% Level; \(*\) - Significant at 10% Level; \(\dagger\) LAMBDA = \(\frac{\hat{\phi}_i}{1 - \Phi_i}\).
variable (represented by NONWHITE) has a significant positive impact on household CC debt. The CC borrowing limit (CREDITLIMIT) has a positive effect on CC borrowing. Further, the volume of HELOC debt has a significantly negative influence on the CC borrowing of the household. Finally, the estimated value of $\sigma_{1u}$ is -0.086, which however is not significantly different from zero. Therefore, from my empirical results I can conclude that there is evidence of simultaneity and no evidence of sample selection in the estimates of the CC debt equations for borrowers carrying HELOC debt.

Table 1.5 presents the OLS (for comparison) and the probit two-stage estimates of the CC debt equation for individuals with no HELOC debt. The results indicate that the monetary wealth variables have negative effects on the CC debt carried by households with no HELOC debt. The CC rate of interest rate (RCI) has the expected negative coefficient. Among the demographic variables, only AGE has a significant negative estimated coefficient. The CC borrowing limit (CREDITLIMIT) has a significant positive effect on CC borrowing. Finally, the estimated value of $\sigma_{3u}$ is -4.88, which is also statistically significant, implying that HELOC non-debtors have lower average CC borrowings. Hence, my results indicate that there is evidence of sample selection in the estimates of the CC debt equations for those with no HELOC debt.

Using the probit and probit two-stage estimates for HELOC debt, we can derive a consistent estimate of the threshold or reservation debt level for each household beyond which it would be observed to carry HELOC debt. Thus for example, for a household with median household characteristics, which would give us a household with $81,000 of annual income, the threshold level of debt which would induce it to turn to HELOC
borrowing would be $64,000. We find, *ceteris paribus*, that HELOC borrowing becomes more attractive as income increases.

### 1.6 Summary

This chapter of my thesis has addressed consumer’s choice of incurring debt in the presence of CCs and HELOCs. Using a framework of risk management, I show that consumers borrow on lines of credit in order to hedge against optimally uninsured risks and the choice between the two principal lines of credit facing consumers, namely CCs and HELOCs, is guided by the amount of borrowing that the consumers wish to make on their lines of credit. My framework explains the observed lack of usage among lines of credit holders. I find that for very small borrowing needs CCs are exclusively used by consumers, for relatively large borrowing demands they use only HELOCs, and for extremely large desired debts they prefer to use both the lines of credit. The reservation debt levels that guide the switch from CCs to HELOCs are determined by the fixed costs of holding HELOCs, consumers’ preferences, and wealth-income-risk profiles. For consumers already possessing both CCs and HELOCs and with relatively small borrowing needs, transferring balances away from CCs and into HELOCs is never going to make them worse off. However, the costs associated with HELOCs will prevent consumers from taking out HELOCs for very small borrowing demands. Moreover, the risk of losing the home, represented by the *cost of collateralization*, will make debt consolidation into HELOCs utility reducing for very large amounts of desired debt. Therefore, in my effort to explain the choice between CCs and HELOCs, I address the issue of *debt consolidation* in the lines of credit market. By modeling the costs of
HELOCs (other than the interest costs) along with the benefits, I not only analyze the decision to hold debt on HELOCs, but also investigate the factors preventing the transfer of balances away from CCs and into HELOCs. As a result, my research gives a rational explanation for the apparently puzzling phenomenon of consumers carrying debt on HELOCs as well as CCs.

Using the *Survey of Consumer Finances* (1996 and 1998), I estimate the coefficients of the variables influencing CC debt, HELOC debt and the reservation level of HELOC debt. My estimation takes account of the endogeneity that is introduced as a result of consumers’ *debt consolidation* motives. I find that the endogenous variable, HELOC debt, has a significant negative influence on the amount of CC debt carried by households.

The results of this chapter help me better understand the choice of borrowing on consumer lines of credit. Consumers’ wealth-income profiles dictate the nature of the risks they face and different lines of credit available to them help them finance these risks of varying magnitude. The motive to *consolidate debt* brings in simultaneity in consumer’s choice of borrowing on various lines of credit, which I have incorporated both theoretically and econometrically.

The *fixed* costs and the *costs of collateralization* associated with HELOCs are the major impediments to their use by consumers. A policy implication for banks marketing HELOCs as an alternative to CCs can be the waiver of some of the *fixed* costs that, according to this chapter, positively influence borrowers’ reservation debt of taking out HELOCs. Further, the *costs of collateralization* adversely influence the transfer of balances away from CCs and into HELOCs. Banks can formulate the HELOC loan
contracts in a manner that debt renegotiation and the possibility of refinancing outstanding debt are kept as options for defaulting borrowers. These loan arrangements will reduce the likelihood of losing the home in case of default, hence are likely to reduce borrowers’ perceived *costs of collateralization* and thereby making HELOCs more attractive.
Table 1.6: Patterns of indebtedness on HELOCs and credit cards.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Debt on HELOC</th>
<th>No Debt on HELOC</th>
<th>Total Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Debt on CC</td>
<td>172</td>
<td>1657</td>
<td>1829</td>
</tr>
<tr>
<td>No Debt on CC</td>
<td>174</td>
<td>3154</td>
<td>3328</td>
</tr>
<tr>
<td>Total Observation</td>
<td>346</td>
<td>4811</td>
<td>5157</td>
</tr>
</tbody>
</table>

Table 1.7: Means and standard deviations of credit card and HELOC debts.7

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCI</td>
<td>4.6</td>
<td>8.3</td>
</tr>
<tr>
<td>DHI</td>
<td>46.1</td>
<td>148.7</td>
</tr>
</tbody>
</table>

7 Refer to page 29 for the definitions of the variables used in the table. All monetary variables are in thousand dollars.
<table>
<thead>
<tr>
<th>Utilization Rate in CC less than 1</th>
<th>342</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utilization Rate in CC equal to 1</td>
<td>2</td>
</tr>
<tr>
<td>Utilization Rate in CC greater than 1</td>
<td>2</td>
</tr>
<tr>
<td>Total Number of Observations</td>
<td>346</td>
</tr>
</tbody>
</table>

Table 1.8: Utilization rates in credit cards for HELOC debtors.\(^8\)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCI</td>
<td>14.6</td>
<td>4.3</td>
</tr>
<tr>
<td>RHI</td>
<td>9.5</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Table 1.9: Means and standard deviations of credit card and HELOC interest rates.\(^9\)

\(^8\) Utilization Rate for Credit Cards = Credit Card Debt/Credit Limit.

\(^9\) Refer to page 29 for the definitions of the variables used in the table.
<table>
<thead>
<tr>
<th>Variables</th>
<th>CC Debtors</th>
<th>HELOC Debtors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Mean</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>111.9</td>
<td>276.4</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>21.7</td>
<td>50.3</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>695.0</td>
<td>1566.7</td>
</tr>
<tr>
<td>INCOME</td>
<td>99.7</td>
<td>208.7</td>
</tr>
<tr>
<td>ITEMIZE</td>
<td>0.7</td>
<td>0.9</td>
</tr>
<tr>
<td>RCI</td>
<td>13.9</td>
<td>14.1</td>
</tr>
<tr>
<td>CREDITLIMIT</td>
<td>19.7</td>
<td>30.1</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>3.0</td>
<td>3.1</td>
</tr>
<tr>
<td>MORTGAGERATE</td>
<td>6.9</td>
<td>6.4</td>
</tr>
<tr>
<td>MORTGAGE</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>AGE</td>
<td>47.1</td>
<td>51.1</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>13.8</td>
<td>15.0</td>
</tr>
<tr>
<td>REPAYMENTFREQ</td>
<td>1.6</td>
<td>2.0</td>
</tr>
<tr>
<td>RISK1</td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td>RISK3</td>
<td>0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>0.2</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Table 1.10: Means of variables for credit card and HELOC debtors.\(^{10}\)

\(^{10}\)Refer to page 29 for the definitions of the variables used in the table. All monetary variables are in thousand dollars.
<table>
<thead>
<tr>
<th>Variables</th>
<th>HELOC Debtors</th>
<th>HELOC Non-Debtors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Mean</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>276.4</td>
<td>372.7</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>50.3</td>
<td>244.6</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>1566.7</td>
<td>4951.6</td>
</tr>
<tr>
<td>INCOME</td>
<td>208.7</td>
<td>632.7</td>
</tr>
<tr>
<td>ITEMIZE</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>3.1</td>
<td>2.7</td>
</tr>
<tr>
<td>MORTGAGE</td>
<td>0.8</td>
<td>0.6</td>
</tr>
<tr>
<td>MORTGAGERATE</td>
<td>6.4</td>
<td>4.9</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>AGE</td>
<td>51.1</td>
<td>53.6</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>15.0</td>
<td>14.5</td>
</tr>
<tr>
<td>REPAYMENTFREQ</td>
<td>2.0</td>
<td>1.2</td>
</tr>
<tr>
<td>RISK1</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>RISK3</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Table 1.11: Means of variables for HELOC debtors and HELOC non-debtors.\(^\text{11}\)

\(^{11}\) Refer to page 29 for the definitions of the variables used in the table. All monetary variables are in thousand dollars.
CHAPTER 2

COLLATERAL AND SORTING: AN EMPIRICAL INVESTIGATION INTO THE MARKET FOR HOME EQUITY LINES OF CREDIT

2.1 Introduction

Collateral has played an important role in majority of the commercial loan contracts offered by the banks. With the advent of Home Equity Loans (HELs) and Home Equity Lines of Credit (HELOCs), secured lending is gaining prevalence in the consumer credit market as well. Several theoretical studies in commercial loans have tried to analyze the relationship between collateral and credit risk. The dispersion of interest rates in the secured credit market primarily depends on the role that collateral plays in sorting borrowers according to their riskiness. The theoretical studies have predicted different roles of collateral in the different sorting equilibria of the secured credit market. This chapter of my thesis empirically investigates the validity of the various hypotheses regarding the role of collateral within the market for collateralized HELOCs. I try to understand the nature of the spread of HELOC interest rates and the role of collateral in explaining such a spread.

Some issues concerning the use of collateral have been explored in the literature of the credit market. Barro (1976) focused on the loan rate when collateral is stochastic;
however, he did not provide an explanation for the existence of collateral. Scott (1977) showed that bankruptcy costs are reduced with the use of secured credit, therefore increasing the value of the firm. Smith and Warner (1979), criticizing Scott (1977), offer the moral hazard element as the explanation for the use of collateral. They argue that secured debt prevents the borrower from “asset-substitution” or perhaps from “consuming” the project to be financed, an issue initially raised by Jensen and Meckling (1976). The empirical implications of Smith and Warner for collateral-risk relationship depend on how asset-substitution-related monitoring costs are related to risk. Stulz and Johnson (1985) investigate the properties of secured and unsecured debt with the help of contingent-claims approach. They also analyze the role that secured debt plays in solving Myers’ (1977) underinvestment problem. Low-risk firms are unlikely to issue secured debt because they are unlikely to have an underinvestment problem. However, firms with potential underinvestment problem may issue secured debt under certain conditions. For this latter group, Stulz and Johnson show that the lower the variance of the return on the collateral asset relative to the variance of the return of the noncollateral asset, the more likely that collateral can solve the underinvestment problem. However, the testable implications of the Stulz and Johnson model are ambiguous with respect to the average riskiness of secured borrowers relative to unsecured borrowers. An alternative explanation for the secured lending arrangement where the borrower recognizes the expected loss of the collateral in negotiating credit contracts is the sorting role of the collateral in asymmetrically informed environments.

Conventional wisdom in the banking community associates the use of collateral with observably riskier borrowers. In the case of seasonal loan facilities, Morsman (1986,
p. 5) notes that banks are “normally secured by a perfected security interest in accounts receivable, inventory, and equipment. [However,] exceptions can occur with well-capitalized companies with no other types of debt and a history of seasonal payout.” Therefore, observably risky borrowers are required to pledge collateral, while observably safe borrowers are not. This is referred to as the sorting-by-observed-risk paradigm.

There is some theoretical support for this positive association between borrower risk and collateral. Boot, Thakor, and Udell (1991) consider a model where borrower’s risk type is observable to the lender, while borrower’s action is privately known. The authors obtain sufficient conditions under which observably riskier borrowers pledge more collateral in equilibrium. Swary and Udell (1988) provide another motivation for the use of collateral. They suggest that secured debt may be useful in enforcing optimal firm closure (or bankruptcy). The magnitude of the closure problem in their model is positively associated with firm risk. Hence, observably riskier borrowers are likely to pledge more collateral, consistent with the sorting-by-observed-risk paradigm.

Much of the theoretical literature however, focuses on information about risk known only to borrowers. A paradigm known as the sorting-by-private-information paradigm has emerged as a result of this theoretical research. Besanko and Thakor (1987a) consider a model where the lenders are at an informational disadvantage with respect to borrower default probabilities. They find that in equilibrium, low-risk borrowers pledge more collateral than their high-risk counterparts. Besanko and Thakor (1987b) find a similar negative relationship between collateral and borrower risk under loan contracting with multi-dimensional pricing menu, including loan quantity, interest rate, collateral, and potential rationing. Chan and Kanatas (1985) and Bester (1985) find
that low-risk borrowers pledge more collateral than high-risk borrowers because collateral-associated costs produce different marginal rates of substitution between collateral and interest rate. Bester incorporates collateral as screening mechanism in the Stiglitz and Weiss (1981) credit rationing model and shows that rationing now becomes unnecessary. Similarly, Chan and Kanatas (1985) show that collateral is useful when the credit applicant’s default risk is privately known or when the applicant and the lender have different beliefs concerning the applicant’s project. However, given insufficient collateral, they find that rationing has a useful sorting role. Chan and Thakor (1987) assume the existence of both adverse selection and moral hazard and examine the form of the optimal secured loan contract. Finally, Igawa and Kanatas (1990) examine the use of collateral under asymmetric information and moral hazard. In their model, the moral hazard element originates from the use of collateral while, in Chan and Thakor (1987), it is assumed that moral hazard exists independent of the collateral. Igawa and Kanatas (1990) show that the optimal secured loan contract for higher quality borrowers involves overcollateralization. There is underinvestment relative to first best in maintenance of the pledged assets but overinvestment relative to the level that would be chosen without bank monitoring. Self-financing and unsecured credit are chosen by the intermediate and lowest quality borrowers, respectively.

There have been some empirical studies regarding collateral and credit risk in the market for commercial loans. Orgler (1970) complied a data set on individual loans from bank examination files and distinguished ‘good’ from ‘bad’ loans on the basis of ‘criticisms’ of bank examiners. He regressed a good-bad dummy variable on a secured-unsecured dummy variable and several control variables and found secured loans to be
riskier. Hence, Orgler found that riskier borrowers pledge more collateral. Hester (1979) used the data set from a 1972 survey that included loan contract terms and limited information on the borrowers. He regressed a secured-unsecured dummy variable on variables measuring risk and on numerous control variables. His results were consistent with the hypothesis that riskier borrowers pledge more collateral. Berger and Udell (1990) used Federal Reserve’s Survey of Terms of Bank Lending and obtained empirical evidence for collateral having a positive association with the risk-type of the borrowers. The empirically verified positive association between risk and collateral in corporate loans could be because banks have effective monitoring mechanisms and therefore a near perfect knowledge of the risk-types of their corporate clients.

Studies involving collateralized consumer loans have largely focused on mortgage and auto-loan markets. Recent research on secured consumer credit has expanded to include HELs and HELOCs. Firms and consumers are fundamentally separate economic entities, differing in their needs and purposes for loans. Theoretical and empirical literature on consumer credit, in general, and on secured consumer credit, in particular, has therefore become quite distinct and rich. Most empirical studies on secured consumer credit, especially within banks, have used the Loan to Value (LTV) ratio as a major explanatory variable in the assessment of the risk assumed by the banks and hence in the determination of the rate of interest. LTV (as opposed to the value of the collateral alone) should logically explain a significant portion of the risk (or interest rate) spread of secured credit (both consumer and corporate) because for a given value of the collateral and a given risk-type of the borrower, the higher is the loan extended, relatively lower is the value recovered by the bank in the case of default and hence the higher should be the
interest rate (or price of the loan) charged. However, using LTV to explain the interest
dispersion of collateralized lines of credit, such as HELOCs, is fundamentally flawed.
For any traditional loan, the amount of loan extended by a bank is automatically assumed
to be borrowed by the borrower. Hence for traditional loans, banks assume the risk of the
entire loan amount provided to the borrower. That is, however, not the case for lines of
credit. A line of credit is a borrowing instrument where the borrower can borrow up to
the credit limit (or borrowing limit). The banks do not assume any risk unless the
borrower, irrespective of his/her risk-type, borrows on the line. Therefore the Borrowing
to Value ratio (BTV), instead of LTV, is the relevant measure of the risk assumed by the
banks in the case of lines of credit. However, the actual borrowing is typically not
observed by the banks during the determination of their risk exposure (or the interest
rate). The banks have the information on only the value of the collateral (the equity in the
home) pledged by the borrowers while they set the loan terms. However, when the
amount of loan extended is not informative of the risk exposure, the estimated borrowing
and the value of the collateral pledged by the borrowers become the crucial variables on
which the banks base their loan decisions. The value of the collateral and the estimated
borrowing, instead of LTV, are therefore more likely to play a significant role in
explaining the risk spread and the loan price dispersion of collateralized lines of credit,
such as HELOCs.

Here I empirically investigate into the nature of association prevalent between the
value of the collateral and credit risk within the market for HELOCs. The econometric
model that I propose tries to estimate the actual borrowing of a household, so crucial in
understanding the risk exposure, with the HELOC rate of interest as an endogenous
variable. The HELOC rate of interest is further proposed to be determined by the amount of the collateral pledged by the borrower, the borrower’s credit history and by the characteristics of agreed secured loan contracts, such as, the required frequency and the rate of repayment. I examine the nature of the information asymmetry that is present between borrowers and lenders of HELOCs and explain how the value of the collateral helps to mitigate this information asymmetry. As a result, I explain the dispersion of HELOC interest rates and the role that collateral plays in explaining such dispersion. My empirical work supports a negative association between the value of the collateral pledged by the borrowers and the HELOC rates of interest charged by the banks, as opposed to a positive association supported by the empirical literature on commercial loans.

2.2 Data

The data used in this study is a pooled sample of 1995 and 1998 U.S. Surveys of Consumer Finances (SCF). SCF is a nationwide survey conducted by National Opinion Research Center (NORC) on behalf of the Board of Governors of the Federal Reserve System of United States. In order to adjust the asset and liability variables to the 1998 dollars, a factor of 1.0622 was applied to the figures for 1995. To adjust the family income variables of 1995 I applied a factor of 1.0904. These are widely used factors devised to compare SCF figures of 1995 and 1998.

Since I want to model the decision to borrow on HELOCs and understand the spread of HELOC interest rates, I select a sample of 5,995 households who have positive equity in their homes. There are two types of sample members:
I. \( D^H = r_H = 0 \), where \( D^H \) and \( r_H \) are the observed HELOC debt and interest rate respectively.

II. \( D^H > 0 \) and \( r_H > 0 \).

Table 2.6 compares the average consumer profiles of HELOC debtors and HELOC non-debtors.

### 2.3 The econometric model

Using the model for HELOC debt holding described in the first chapter of this thesis, I have the consumer’s discounted expected lifetime utility from carrying \( D_0^{**} \) amount of HELOC debt in period 0 to be,

\[
V^{H**} = V_0^{H**} + \delta V_1^{H**}
\]

where

\[
V_0^{H**} = (1 - p) U(W_0 - pq^{**} - \tau) + p U(W_0 - pq^{**} - \tau - \frac{\alpha}{(1-\alpha)}D_0^{**} - cD_0^{**})
\]

\[
V_1^{H**} = (1 - p) U(W_1 - \tau) + p U(W_1 - \tau - (1 + r_H(1-t))D_0^{**})
\]

Hence I have the desired HELOC debt to be, \( D_0^{**} = H (\tau, c, t, r_H, W_0, W_1, \alpha, p, \delta) \), and the optimal unconditional HELOC debt as, \( D_0^{*} = h (\tau, c, t, r_H, W_0, W_1, \alpha, p, \delta) \). For household \( ‘i’ \), I have, \( D_i^{H*} = h (\tau_i, c_i, t_i, r_{Hi}, W_{0i}, W_{1i}, \alpha_i, p_i, \delta_i) \).

The dummy variable which determines whether household \( ‘i’ \) itemizes tax-deductions or not, and household income (jointly represented by vector \( T_i \)) capture the income-tax rates \( (t_i) \). The fixed costs of obtaining HELOCs \( (\tau_i) \) have no variation across
households, i.e. I have $\tau_i = \tau \forall i$. Therefore, the fixed costs go into the constant term of the HELOC debt equation. Moreover, I use the period 0 wealth ($W_{0i}$) and the period 1 wealth level ($W_{1i}$) interchangeably for my estimation purposes. Let me again refer to the following vectors:

- $W_{0i}$: Equity in the Home, Liquid Assets, Non-House-Non-Financial Assets and Family Assets (represented by the size of the household);
- $F_i$: Incidence of Mortgage Debt, Debt Repayment Frequency and Mortgage Rate of Interest

The marginal cost of collateralization of credit, $c_i$, is again considered to be a function of the individual’s risk-type. I have the dummy defining the incidence of delinquency, the dummies capturing household’s attitude towards risk and $\alpha_i$ (jointly represented by Risk$_i$), capturing household’s risk. Let me again assume that the discount factor, $\delta_i$, is captured by variables such as Age, Income, Household Size, Race and Education Level of the household (jointly represented by vector $S_i$). Hence I have

$$c_i = \alpha_0 + \alpha_1^i \text{Risk}_i + \varepsilon_{1i}$$
$$t_i = \alpha_2 + \alpha_3^i T_i + \varepsilon_{2i}$$
$$\delta_i = \varphi_i S_i + \eta_i$$

Substituting for $c_i$, $t_i$, $\delta_i$ and $\tau_i$ into $D_i^{H*}$; using $W_{0i}$, $\alpha_i$ and imposing the assumption of randomness on the probability of “loss”, $p_i$, I have a structural form equation for $D_i^{H*}$

$$D_i^{H*} = \gamma r_{Hi} + \beta_1^i X_{1i} + \nu_{1i}$$

where $X_{1i}$ is a vector of exogenous variables influencing $D_i^{H*}$.
Assuming that Equity in the home (HOMEQUITY), Risk, and F influence \( r_{Hi} \), I have a reduced form equation for \( r_{Hi} \):

\[
\begin{align*}
r_{Hi} &= \beta^2 X_{2i} + v_{2i} \\
&= \beta^2 X_{2i} + v_{2i} \\
&= \beta^2 X_{2i} + v_{2i} \\
&= \beta^2 X_{2i} + v_{2i} \tag{15}
\end{align*}
\]

where \( X_{2i} \) is a vector of exogenous variables that includes the amount of collateral pledged by household ‘i’ (i.e. the equity in his/her home) as a variable. I consider the following econometric model:

\[
\begin{align*}
D^H_i &= D^H* = \gamma r_{Hi} + \beta^* X_{2i} + v_{1i} \\
r_{Hi} &= \beta^2 X_{2i} + v_{2i} \\
r_{Hi} &= \beta^2 X_{2i} + v_{2i} \\
D^H_i &= 0 \\
&= 0 \\
&= 0 \\
&= 0 \\
&= 0 \\
&= 0 \\
&= 0 \\
&= 0 \\
&= 0 \tag{ii}
\end{align*}
\]

where \( v_{1i} \) and \( v_{2i} \) follow Bivariate Normal with means zero, variances \( \sigma^2_1 \) and \( \sigma^2_2 \) respectively and with covariance \( \sigma_{12} \). If \( X_{2i} \) contains at least one variable that is not included in \( X_{1i} \), then all the parameters of the model are identified. The vector \( F_i \) contains information about the incidence of mortgage debt among households, mortgage rates of interest they face and their debt repayment frequency. Banks often market HELOCs as a “cash-out” option when households decide to refinance their existing mortgage debt. The HELOC rate of interest, therefore, often depends on household’s refinancing decision, which in turn is influenced by the interest rate charged on the existing mortgage debt. However, a household can take out a HELOC even without refinancing his/her mortgage debt. Therefore, the decision to take out a HELOC and the amount of borrowing actually made on it should be independent of household’s refinancing decision. Hence, I can logically include at least one variable in vector \( X_{2i} \), namely the mortgage interest rate, which is not included in vector \( X_{1i} \). In order to correct for the endogeneity present in the
HELOC debt equation, the two-stage estimation procedures in the literature use the estimated HELOC rate of interest, \( \hat{r}_{HELOC} \), as an instrument.

Maximum Likelihood Estimation Procedure is used to estimate the proposed econometric model. To form the likelihood function I have to relate the dependent variables to their empirical counterparts, and describe the process by which the observable counterparts are generated in terms of the underlying stochastic components.

A consumer is observed to carry debt on HELOC if

\[ D_{i}^{HELOC} > 0. \]

Substituting the HELOC interest rate equation into the HELOC debt function, the HELOC debt-holding decision can be written as

\[ \beta_{1}'X_{1i} + \gamma\beta_{2}'X_{2i} > - (v_{1i} + \gamma v_{2i}) \]

or,

\[ I_{i} > v_{i} \]

where, \( v_{i} \sim N \left( 0, \sigma_{v1}^{2} + \gamma^{2}\sigma_{v2}^{2} + 2\gamma\sigma_{12} \right) \equiv N \left( 0, \sigma_{v}^{2} \right) \)

\[ I_{i} = \beta_{1}'X_{1i} + \gamma\beta_{2}'X_{2i}. \]

The likelihood of observing a HELOC non-debtor is

\[ \Pr ob(I_{i} < v_{i}) = \int_{-\infty}^{\frac{I_{i}}{\sigma_{v}}} \frac{1}{\sqrt{2\pi}\sigma_{v}} e^{-\frac{\sigma_{v}^{2}}{2}} d\sigma = 1 - \Phi\left( \frac{I_{i}}{\sigma_{v}} \right) = \Phi\left( -\frac{I_{i}}{\sigma_{v}} \right) \]

where \( \Phi \) is the standard normal cumulative density function.

Hence the likelihood of the data consisting (say) of \( N \) households and of \( M \) HELOC non-debtors is
\[ L = \prod_{i=1}^{M} \Phi\left( \frac{-I_{i}}{\sigma_v} \right) \prod_{i=M+1}^{N} b(v_{1i}, v_{2i}) = \prod_{i=1}^{M} \Phi\left( \frac{-I_{i}}{\sigma_v} \right) \prod_{i=M+1}^{N} n(v_{2i}) n(v_{1i}|v_{2i}) \]

where \( b(.) \) is the Bivariate Normal density function, \( n(.) \) is the Normal density function and

\[
D_i^H = \text{Observed HELOC debt}
\]

\[
v_{1i} = D_i^H - \beta_1 X_{1i} - \gamma r_{Hi}
\]

\[
v_{2i} = r_{Hi} - \beta_2 X_{2i}.
\]

Now, \( v_{2i} \sim N(0, \sigma_2^2) \)

\[
v_{1i}|v_{2i} \sim N\left( \frac{\rho \sigma_1 v_{2i}}{\sigma_2}, \sigma_1^2 (1-\rho^2) \right), \text{ where } \rho = \frac{\sigma_{12}}{\sigma_1 \sigma_2}.
\]

Let, \( \sigma_c^2 = \sigma_1^2 (1-\rho^2) \) and

\[
T_i = \frac{v_{1i}}{\sigma_2} \frac{\sigma_c}{\rho \sigma_1 v_{2i}}.
\]

The corresponding log-likelihood function can be written as

\[
\log L = \sum_{i=1}^{M} \log[\Phi\left( \frac{-I_{i}}{\sigma_v} \right)] + \sum_{i=M+1}^{N} \frac{\phi\left( \frac{v_{2i}}{\sigma_2} \right)}{\sigma_2} + \sum_{i=M+1}^{N} \frac{\phi(T_i)}{\sigma_c} \]

where \( \phi(.) \) is the Standard Normal density function.

A multi-step procedure was used to estimate the parameters of the model. First, the parameters of the econometric model were estimated by \textit{probit two-stage method} as described by Lee et al. (1980). This two-step procedure yielded consistent estimates of all the parameters of the model. In order to obtain asymptotically efficient parameter
estimates, these consistent estimates were used as initial values for the final maximization of the log-likelihood function.

Let \( \delta_i = -\frac{I_i}{\sigma_v} \) & \( \lambda(\delta_i) = \frac{\phi(\delta_i)}{1 - \Phi(\delta_i)} \). Let me further define a dummy variable, \( D_i \), such that,

\[
D_i = 1 \text{ if household } 'i' \text{ carries HELOC debt (i.e. if } D_i^{H*} > 0) \\
= 0 \text{ otherwise.}
\]

For HELOC debtors,

\[
D_i^H = y_{Hi} + \beta'_1 X_{1i} + \sigma_v \lambda(\delta_i) + v_{3i}
\]

\[
r_{Hi} = \beta'_2 X_{2i} + \mu \lambda(\delta_i) + v_{4i}
\]

where \( \mu = \frac{\gamma \sigma_2^2 + \sigma_{12}}{\sigma_v} \).

Consistent estimates of \( \delta_i \) can be obtained by running a probit of the decision to carry HELOC debt. Then I can estimate the following equation by OLS:

\[
r_{Hi} = \beta'_2 X_{2i} + \mu \lambda(\hat{\delta_i}) + v_{4i}.
\]

I then obtain \( \hat{r}_{Hi} \) from the previous OLS regression and estimate the following equation by OLS:

\[
D_i^H = y_{Hi}^{*} + \beta'_1 X_{1i} + \sigma_v \lambda(\hat{\delta_i}) + v_{3i}.
\]

This two-step procedure will give me consistent estimates of all the parameters of the model, which are then used as starting values for the maximum likelihood procedure.
Table 2.1: Full information maximum likelihood estimates of HELOC rates of interest. \footnote{Refer to page 29 for the definitions of the variables used in the above tables. I have, *** - Significant at 1\% Level; ** - Significant at 5\% Level; * - Significant at 10\% Level.}

\begin{table}[h]
\centering
\begin{tabular}{lcc}
\hline
Variables & Maximum Likelihood & \\
& Coefficient & S.E. & \\
\hline
CONSTANT & 3.486*** & 0.718 & \\
HOMEQUITY & -0.0003** & 0.0001 & \\
RISK1 & -0.014 & 0.316 & \\
RISK3 & -0.537 & 0.532 & \\
DELINQUENCY & 0.505 & 1.581 & \\
ALPHAI & 3.788 & 2.852 & \\
MORTGAGE & -3.271*** & 0.885 & \\
MORTGAGERATE & 0.46*** & 0.084 & \\
REPAYMENTFREQ & 2.672*** & 0.329 & \\
\hline
\end{tabular}
\end{table}

2.4 Results and discussion

Table 2.1 presents the results for the Maximum Likelihood estimation for HELOC rates of interest. The value of the collateral (HOMEQUITY) has a significant negative influence on the HELOC rate of interest charged by the banks. Therefore, my Maximum Likelihood estimation provides an empirical support for the sorting-by-private-information paradigm. The borrowers who put in higher amounts of collateral signal their superior risk-types and therefore are rewarded with lower interest rates by the banks. Among the HELOC debtors, those who carry mortgage debt (MORTGAGE = 1) get lower HELOC interest rates from banks. The mortgage rate of interest (MORTGAGERATE) and the HELOC rate of interest (RHI) have a direct estimated
<table>
<thead>
<tr>
<th>Variables</th>
<th>Maximum Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>-52.916</td>
</tr>
<tr>
<td>HOMEQUITY</td>
<td>0.028***</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>0.003</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>-0.003***</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>4.722*</td>
</tr>
<tr>
<td>RISK1</td>
<td>19.988***</td>
</tr>
<tr>
<td>RISK3</td>
<td>-5.592</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>8.033</td>
</tr>
<tr>
<td>INCOME</td>
<td>-0.02***</td>
</tr>
<tr>
<td>ITEMIZE</td>
<td>16.013*</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>-37.318</td>
</tr>
<tr>
<td>AGE</td>
<td>-1.93***</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>0.868</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>3.611</td>
</tr>
<tr>
<td>RHI</td>
<td>-3.2*</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>112.404***</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>2.476****</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.182***</td>
</tr>
</tbody>
</table>

-Log-L = -3751.253

Table 2.2: Full information maximum likelihood estimates of HELOC debt.\(^{13}\)

---

\(^{13}\) Refer to page 29 for the definitions of the variables used in the above tables. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level.
relationship. Finally, I have empirical evidence of a positive association between the variable capturing repayment frequency (REPAYMENTFREQ) and the HELOC rate of interest.

Lastly, I have Table 2.2 presenting the results for the Maximum Likelihood estimation for HELOC debt. All the variables capturing household wealth, except NHNFINASSET, have estimated positive impact on the volume of HELOC debt carried by the household. The predicted signs for RISK1 and ITEMIZE are positive and significant. Household Income (INCOME) has a negative predicted sign. The demographic variable, AGE, has a negative predicted effect on HELOC borrowing. The HELOC rate of interest rate has a significant negative coefficient in explaining the HELOC debt carried by households. The Maximum Likelihood estimates of the error variances ($\sigma_1$ and $\sigma_2$) are both significant. Finally, I have the estimate for $\rho = \frac{\sigma_{12}}{\sigma_1\sigma_2}$ to be positive and significant.

2.5 Summary

This chapter has addressed the issue of use of collateral in the market for HELOCs. I explored the role that collateral plays in sorting borrowers according to their risk-types and thereby explaining the observed spread of HELOC rates of interest. There is a rich theoretical and empirical literature on the issues involving secured corporate lending. The bulk of the literature dealt with the aspect of asymmetric information prevailing between borrowers and lenders. Researchers investigated the role collateral plays in mitigating this asymmetric information. Two distinct paradigms have emerged out of the theoretical literature on secured corporate lending - the sorting-by-observed-
risk paradigm and the sorting-by-private-information paradigm. In this chapter I empirically tested which paradigm holds for the market for HELOCs.

The existing empirical literature exploring the issue of collateral was also primarily focused on commercial loans. Moreover, the empirical papers on commercial loans find evidence for the hypothesis that riskier borrowers are seen to pledge more collateral, consistent with conventional banking wisdom and the sorting-by-observed-risk paradigm. The empirically verified positive association between risk and collateral in corporate loans could be because banks have effective monitoring mechanisms and therefore a near perfect knowledge of the risk-types of their corporate clients. Using the Survey of Consumer Finances (1996 and 1998), I estimate the choice of borrowing on collateralized HELOCs together with the coefficients of the variables influencing HELOC debt and HELOC rates of interest. My estimation takes account of the endogeneity and untangles the relationship existing between the HELOC rates of interest and the HELOC debt. I find that the endogenous variable, the HELOC rate of interest, has a significant negative influence on the amount of HELOC debt carried by households. Moreover, the higher is the value of the collateral pledged by the borrower, the lower is the rate of interest that banks charge for the loan. This negative relationship conforms to the sorting-by-private-information paradigm. Therefore, the value of the collateral (i.e. the equity in home) serves as a signal for borrower quality. A borrower who pledges higher amount of collateral is inferred to have a better credit-worthiness and therefore is charged a lower HELOC rate of interest by banks. Though the data on secured commercial loans suggest that the sorting-by-observed-risk paradigm is empirically
dominant, the data on secured consumer lines of credit, namely HELOCs, support the 

*sorting-by-private-information paradigm.*

My results suggest that collateralization of loans improves borrower quality and therefore reduces bank risk. As a policy implication, I may infer that it is appropriate to consider collateral in regulatory decisions. Banks with very low proportions of secured loans should be examined more frequently or supervised more carefully. Bank regulatory mechanisms that are already in place largely conform to the policy implication suggested in this study. Moreover, our empirical framework that used the estimated borrowing along with the value of the collateral in order to price HELOC loans can replace the existing pricing schemes based primarily on LTVs.

As an extension to the problem addressed in this chapter, one may explain the credit-price dispersion in the combined market of the two major consumer lines of credit, namely credit cards and HELOCs. In order test the role of collateral in explaining the interest rate dispersion of this combined market one needs the data on rates of interest charged on non-collateralized credit card loans along with the information on the amount of collateral pledged and the rates of interest charged on the secured HELOC loans. However, the *Survey of Consumer Finance* does not provide the data on HELOC rates of interest for consumers who have HELOCs and are not borrowing on them. Therefore, a richer data set containing information on rates of interest for all HELOC holders is necessary to test the role that collateral plays in sorting borrowers according to their risk-types in the combined market for credit cards and HELOCs.

Another extension could be to test the role of debt renegotiation in defining the nature of collateral pledged by borrowers. It is generally hypothesized that if the creditor
is precommited not to forgive any portion of outstanding debt, a limited liability arrangement is optimal. For instance in case of auto loans, one sees a limited liability loan arrangement where only the car is lost in the event of a default. In auto loans, therefore, only inside collateral is pledged by the borrowers. However, in the absence of any creditor precommitment, debt is secured by additional outside assets. In HELOC loan contracts, for example, one does not see any sort of creditor precommitment. If the defaulting debtor can successfully refinance the outstanding debt, then the home is not foreclosed. Hence, HELOC loan contracts are seen to involve outside collateral. One may empirically test the role of creditor precommitment (or debt renegotiation) in consumer’s choice of the nature of collateral pledged in a loan contract.
<table>
<thead>
<tr>
<th>Variables</th>
<th>HELOC Debtors</th>
<th>HELOC Non-Debtors</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOMEQUITY</td>
<td>264.9</td>
<td>331.9</td>
</tr>
<tr>
<td>LIQUIDASSET</td>
<td>48.0</td>
<td>216.8</td>
</tr>
<tr>
<td>NHNFINASSET</td>
<td>1489.2</td>
<td>4279.3</td>
</tr>
<tr>
<td>INCOME</td>
<td>200.8</td>
<td>553.8</td>
</tr>
<tr>
<td>ITEMIZE</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>3.1</td>
<td>2.7</td>
</tr>
<tr>
<td>MORTGAGE</td>
<td>0.8</td>
<td>0.6</td>
</tr>
<tr>
<td>MORTGAGERATE</td>
<td>6.3</td>
<td>4.8</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>AGE</td>
<td>50.8</td>
<td>53.8</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>14.9</td>
<td>14.1</td>
</tr>
<tr>
<td>REPAYMENTFREQ</td>
<td>2.0</td>
<td>1.1</td>
</tr>
<tr>
<td>RISK1</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>RISK3</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td>NONWHITE</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Table 2.3: Means of variables for HELOC debtors and HELOC non-debtors.\(^{14}\)

\(^{14}\) Refer to page 29 for the definitions of the variables used in the table. All monetary variables are in thousand dollars.
CHAPTER 3

DETERMINANTS OF BORROWING LIMITS ON CREDIT CARDS

3.1 Introduction

It is well accepted that borrowing limits on collateralized loans are primarily determined by the amounts of collateral pledged by the borrowers. However for non-collateralized loans, such as those on credit card (CCs), the information about borrowers’ repayment abilities plays a crucial role in the determination of the borrowing limits or the credit limits. In the presence of asymmetric information between the borrower and the lender, and in the absence of collateral, credit rationing is argued to occur in the credit market. Imperfect information about borrower risk induces banks to refuse credit to some borrowers even if the latter would accept higher interest rates for their loans. Borrowers’ credit histories provide some critical information about their risk-types, which banks use to alleviate some of the informational asymmetry and to improve the quality of their loan supply decision. Information about borrowers’ credit-worthiness helps banks sort their client pool according to risk classes. However, banks do not have a perfect knowledge about borrower risk. Therefore, credit rationing still persists in the CC market. Critical credit information however, provides some guidance on how to ration credit to deserving borrowers. Borrowers with no or ‘bad’ credit histories are more likely to be refused
access to credit cards (CCs) by the banks. Among the CC holders, those with ‘better’
credit histories are perceived to have higher repayment abilities and therefore are likely to
be provided with higher CC borrowing limits. Profit-maximizing banks choose to provide
exactly that amount of credit to their borrowers, which maximize their expected profits.
Therefore, a careful analysis of the ingredients of borrowers’ credit-worthiness will help
me understand the determinants of CC borrowing limit.

A typical CC contract is two-dimensional. Banks offer a rate of interest along
with a preset borrowing limit to their potential borrowers. A typical bank’s profit
maximization exercise implies that the CC loan supply function, like any other supply
function, crucially depends on the price of loan, the rate of interest. However, the two-
dimensional nature of the loan contract also makes the CC interest rates endogenous.
Empirical identification of the determinants of CC borrowing limits requires me to
correct for this endogeneity. Moreover, not all individuals have CCs. The set of CC
holders is a selected sample and hence my estimation needs to account for the sample
selection bias as well. In this chapter, I plan to accomplish ‘consistent’ and ‘efficient’
parameter estimation with the choice of a correct econometric model and with the help of
an appropriate econometric technique.

3.2 Background

Beginning with Ausubel (1991), researchers began to look into the consumer lines
of credit, especially into CCs. The bulk of the literature on CCs concentrated on
explaining why the average CC interest rates remained sticky at such a high level.
Ausubel (1991) argued that the reason for this downward-rigid interest rates and the
presence of supernormal profits was the failure of competition in the CC market. He partly attributed this failure of competition to the myopic consumers who failed to foresee indebtedness and interest payments on their outstanding balances. Brito and Hartley (1995), on the other hand, argued that the consumers carried high-interest CC debts, not due to myopia but due to the fact that obtaining low-interest bank loans involved transaction costs. Mester’s (1994) view was that the low-risk borrowers who had access to low interest collateralized loans left the CC market. This made the average client pool of the CC market riskier and thereby preventing the interest rates from going down.

Kerr (2002) focused on the issue of interest rate dispersion within the CC market. His study considered a two-fold information asymmetry – one is between the banks (i.e. the lenders) and the borrowers and the other is within the banks themselves. Some banks (the External Banks) have access to only the publicly available credit histories while some others (the Home Banks) have additional access to the borrowers’ private financial accounts. He argued that in equilibrium, the average rate of interest charged by the External Banks would be higher than that charged by the Home Banks because the average borrower associated with the External Banks would be riskier.

Most of the existing literature on CCs focused on analyzing various aspects of the credit card rates of interest. Despite the fact that credit card loan contracts are essentially two-dimensional, researchers have largely ignored the credit limit dimension of the contract. Dunn and Kim (2002) argued that banks in order to strategize against Ponzi-schemers in the credit card market tend to provide lower credit limits to high-risk borrowers despite giving them larger number of cards. Though they found some
empirical support for their hypothesis on credit limits, they chose to focus their formal empirical analysis on credit card default estimation. Gross and Souleles (2002) utilize a unique new dataset of credit card accounts to analyze how people respond to changes in credit supply. They find that increases in credit limits generate an immediate and significant rise in debt, consistent with the buffer-stock models of precautionary saving, as cited in Deaton (1991), Carroll (1992), and Ludvigson (1999). However, I find that there has been a serious lack of theoretical and empirical investigation into the aspects of credit card borrowing limits. In this chapter of my thesis, I make an effort to fill in that void. I build a general model capturing the key elements of credit card loan contracts and test the relationship between borrower quality and the CC borrowing limit, correcting for banks’ selection of CC holders and for the influence of the endogenous variable, the CC interest rate.

3.3 The simple model

The CC market consists of numerous profit maximizing banks. The banks are assumed to procure funds at a rate $r_F$. Based on publicly available credit reports, banks separate their clients into risk classes. Let me assume that the representative class, $i \in [\hat{i}, \overline{i}]$. A typical loan contract provided to class ‘i’ consists of a vector $(L_i, r_i)$. In this simple model, I do not differentiate between a line of credit and a traditional loan. Therefore the loan, $L_i$, extended by the banks to class ‘i’ is automatically assumed to be borrowed by every borrower belonging to that class. Let me further assume that there is only one borrower in every risk class ‘i’ and that banks face a negatively-sloped inverse demand curve, which is to assume that $r_i = r(L_i)$, such that $r'(L_i) < 0$. Let me define $(1 +
r_F = R_F and (1 + r_i) = R_i; hence I have R'(L_i) < 0. In other words, the market structure is assumed to be monopolistically competitive at every risk class ‘i’. Banks assign a different repayment probability, \( \rho_i \in [0,1] \), to every risk class ‘i’. Finally, I assume that the repayment probability of the borrower representing class ‘i’ is a function of the amount owed, \( D_i = R_i L_i \), and the risk class measure, \( i \). Therefore I have, \( \rho_i = \rho(D_i, i) \), such that,

\[
\frac{\partial \rho(.)}{\partial D_i} < 0 \; \& \; \frac{\partial \rho(.)}{\partial i} > 0.
\]

3.3.1 A bank’s profit maximization problem

The expected profit from extending a loan contract \((L_i, r_i)\) to class ‘i’ is given by \( \Pi^i\). For class ‘i’, a bank’s profit maximization problem is given by:

\[
\max_{L_i} \Pi^i = \{\rho(R(L_i)L_i, i)R(L_i) - R_F \}L_i.
\]

Let me assume that \( \Pi^i \mid_{L_i} < 0 \).

Partially differentiating \( \Pi^i \) with respect to \( L_i \) and setting it zero I get,

\[
\Pi^i_{L_i} = \rho(R(L_i^*)L_i^*, i)R(L_i^*) - R_F + L_i^*[R(L_i^*)] \frac{\partial \rho(R(L_i^*)L_i^*, i)}{\partial D_i} (R(L_i^*) + R'(L_i^*)L_i^*)
\]

\[+ \rho(R(L_i^*)L_i^*, i)R'(L_i^*)] = 0
\]

(16)

Proposition 1

i. Banks choose \( L_i^* \) & \( r_i^* = r(L_i^*) \), such that \( \Pi^i_{L_i}(L_i^*, r_i^*) = 0 = \Pi^i(L_i^*, r_i^*) \).

ii. For all banks, maximizing the total expected profit over all classes is equivalent to integrating over all classes the maximized profit of every class.
Using equation (16) and the zero profit condition for class ‘i’ [i.e. \( \Pi^i(L_i^*, r_i^*) = 0 \)], a typical bank’s optimal loan contract for class ‘i’ can be written in terms of the following set of structural equations:

\[
L_i^* = \tilde{L}(r_i^*, r_F, i) \tag{17}
\]

\[
r_i^* = \tilde{r}(L_i^*, r_F, i) \tag{18}
\]

However, due to the lack of sufficient number of identifying restrictions, the testable econometric model consists of the following bivariate system:

\[
L_i^* = \tilde{L}(r_i^*, r_F, i) \tag{19}
\]

\[
r_i^* = \tilde{R}(r_F, i)
\]

The above econometric model can be tested using consumer level data. I can potentially test the signs of the following partial derivatives: \( \frac{\partial L_i^*}{\partial r_i}, \frac{\partial L_i^*}{\partial r_F}, \frac{\partial L_i^*}{\partial i}, \frac{\partial r_i^*}{\partial r_F}, \text{ and } \frac{\partial r_i^*}{\partial i} \). \(^{15}\)

### 3.4 The general model

Let me now consider a model where the banks are competitively offering non-collateralized lines of credit, such as credit cards. A line of credit is a borrowing instrument whereby the borrower is offered a borrowing limit (or credit limit) and a rate of interest. The borrower can borrow up to the credit limit. Moreover, interest charges accrue only if some positive amount is borrowed on the line. A line of credit contract is a more general loan contract where the traditional fixed loan contract can be incorporated as a special case when the borrower borrows exactly the limit amount at the very outset.

\(^{15}\) See Appendix for a discussion about the derivations of the partial derivatives.
A typical credit card contract offered to class ‘i’ consists of a vector \((L_i, r_i)\). Using the framework put forward in the first chapter of this thesis, I argue that borrowers primarily use lines of credit in order to hedge against uninsured risks. This framework makes the desired borrowings on lines of credit to be random variables, functions of underlying wealth shocks and the rates of interest. Let \(\theta_i\) represent the underlying wealth shock, such that I have the optimal borrowing demand as, \(B_i = B(\theta_i, r_i)\) & \(\theta_i \sim G(\theta_i)\). Hence I can write, \(B_i \sim F(B_i), F'(B_i) = f(B_i) & B_i \in (-\infty, \infty)\). Using the optimal borrowing function, I can derive a negatively-sloped inverse demand curve for consumer ‘i’, which means that \(r_i = r(B_i)\), such that \(r'(B_i) < 0\). The repayment probability is again a function of the amount owed by the borrower representing class ‘i’ (\(D_i = R_iB_i\)) and the risk class measure, \(i\). Therefore I can similarly write the class ‘i’ repayment probability as, \(\rho_i = \rho(D_i, i)\), such that, \(\frac{\partial \rho(.)}{\partial D_i} < 0, \frac{\partial \rho(.)}{\partial i} > 0 \& \rho_i \in [0,1]\). Let me now consider a typical banks’ profit maximization problem where the bank is offering a line of credit, such as credit card.

3.4.1 A bank’s profit maximization problem

The expected profit from offering a line of credit contract \((L_i, r_i)\) to class ‘i’ is represented by \(\pi^i\). For class ‘i’, a bank’s profit maximization problem is given by:

\[
\max_{L_i} \pi^i = \int_{-\infty}^{\infty} [\rho(R(B_i)|B_i, i)R(B_i) - R_F]B_i f(B_i)dB_i + \\
\int_{-\infty}^{\infty} [\rho(R(L_i)|L_i, i)R(L_i) - R_F]L_i f(B_i)dB_i
\]
\[
\pi^i_{L_i} = \left[ \rho(R(B_i)B_i,i)R(B_i) - R_F \right] B_i f(B_i) dB_i + \\
\left[ 1 - F(L_i) \right] \left[ \rho(R(L_i)L_i,i)R(L_i) - R_F \right] L_i
\]

Let me again assume that \( \pi^i_{L_i} < 0 \).

Partially differentiating \( \pi^i \) with respect to \( L_i \) and setting it zero I get,

\[
\pi^i_{L_i} = \left[ \rho(.)R(L_i^{**}) - R_F \right] L_i^{**} f(L_i^{**}) + \\
\left[ 1 - F(L_i^{**}) \right] \left[ L_i^{**} \left\{ R(L_i^{**}) \frac{\partial \rho(.)}{\partial D_i} (R(L_i^{**}) + R'(L_i^{**})L_i^{**}) + \rho(.)R'(L_i^{**}) \right\} + \\
\rho(.)R(L_i^{**}) - R_F \right] - \left[ \rho(.)R(L_i^{**}) - R_F \right] L_i^{**} f(L_i^{**})
\]
or,

\[
\pi^i_{L_i} = \left[ 1 - F(L_i^{**}) \right] \left[ L_i^{**} \left\{ R(L_i^{**}) \frac{\partial \rho(.)}{\partial D_i} (R(L_i^{**}) + R'(L_i^{**})L_i^{**}) + \rho(.)R'(L_i^{**}) \right\} + \\
\rho(.)R(L_i^{**}) - R_F \right] = 0
\]

(20)

**Proposition 2**

1. Banks choose \( L_i^{**} \) & \( r_i^{**} = r(L_i^{**}) \), such that \( \pi^i_{L_i} (L_i^{**},r_i^{**}) = 0 = \pi^i (L_i^{**},r_i^{**}) \).

2. For all banks, maximizing the total expected profit over all classes is equivalent to integrating over all classes the maximized profit of every class.

Using equation (20), the zero profit condition for class ‘i’ [i.e. \( \pi^i (L_i^{**},r_i^{**}) = 0 \)] and the fact that \( B_i = B(\theta_i,r_i) \), the bank’s optimal line of credit contract for class ‘i’ can be represented by the following set of structural equations:
\[ L_i^{**} = L(r_i^{**}, r_F, \theta_i, i) \]  \hspace{1cm} (21)

\[ r_i^{**} = r(L_i^{**}, r_F, \theta_i, i) \]  \hspace{1cm} (22)

Again, due to the lack of sufficient number of identifying restrictions, the testable econometric model becomes the following bivariate system:

\[ L_i^{**} = L(r_i^{**}, r_F, \theta_i, i) \]

\[ r_i^{**} = R(r_F, \theta_i, i) \]  \hspace{1cm} (23)

Therefore, my general theory on line of credit contracts yields to a bivariate econometric model that can be used for empirical analysis. Using my data set, I can potentially test the signs of the following partial derivatives -

\[ \frac{\partial L_i^{**}}{\partial r_i^{**}}, \frac{\partial L_i^{**}}{\partial r_F}, \frac{\partial L_i^{**}}{\partial i}, \frac{\partial r_i^{**}}{\partial r_F} & \frac{\partial r_i^{**}}{\partial i} \]  \hspace{1cm} 16

Using the derivations shown in the appendix, the second-order condition, given by \( \pi_{Li}^i < 0 \), and assuming, \( \pi_i^i > 0, \pi_{i,i}^i > 0 \) & \( \pi_{Li}^i < 0 \), I can attain the following testable predictions out of my general theoretical model of line of credit contracts: \( \frac{\partial r_i^{**}}{\partial i} < 0 \) and \( \frac{\partial r_i^{**}}{\partial r_F} > 0 \). I also have unambiguous predicted signs for the following partial derivatives of the reduced form optimal borrowing limit offered to borrower ‘i’:

\[ \frac{\partial L_i^{**}}{\partial i} > 0 \) & \( \frac{\partial L_i^{**}}{\partial r_F} < 0 \). However, the signs for the partial derivatives of the structural form optimal borrowing limit function, such as, \( \frac{\partial L_i^{**}}{\partial i}, \frac{\partial L_i^{**}}{\partial r_F} \) and \( \frac{\partial L_i^{**}}{\partial r_i^{**}} \), are ambiguous. I hope to use my empirical findings to shed some light on these ambiguous signs.

---

16 See Appendix for a discussion about the derivations of the partial derivatives.
3.5 Data

The data used in this study is the 1998 *U.S. Survey of Consumer Finances* (SCF). SCF is a nationwide survey conducted by National Opinion Research Center (NORC) on behalf of the Federal Reserve Bank of United States. This recent wave of the SCF provides a large and rich data set on household assets, liabilities, demographic characteristics and a number of variables capturing household attitudes. In 1998, 4,305 families were surveyed. This sample had 3,233 households with at least one bank-type CC, which was 75.1% of the total number of households in the sample.

Table 3.7 compares the average consumer profiles for the CC holders and the CC non-holders.

3.6 The econometric model

I have household ‘i’ representing class ‘i’. Let \( L_i^{**} \) denote bank’s profit maximizing borrowing limit extended to household ‘i’. According to my general model explaining the line of credit market I have, \( L_i^{**} = L(r_i^{**}, r_F, \theta_i, i) \).

The variable, \( r_F \), has no variation across households. Therefore the effect of \( r_F \) on \( L_i^{**} \) cannot be empirically tested. Moreover, let the vector \( X_{1i} \) denote the information on household ‘i’ that banks use to define his/her risk-measure ‘i’. The vector \( X_{1i} \) consists of variables included in publicly available credit reports and the variables that banks gather in the process of credit card applications. For a complete list of variables included in an individual credit report, refer to Table 3.8. Hence, \( X_{1i} \) consists of personal information, such as, employment status, age and size of household ‘i’. It also has information on credit history variables, such as, access to alternate lines of credit (such as Home Equity...
Lines of Credit), fraction of mortgage and (or) Home Equity Line of Credit debt repaid, the timeliness of payments, bankruptcy record and credit inquiries. Finally, vector $X_{1i}$ has the information on household income, which is gathered during the credit card application process. Thus using $r_F$ and $X_{1i}$, I have the structural form equation for $L_i^*$ as

$$L_i^* = \beta_1 X_{1i} + \gamma r_i^* + v_{1i}$$  \hspace{1cm} (24)$$

In equation (24), the banks’ opportunity cost of funds, $r_F$, contributes to the constant term and the underlying wealth shock influencing household’s desired borrowing ($\theta_i$), goes into the error term, $v_{1i}$.

Since the optimal credit card interest rate is given by $r_i^* = R(r_F, \theta_i, i)$, using $r_F$ and $X_{1i}$, I have a reduced form equation for $r_i^*$

$$r_i^* = \beta_2 X_{2i} + v_{2i}.$$  \hspace{1cm} (25)$$

Also in equation (25), the variable, $r_F$, contributes to the constant term and the underlying wealth shock ($\theta_i$) goes into the error term, $v_{2i}$.

The vector $X_{2i}$ consists of the vector $X_{1i}$ and some identifying variables capturing aspects of household’s search behavior, such as, household’s propensity to shop around for best rates before major savings and investment decisions and rates of interest on alternate lines of credit, such as, Home Equity Lines of Credit (HELOCs).

The combination $(L_i^*, r_i^*)$ is observed if banks offer a credit card to household ‘$i$’, i.e. if, $L_i^* > 0$. Let me therefore consider the following econometric model:
In the above equations, $L_i$ and $r_i$ are the observed credit card borrowing limit and interest rate respectively; $X_{1i}$ and $X_{2i}$ are vectors of exogenous variables; $v_{1i}$ and $v_{2i}$ follow Bivariate Normal with means zero, variances $\sigma_1^2$ and $\sigma_2^2$ respectively and with covariance $\sigma_{12}$. If $X_{2i}$ contains at least one variable that is not included in $X_{1i}$, then all the parameters of the model are identified. In order to correct for the endogeneity present in the credit card borrowing limit equation, the two-stage estimation procedures in the literature use the estimated credit card interest rate, $r_i^*$, as an instrument.

Maximum Likelihood Estimation Procedure is used to estimate the proposed econometric model. To form the likelihood function I have to relate the dependent variables to their empirical counterparts, and describe the process by which the observable counterparts are generated in terms of the underlying stochastic components. A household is observed to have a credit card if

$$L_i^{**} > 0.$$  

Substituting the credit card interest rate equation into the borrowing limit equation, the credit card offering decision can be written as

$$\beta_1'X_{1i} + \gamma\beta_2'X_{2i} > -(v_{1i} + \gamma v_{2i})$$

or,

$$I_i > v_i$$
where, \( v_i \sim N(0, \sigma_1^2 + \gamma^2 \sigma_2^2 + 2\gamma\sigma_{12}) \equiv N(0, \sigma_v^2) \)

\[ I_i = \beta_1 X_{1i} + \gamma \beta_2 X_{2i}. \]

The likelihood of observing a household without a credit card is

\[ \Pr ob(I_i < v_i) = \int_{I_i/\sigma_v}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{\sigma^2}{2}} d\sigma = 1 - \Phi\left(\frac{I_i}{\sigma_v}\right) = \Phi\left(-\frac{I_i}{\sigma_v}\right) \]

where \( \Phi \) is the standard normal cumulative density function.

Hence the likelihood of the data consisting (say) of \( N \) households and of \( M \) households without credit cards is

\[ L = \prod_{i=1}^{M} \Phi\left(-\frac{I_i}{\sigma_v}\right) \prod_{i=M+1}^{N} b(v_{1i}, v_{2i}) = \prod_{i=1}^{M} \Phi\left(-\frac{I_i}{\sigma_v}\right) \prod_{i=M+1}^{N} n(v_{1i} | v_{2i}) n(v_{2i}) \]

where \( b(.) \) is the Bivariate Normal density function, \( n(.) \) is the Normal density function and

\[ v_{1i} = L_i - \beta_1 X_{1i} - \gamma r_i \]

\[ v_{2i} = r_i - \beta_2 X_{2i}. \]

Now, \( v_{2i} \sim N(0, \sigma_2^2) \)

\[ v_{1i} | v_{2i} \sim N\left(\frac{\rho \sigma_1 v_{2i}}{\sigma_2}, \sigma_1^2 (1 - \rho^2)\right), \text{ where } \rho = \frac{\sigma_{12}}{\sigma_1 \sigma_2}. \]

Let, \( \sigma_c^2 = \sigma_1^2 (1 - \rho^2) \) and

\[ T_i = \frac{v_{1i} \rho \sigma_1 v_{2i}}{\sigma_2 \sigma_c}. \]

The corresponding log-likelihood function can be written as
\[
\log L = \sum_{i=1}^{M} \log[\Phi(-\frac{I_i}{\sigma_v})] + \sum_{i=M+1}^{N} \frac{\phi\left(\frac{V_{2i}}{\sigma_2}\right)}{\sigma_2} + \sum_{i=M+1}^{N} \frac{\phi(T_i)}{\sigma_c}
\]

where \(\phi(.)\) is the Standard Normal density function.

A multi-step procedure was used to estimate the parameters of the model. First, the parameters of the econometric model were estimated by probit two-stage method as described by Lee et al. (1980). This two-step procedure yielded consistent estimates of all the parameters of the model. In order to obtain asymptotically efficient parameter estimates, these consistent estimates were used as initial values for the final maximization of the log-likelihood function.

Let \(\delta_i = -\frac{I_i}{\sigma_v} \& \lambda(\delta_i) = \frac{\phi(\delta_i)}{1 - \Phi(\delta_i)}\). Let me further define a dummy variable, \(D_i\), such that

\(D_i = 1\) if household ‘i’ has a credit card (i.e. \(L_i^{**} > 0\))

\(= 0\) otherwise.

For credit card holders, \(L_i = \beta'_i X_{ii} + \gamma_i + \sigma_i \lambda(\delta_i) + v_{3i}\)

\(r_i = \beta'_i X_{2i} + \mu \lambda(\delta_i) + v_{4i}\)

where \(\mu = \frac{\gamma \sigma^2 + \sigma_{12}}{\sigma_v}\).

Consistent estimates of \(\delta_i\) can be obtained by running a probit of the decision to offer a credit card. Then I can estimate the following equation by OLS:

\(r_i = \beta'_i X_{2i} + \mu \lambda(\delta_i) + v_{4i}\)
I then obtain \( \hat{r}_i \) from the previous OLS regression and estimate the following equation by OLS:

\[
L_i = \beta_i'X_{ii} + \gamma_i + \sigma_i\lambda(\hat{\delta}_i) + v_{3i}.
\]

This two-step procedure will give me consistent estimates of all the parameters of the model, which are then used as starting values for the maximum likelihood procedure.

3.7 Results and Discussion

Table 3.1 presents the definitions of the variables used in the econometric analyses of this chapter.

Table 3.2 presents the results of a probit equation explaining the decision to offer a credit card to a potential borrower. The household’s income (LOGINCOME), age and being self-employed significantly improve the likelihood of getting a credit card. However, the size of the household, unemployment, the incidence of delinquency and the declaration of bankruptcy diminish the chance of receiving a credit card. If the household is liquidity constrained, then I have a higher probability of being denied a credit card. Finally, the more the household looks around for better rates (SHOPINVEST) or if the household has a Home Equity Line of Credit taken out (captured by the variable HELOC), the more likely is the incidence of a credit card. In general, the results indicate that the higher is the household’s credit-worthiness, the greater is the likelihood of obtaining a credit card.
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>TYPE</th>
<th>EXPLANATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>RHI</td>
<td>CONTINUOUS</td>
<td>HELOC Rate of Interest (Maximum Interest Rate charged among the different HELOCs taken out by the household)</td>
</tr>
<tr>
<td>RCI</td>
<td>CONTINUOUS</td>
<td>CC Rate of Interest</td>
</tr>
<tr>
<td>DELinquency</td>
<td>BINARY</td>
<td>1 – Got behind in payments by two months or more</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>BANKruptcy</td>
<td>BINARY</td>
<td>1 – Declared bankruptcy</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>LOGclimit</td>
<td>CONTINUOUS</td>
<td>Logarithm of CC Borrowing Limit</td>
</tr>
<tr>
<td>LOGincome</td>
<td>CONTINUOUS</td>
<td>Logarithm Income</td>
</tr>
<tr>
<td>alphai</td>
<td>CONTINUOUS</td>
<td>Fraction of HELOC and Mortgage Debt Repaid</td>
</tr>
<tr>
<td>householdsize</td>
<td>CONTINUOUS</td>
<td>Household Size</td>
</tr>
<tr>
<td>age</td>
<td>CONTINUOUS</td>
<td>Age of the Household</td>
</tr>
<tr>
<td>employment1</td>
<td>BINARY</td>
<td>1 – Not Working</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>employment2</td>
<td>BINARY</td>
<td>1 – Retired</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>employment3</td>
<td>BINARY</td>
<td>1 – Working and Not Self-Employed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>employment4</td>
<td>BINARY</td>
<td>1 – Working and Self-Employed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>liqconstraint</td>
<td>BINARY</td>
<td>1 – Did not get as much credit as applied for, despite reapplying or did not reapply after the first refusal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>heloc</td>
<td>BINARY</td>
<td>1 – Has a HELOC taken out</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 – Otherwise</td>
</tr>
<tr>
<td>shopinvest</td>
<td>CATEGORICAL</td>
<td>0 – Almost No Shopping for the very best terms</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 – Moderate Shopping</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 – Great Deal of Shopping</td>
</tr>
</tbody>
</table>

Table 3.1: Variable list.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-2.878***</td>
<td>0.183</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>-0.039**</td>
<td>0.017</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>-0.309***</td>
<td>0.101</td>
</tr>
<tr>
<td>BANKRUPTCY</td>
<td>-0.229***</td>
<td>0.085</td>
</tr>
<tr>
<td>LOGINCOME</td>
<td>0.304***</td>
<td>0.016</td>
</tr>
<tr>
<td>EMPLOYMENT1</td>
<td>-0.614***</td>
<td>0.074</td>
</tr>
<tr>
<td>EMPLOYMENT2</td>
<td>-0.073</td>
<td>0.09</td>
</tr>
<tr>
<td>EMPLOYMENT4</td>
<td>0.469***</td>
<td>0.076</td>
</tr>
<tr>
<td>SHOPINVEST</td>
<td>0.298***</td>
<td>0.033</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.386</td>
<td>0.79</td>
</tr>
<tr>
<td>AGE</td>
<td>0.004*</td>
<td>0.002</td>
</tr>
<tr>
<td>LIQCONSTRAINT</td>
<td>-0.31***</td>
<td>0.087</td>
</tr>
<tr>
<td>HELOC</td>
<td>0.645***</td>
<td>0.187</td>
</tr>
<tr>
<td>RHI</td>
<td>0.012</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Table 3.2: Probit equation explaining the decision to offer a credit card to a potential borrower.\textsuperscript{17}

\textsuperscript{17} Refer to page 79 for the definitions of the variables used in the table. I have, ** - Significant at 1% Level; *** - Significant at 5% Level; * - Significant at 10% Level.
Table 3.3 presents the results for the probit two-stage regression for credit card rates of interest (RCI) among the credit card holders. The incidence of delinquency or bankruptcy positively influences banks’ offer of a credit card interest rate to household ‘i’. If the household is liquidity constrained, then it is also likely to result in a higher credit card rate of interest charged by the banks. If the household shops around for the best rates, then he/she lands up with a lower interest rate on credit card. The rate on alternative line of credit, such as HELOC, also reduces the offered credit card rate of interest. Finally, the estimated value of $\mu$ is 0.749. Since this estimated value is not significantly different from zero, I conclude that there is no empirical evidence of sample selection in the estimates of the credit card rate of interest equation. Therefore my empirical results conclude that the better is the credit-worthiness of the household, the lower is the interest rate on the credit card charged by the banks, which means that I have empirical support for the following: $\frac{\partial r_i^*}{\partial i} < 0$. Again controlling for the credit-risk of the household, the more pronounced is his/her search behavior, the lower is the credit card rate of interest obtained.

Table 3.4 presents the probit two-stage estimates of the credit card borrowing limit (LOGCLIMIT) equation for credit card holders. The higher is the income of the household, the higher is the credit limit offered by the banks. If the household is self-employed or if he/she already has a HELOC taken out, then again he/she receives a higher credit card borrowing limit from the banks. The endogenous variable, the credit
<table>
<thead>
<tr>
<th>Variables</th>
<th>Probit Two-Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>12.655***</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>-0.038</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>1.567***</td>
</tr>
<tr>
<td>BANKRUPTCY</td>
<td>0.591*</td>
</tr>
<tr>
<td>LOGINCOME</td>
<td>0.141</td>
</tr>
<tr>
<td>EMPLOYMENT1</td>
<td>-0.042</td>
</tr>
<tr>
<td>EMPLOYMENT2</td>
<td>0.211</td>
</tr>
<tr>
<td>EMPLOYMENT4</td>
<td>-0.08</td>
</tr>
<tr>
<td>LIQCONSTRAINT</td>
<td>1.361***</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.2</td>
</tr>
<tr>
<td>AGE</td>
<td>0.007</td>
</tr>
<tr>
<td>SHOPINVEST</td>
<td>-0.346**</td>
</tr>
<tr>
<td>HELOC</td>
<td>0.445</td>
</tr>
<tr>
<td>RHI</td>
<td>-0.09*</td>
</tr>
<tr>
<td>LAMBDA+</td>
<td>0.749</td>
</tr>
</tbody>
</table>

$\bar{R}^2 = 0.02$
F-value = 5.11***
$\sigma^2 = 4.5$
N = 3233

Table 3.3: Probit two-stage estimates of credit card rates of interest, RCI (RCI = 0 for 1072 obs.).

---

18 Refer to page 79 for the definitions of the variables used in the table. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level; $^+$ LAMBDA = $\frac{\hat{\phi}_i}{1 - \Phi_i}$. 

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<table>
<thead>
<tr>
<th>Variables</th>
<th>Probit Two-Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>10.485***</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>-0.004</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>-0.167</td>
</tr>
<tr>
<td>BANKRUPTCY</td>
<td>-0.319</td>
</tr>
<tr>
<td>LOGINCOME</td>
<td>0.359***</td>
</tr>
<tr>
<td>EMPLOYMENT1</td>
<td>-0.326</td>
</tr>
<tr>
<td>EMPLOYMENT2</td>
<td>0.063</td>
</tr>
<tr>
<td>EMPLOYMENT4</td>
<td>0.353***</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.108</td>
</tr>
<tr>
<td>AGE</td>
<td>0.014***</td>
</tr>
<tr>
<td>LIQCONSTRAINT</td>
<td>0.101</td>
</tr>
<tr>
<td>HELOC</td>
<td>0.432**</td>
</tr>
<tr>
<td>RCI</td>
<td>-0.428**</td>
</tr>
<tr>
<td>LAMBDA*</td>
<td>0.796*</td>
</tr>
</tbody>
</table>

-LogL = -7717.693
$\sigma_1 = 2.679$
$\sigma_12 = 9.263$
N = 3233

Table 3.4: Probit two-stage estimates of credit card borrowing limit, LOGCLIMIT
(LOGCLIMIT = 0 for 1072 obs.).

19 Refer to page 79 for the definitions of the variables used in the above tables. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level; ^ LAMBDA = $\frac{\hat{\phi}_i}{1 - \Phi_i}$. 

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card rate of interest, has a negative effect on the bank’s loan supply. This result contrasts with the typical notion of a positively sloped supply curve. However, in my framework of asymmetric information, a negatively sloped loan supply function makes perfect intuitive sense. Charging a higher credit card rate of interest raises the (ex post) default probability of a borrower of any given (ex ante) risk-type. A typical bank’s optimal loan supply should, therefore, fall in order to compensate for this rise in default risk. Finally, the estimated value of $\sigma_v$ is 0.796. Since the estimated value is also significant, I conclude that there is empirical evidence of sample selection in the estimates of the credit card borrowing limit equation. The estimated effect of sample selection is also positive. Therefore, the higher is the credit-worthiness of the borrower, the higher is the likelihood of being offered a credit card and the higher is the borrowing limit extended by the banks. Hence my empirical results support the following predictions: $\frac{\partial L^{**}}{\partial r_i} < 0$ and $\frac{\partial L^{**}}{\partial i} > 0$.

The Full-Information Maximum Likelihood estimates of the credit card rate of interest equation are presented in Table 3.5. The incidence of delinquency or bankruptcy positively influences banks’ offer of a credit card interest rate to household ‘i’. If the household is unemployed or liquidity constrained, then it is again likely to result in a higher credit card rate of interest charged by the banks. The income of the household or being self-employed depresses the offered rate of interest in credit card contracts. Finally, if the household shops around for the best rates, then he/she lands up with a lower interest rate on credit card. Hence, active search for lower rates pays off by actually fetching one for a household of any risk-type. Moreover, my maximum likelihood estimates conforms
<table>
<thead>
<tr>
<th>Variables</th>
<th>Maximum Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>20.959***</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>0.036</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>2.072***</td>
</tr>
<tr>
<td>BANKRUPTCY</td>
<td>0.975***</td>
</tr>
<tr>
<td>LOGINCOME</td>
<td>-0.411***</td>
</tr>
<tr>
<td>EMPLOYMENT1</td>
<td>1.756***</td>
</tr>
<tr>
<td>EMPLOYMENT2</td>
<td>0.342</td>
</tr>
<tr>
<td>EMPLOYMENT4</td>
<td>-0.425*</td>
</tr>
<tr>
<td>LIQCONSTRAINT</td>
<td>2.079***</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.09</td>
</tr>
<tr>
<td>AGE</td>
<td>0.003</td>
</tr>
<tr>
<td>SHOPINVEST</td>
<td>-0.944***</td>
</tr>
<tr>
<td>HELOC</td>
<td>-0.441</td>
</tr>
<tr>
<td>RHI</td>
<td>-0.075</td>
</tr>
</tbody>
</table>

Table 3.5: Full information maximum likelihood estimates of credit card rates of interest.\(^{20}\)

---

\(^{20}\) Refer to page 79 for the definitions of the variables used in the above tables. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>16.348***</td>
<td>2.958</td>
</tr>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>-0.068</td>
<td>0.071</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>0.797</td>
<td>0.608</td>
</tr>
<tr>
<td>BANKRUPTCY</td>
<td>0.009</td>
<td>0.381</td>
</tr>
<tr>
<td>LOGINCOME</td>
<td>0.658***</td>
<td>0.091</td>
</tr>
<tr>
<td>EMPLOYMENT1</td>
<td>-1.108**</td>
<td>0.482</td>
</tr>
<tr>
<td>EMPLOYMENT2</td>
<td>0.161</td>
<td>0.36</td>
</tr>
<tr>
<td>EMPLOYMENT4</td>
<td>0.441*</td>
<td>0.246</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.284</td>
<td>2.79</td>
</tr>
<tr>
<td>AGE</td>
<td>0.02**</td>
<td>0.009</td>
</tr>
<tr>
<td>LIQCONSTRAINT</td>
<td>0.776</td>
<td>0.535</td>
</tr>
<tr>
<td>HELOC</td>
<td>0.688*</td>
<td>0.375</td>
</tr>
<tr>
<td>RCI</td>
<td>-1.126***</td>
<td>0.164</td>
</tr>
<tr>
<td>(\sigma_1)</td>
<td>5.317***</td>
<td>0.617</td>
</tr>
<tr>
<td>(\sigma_2)</td>
<td>5.018***</td>
<td>0.158</td>
</tr>
<tr>
<td>(\rho)</td>
<td>0.675***</td>
<td>0.081</td>
</tr>
</tbody>
</table>

\(-\text{Log-L} = -13941.71\)

Table 3.6: Full information maximum likelihood estimates of credit card borrowing limit.\textsuperscript{21}

\textsuperscript{21} Refer to page 79 for the definitions of the variables used in the above tables. I have, *** - Significant at 1% Level; ** - Significant at 5% Level; * - Significant at 10% Level.
to the probit two-stage prediction of \( \frac{\partial r_i}{\partial i} < 0 \).

Finally, I have Table 3.6 presenting the Full-Information Maximum Likelihood estimates of the credit card borrowing limit equation. The higher is the income or the age of the household, the higher is the credit limit offered by the banks. If the household is self-employed or if he/she already has a HELOC taken out, then again he/she receives a higher credit card borrowing limit from the banks. Unemployed households, however, fetch lower credit card borrowing limits from banks. The endogenous variable, the credit card rate of interest, again has a negative effect on the bank’s loan supply. Hence my maximum likelihood estimates are consistent with the probit two-stage results supporting:

\[
\frac{\partial L_i}{\partial r_i} < 0 \quad \text{and} \quad \frac{\partial L_i}{\partial i} > 0.
\]

### 3.8 Summary

Lines of credit contracts are fundamentally different from the traditional fixed loan contracts. Therefore, understanding the key elements of a non-collateralized line of credit, such as credit card, requires a theoretical separation of the choice of the amount of borrowing and the choice of the amount of credit limit, the two-dimensional nature of the contract and the market structure under which the borrowers and lenders operate. In this chapter I have been able to theoretically identify the crucial features of the credit card contracts offered by the banks. I have then tested the nature of the association between the borrower quality and the offered pair of credit card borrowing limit and rate of interest. I have also untangled the relationship between the endogenous variable, the credit card rate of interest, and the borrowing limit.
My results support the fact that banks use publicly available information on potential borrowers to assess credit risk and formulate the nature of the credit card contracts to offer. The credit card market shows clear evidence of credit rationing. The lowest quality borrowers are refused access to credit cards by the banks. Among the credit card holders, those with ‘better’ credit histories are perceived to have higher repayment probabilities and therefore are provided with higher credit card borrowing limits and with lower interest rates. Controlling for the assessed risk-type of the borrower, a greater search for the best rates on loans significantly reduces the rate of interest that a borrower is charged on credit cards. Finally, contrary to the conventional notion of a positively sloped supply function, I have empirical support for a negative relationship between the supply of loan (i.e. the borrowing limit) and the price of the loan (i.e. the rate of interest) for credit cards. A higher interest rate raises the ex post default probability of a borrower of any given ex ante risk-type, therefore the optimal borrowing limit should fall in order to compensate for the rise in default risk.

Several empirical studies have shown that a household’s actual amount of borrowing on credit card does affect his/her credit card borrowing limit offered by the banks. For instance, the credit card borrowing limit offered to a ‘convenience user’ (i.e. a household with no credit card borrowing) of a given risk-type is quite different from the one offered to a household belonging to the same risk-class yet already borrowing up to the credit limit. As an extension to the research conducted in this chapter one may try to estimate a more general econometric model with two endogenous variables, the actual amount of borrowing and the credit card rate of interest, simultaneously affecting the credit card borrowing limit offered to a household in a given risk-class.
<table>
<thead>
<tr>
<th>Variables</th>
<th>CC Holders Mean</th>
<th>CC Non-Holders Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOUSEHOLDSIZE</td>
<td>2.7</td>
<td>2.6</td>
</tr>
<tr>
<td>DELINQUENCY</td>
<td>0.03</td>
<td>0.1</td>
</tr>
<tr>
<td>BANKRUPTCY</td>
<td>0.06</td>
<td>0.1</td>
</tr>
<tr>
<td>LOGINCOME</td>
<td>11.4</td>
<td>9.4</td>
</tr>
<tr>
<td>EMPLOYMENT1</td>
<td>0.06</td>
<td>0.3</td>
</tr>
<tr>
<td>EMPLOYMENT2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>EMPLOYMENT4</td>
<td>0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>SHOPINVEST</td>
<td>1.2</td>
<td>0.9</td>
</tr>
<tr>
<td>ALPHAI</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
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<td>50.8</td>
<td>47.0</td>
</tr>
<tr>
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<td>0.1</td>
</tr>
<tr>
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<td>0.02</td>
</tr>
<tr>
<td>RHI</td>
<td>0.6</td>
<td>0.1</td>
</tr>
<tr>
<td>RCI</td>
<td>14.5</td>
<td>-</td>
</tr>
<tr>
<td>LOGCLIMIT</td>
<td>9.5</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3.7: Means of variables for credit card holders and credit card non-holders.\(^{22}\)

\(^{22}\) Refer to page 79 for the definitions of the variables used in the above tables. All monetary variables are in thousand dollars.
| Personal Information | • Name  
• Current and previous address  
• Social Security Number  
• Telephone Number  
• Date of Birth  
• Current and previous employers |
|---|---|
| Credit History | Type of Accounts:  
1. Retail credit cards  
2. Bank loans  
3. Finance company loans  
4. Mortgages  
5. Bank credit cards  
Information Available:  
1. Account number  
2. Creditor’s name  
3. Amount borrowed  
4. Amount owed  
5. Credit limit  
6. Dates when accounts were opened, updated or closed  
7. Timeliness of payments  
8. Late payments |
| Public Records | • Tax liens  
• Bankruptcies  
• Court judgments |
| Inquiries | List of all parties who have requested a copy of your credit report |

Table 3.8: Credit report details.\(^{23}\)

\(^{23}\) Source: TransUnion
A. APPENDIX

I have the set of quasi-structural equations for the general model to be:

\[ L_i^{**} = L(r_i^{**}, r_F, \theta_i, i) \]  \hspace{1cm} (21)

\[ r_i^{**} = R(r_F, \theta_i, i) \]  \hspace{1cm} (23)

Substituting equation (23) into equation (21), I have a reduced form equation for the optimal credit card borrowing limit as:

\[ L_i^{**} = L^R(r_F, \theta_i, i) \]  \hspace{1cm} (26)

Using equations (23) and (26), I can write the equilibrium conditions of the general model as:

\[ \pi^i_{L_1}(L_i^{**}, r_i^{**}; r_F, \theta_i, i) = 0 \]  \hspace{1cm} (27)

\[ \pi^i(L_i^{**}, r_i^{**}; r_F, \theta_i, i) = 0 \]  \hspace{1cm} (28)

Partially differentiating equation (27) with respect to ‘i’ I have,

\[ \pi^i_{L_1}(L_i^{**}, r_i^{**}; r_F, \theta_i, i) \frac{\partial L_i^{**}}{\partial i} + \pi^i_{L_2}(L_i^{**}, r_i^{**}; r_F, \theta_i, i) \frac{\partial r_i^{**}}{\partial i} + \]

\[ \pi^i(L_i^{**}, r_i^{**}; r_F, \theta_i, i) = 0 \]  \hspace{1cm} (29)

Again, partially differentiating equation (28) with respect to ‘i’ I have,

\[ \pi^i_{L_1}(L_i^{**}, r_i^{**}; r_F, \theta_i, i) \frac{\partial L_i^{**}}{\partial i} + \pi^i_{L_2}(L_i^{**}, r_i^{**}; r_F, \theta_i, i) \frac{\partial r_i^{**}}{\partial i} + \]

\[ \pi^i(L_i^{**}, r_i^{**}; r_F, i, \theta_i) = 0 \]  \hspace{1cm} (30)

Using the first order condition of profit maximization, I can write equation (30) as,

\[ \pi^i_{L_1}(L_i^{**}, r_i^{**}; r_F, i, \theta_i) \frac{\partial r_i^{**}}{\partial i} + \pi^i(L_i^{**}, r_i^{**}; r_F, i, \theta_i) = 0 \]  \hspace{1cm} (31)

Solving equations (29) and (31) and suppressing the arguments I get,
\[
\frac{\partial L_{r_i}^{**}}{\partial i} = \frac{\begin{vmatrix}
\pi_{L_i} & \pi_{L_{r_i}}
\pi_i & \pi_i
\pi_i & \pi_i
\end{vmatrix}}{D} = C
\]

(32)

\[
\frac{\partial r_{r_i}^{**}}{\partial i} = \frac{\begin{vmatrix}
\pi_{L_{r_i}} & \pi_{L_{r_i}}
\pi_{r_i} & \pi_{r_i}
\pi_{r_i} & \pi_{r_i}
\end{vmatrix}}{D} = E
\]

(33)

Similarly I can solve for,

\[
\frac{\partial L_{r_i}^{**}}{\partial r_F} = \frac{\begin{vmatrix}
\pi_{L_{r_F}} & \pi_{L_{r_{r_i}}}
\pi_{r_F} & \pi_{r_i}
\pi_{r_{r_i}} & \pi_{r_{r_i}}
\end{vmatrix}}{D} = F
\]

(34)

\[
\frac{\partial r_{r_i}^{**}}{\partial r_F} = \frac{\begin{vmatrix}
\pi_{L_{r_F}} & \pi_{L_{r_{r_i}}}
\pi_{r_F} & \pi_{r_i}
\pi_{r_{r_i}} & \pi_{r_{r_i}}
\end{vmatrix}}{D} = G
\]

(35)

Moreover I know that,

\[
L_{r_i}^{**} = L(R(r_F, \theta, i), r_F, \theta, i).
\]

Hence I have,

\[
\frac{\partial L_{r_i}^{**}}{\partial i} = \frac{\partial L_i^{**}}{\partial r_i^{**}} \frac{\partial r_i^{**}}{\partial i} + \frac{\partial L_i^{**}}{\partial i}
\]

(36)

\[
\frac{\partial L_{r_i}^{**}}{\partial r_F} = \frac{\partial L_i^{**}}{\partial r_i^{**}} \frac{\partial r_i^{**}}{\partial r_F} + \frac{\partial L_i^{**}}{\partial r_F}
\]

(37)
Therefore, the theoretically predicted signs of the partial derivatives derived above and that of \( \frac{\partial L_i^{**}}{\partial r_i} \), \( \frac{\partial L_i^{**}}{\partial i} \) and \( \frac{\partial L_i^{**}}{\partial r_F} \) will crucially depend on the signs of the determinants C, E, F, G and D.

I know that the repayment probability for borrower ‘i’, \( \rho_i = \rho(D_i,i) \), satisfies, \( \frac{\partial \rho(.)}{\partial D_i} < 0, \frac{\partial \rho(.)}{\partial i} > 0 \) & \( \rho_i \in [0,1] \). Therefore, I have \( \pi_i^i > 0 \). The very nature of the profit function also guarantees that we have \( \pi_{ir}^i < 0 \) & \( \pi_{L,F}^i < 0 \). Let me further assume that we have \( \pi_{r,n}^i > 0, \pi_{L,n}^i > 0 \) & \( \pi_{L,F}^i < 0 \).

Given my assumptions and the second-order condition i.e. \( \pi_{L,F}^i < 0 \), I have the following signs: \( \frac{\partial r_i^{**}}{\partial i} < 0 \) & \( \frac{\partial r_i^{**}}{\partial r_F} > 0 \). I also have \( \frac{\partial L_i^{**}}{\partial i} > 0 \) & \( \frac{\partial L_i^{**}}{\partial r_F} < 0 \). From equations (34) and (35), I conclude that the signs of \( \frac{\partial L_i^{**}}{\partial i} \), \( \frac{\partial L_i^{**}}{\partial r_F} \) and \( \frac{\partial L_i^{**}}{\partial r_i} \) are ambiguous.

I can similarly derive the expressions for the partial derivatives of my simple model of loan contract using the relevant first order condition and the zero profit condition. Since the simple model is a special case of the general model, the derivations of partial derivatives for that model are considered to be redundant.


Governors of the Federal Reserve System (July): 571-583.


 Kerr, Sougata (2002), “Interest Rate Dispersion Due to Information Asymmetry in the Credit Card Market: An Empirical Study,” Unpublished paper, The Ohio State University, Columbus, OH.


