# DETERMINANTS OF BORROWING LIMITS ON CREDIT CARDS[*]

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ABSTRACT

In the credit card market, banks have to decide on the borrowing limits of their potential customers, when the amounts of borrowing to be incurred on these lines are uncertain. This borrowing uncertainty can make the market incomplete and create ex post misallocations. Households who are denied credit could well turn out to have ex post higher repayment probabilities than some credit card holders who borrow large portions of their borrowing limits. Similar misallocations may exist within the credit card holders as well. Our setup also explains how new information on borrowing patterns will generate revisions of existing contracts and counter offers (such as balance transfer offers) from competing banks. Using data from the U.S. *Survey of Consumer Finances*, we propose an empirical solution to this misallocation problem. We show how this dataset can be used by banks to explain the observed borrowing patterns of their customers and how these borrowing estimates will help banks to better select and retain their customers by enabling them to device better contracts. We find support for a positive relationship between the proxies of borrower quality and the approved borrowing limits on credit cards, controlling for the banks' selection of credit card holders and the endogeneity of interest rates. We also find evidence for a positively-sloped credit supply function.

*JEL classification: D4, D8, G2*

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## 1. Introduction

We envision an environment considered by Dey (2006), where consumers use lines of credit as payment instruments and to smooth consumption across states and time periods within a complete market framework. Given the interest rates, insurance premiums, discount factors, wealth and the wealth shocks, all consumers in this model know when and how much to borrow in all the states of the world. Some consumers decide not to borrow at all times and in all states (savers and/or convenience users.[1]) A portion of consumers decide to borrow a fixed amount in all states and at some time in their life-cycle (pure intertemporal borrowing.) Finally, some consumers have state-contingent borrowing behavior. Based on observed customer borrowing patterns and primarily lacking (or not utilizing) information on customer wealth, banks can only generate a borrowing distribution of every consumer belonging to a risk class.[2] Banks are forced to treat the borrowing of a consumer in a risk class as a random variable because lacking (or not utilizing) mainly the customer wealth information, all variations in customer borrowing patterns are indistinguishable for them from the variations caused by the realizations of the wealth shocks alone. This borrowing uncertainty, which is unique to lines of credit, can make the market incomplete and create ex post misallocations. Using data from the U.S. *Survey of Consumer Finances*, we propose an empirical solution to this misallocation problem, making banks better select and retain their customers by enabling them to device better contracts.

Publicly available information about borrowers' creditworthiness helps banks sort their client pool into broad risk classes by way of their credit scoring systems. Banks do not, however, have perfect knowledge about individual borrower risk-type. Even if they did, in the case of lines of credit, such as credit cards, banks face a new source of uncertainty, i.e., they do not know how much a borrower will actually borrow on the line—a key determinant of the borrower's repayment probability. Profit-maximizing banks choose to provide exactly the amount of credit to their borrowers that maximize their expected profits. Facing the borrowing uncertainty, banks tend to offer every risk class a credit limit and charge an interest rate based on full exposure. Banks may also

[1] These are consumers who use lines of credit for transactions purposes alone.
[2] The environment considered here is of information asymmetry because clearly for the case of the first two sets of consumers, the banks have inferior information set.

prefer to ration out some less creditworthy consumers. However, individuals who are rationed out of the credit card market could very well turn out to have ex post higher repayment probabilities than some credit card holders who borrow large fractions of their credit limits. Similar misallocations may exist within the credit card holders as well. Thus, not only can borrowing uncertainty in the credit card market make the market incomplete (existence of credit rationing), but it can also result in ex post misallocations. Our modeling setup also explains how new information on borrowing patterns will generate revisions of existing contracts (changes in credit limits and/or interest rates) and counter offers (such as balance transfer offers) from competing banks.

Even if standard theory tells them that credit card borrowings are functions of borrowers' wealth, banks typically do not have (or do not use) that information for their customers (except for income, which is self-reported and often unreliable). Lacking mainly the consumer wealth information, banks are unable to explain some systematic variations of their customer borrowing patterns and hence treating borrowing as a pure random variable seems like the only reasonable alternative for them. But, here comes the use of external surveys such as the US *Survey of Consumer Finances*. Just as banks use the publicly available credit bureau information to generate credit scores of their customers, they may find the available and yet unused consumer wealth information in the US *Survey of Consumer Finances* to be quite helpful in explaining customer borrowing patterns and thus improving their credit supply decisions. The empirical contracting scheme goes as follows – first, explain the observed borrowing patterns based on available and yet unused consumer wealth information; second, use the estimated borrowings to generate the corresponding interest rates (inverse demand functions); finally, use the interest rates to determine the borrowing limits (credit-supply functions).

A typical credit card contract is two-dimensional.[3] Banks offer a rate of interest along with a pre-set borrowing limit to their potential borrowers. Borrowers then decide on how much of that credit to utilize at the offered rate of interest. The two-dimensional nature of the loan contracts makes credit card interest rates endogenous. Empirical identification of the determinants of credit card borrowing limits requires us to correct for

[3] Although, the non-price terms of credit contracts were always important in corporate lines of credit and are becoming increasingly important in consumers lines of credit, here we choose to focus on a two-dimensional contract (limit and price) only. See Strahan (1999) and Agarwal *et al.* (2006) for a discussion.

this endogeneity. Moreover, not all individuals are given credit cards by the banks. The set of credit card holders is a selected sample and therefore our estimation needs to account for this sample selection bias as well. We find that wealthier consumers borrow less on credit cards. Our estimation also reveals how the credit card interest rates are positively affected by the credit card balances carried by households. Controlling for risk, if banks *exogenously* charge lower rates for their credit (in response to lower balances of wealthier customers), they should be induced to extend less credit as well. Hence, we find evidence for a positively-sloped optimal credit supply function, as expected. We also find a positive relationship between the proxies of borrower quality and the borrowing limits on credit cards. In section 2, we describe the background and previous research on these issues. In section 3, we introduce the theoretical model. The data are described and the econometric model built in sections 4 and 5, respectively. Section 6 describes the empirical results and section 7 offers some conclusions.

**2. Background**

Beginning with Ausubel (1991, 1999), researchers have examined consumer lines of credit, especially with regards to credit cards. The bulk of the literature on credit cards concentrates on explaining why the average credit card interest rates remain sticky at a high level. Ausubel (1991) argues that the reason for the downward rigidity of credit card interest rates and supernormal profits is the failure of competition in the credit card market. He partly attributes this failure to myopic consumers who do not foresee indebtedness and interest payments on their outstanding balances. Ausubel (1999) finds empirical evidence of adverse selection and a lack of foresight among consumers regarding their credit card indebtedness. Brito and Hartley (1995), however, argue that consumers carry high-interest credit card debt not because of myopia, but because low-interest bank loans involve transactions costs. Mester's (1994) view is that low-risk borrowers who have access to low-interest collateralized loans leave the credit card market. This makes the average client pool of the credit card market riskier, thereby preventing interest rates from going down. Park (1997) shows the option-value nature of credit cards in order to explain their price stickiness. He argues that the interest rate that produces zero profit for credit card issuers is higher than the interest rates on most other loans, because rational credit card holders borrow more money when they become riskier. An empirical paper by Calem and Mester (1995) finds evidence that consumers are reluctant to search for lower rates because of high search costs in this market. Cargill and Wendel (1996) suggest 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. Kerr (2002) focuses on interest rate dispersion within the credit card market. He studies a two-fold information asymmetry: one between the banks (i.e., the lenders) and the borrowers, and the other within the banks themselves. Some banks (the external banks) have access to only the publicly available credit histories, while others (the home banks) have additional access to borrowers' private financial accounts. Kerr argues that, in equilibrium, the average rate of interest charged by the so-called external banks would be higher than that charged by the home banks, because the average borrower associated with the external banks would be riskier.

Even though credit card contracts are essentially two-dimensional, researchers in the earlier literature primarily focused on only the pricing aspect of those contracts. Gross and Souleles (2002) broke that trend by utilizing a unique new dataset on 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).[4] Gross and Souleles also find evidence of significant interest-elasticity of credit card debt within their sample. Dunn and Kim (2002) argue 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 a larger number of cards. Though they find some empirical support for their hypothesis on credit limits, Dunn and Kim choose to focus their formal empirical analysis on an estimation of credit card default rates. Castronova and Hagstrom (2004) find that the action in the credit market is mostly in the limits and not in the balances. Finally, a recent paper by Musto and Souleles (2005) shows how the amount of credit received by consumers significantly increases with their credit scores.

[4] Laibson *et al.* (2000) have been very influential in renewing interest of economic researchers in solving consumption puzzles that existing theories have failed to reconcile.

In this paper, we build a simple theoretical model that captures the key elements of credit card contracts. We show how banks, facing borrowing uncertainty, tend to offer consumers with different risk profiles different credit limits and charge interest rates based on full exposure, potentially resulting in market incompleteness and ex post misallocations. Our setup also explains how new information on borrowing patterns will generate revisions of existing contracts and counter offers (such as balance transfer offers) from competing banks. We show how banks may find the available and yet unused consumer wealth information in the US *Survey of Consumer Finances* to be quite helpful in explaining customer borrowing patterns and thus improving their credit supply decisions.

## 3. A Theoretical Model

Consider a model where 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 an interest rate. The borrower can borrow up to the credit limit. Interest charges accrue only if some positive amount is borrowed on the line. A line of credit contract incorporates the traditional fixed-loan contract as a special case when the entire credit limit is borrowed at the very outset. Banks are assumed to procure funds at a rate $r_F$. Based on publicly available credit reports, banks are able to partition their clients into broad risk classes. Let us assume that these classes, represented by $i$, are such that $i \in [\underline{i}, \bar{i}]$. The variable $i$ can be considered the credit score that credit bureaus construct for all potential borrowers. Let us also assume for simplicity that there is only one borrower in every risk class, $i$.[5] A typical credit card contract offered to class $i$ consists of a vector ($L_i$, $r_i$), where $L_i$ is the credit limit and $r_i$ is the interest rate. Using the framework put forward by Dey (2006), we argue that borrowers use lines of credit as payment instruments and to smooth consumption across states and time periods within a complete market framework. Given the interest rates, insurance premiums, discount factors, wealth and the wealth shocks, consumers in this model know when and how much to borrow in all the states of the

[5] We therefore assume that banks offer the same contract to all individuals within a particular risk class (with the same credit score), despite the potential heterogeneity in their repayment abilities.

world. Some consumers decide not to borrow at all times and in all states (savers and/or convenience users.) A portion of consumers decide to borrow a fixed amount in all states and at some time in their life-cycle (pure intertemporal borrowing.) Finally, some consumers have state-contingent borrowing behavior. Based on observed customer borrowing patterns and lacking (or not utilizing) information on customer wealth, banks can only generate a borrowing distribution of every consumer belonging to a risk class. Banks are forced to treat the borrowing of a consumer in a risk class as a random variable because lacking (or not utilizing) mainly the customer wealth information, all variations in customer borrowing patterns are indistinguishable for them from the variations caused by the realizations of the wealth shocks alone. The environment considered here is of information asymmetry because clearly for the case of the first two sets of consumers, the banks have inferior information set. Moreover, the consumers with credit cards in Dey's model are not liquidity-constrained.[6] Hence for the banks in the credit card market, this framework essentially makes borrowing on credit cards for risk class *i* become a random variable – functions of the index *i*, interest rate, insurance premium, discount factor, wealth[7], and wealth shock. Let $P_i$ denote the insurance premium, $\delta_i$ denote the discount factor, $W_i$ denote the wealth and $\theta_i$ represent the wealth shock that borrower *i* faces, such that we have the credit card borrowing as $B_i = B(r_i; i, P_i, \delta_i, W_i, \theta_i); \theta_i \sim G(\theta_i)$, where $\theta_i \in (-\infty, \infty)$. We can write $B_i \sim F(B_i)$, $F'(B_i) = f(B_i)$, where $B_i \in (-\infty, \infty)$. Moreover, $\theta_i$'s are assumed to be independent of each other (and so are $B_i$'s). Using the optimal borrowing function, we can derive an inverse demand curve for borrower *i* as $r_i = r(B_i; i, P_i, \delta_i, W_i, \theta_i)$. The repayment probability for a borrower increases with the risk class measure, *i*, and decreases with the amount owed, $D_i$, where $D_i = R_i B_i$ and $R_i = (1 + r_i) = R(B_i; i, P_i, \delta_i, W_i, \theta_i)$.[8] We represent the class *i* repayment probability as $\rho_i = \rho(D_i, i)$, such that $\frac{\partial \rho(.)}{\partial D_i} < 0$, $\frac{\partial \rho(.)}{\partial i} > 0$, and $\rho_i \in [0,1]$. The only uncertainty that

[6] Average credit card borrowing is usually well below the average credit limit; see Table 3 for empirical evidence based on the US *Survey of Consumer Finance*, 1998. Although a portion of this unused line could be explained by the typical household's use of credit cards for precautionary purposes, it is unlikely to account for the entire gap.
[7] Wealth includes net worth (difference between gross assets and liabilities), household size and income.
[8] Similarly, $R_F = (1 + r_F)$.

banks have about borrowers' repayment probabilities arises from their inability to know the actual borrowings to be undertaken on the lines they extend. In the following section, we consider a typical bank's profit-maximization problem where it is offering an unsecured line of credit, such as a credit card.

### 3.1 A bank's profit-maximization problem

The expected profit from offering an unsecured 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:

$$\underset{L_i}{Max}\,\pi^i = \int_{-\infty}^{L_i} [\rho(R(B_i;i,P_i,\delta_i,W_i,\theta_i)B_i,i)R(B_i;i,P_i,\delta_i,W_i,\theta_i) - R_F]B_i f(B_i)dB_i +$$

$$\int_{L_i}^{\infty} [\rho(R(L_i;i,P_i,\delta_i,W_i,\theta_i)L_i,i)R(L_i;i,P_i,\delta_i,W_i,\theta_i) - R_F]L_i f(B_i)dB_i$$

$$= \int_{-\infty}^{L_i} [\rho(R(B_i;i,P_i,\delta_i,W_i,\theta_i)B_i,i)R(B_i;i,P_i,\delta_i,W_i,\theta_i) - R_F]B_i f(B_i)dB_i +$$

$$[1-F(L_i)][\rho(R(L_i;i,P_i,\delta_i,W_i,\theta_i)L_i,i)R(L_i;i,P_i,\delta_i,W_i,\theta_i) - R_F]L_i.$$

Let us assume that $\pi^i{}_{L_iL_i} < 0$.

Partially differentiating $\pi^i$ with respect to $L_i$ and setting it to zero, we get,

$$\pi^i_{L_i}\Big|_{L_i^*} = [\rho(.)|_{L_i^*} R(L_i^*;.) - R_F]L_i^* f(L_i^*) +$$

$$[1-F(L_i^*)][L_i^*\{R(L_i^*;.)\frac{\partial\rho(.)}{\partial D_i}\bigg|_{L_i^*}(R(L_i^*;.) + R'(L_i^*;.)L_i^*) + \rho(.)|_{L_i^*} R'(L_i^*;.)\} +$$

$$\rho(.)|_{L_i^*} R(L_i^*;.) - R_F] - [\rho(.)|_{L_i^*} R(L_i^*;.) - R_F]L_i^* f(L_i^*) = 0,$$

or,

$$\pi^i_{L_i}\Big|_{L_i^*} =$$

$$[1-F(L_i^*)][L_i^*\{R(L_i^*;.)\frac{\partial\rho(.)}{\partial D_i}\bigg|_{L_i^*}(R(L_i^*;.) + R'(L_i^*;.)L_i^*) + \rho(.)|_{L_i^*} R'(L_i^*;.)\} +$$

$$\rho(.)|_{L_i^*} R(L_i^*;.) - R_F] = 0. \qquad (1)$$

***Proposition*:**

(i) Banks choose $L_i^*$ and $r_i^* = r(L_i^*; i, P_i, \delta_i, W_i, \theta_i, r_F)$,[9] such that $\pi_{L_i}^i(L_i^*, r_i^*) = 0 = \pi^i(L_i^*, r_i^*)$. For all risk classes yielding $\pi^i(L_i^*, r_i^*) < 0$, the banks choose $L_i^* \leq 0$.

(ii) For all banks, maximizing the total expected profit over all risk classes is equivalent to integrating over all risk classes the maximized expected profit of every risk class.[10]

The optimal credit card contract offered to borrower *i*, given by the pair $(L_i^*, r_i^*)$, is chosen such that, if $L_i^*$ is actually borrowed at price $r_i^* = r(L_i^*; i, P_i, \delta_i, W_i, \theta_i, r_F)$, our bank's profit maximization and zero-profit conditions are simultaneously satisfied for the risk class that borrower *i* represents. We find how banks, facing borrowing uncertainty, tend to offer consumers with different risk profiles different credit limits and charge interest rates based on full exposure. Banks may also deny credit to some risk classes who yield negative expected profits. However, individuals who are rationed out of the credit card market could very well turn out to have ex post higher repayment probabilities than some credit card holders who borrow large fractions of their credit limits. Similar misallocations may exist within the credit card holders as well. The question that naturally follows is that can banks do better. Banks through their credit card lending business gather information on the borrowing patterns of their existing customers. This new information helps them revise their existing credit contracts (through changes in credit limits and/or interest rates). Information on observed borrowing pattern also generates counter offers (such as balance transfer offers) from competing banks.

The question that remains is that can the borrowing information of their customers be used to better design their credit contracts and reduce the possibility of the ex post misallocations. The answer is no unless they find ways to explain the observed borrowing patterns of their customers. If the credit card borrowings were solely due to realizations of wealth shocks, then there would have been no way to explain the observed

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[9] Banks' choice of optimal interest rates based on the assumption of full exposure may also provide an explanation for these rates being so high on average.

[10] This follows from the fact that wealth shocks, $\theta_i$'s, (and therefore actual borrowings, $B_i$'s,) are independent of each other and banks are forced to make zero expected profits in every risk class.

borrowing patterns of consumers. However, significant portions of credit card borrowings among consumers are purely due to intertemporal consumption smoothing. Information about consumers' wealth is crucial in explaining these sorts of borrowing patterns. Even if standard theory tells them that credit card borrowings are functions of borrowers' wealth ($W_i$), banks typically do not have (or do not utilize) that information for their customers (except for income, which is self-reported and often unreliable). Although available demographic variables provide banks some measure of the discount factors of their customers, they possess no knowledge of the insurance premiums either. Lacking mainly the consumer wealth information, banks are unable to explain some systematic variations of their customer borrowing patterns and hence treating borrowing as a pure random variable and offering the contract $(L_i^*, r_i^*)$ seems like the only reasonable alternative. But, here comes the use of external surveys such as the US *Survey of Consumer Finances*. Just as banks use the publicly available credit bureau information to generate credit scores of their customers, they may find the available and yet unused consumer wealth information in the US *Survey of Consumer Finances* to be quite helpful in improving their credit supply decisions. Below we put forward an empirical contracting scheme. Our empirical results are solely based on the US *Survey of Consumer Finances* data; however, banks may wish to customize their empirical contracting schemes by exploiting their own customer information and the information present in the US *Survey of Consumer Finances* data.[11]

Step 0: Estimate the selection criterion of credit card holders as a function of exogenous variables.

Step 1: Estimate the observed credit card borrowing as a function of exogenous variables:

$$D_i^{**} = D^{**}(W_i, i, \delta_i, \theta_i, r_F). \tag{2}$$

Step 2: Estimate the inverse demand function of observed credit card borrowing:

$$r_i^{**} = r(D_i^{**}; i, \delta_i, \theta_i, r_F). \tag{3}$$

[11] Large commercial banks often fail to fully integrate all the information they have on their customers primarily due to a lack of communication among the various business lines under their umbrella. The empirical scheme suggested in this paper can lead to improvements in their decision-making process if they just manage to utilize the information they already possess even without relying on outside surveys such as the US *Survey of Consumer Finances*.

Step 3: Estimate the credit card borrowing limit function:

$$L_i^{**} = L(r_i^{**}; i, \delta_i, \theta_i, r_F). \tag{4}$$

## 4. Data

The data used in this study are from the 1998 U.S. *Survey of Consumer Finances* (SCF). SCF is a nationwide survey conducted by the National Opinion Research Center and the U.S. Federal Reserve Board. The 1998 SCF provides a large and rich dataset on household assets, liabilities, demographic characteristics, and a number of variables that capture household attitudes. In 1998, 4,305 households were surveyed and 3,233 of them had at least one bank-type credit card, which amounts to 75.1 per cent of the total number of households in the sample.

**Table 1: Definition of Variables**

| Variables | Type | Explanation |
|---|---|---|
| LOGNETWORTH | Continuous | Logarithm of the difference between gross assets and liabilities |
| DELINQUENCY | Binary | 1 – Got behind in payments by two months or more<br>0 – Otherwise |
| BANKRUPTCY | Binary | 1 – Declared bankruptcy<br>0 – Otherwise |
| CREDITRATE | Continuous | Credit card interest rate – rate on the credit card with the largest balance or on the one most recently used |
| LOGCLIMIT | Continuous | Logarithm of credit card borrowing limit |
| LOGINCOME | Continuous | Logarithm of income |
| HOUSEHOLDSIZE | Continuous | Household size |
| AGE | Continuous | Age of the household |
| NOTWORKING | Binary | 1 – Not working<br>0 – Otherwise |
| RETIRED | Binary | 1 – Retired<br>0 – Otherwise |
| REGULAREMP | Binary | 1 – Working and not self-employed<br>0 – Otherwise |
| SELFEMPLOYED | Binary | 1 – Working and self-employed<br>0 – Otherwise |
| LOGCREDITDEBT | Continuous | Logarithm of credit card balances |

Table 1 defines the variables used in our econometric analyses. Table 2 compares the mean characteristics of consumers with credit cards against those without and Table 3 shows the pattern of credit card utilization rates and a comparison of the average credit card balance and borrowing limit.

**Table 2: Credit Card Holders and Non-Holders**[12]

| Variables | Credit card Holders | Credit card Non-holders |
|---|---|---|
| | Mean | Mean |
| LOGNETWORTH | 12.3 | 7.9 |
| HOUSEHOLDSIZE | 2.7 | 2.6 |
| DELINQUENCY | 0.03 | 0.1 |
| BANKRUPTCY | 0.06 | 0.1 |
| LOGINCOME | 11.4 | 9.4 |
| NOTWORKING | 0.06 | 0.3 |
| RETIRED | 0.2 | 0.2 |
| SELFEMPLOYED | 0.3 | 0.1 |
| AGE | 50.8 | 47.0 |
| CREDITRATE | 14.5 | - |
| LOGCLIMIT | 9.5 | - |
| LOGCREDITDEBT | 3.04 | - |

**Table 3: Credit Card Utilization Rates**

| Utilization Rate | Number of Households | % of Credit Card Holders |
|---|---|---|
| Utilization Rate < 1 | 3170 | 98.1% |
| Utilization Rate ≥ 1 | 63 | 1.9% |
| Variable | Mean | Median |
| LOGCREDITDEBT | 3.04 | 0 |
| LOGCLIMIT | 9.5 | 9.6 |

[12] Table 1 defines the variables used in all the tables of all subsequent sections.

## 5. The Econometric Model

Household $i$ now represents the risk class (or borrower) $i$. According to Step 3 of our empirical contracting scheme described above, we have the credit card borrowing limit function as $L_i^{**} = L(r_i^{**}; i, \delta_i, \theta_i, r_F)$.

The variable $r_F$ has no variation across households as all banks in the credit card market are assumed have access to a common funds market. The vector $X_{1i}$ contains all information available in credit reports on household $i$ that banks use to define their risk measure $i$ and the discount factor $\delta_i$. The vector $X_{1i}$ also contains information that banks gather while processing their credit card applications, such as income. Table 4 provides a complete list of variables included in an individual credit report. We postulate a linear structural-form equation for $L_i^{**}$ as

$$L_i^{**} = \gamma r_i^{**} + \beta_1' X_{1i} + v_{1i}. \tag{5}$$

In equation (5), the banks' opportunity cost of funds, $r_F$, contributes to the constant term, and the wealth shock that influences a household's borrowing level ($\theta_i$) goes into the error term, $v_{1i}$.

Since the choice of the credit card interest rate (according to Step 2 of our empirical contracting scheme) is given by $r_i^{**} = r(D_i^{**}; i, \delta_i, \theta_i, r_F)$, the linear structural-form equation for $r_i^{**}$ is given by

$$r_i^{**} = \alpha D_i^{**} + \beta_2' X_{1i} + v_{2i}. \tag{6}$$

Also in equation (6), the variable $r_F$ contributes to the constant term and the wealth shock ($\theta_i$) goes into the error term, $v_{2i}$.

Following Step 1 of our empirical contracting scheme, we use the expression of the observed credit card borrowing, $D_i^{**} = D^{**}(W_i, i, \delta_i, \theta_i, r_F)$, to postulate the following linear reduced-form equation:

$$D_i^{**} = \beta_3' X_{3i} + v_{3i}. \tag{7}$$

Similarly, $r_F$ contributes to the constant term and the wealth shock ($\theta_i$) goes into the error term, $v_{3i}$. The vector $X_{3i}$ contains all variables included in vector $X_{1i}$ and the information on household's size and net-worth.

**Table 4: Credit Report Details**

| | |
|---|---|
| Personal information | • Name<br>• Current and previous address<br>• Social security number<br>• Telephone number<br>• Date of birth<br>• Current and previous employers |
| Credit History | Type of accounts:<br>1. Retail credit cards<br>2. Bank loans<br>3. Finance company loans<br>4. Mortgages<br>5. Bank credit cards<br><br>Information available:<br>1. Account number<br>2. Creditor's name<br>3. Amount borrowed<br>4. Amount owed<br>5. Credit limit<br>6. Dates when accounts were opened, updated, or closed<br>7. Timeliness of payments<br>8. Late payments |
| Public records | ▪ Tax liens<br>▪ Bankruptcies<br>▪ Court judgments |
| Inquiries | List of all parties who have requested a copy of your credit report |

Source: TransUnion

The combination $(L_i^{**}, r_i^{**}, D_i^{**})$ is observed if the household possess a credit card, i.e., if we have $L_i^{**} > 0$. Let us therefore consider the following econometric model:

$$\left.\begin{aligned} L_i &= L_i^{**} = \gamma r_i^{**} + \beta_1^{'} X_{1i} + v_{1i} \\ r_i &= r_i^{**} = \alpha D_i^{**} + \beta_2^{'} X_{1i} + v_{2i} \\ D_i &= D_i^{**} = \beta_3^{'} X_{3i} + v_{3i} \end{aligned}\right\} \qquad \text{if } L_i^{**} > 0 \text{, and}$$

$$\left.\begin{aligned} L_i &= 0 \\ r_i &= 0 \\ D_i &= 0 \end{aligned}\right\} \qquad \text{otherwise.}$$

In the equations above, $L_i$, $r_i$ and $D_i$ represent the observed credit card borrowing limit, interest rate and borrowing, respectively; $X_{1i}$ and $X_{3i}$ are vectors of exogenous variables; $v_{1i}$, $v_{2i}$ and $v_{3i}$ follow trivariate normal with means zero, variances $\sigma_1^2$, $\sigma_2^2$ and $\sigma_3^2$, respectively, and with covariances $\sigma_{12}$, $\sigma_{23}$ and $\sigma_{13}$. If $X_{3i}$ contains at least one variable that is not included in $X_{1i}$, then all the parameters of the model are identified. Since $X_{3i}$ has variables such as net-worth and household size that are not present in $X_{1i}$, we have satisfied the identifying restriction of our econometric model.

The parameters of the econometric model are estimated using the two-stage probit method described by Lee, Maddala, and Trost (1980). This two-step procedure yields consistent estimates of all the parameters of the model. Let us first define a dummy variable, $I_i$, such that,

$I_i = 1$ if household $i$ has a credit card (i.e., $L_i^{**} > 0$)

$= 0$ otherwise.

We then estimate a probit model on the availability of credit card (Step 0). Next we estimate the credit card borrowing equation, correcting for the sample selection (Step 1). We use the estimated credit card balances as an instrument and estimate the structural equation explaining the credit card interest rate (Step 2). Finally, we use the estimated credit card interest rates as an instrument and estimate the credit card borrowing limit equation (Step 3).

## 6. Results and Discussion

Table 5 reports the results of a probit estimation that explains the availability of credit card for a typical household. Being self-employed, having a high income and net worth significantly improve the likelihood of getting a credit card. The size of the household, delinquency, bankruptcy, unemployment and age diminish the chance of obtaining a credit card. In general, the results indicate that the higher the household's creditworthiness, the greater their likelihood of obtaining a credit card.

Table 6 explains the estimation results of credit card borrowing. We find that among credit card holders, households with high net worth and income and those who are retired or self-employed are less induced to carry credit card balances. However, our results show that bigger-sized households who have an unemployed head with a history

**Table 5: Probit Model for Credit Card Availability**

| Variables | Coefficient | Standard error (S.E.) |
|---|---|---|
| CONSTANT | $-2.5^{***}$ | 0.2 |
| LOGNETWORTH | $0.1^{***}$ | 0.01 |
| HOUSEHOLDSIZE | $-0.05^{***}$ | 0.02 |
| DELINQUENCY | $-0.2^{*}$ | 0.1 |
| BANKRUPTCY | $-0.3^{***}$ | 0.1 |
| LOGINCOME | $0.3^{***}$ | 0.02 |
| NOTWORKING | $-0.5^{***}$ | 0.1 |
| RETIRED | -0.1 | 0.09 |
| SELFEMPLOYED | $0.3^{***}$ | 0.1 |
| AGE | $-0.005^{**}$ | 0.002 |

$^{***}$ Significant at 1 per cent; $^{**}$ significant at 5 per cent; $^{*}$ significant at 10 per cent.

**Table 6: Two-Stage Probit for Credit Card Debt**

| Variables | Two-stage probit | |
|---|---|---|
| | Coefficient | S.E. |
| CONSTANT | $16.5^{***}$ | 0.96 |
| LOGNETWORTH | $-0.4^{***}$ | 0.03 |
| HOUSEHOLDSIZE | $0.3^{***}$ | 0.1 |
| DELINQUENCY | $1.6^{***}$ | 0.4 |
| BANKRUPTCY | $1.5^{***}$ | 0.3 |
| LOGINCOME | $-0.6^{***}$ | 0.1 |
| NOTWORKING | $0.5^{*}$ | 0.3 |
| RETIRED | $-1.4^{***}$ | 0.2 |
| SELFEMPLOYED | $-0.5^{***}$ | 0.2 |
| AGE | -0.009 | 0.006 |
| SELECTION | $-3.9^{***}$ | 0.5 |
| | -LogL = -8407.7<br>$\sigma_3 = 3.97$<br>$N = 3233$ | |

$^{***}$ Significant at 1 per cent; $^{**}$ significant at 5 per cent; $^{*}$ significant at 10 per cent.

of delinquency or bankruptcy, carry bigger credit card debt. Hence we find that riskier households tend to carry larger credit card balances, although wealthier households borrow less. Moreover, from our results we may infer that the correction for sample selection does seem to matter significantly for our estimation.

**Table 7: Inverse Demand Function for Credit Card Debt**

| Variables | Two-stage probit | |
|---|---|---|
| | Coefficient | S.E. |
| CONSTANT | 9.97*** | 1.7 |
| DELINQUENCY | 1.7*** | 0.6 |
| BANKRUPTCY | 0.5 | 0.4 |
| LOGINCOME | 0.3** | 0.1 |
| NOTWORKING | -0.2 | 0.5 |
| RETIRED | 0.4 | 0.4 |
| SELFEMPLOYED | 0.1 | 0.3 |
| AGE | 0.015 | 0.01 |
| LOGCREDITDEBT | 0.1 | 0.1 |
| SELECTION | 1.4** | 0.6 |
| | -LogL = -9999.1<br>$\sigma_2$ = 5.4<br>$N$ = 3233 | |

*** Significant at 1 per cent; ** significant at 5 per cent; * significant at 10 per cent.

Table 7 presents the estimates of an inverse demand function of credit card balances. We find that a history of delinquency and a higher income do seem to indicate towards charging a typical household a higher credit card interest rate by the banks. The sign of the coefficient of households' income is a bit counter-intuitive, although the estimates for credit card borrowing limits later show that controlling for interest rates, a higher income should fetch a higher credit limit from the banks. We also find that if their customers *exogenously* tend to carry lower credit card balances (due to the presence of higher wealth levels), it should optimally induce (though not significantly) banks to lower their credit card rates. Again our results show that the correction for sample selection does seem to matter significantly for our estimation.

Finally, Table 8 shows the results for the structural equation estimation of the credit card borrowing limits. We see that higher income and age and being self-employed must optimally fetch a higher borrowing limit on credit cards. Moreover, households with a history of delinquency or bankruptcy should face stricter credit limits. Hence our results, in general, tend to support the fact that the higher the household's creditworthiness, the greater should be the offered borrowing limit on credit cards.

Controlling for risk, if banks *exogenously* charge lower rates for their credit (in response to lower balances of wealthier customers), they should be induced to extend less credit as well. Hence, we find evidence for a positively-sloped optimal credit supply function, as expected. Finally, we also find empirical support for sample selection in our credit limit estimates.

**Table 8: Estimates for Credit Limit Equation**

| Variables | Two-stage probit Coefficient | S.E. |
|---|---|---|
| CONSTANT | $4.2^{***}$ | 1.4 |
| DELINQUENCY | $-1.3^{***}$ | 0.3 |
| BANKRUPTCY | $-0.7^{***}$ | 0.2 |
| LOGINCOME | $0.1^{***}$ | 0.05 |
| NOTWORKING | 0.1 | 0.2 |
| RETIRED | -0.1 | 0.2 |
| SELFEMPLOYED | $0.3^{***}$ | 0.1 |
| AGE | $0.01^{*}$ | 0.004 |
| CREDITRATE | $0.2^{**}$ | 0.1 |
| SELECTION | $-0.8^{**}$ | 0.3 |
| | -LogL = -7291.6<br>$\sigma_1 = 2.4$<br>$N = 3233$ | |

$^{***}$ Significant at 1 per cent; $^{**}$ significant at 5 per cent; $^{*}$ significant at 10 per cent.

## 7. Conclusions

Line of credit contracts (such as credit card contracts) are fundamentally different from traditional fixed-loan contracts. In the credit card market, banks have to decide on the borrowing limits of their potential customers, when the amounts of borrowing to be incurred on these lines are uncertain. This borrowing uncertainty can make the market incomplete and create ex post misallocations. Households who are denied credit could well turn out to have ex post higher repayment probabilities than some credit card holders who borrow large portions of their borrowing limits. Similar misallocations may exist within the credit card holders as well. Our setup also explains how new information on borrowing patterns will generate revisions of existing contracts and counter offers (such as balance transfer offers) from competing banks. Using data from the U.S. *Survey of*

*Consumer Finances*, we propose an empirical solution to this misallocation problem. We show how this dataset can be used by banks to explain the observed borrowing patterns of their customers and how these borrowing estimates will help banks to better select and retain their customers by enabling them to device better contracts.

Even if standard theory tells them that credit card borrowings are functions of borrowers' wealth, banks typically do not have (or do not use) that information for their customers (except for income, which is self-reported and often unreliable). Lacking mainly the consumer wealth information, banks are unable to explain some systematic variations of their customer borrowing patterns and hence treating borrowing as a pure random variable seems like the only reasonable alternative for them. But, here comes the use of external surveys such as the US *Survey of Consumer Finances*. Just as banks use the publicly available credit bureau information to generate credit scores of their customers, they may find the available and yet unused consumer wealth information in the US *Survey of Consumer Finances* to be quite helpful in improving their credit supply decisions. The empirical contracting scheme goes as follows – first, explain the observed borrowing patterns based on available and yet unused consumer wealth information; second, use the estimated borrowings to generate the corresponding interest rates (inverse demand functions); finally, use the interest rates to determine the borrowing limits (credit-supply functions). Our estimation reveals that wealthier consumers borrow less on credit cards. We also find that the credit card interest rates are positively affected by the credit card balances carried by households. Controlling for risk, if banks *exogenously* charge lower rates for their credit (in response to lower balances of wealthier customers), they should be induced to extend less credit as well. Hence, we find evidence for a positively-sloped optimal credit supply function, as expected. We also find a positive relationship between the proxies of borrower quality and the borrowing limits on credit cards.

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