Do Banks Use Private Information from Consumer Accounts? Evidence of Relationship Lending in Credit Card Interest Rate Heterogeneity

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December, 2004

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Abstract

This paper looks at the importance of relationship lending in the credit card market. Credit bureaus are the major source of information for banks in their card approval and pricing processes. They collect information primarily on the debt side of a consumer's portfolio rather than on a consumer's assets. However, the latter private information is available to a "home bank" with which the consumer has other financial dealings. We test whether home banks are using this private information to make lower interest offers to their own customers who are good credit risks. An endogenous switching regression model incorporating the self-selection of consumers to use a home bank card versus an external bank card is used. The results show that home banks are able to make lower interest offers to their internal customers whose default risks are lower, and this has contributed to interest rate heterogeneity in the credit card market. In addition, we test whether home banks are able to extract information monopoly rents from the low credit risks, but find no evidence of rents in this market.

Keywords: Credit cards, Relationship lending, Information asymmetry, Interest rates, Default heterogeneity

JEL classification: D12, D82, G21, C34

1. Introduction

The rapid growth of the credit card industry in the last decade has attracted considerable attention among researchers and policy-makers. An especially notable phenomenon in this market is the fact that interest rates have become much more dispersed in recent years and since the late 1990s have ranged from 9 to 24 percent. This dispersion of rates is largely due to banks' greater use of risk-based pricing which reflects the creditworthiness of different consumers. One critical type of information used in this process comes from credit bureaus and is available to all banks. However, much valuable information about creditworthiness is not available in credit bureaus. The current paper examines the issue of whether banks' private information arising from *relationship lending* with their own customers is also used in addition to the publicly available credit bureau information to assess default heterogeneity of borrowers. We find that relationship lending does play an important role in assessing default heterogeneity and leads to heterogeneous pricing in the credit card market beyond what could be expected to arise from the use of credit bureau information.

We refer to the bank with which a consumer has other financial dealings as the *home bank* (HB), while the bank with only credit bureau information for that consumer is referred to as the *external bank* (EB). We model interest rate competition among banks by incorporating this information asymmetry between sellers. The predictions of our model are tested with a structural econometric model that takes account of the endogenous decision of the consumer to choose between credit cards. We find that HBs are able to select a pool of the more creditworthy by offering lower interest rates. We also find evidence of a winner's curse for banks that do not have this private information advantage.

2. Background

Much of the previous research on the credit card market focused on the phenomena of high and sticky rates prevalent in the 1980s. One line of literature attributes these phenomena to the failure of interest rate competition due to consumer insensitivity to interest rates (Ausubel, 1991) and lack of search (Calem and Mester, 1995). Brito and Hartley (1995), while retaining the assumptions of consumer rationality and competition among banks, introduced transaction costs on alternative forms of borrowing as an explanation for the high average interest rates on credit cards. Beginning in the mid-1990s, interest rates in this market started to decline and have shown much variability as price competition has increased. Reasons for this increased competition include greater consumer sensitivity to credit card interest rates (Gross and Souleles, 2001) and more interest-rate search by debt-carrying credit card users (Kerr and Dunn, 2002; Kim, Dunn, and Mumy, 2004). Gross and Souleles find that credit card debt has become increasingly interest elastic, with approximately half of the effect resulting from balance switching.

Another notable feature of the late 1990s credit card market was a wide dispersion of interest rates, ranging from low introductory offers of zero percent up to rates well over 20 percent. Information from credit bureaus[1] has been one of the major factors for this dispersion since it allows banks to distinguish default heterogeneity among consumers and leads to separating equilibria in interest rates. In this context, the current paper differentiates between "public information" (i.e., credit bureau information on consumers' credit histories) available to all credit card issuers and "private information" (i.e., consumers' income and expenditure cycles, checking or savings account balances, net worth, etc.) available only to banks involved in

[1] In conducting pre-approved solicitations, credit card issuers have broad access to detailed credit bureau information about the entire pool of individuals being solicited, non-respondents as well as respondents.

additional relationships with their credit card holders. Specifically, we test whether banks use private information to assess default heterogeneity of borrowers and select a more credit-worthy client pool by offering them lower rates in equilibrium.

The benefit of private information in lending has been an active area of research in corporate finance. However, this literature has, to our knowledge, focused only on commercial lending and has not been explored for consumer banking. Theoretical aspects of relationship lending were developed by Sharpe (1990), Peterson and Rajan (1995), and Boot and Thakor (1994). The first strand of empirical literature in the area sought to address the question of whether bank-borrower relationships over time are value-enhancing for the borrowing firm (Lummer and McConell, 1989, and Wansley, DeGannaro, Elayan and Collins, 1992). These authors find evidence that the renewal of existing "bank lines of credit" induces positive returns on the borrowing firm's stock. According to these papers, credit renewal by a bank, which is a repository of private information on the firm, is regarded as a positive signal by the market.

A second line of this literature has looked directly at the duration of the bank-borrower relationship (Peterson and Rajan, 1994, and Berger and Udell, 1995). These studies are unanimous in their findings that longer relationships result in greater availability of credit and lower required collateral for firms. Berger and Udell also show that borrowers with longer relationships pay lower interest rates. Recently, using data from an anonymous Canadian bank, Mester, Nakamura, and Renault (2002) have documented the propagation of private information within a bank, focusing on commercial lines of credit.

The earlier work on relationship banking was not only confined to commercial banking, but was also based on reduced form model estimation. Hence it was not able to capture the endogenous selection of agents, i.e., the borrowers. This is a significant point because the choice made by the borrower between an insider bank and an external *de novo* lender depends crucially on the terms of the offers. The terms of the contracts, in turn, are based on the information sets available to the two types of lenders. The structural form estimation used in the current paper, incorporating the endogenous selection of the consumer based on relative offers, allows us to identify the specific channels through which private information is generated, and how banks use this information to determine contract terms in consumer lending. None of the earlier work has empirically modeled these aspects of relationship lending.

For our purposes, HBs are those credit card banks that have multiple relationships with consumers through additional checking, savings, or money-market accounts, etc. The provision of such financial services by HBs expands their information set with data from the assets side of the consumers' portfolio such as liquid assets, net worth, and the volatility of the income cycle (regularity in checking cycles, direct deposit accounts, etc.). This information helps them to assess a consumer's repayment probability and should then be reflected in the interest rates offered by HBs to their customers. On the other hand, EBs, where the consumer merely holds credit card accounts, will not be privy to this information, leading to an information asymmetry between sellers. The crux of these ideas dates back to Stiglitz and Weiss (1981), where adverse selection results in the external banks ending up with a client pool at the far right of the risk distribution—a problem prevented in the current case precisely because of the existence of some public information (credit bureaus).

Incorporating the information asymmetry arising from relationship lending into a framework of interest rate competition, our model shows that within each risk class based on public information, banks having additional private information are able to select the "good" credit risks by offering them lower rates in equilibrium. The model used in this paper is similar to the model of commercial lending used by Sharpe (1990) and von Thadden (2004). In Sharpe's model, low-risk firms are informationally captured and charged a rate that is above the "fair" rate because of a single insider and high costs of information revelation to a potential new lender. Von Thadden shows that the Nash equilibrium for Sharpe's model is a mixed-strategy equilibrium in which both inside and outside banks randomize their interest-rate offers. This results in only a partial informational capture by the inside bank and so allows for additional dispersion in rates.[2]

The assumption of a single insider is more likely to hold for commercial loan markets with collateralized debt and its associated transaction costs of borrowing.[3] In consumer lending, unlike commercial lending, there are few, if any, transaction costs that might prevent a consumer from holding multiple non-credit card financial accounts in more than one bank. This allows for more than one seller with private information on a customer, thus preventing an information monopoly. This, along with the assumption of Bertrand competition, results in HBs offering lower rates to the good credit risks. The assumption of multiple insiders is not essential, however, because the same outcome would occur if banks can acquire a reputation for offering lower rates to their good customers (or alternatively, make an actual commitment to do so), which would affect the consumer's initial choice of home bank.[4]

To test the predictions of the theoretical model, we use data from the 1998 *Survey of Consumer Finances*. We employ an endogenous switching regression model similar to the "union membership model" of Lee (1978) to capture the aspect of self-selection by consumers into two categories—those who have their primary credit card with their HB and those who have

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[2] The solution given by Sharpe (1990) also predicts limited informational capture and dispersion of rates but is not a Nash equilibrium (von Thadden, 2004).
[3] In commercial lending, because of multiple claims in the event of firm bankruptcy, ex-ante contracts need to be written, which increases the associated transaction costs of borrowing.
[4] Sharpe's model, on the other hand, explicitly rules out any kind of multi-period commitment by the bank.

their primary card with an EB. In our econometric model, we assume that both banks make interest-rate offers to consumers based on signals received about individuals' creditworthiness. Individuals then select their primary card based on the interest rate, as well as on consumer-specific characteristics. Thus the complete model contains two interest rate offer equations, one by each type of bank, and a selection equation for the consumer. Both two-stage and maximum likelihood methods are used to estimate the empirical model. Our results provide strong evidence in favor of the information asymmetry hypothesis: private information enables HBs to select consumers with lower risks of default by offering them lower interest rates compared to the EBs, which have access only to public information.

The testable implications for the empirical study are derived in the next section from a theoretical model which incorporates the information asymmetry between banks. The data are described in Section 4. Section 5 discusses the econometric methodology used to test the propositions of our theoretical model. The results of the empirical tests are discussed in Section 6, and our conclusions are presented in Section 7.

3. Models of Interest Rate Competition

In this section, we model the nature of interest-rate competition among credit card issuers faced with different types of consumers. We assume there are numerous profit-maximizing banks in this market, competing on prices, i.e., interest rates, and no significant barriers to entry. The cost of funds to banks is fixed at $\bar{r}$, and interest is the only source of revenue. The line of credit extended is determined exogenously and is normalized to be $1.[5] A continuum of consumers is characterized by public information X_E that is available to all banks (e.g., from

[5] We exclude endogeneity in loan amounts and resulting credit rationing issues.

credit bureaus) and by private information X_H that is available only to the one or more HBs with whom the consumer has other financial dealings. The consumer's repayment probability is then $\theta = \theta(X_E, X_H)$.

Banks make credit-card offers to the consumer, with interest rates based on their available information. Although the consumer can hold multiple cards from more than one bank, the *primary* card that we focus on here is the one on which he/she keeps the largest outstanding balance. From a rational consumer's point of view, this card should have the lowest interest rate and can be held either with an EB or a HB. If the consumer receives equal offers (which can happen with positive probability if X_H is discrete), and one offer is from a HB, then the consumer selects the HB card with probability ρ; if there are equal offers from different EBs, then each has an equal probability of selection.

(a) First, suppose that all banks have only publicly available credit bureau information (or equivalently, that X_H is not informative about the repayment probability). Then competitive equilibrium leads to the zero-profit interest rate

$$r_0(X_E) = \frac{1+\bar{r}}{\theta_0(X_E)} - 1, \tag{1}$$

for consumers of type X_E, where θ_0 is the average repayment probability,

$$\theta_0(X_E) = E[\theta \mid X_E].$$

In this case, all banks make zero profit, and the distribution of interest rates does not depend on the type of bank.

(b) Next, suppose that the private information X_H takes on two discrete values, *h* and *l*, corresponding to high and low repayment probabilities, as in Sharpe (1990). The derivation of the equilibrium is the same for all X_E, so without loss we can condition on a specific value of the public information and suppress the argument X_E in the following discussion. Let $\lambda = \lambda(X_E)$ be the fraction of consumers of type *h*, with repayment probability $\theta_h = \theta(X_E, h)$, while the remaining fraction $1-\lambda$ are of type *l* with repayment probability $\theta_l = \theta(X_E, l)$, where $\theta_h > \theta_l$. Then

$$\theta_0 = \lambda\theta_h + (1-\lambda)\theta_l .$$

The benchmark interest rates r_h and r_l are defined as the respective zero profit interest rates for types *h* and *l*:

$$r_h = \frac{1+\bar{r}}{\theta_h} - 1, \qquad r_l = \frac{1+\bar{r}}{\theta_l} - 1. \tag{2}$$

As $\theta_h > \theta_0 > \theta_l$, this implies $r_h < r_0 < r_l$.

(b.1) First, suppose that each consumer has more than one HB, leading to the creation of multiple insiders and so eliminating any information monopoly.[6] The Nash equilibrium is the competitive outcome: HBs offer the interest rate r_h to their type *h* customers and r_l to their type *l* customers, while EBs offer the interest rate r_l indiscriminately and so attract only type *l* customers. All banks make zero profits. The fraction of consumers holding HB cards is $\lambda + \rho(1-\lambda)$, while the fraction holding EB cards is $(1-\rho)(1-\lambda)$. The corresponding average interest rates of the HBs, r_H, and the EBs, r_E, are

$$r_H = \frac{\lambda r_h + \rho(1-\lambda) r_l}{\lambda + \rho(1-\lambda)}, \qquad r_E = r_l ,$$

while the average repayment probabilities for HB and EB customers are

$$\bar{\theta}_H = \frac{\lambda\theta_h + \rho(1-\lambda)\theta_l}{\lambda + \rho(1-\lambda)}, \qquad \bar{\theta}_E = \theta_l .$$

[6] In the Survey of Consumer Finances sample, 31.6% of those using their HB cards have more than one financial account at commercial banks, savings and loans, or savings banks.

(b.2) An alternative situation is that of a single insider, again with two discrete values for the private information. This is essentially the same as Sharpe's model of information asymmetry in commercial lending (Sharpe, 1990). In the absence of reputational effects or multi-period commitments by banks, HBs can now extract some rent from their information monopoly. As shown by von Thadden (2004), the Nash equilibrium is a mixed-strategy equilibrium in which both HBs and EBs randomize offers and lend to a mix of types *h* and *l*. While the HBs still have a higher proportion of type-*h* borrowers than the EBs, the average interest rate of EB customers may or may not be higher that that of HB customers, depending on the parameter values of θ_l, θ_h, λ and ρ. The expected EB profit is zero, as before, while the expected profit of the HBs is positive. There is limited information capture in that the average expected HB profit per individual is $\lambda\theta_h(r_0 - r_h)$ rather than the full monopoly rent of $\lambda\theta_h(r_l - r_h)$.

(c) Instead of taking two discrete values, we can consider the case where $\theta(X_H)$ is uniformly distributed on the interval $[\theta_l, \theta_h]$. Comparing these two models may give some insight into the robustness of conclusions drawn from the mixed-strategy equilibrium outcome.

(c.1) The case of multiple insiders, HBs, with a continuous distribution for θ leads to the unrealistic conclusion that all EBs would, in effect, be forced out of the market in equilibrium, and so this case will not be considered here.

(c.2) In the information monopoly case, the HBs now pursue a pure strategy, offering each customer an interest rate determined by θ, while the EBs make randomized offers as in von Thadden (2004). As before, the expected profit is positive for HBs and zero for EBs. Details and further discussion of the mixed-strategy equilibrium outcomes in the information-monopoly cases (b.2) and (c.2) are given in Section A.1 in the appendix.

We can therefore draw the following conclusions and their testable implications. If HBs have private information about θ, then, conditional on X_E (public information):

(I) The HB offered interest rate should be decreasing with θ.

(II) The EB offered interest rate should not depend on θ.

These two conclusions yield the testable implication that the private information variables that predict repayment probabilities should affect the HB interest rates and not the EB interest rates.

(III) On average, the repayment probability θ will be higher for HB customers than for EB customers.

According to this prediction, the repayment probability of HB consumers will be higher (lower risks) compared to the EB consumers. Together with predictions (I) and (II), this implies that the average interest rate for HB consumers will be lower than the average rate for consumers using an EB card.

If, in addition, the private information gives HBs an information monopoly, allowing them to appropriate an information rent, then

(IV) HBs should make positive profits relative to EBs.

This implies that the actual interest rate charged by the HBs will be higher than the zero-profit rate (which can be estimated from the average default probability of HB customers and the cost of funds).

The randomization of offers will result in a winner's curse effect on the EBs where some type *l* individuals will select the EB card precisely because they receive lower rates from EBs than their own HBs. The magnitude of rent appropriated by the HBs from their type *h* customers and the winner's curse of the EBs are empirical questions that would depend on the extent of competition prevailing in this market. We test for both these effects and find (1) evidence of a winner's curse effect for the external banks but (2) no evidence of information rent.

4. Data and Descriptive Statistics

We use the 1998 *Survey of Consumer Finances* (SCF), which contains: (i) public information carried by credit bureaus (mortgages, home equity lines, credit card balances, delinquency, bankruptcy history, etc.); and (ii) private information on consumer income, liquid assets, and net worth—data which would be available only to a HB through other accounts and services provided to their customers.[7] These variables serve as proxies for the income and expenditure streams of each consumer, which in turn serve as proxies for default risk.

The SCF also maps the network of relationships that consumers have with financial institutions, allowing us to determine whether the primary credit card used belongs to a bank with which they have other financial dealings (HB). Following the SCF convention, the primary card is taken to be the one on which the consumer has the largest balance, while for zero-balance consumers it is the card applied for and received most recently. We use the interest rate on this primary card in all tests since, from a rational consumer's perspective, the card with the largest outstanding balance should be the one which offers the lowest interest rate among all cards held.[8]

Our study is confined to those individuals who have some form of bank credit card.[9] Among these we consider only those cases with interest rates above 6.5%. Any lower rate in the 1997-98 period was an introductory rate since the federal funds rate during this time was around

[7] While the private information variables in the SCF may not correspond exactly to the HBs' information set, we expect there to be a high degree of correlation. Furthermore, measurement error, if any, in the banks' private information will lead to an underestimation of its significance.
[8] For our consumer, the primary card is always the lowest interest card even when other benefits are associated with a card — for example, frequent flier miles. This is because those benefits are tied to usage of the card and not interest-paying debt on the card. Hence a rational card user should always shift outstanding balances to the lowest-interest card, regardless of other benefits that come with card use.
[9] Visa, MasterCard, Discover or American Express cards.

5.5%.[10] Our final sample contains 2,265 cases — 861 cases with HB primary cards and 1,401 with EB primary cards. Variable definitions and descriptive statistics are given in Table 1. We see there that consumers whose primary card is with an EB have lower net worth, less liquid assets, and are more prone to miss payments or declare bankruptcy than those whose primary card is with a HB. Thus a casual look at the data suggests that the average consumer who uses an EB card is on a weaker financial footing then the average consumer who uses a HB card. More importantly, the average interest rate of consumers with HB cards is one percentage point lower than the average rate of consumers with accounts held at EBs.[11]

To see how the interest rates offered vary across the home and external bank sample, we estimate the probability density function of the rates across these two bank types using a Gaussian kernel with a data-based bandwidth suggested by Silverman (1986). Figure 1 shows the distribution of rates across the two samples. The rates offered to consumers having a HB card are lower and have a bimodal density function with a roughly 5-point spread between modes. The distribution of rates clearly shows that the interest rates on the primary debt-carrying card of consumers are notably lower if the account is held with a HB than if it is held with an EB. This validates one of the testable implications that arise from our theoretical model.

5. Econometric Analysis

The econometric model is a three-equation system representing the HB interest rate offer, the EB interest rate offer, and the consumer's choice of the HB card or the EB card as the primary card. Since the focus here is on a comparison of HB and EB interest rates rather than on credit-card holding, we estimate the model for the population of individuals holding at least one

[10] It has been documented that credit card-backed securities offered yields in the vicinity of 1% above those of Treasury securities in this period. Hence the cost of funds for credit card issuers was at least 6.5%.
[11] This result also holds in an OLS regression after we control for all the consumer characteristics in Table 1.

bank credit card. As in the theoretical model of Section 3, we assume that both types of banks make interest rate offers to consumers based on signals they receive about individuals' creditworthiness. Individuals then select which card to use as their primary card based on which interest rate is lower, as well as other consumer-specific characteristics and non-price dimensions of the offers.[12] Because the SCF data contain interest-rate information only for the consumer's primary card, we therefore estimate the equation system as a partial-observability switching regression model.[13]

The structural equations for the interest rates offers are

$$r_{H,i} = X_{1,i}\beta_{11} + X_{2,i}\beta_{12} + u_{1,i} \tag{3a}$$

$$r_{E,i} = X_{1,i}\beta_{21} + X_{2,i}\beta_{22} + u_{2,i} \tag{3b}$$

where $r_{H,i}$ and $r_{E,i}$ are the lowest rates received by individual i from his/her HBs and EBs, and $X_{1,i}$ and $X_{2,i}$ are the vectors of consumer characteristics which signal creditworthiness based on public and private information respectively. The consumer selects the HB card if $r_{E,i} - r_{H,i} > \eta_i$ where η_i summarizes the preference for a card based on non-interest terms. It can be represented as

$$\eta_i = \delta_0 + \alpha_1 W_i + \alpha_2 C_i + v_i .$$

W_i is a vector of individual-specific characteristics (whether the cardholder is a convenience user, the cardholder's propensity to search for better credit terms, and ratio of average monthly payments on rents, mortgages, autos and leases to monthly income) that determine preference for a card, and C_i is a non-price dimension of the offer (credit line). In other words, if the consumer

[12] It is, of course, possible that some credit-card holders may not have received competing offers. We will treat this as equivalent to a competing offer with an interest-rate differential sufficiently high that the probability of choosing the competing card is negligibly small.
[13] This is similar to the union membership model of Lee (1978).

selects the HB card, it is because the HB interest rate is sufficiently lower than the EB rate to compensate for all other characteristics that determine the preference for a card. Substituting η_i into the above inequality allows us to represent consumer selection by the latent-variable equation

$$I_i^* = \delta_0 + \delta_1 (r_{E,i} - r_{H,i}) + \alpha_1 W_i + \alpha_2 C_i + v_i \tag{4}$$

where the HB card is chosen if $I_i^* > 0$.[14] The error terms $u_{1,i}$, $u_{2,i}$ and v_i are assumed to be jointly normally distributed with zero means and variances σ_1^2, σ_2^2, and σ_v^2.

Endogeneity arises from the fact that the interest rates, which are the dependent variables in the interest rate equations (3a) and (3b), also determine the choice by the individual in the selection equation (4). To deal with this endogeneity, we follow the procedure proposed by Lee (1978) where (3a) and (3b) are used to substitute for the interest differential in (4). This gives the reduced-form probit equation

$$I_i^* = Z_i \gamma + \varepsilon_i \tag{5}$$

where Z_i includes $X_{1,i}$, $X_{2,i}$, W_i and C_i, while ε_i is the composite error term $\delta_1 (u_{2,i} - u_{1,i}) + v_i$ rescaled so as to give the conventional normalization $\sigma_\varepsilon^2 = 1$. Thus the model to be estimated consists of the three equations (3a), (3b) and (5), with the observed dependent variables

$$I_i = \begin{cases} 1 \text{ when } I_i^* > 0 \\ 0 \text{ when } I_i^* \le 0 \end{cases}$$

and

[14] The coefficient δ_1 was introduced to allow for the conventional rescaling of the latent variable, I_i^*, in the probit model.

$$r_i = \begin{cases} r_{H,i} & \text{when } I_i^* > 0 \\ r_{E,i} & \text{when } I_i^* \le 0 \end{cases}$$

We estimate the model both by the two-stage method and by maximum likelihood. Details are given in Section A.2 in the appendix, and the results are reported below in Section 5. The magnitude of the self-selection effect is represented in the two-stage estimates by the covariance parameters $\sigma_{1,\varepsilon} = \mathrm{cov}(u_{1,i}, \varepsilon_i)$ and $\sigma_{2,\varepsilon} = \mathrm{cov}(u_{2,i}, \varepsilon_i)$, while the ML results give the corresponding correlation coefficients ρ_1 and ρ_2.

According to prediction (I) in Section 3, β_{12} should be significant, with negative coefficients for those variables known to the HB that signal lower risk, i.e., liquid assets, net worth, and the proxies corresponding to lower income volatility. On the other hand, according to prediction (II), β_{22} should not be significantly different from zero, since EBs do not possess the information represented by X_2.

Self-selection corresponds to a negative sign for $\sigma_{1\varepsilon}$ and a positive sign for $\sigma_{2\varepsilon}$, i.e., the expected interest rate for a particular card conditioned on selection is predicted to be lower than the average unconditional rate.[15] However, the present data do not allow us to determine the extent to which the stochastic terms $u_{1,i}$ and $u_{2,i}$ are due to (i) unobserved information available to the bank, leading to selection of more creditworthy customers, (ii) strategic randomization of offers, and (iii) random errors. Both (ii) and (iii) lead to a winner's curse effect. Under the assumption that no private unobserved information is available to the EBs, a positive sign for $\sigma_{2\varepsilon}$ implies a winner's curse effect for the EBs.

[15] Note that this prediction would not hold if unobserved non-price features of the offer are sufficiently attractive that they more than offset a lower interest rate.

Delinquency model. The next step is to investigate default probabilities. This will allow us to determine whether the private information variables X_2 do in fact correspond to lower default probabilities, as was assumed above in testing prediction (I). Modeling the default probabilities will also allow us to test the remaining predictions from Section 3, i.e., (III) lower average default probabilities for HB customers and (IV) positive HB profits.

Assuming that delinquency is an indicator for future default, we estimate an ordered probit model where the delinquency variable has three categories: $D_i = 1$ if respondent i had missed a monthly payment but not fallen behind by two months, $D_i = 2$ if they were behind in their payments by two months or more, and $D_i = 0$ otherwise. These are treated as an ordered categorization of the latent variable

$$D_i^* = X_i \beta + \eta_i$$

where the explanatory variables X are the same public and private information variables as in the interest rate equations, other than the delinquency variable.[16]

Besides determining whether these variables have a significant effect on delinquency, this model also allows us to estimate the probabilities $\Pr(D_i = 1)$ and $\Pr(D_i = 2)$, which serve as proxies for the actual default probabilities in testing prediction (III). Finally, to estimate the profit differential between HBs and EBs, we make the further assumption that the expected rate of losses (charge-offs) for banks is approximately equal to the "60 days delinquency rate" given by $\Pr(D_i = 2)$.

[16] The inclusion of bankruptcy as an independent variable in this equation might create endogeneity issues since delinquencies are often a precursor to bankruptcy. However, this problem does not occur here as all bankruptcies in these data were filed more than one year prior to the survey, and as such precede the delinquency variable which reflects late payments over the past one year only.

6. Empirical Results

The two-stage estimates are presented in Table 2. The first two columns of this table represent the interest rate equations on public (i.e., credit bureau) and private information variables for the HB and the EB. The selection probit in column 3 includes four additional identification variables: a dummy variable for convenience users, a dummy for the propensity to search for credit cards, the ratio of monthly payments to income, and the log of the credit line. The "convenience user" variable is important because consumers who do not borrow on their cards might put more emphasis on other features, such as frequent flier miles, rather than interest rates when selecting among cards. The propensity to search for credit cards is included as a proxy for both the pecuniary and nonpecuniary search costs of consumers. Average monthly payments on mortgages, rent, auto loans and other leases relative to monthly income are included because high-payment consumers are likely to be more sensitive to interest rates rather than other features of the card. Finally, the total credit line offered captures another non-price dimension of bank offers and hence also influences the liquidity-constrained consumer's choice of cards.

The estimates in Table 2 support predictions (I) and (II). We find: (i) all variables reflecting private information—liquid assets, net worth, and employment proxies for income volatility—are significant in determining interest rates for HBs but not for EBs; and (ii) only the credit bureau variables—utilization rates on credit cards, home equity lines of credit, as well as past delinquency and the bankruptcy history of the consumer—are significant in determining interest rate offers for EBs. Surprisingly, none of the public information variables are significant in determining rate offers for the HBs, indicating a smaller role for credit bureau information for HBs when determining offers for their own customers. Also, three of the four consumer-preference variables are significant in the selection equation. The signs on all financial variables are as expected for both HBs and EBs. For instance, those with delinquent accounts or bankruptcy filings are charged a higher interest rate by EBs, while those with higher liquid assets and lower income volatility are charged a lower interest rate by their HBs.[17]

The estimates also provide evidence of selection, since $\sigma_{1,\varepsilon}$ (which appears as the coefficient of the inverse Mills ratio in the second-stage equation (A5) for the HB interest rate) is negative and significant, thereby indicating that the expected interest rate of the home bank card holders conditioned on selection is lower than the unconditional expectation. On the other hand, there is no evidence of selection for the EB cardholders.

The maximum likelihood estimates of the selection model (Table 3) are qualitatively similar to the two-stage estimates. The only differences are that (i) the ratio of average monthly payments to income is not significant in the selection equation, and (ii) both of the correlation coefficients ρ_1 and ρ_2 are now significant, with signs corresponding to a selection effect (i.e., interest rates are lower when conditioning on selection).

According to the interest-rate equation coefficients, HBs are able to attract the good credit risks among their deposit customers by making lower interest-rate offers on the basis of favorable private information. However, as none of the private information variables are significant in the EB interest-rate equation, the EB offer is attractive only to customers who are offered higher rates by the HBs on the basis of adverse private information. If we now also consider the unexplained heterogeneity of interest rate offers, the selectivity effect shows that the average HB card holder received a below-average HB interest-rate offer, and according to the maximum likelihood results, the average EB card holder likewise had a below-average EB

[17] The sign on the home equity utilization rate might at first glance appear unintuitive. However, home equity lines are a substitute for credit cards, especially for consumers wishing to consolidate their debts, and banks must compete for these customers by offering lower rates.

offer.[18] For HBs, we can reasonably ascribe part of this unexplained heterogeneity to unobserved private information, thus further enhancing the HBs ability to attract good credit risks through lower offers. For EBs, on the other hand, the absence of observed private information strongly suggests that there is no unobserved private information either. Instead, the unexplained heterogeneity of EB offers may be attributed to the strategic randomization of offers by EBs, and acceptance of below-average offers then leads to a winner's curse effect for the EBs. These arguments hold provided that HBs actually succeed in attracting cardholders with lower average default risk than EB cardholders, and later in this section we show that this is in fact the case.

Next we focus on a critical underlying assumption: private information predicts interest rates because it actually predicts repayment probabilities (implicit in the test of predictions I and II), and so allows HBs to select a lower-risk pool (prediction III). As discussed in the previous section, we assume that delinquency is an indicator for future default, and estimate an ordered probit model for the delinquency variable. The results, presented in Table 4, show that liquid assets, net worth, and the employment dummies serving as proxies for income volatility are highly significant and are thus key predictors of future delinquencies. For example, a thousand-dollar increase in liquid assets reduces the probability of going "sixty days past delinquent" by approximately 2.4 percentage points.

The above analysis is carried out for the entire sample as well as for the EB sample separately. We find that the results are qualitatively similar for the EB consumers—liquid assets and net worth do predict future delinquencies even in this sample. The fact that these variables

[18] "Below average" here means below the average of offers made by that type of bank to all consumers with the same observable characteristics.

are not significant in the EBs' interest rate equations is due to the EBs not having access to this information.

The ordered probit model is also used to estimate $\Pr(D_i = 1)$ (probability of missing a payment in the last year) and $\Pr(D_i = 2)$ (probability of falling behind on payments by two months or more) for the HB and EB samples separately. These estimates, presented in Table 5, show that HB customers have lower probabilities for both default states. Again assuming that delinquency can be used as a proxy for future default, this validates prediction (III), i.e., HBs succeed in attracting a client pool from their own customers who are more creditworthy than the average EB customer.

Finally, to test prediction (IV), we assume that the expected rate of losses for banks is approximately equal to $\Pr(D_i = 2)$. Then Table 5 implies that the loss rate of the HBs credit card portfolio is one point lower than that of the EBs. This difference in expected losses is also reflected in the difference in the average interest rates between the HBs and EBs (approximately 1 percentage point). If we further assume that the EBs are making zero profits then the cost of funds (i.e. prime rate) for the EBs, with an average interest rate of $r_E = 15.72\%$ and a repayment probability of $\theta_E = 95.04\%$, is $\bar{r} = \theta_E(1 + r_E) - 1 = 9.98\%$. Given the cost of funds, we calculate the zero-profit interest rate of the HBs, with repayment probability $\theta_H = 0.96$, as $r_H = (1 + \bar{r}) / \theta_H - 1 = 14.56\%$. The small difference between the actual interest rate charged by the HBs (14.75%) and the zero-profit rate suggests that even though some HBs have an information monopoly arising from relationship lending, it does not result in expropriation of rent from the low credit risks. This, along with the evidence of winner's curse for EBs, suggest that randomization of offers in this competitive market environment have reduced the information capture of the low credit risks and led to more heterogeneous pricing.

7. Summary and Conclusions

This paper has examined the issue of heterogeneity in credit card interest rates. It introduces the notion of *relationship lending* (previously considered only in the context of commercial lending) in the consumer credit market and distinguishes between private information held by a card holder's "home banks" (HBs) as opposed to publicly-available credit bureau information held by "external banks" (EBs). It shows that private information arising from other banking services (checking accounts, savings, etc.) is used by HBs to assess the default potential of their own customers and to select a lower-risk pool by offering them lower interest rates. On the other hand, EBs must depend primarily on information that is available through credit bureaus, and this information asymmetry among card-issuers ultimately has contributed to further rate heterogeneity beyond what arises from the use of bureau information.

The *Survey of Consumer Finances* (1998) data are used to test the implications of the theoretical model. We assume that both HBs and EBs make interest rate offers to consumers based on the information set available to them. Consumers then select their primary card based on the interest rate, some non-price dimensions of the offer, and other consumer-specific characteristics which govern the consumers' choice of card. An endogenous switching regression model that captures the aspect of self-selection by consumers into two categories is used and estimated using maximum likelihood methods.

The empirical results provide strong evidence of the impact of relationship lending in this market. Our results include the following. (1) The average rate on EB credit cards is one percentage point (i.e., 6 percent) higher than home bank cards, and this holds even after controlling for other observables. (2) Variables representing information from the private financial accounts of the consumer (and known only by the HBs) are significant in the HB interest offers but are not significant in the EBs' offer equation. On the other hand, most of the public information variables (available from credit bureau reports) are significant in the interest rate offer equations of EBs but not in the HBs' offers. This clearly suggests that HBs, having access to private information, put less weight on public information. (3) There is evidence of a winner's curse for EBs. (4) The default risk of the HB sample is also one percentage point lower than that of the EB sample.

These results point to a Pareto-improving exchange of information arising out of relationship lending. Consumers having low risks of default are better off holding credit cards with banks where they have other financial accounts. The private information gleaned from other financial accounts held by the consumer at their HBs, enables these banks to make the low-risk consumers interest offers that cannot be matched by an EB for fear of adverse selection. Despite result (4) above, however, there is no conclusive evidence that HBs succeed in using their information monopoly to extract a rent from low-risk consumers.

Appendix

A.1. Mixed-Strategy Equilibrium with a Single Home Bank

As discussed in Section 3, a single HB can extract rent from its information monopoly, in the absence of any kind of multi-period commitments by banks. When X_H takes on two discrete values (i.e., case (b) in Section 3), the structure of the game is equivalent to the second stage of Sharpe's model (Sharpe, 1990), if we condition on a particular risk class X_E and identify the types *h* and *l* with Sharpe's first-stage outcomes *S* and *F*.

The two-period structure of Sharpe's model leads to the parameter restriction (in our notation) $\theta_0 = \lambda$, i.e., the proportion of borrowers who are observed by the HB to be good risks is equal to the average repayment probability. Because the present model does not have this restriction, we restate the results of von Thadden (2004) in a form that applies here. Let $F_H(r)$ be the distribution function of interest rates offered by the HB to consumers of type *h*, and let $F_E(r)$ be the distribution function of interest rates offered by an EB to consumers of type *l*. As before, the HB offers only r_l to consumers of type *l*. If *M* competing EBs make independent offers, then the distribution of the best offer by an EB is given by

$$F_M(r) = 1 - [1 - F_E(r)]^M .$$

Then, following von Thadden (2004), Nash equilibrium implies the offer distributions

$$F_H(r) = 1 - \frac{r_0 - r_h}{r_l - r_0} \cdot \frac{r_l - r}{r - r_h} \quad \text{for } r \in [r_0, r_l] \tag{A1}$$

$$F_M(r) = 1 - \frac{r_0 - r_h}{r - r_h} \quad \text{for } r \in [r_0, r_l), \qquad F_M(r_l) = 1, \tag{A2}$$

which are expressed in terms of the benchmark interest rates r_0, r_h, and r_l defined in equations (1) and (2).

In the alternative model where $\theta(X_H)$ is uniformly distributed on $[\theta_l, \theta_h]$ (i.e., case (c) in Section 3), the following strategies constitute a Nash equilibrium.[19] As before, we condition on X_E. The HBs now adopt a pure strategy, offering an interest rate

$$r_H(\theta) = 2\,\frac{1+\bar{r}}{\theta + \theta_l} - 1 \tag{A3}$$

to their customers, where $\theta = \theta(X_H)$. Note that $r_H(\theta_h) = r_0$, where r_0 is defined as before except that the average repayment probability is now $\theta_0 = (\theta_l + \theta_h)/2$. The EBs randomize their offers, as in von Thadden (2004), but with a modified distribution corresponding to

[19] This follows by a suitable modification of the argument in von Thadden (2004). However, we do not attempt here to show the uniqueness or stability of this equilibrium.

$$F_M(r) = 1 - \frac{(1+r_0)^2}{r_l - r_0} \frac{r_l - r}{(1+r)^2} \text{ for } r \in [r_0, r_l]. \tag{A4}$$

Comparing these results with the case of no private information, we see that the information monopoly leads to higher interest rates for all borrowers. On the other hand, in comparison with the case of multiple HBs, the information monopoly raises interest rates for good credit risks while lowering interest rates for bad credit risks. The expected EB profit is zero, as before, while the expected profit of the HBs relative to the population size is $\lambda\theta_h(r_0 - r_h)$ in model (b) or $\frac{1}{3}\theta_h(r_0 - r_h)$ in model (c).[20]

The offer distributions can be used to calculate average interest rate offers, acceptance rates, and average accepted interest rates for both types of bank (although the actual expressions are highly model-specific.) For the present, we note the following results:

(1) The expected HB-offered interest rate decreases as θ increases, conditional on public information.[21] In model (b.2) this follows immediately from the fact that type *l* customers are offered r_l, while type *h* customers receive an offer distributed between r_0 and r_l. In model (c.2) it is clear that $r_H(\theta)$ in equation (A.3) is a decreasing function of *θ*.

(2) HB card holders have a higher average θ than EB card holders. To verify this in model (b.2), let a_h and a_l be the proportions of type *h* and type *l* customers who accept the HB offer. In this model, $a_h = \frac{1}{2} + \frac{1}{2}(r_0 - r_h)/(r_l - r_h)$ and $a_l = \rho(r_0 - r_h)/(r_l - r_h)$. Thus $a_h > a_l$, which implies $E[\theta \mid HB] > E[\theta \mid EB]$. In model (c.2) direct calculation of the expected values gives the ratio $E[\theta \mid HB]/E[\theta \mid EB] = (2\theta_h + \theta_l)/(\theta_h + 2\theta_l) > 1$.

[20] These expected profits in model (b) are, in fact, the same as in the outcome proposed by Sharpe (1990).
[21] On the other hand, the relationship between the average interest rates paid by those accepting HB cards and those accepting EB cards is ambiguous, depending on the model and the parameter values.

A.2. Estimation of the Switching Regression Model

In the two-stage estimation method, the regression equations in (3a) and (3b) conditioned on selection (5) become

$$r_{H,i} = X_{1,i}\beta_{11} + X_{2,i}\beta_{12} + \sigma_{1\varepsilon}\frac{\phi(Z_i\hat{\gamma})}{\Phi(Z_i\hat{\gamma})} + e_{1,i} \tag{A5}$$

$$r_{E,i} = X_{1,i}\beta_{21} + X_{2,i}\beta_{22} - \sigma_{2\varepsilon}\frac{\phi(Z_i\hat{\gamma})}{1-\Phi(Z_i\hat{\gamma})} + e_{2,i} \tag{A6}$$

where the coefficients of the Heckman correction terms are $\sigma_{1\varepsilon} = \mathrm{cov}(u_{1i}, \varepsilon_i)$ and $\sigma_{2\varepsilon} = \mathrm{cov}(u_{2i}, \varepsilon_i)$, while $\hat{\gamma}$ is estimated from the probit selection equation. As usual, ϕ and Φ represent the standard normal density and distribution functions.

The likelihood function for maximum likelihood estimation can be expressed in the form[22]

$$L = \prod_{I_i=1} f_H(r_{H,i})\Phi\left(A_{1,i}\right).\prod_{I_i=0} f_E(r_{E,i})\Phi\left(-A_{2,i}\right) \tag{A7}$$

where $f_H(\cdot)$ and $f_E(\cdot)$ are the marginal densities of the offered interest rates (3a) and (3b), i.e.,

$$f_H(r_{H,i}) = (1/\sigma_1)\,\phi\left((r_{H,i} - X_{1,i}\,\beta_{11} - X_{2,i}\,\beta_{12})/\sigma_1\right)$$
$$f_E(r_{E,i}) = (1/\sigma_2)\,\phi\left((r_{E,i} - X_{1,i}\,\beta_{21} - X_{2,i}\,\beta_{22})/\sigma_2\right)$$

The terms $\Phi(A_{1,i})$ and $\Phi(-A_{2,i})$ are the selection probabilities conditional on the observed interest rates $r_{H,i}$ and $r_{E,i}$ respectively, with

$$A_{1,i} = \left(Z_i\gamma + (\rho_1/\sigma_1)(r_{H,i} - X_{1,i}\beta_{11} - X_{2,i}\beta_{12})\right)\Big/\sqrt{1-\rho_1^2}$$
$$A_{2,i} = \left(Z_i\gamma + (\rho_2/\sigma_2)(r_{E,i} - X_{1,i}\beta_{21} - X_{2,i}\beta_{22})\right)\Big/\sqrt{1-\rho_2^2}$$

where ρ_j is the correlation between $u_{j,i}$ and ε_i ($j = 1,2$).

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[22] See for example Amemiya (1985).

References

Altman, Edward I. and Anthony Saunders, "Credit Risk Measurement: Developments over the Last 20 Years," *Journal of Banking and Finance*, 21, 1998.

Amemiya, Takeshi, *Advanced Econometrics*, Harvard University Press, 1986.

Ausubel, Lawrence, "The Failure of Competition in the Credit Card Markets," *American Economic Review*, 81(1), March 1991, 50-81.

Ausubel, Lawrence, "Credit Card Defaults, Credit Card Profits and Bankruptcy," *American Bankruptcy Law Journal*, 71, Spring 1997, 249-270.

Ausubel, Lawrence, "Adverse Selection in the Credit Card Market," mimeo, University of Maryland, June 1999.

Ausubel, Lawrence, "Personal Bankruptcies Begin Sharp Decline: Millennium Data Update," mimeo, University of Maryland, January 2000.

Berger, Allen N., and Gregory F. Udell, "Relationship Lending and Lines of Credit in Small Firm Finance," *Journal of Business*, 68(3), July 1995, 351-381.

Black, Sandra and Donald P. Morgan, "Risk and the Democratization of Credit Cards," Federal Reserve Bank of New York, Research Paper No. 9815, June 1998.

Bizer, David S., and Peter M. DeMarzo "Sequential Banking," *Journal of Political Economy*, 100(1), February 1992, 41-61.

Boot, Arnoud W. A., "Relationship Banking: What Do We Know?" *Journal of Financial Intermediation*, 9, 2000, 7-25.

Boot, Arnoud W. A., and Anjan V. Thakor, "Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game," *International Economic Review*, 35, 1994, 899-920.

Brito, Dagobert L., and Peter R. Hartley, "Consumer Rationality and Credit Cards," *Journal of Political Economy*, 103(21), 1995, 400-433.

Calem, Paul S., "The Strange Behavior of Credit Card Market," *Business Review*, Federal Reserve Bank of Philadelphia, January 1992.

Calem, Paul S., and Loretta J. Mester, "Consumer Behavior and Stickiness of Credit Card Interest Rates," *American Economic Review*, 85(5), December 1995, 1327-1336.

Gross, David B., and Nicholas S. Souleles, "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data," National Bureau of Economic Research, Working Paper 8314, June 2001.

Kerr, Sougata, and Lucia Dunn, "Consumer Search Behavior in the Changing Credit Card Market," The Ohio State University, Working Paper No. 02-03, September 2002.

Kim, TaeHyung, Lucia Dunn, and Gene Mumy, "Bank Price Competition, Consumer Search, and Asymmetric Responses to Credit Card Interest Rates," forthcoming in *Economic Inquiry*.

Laderman, Elizabeth, "What's Behind the Problem of Credit Card Loans?" *Economic Letter*, Federal Reserve Bank of San Francisco, July 1996.

Lee, Lung-Fei, "Unionism and Wage Rates: A Simultaneous Equation Model with Qualitative and Limited Dependent Variables," *International Economic Review,* 19(2), June 1978, 415-433.

Lummer, S., and J. McConell, "Further Evidence on the Bank Lending Process and the Capital Market Response to Bank Loan Agreements," *Journal of Financial Econonomics*, 25, 1989, 99-122.

Mester, Loretta J., "Why are Credit Card Rates Sticky?" *Economic Theory*, 4, 1994, 505-530.

Mester, Loretta J., "What's the Point of Credit Scoring?" *Business Review*, Federal Reserve Bank of Philadelphia, October 1997.

Mester, Loretta J., Leonard I. Nakamura, and Micheline Renault, "Checking Accounts and Bank Monitoring," Federal Reserve Bank of Philadelphia, Working Paper No. 01-3/R, July 2002.

Ongena, Steven, and David C. Smith, "What Determines the Number of Bank Relationships? Cross-Country Evidence," *Journal of Financial Intermediation*, 9, 2000, 26-56.

Park, Sangkyun, "Effects of Price Competition in the Credit Card Industry," *Economic Letters*, 57, 1997, 79-85.

Park, Sangkyun, "Option Value of Credit Lines as an Explanation of High Credit Card Rates," Federal Reserve Bank of New York, Research Paper No. 9702, February 1997.

Peterson, Mitchell A., and Raghuram G. Rajan, "The Benefits of Lending Relationships: Evidence from Small Business Data," *Journal of Finance*, 49(1), March 1994, 3-37.

Peterson, Mitchell A., and Raghuram G. Rajan, "The Effect of Credit Market Competition on Lending Relationships," *Quarterly Journal of Economics*, 110, 1995, 406-443.

Sharpe, Steven A., "Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships," *Journal of Finance*, 45(4), September 1990, 1069-1087.

Stiglitz, Joseph E. and Andrew Weiss, "Credit Rationing in Markets with Imperfect Information," *American Economic Review*, 71(3), June 1981, 393-410.

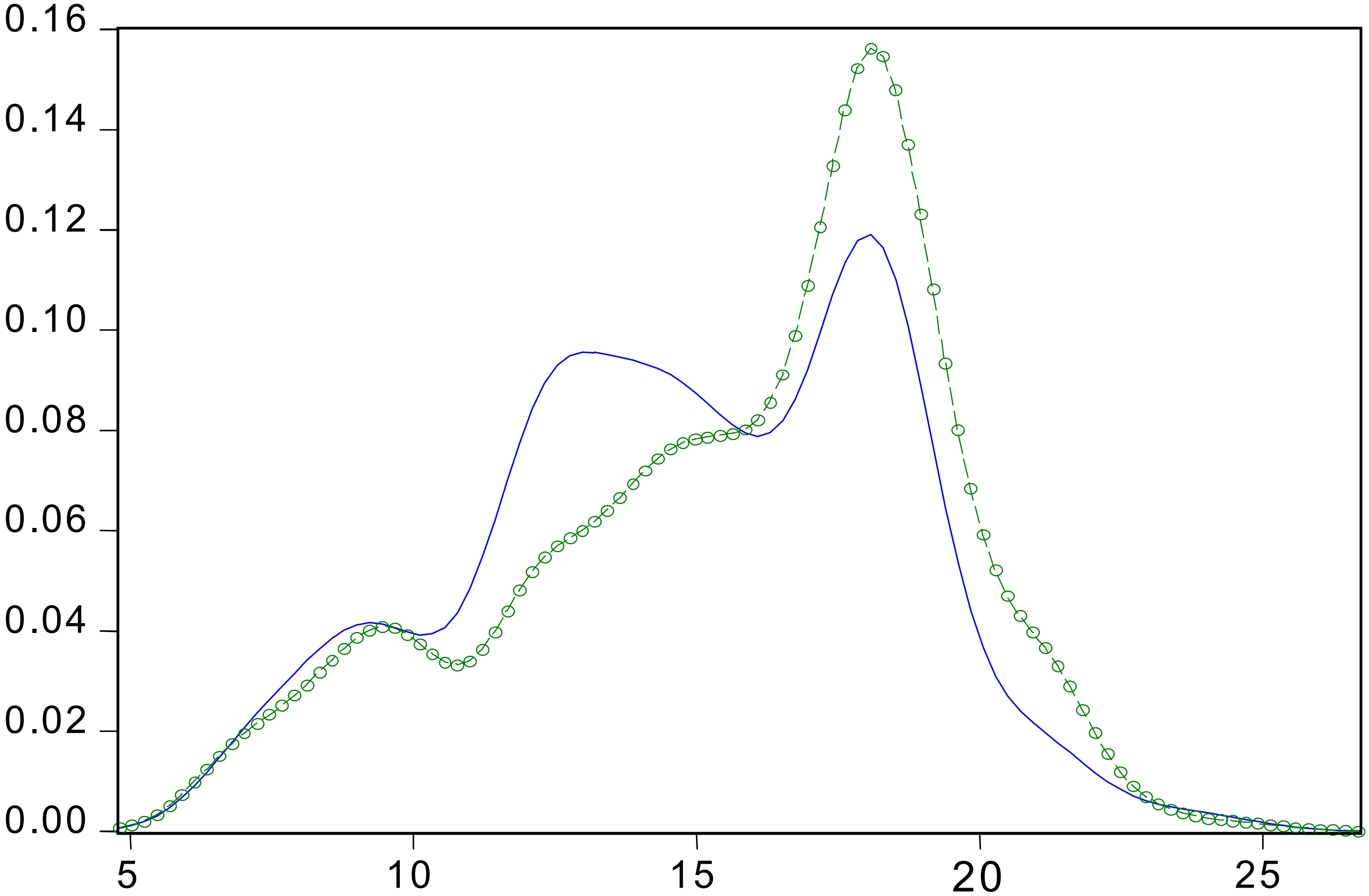
Trost, R. P., "Interpretation of Error Covariances with Non-Random Data: An Empirical Illustration of Returns to College Education," *Atlantic Economic Journal*, 9(3), 1981, 85-90.

von Thadden, Ernst-Ludwig, "Asymmetric Information, Bank Lending and Implicit Contracts: The Winners Curse," *Finance Research Letters*, 1, 2004, 11-23.

Wansley, James, R. DeGannaro, F. Elayan, and C. Collins, "Sources of Value in Lines of Credit: Evidence from the Lender's Perspective," Chicago Bank Structure Conference Proceedings, May 1992.

Yoo, Peter S., "Still Charging: The Growth of Credit Card Debt between 1992 and 1995," *Business Review*, Federal Reserve Bank of St. Louis, February 1998.

Figure 1: Kernel Estimates of Probability Density Functions of Interest Rates of Home and External Banks



Home Bank: ——— **External Bank:** -•-•-•-

Table 1: Variable Descriptions and Means by Bank Type

Variable	Information Type	Home Bank	External Bank
Credit card interest rate (APR)	Private	0.147*	0.157*
Ratio of credit card balance to credit line	Credit bureau	0.319*	0.454*
Ratio of credit card balance to income**	Credit bureau	0.058*	0.077*
Ratio of amount owed on mortgages and other residential debt to initial amount borrowed	Credit bureau	0.421*	0.520*
Ratio of outstanding balances on home equity lines of credit to credit lines	Credit bureau	0.037*	0.044*
Total credit line on all types of cards	Credit bureau	0.124	0.151
Delinquency 0 : Never missed monthly payments 1 : Late/missed monthly payments but less than 2 months 2 : Behind monthly payments by more than 2 months	Credit bureau	0.133*	0.162*
Bankruptcy 1 : Declared bankruptcy in the past 0 : Never declared bankruptcy	Credit bureau	0.063	0.087
Homeowner (dummy variable)	Credit bureau	0.747	0.730
Household income	Private	0.612	0.655
Liquid assets held (checking, savings, money-markets, CDs)	Private	0.575*	0.453*
Net worth (total assets including property – total liabilities)	Private	3.793*	3.611*
Not working (dummy variable)	Private	0.056*	0.085*
Retired (dummy variable)	Private	0.252*	0.156*
Working but not self-employed (dummy variable)	Private	0.590	0.638
Working and self employed (dummy variable)	Private	0.103	0.121
Age of respondent	Credit bureau	51.5*	46.8*
Years of schooling completed	Private	13.6*	13.9*
Ratio of average monthly payments (mortgage, rent, auto, lease) to monthly Income	Consumer Characteristic	0.296	0.228
Convenience user 1 : Usually no balance on credit cards 0 : Otherwise	Consumer Characteristic	0.583	0.505
Shopping propensity 1 : Shops around before making credit decisions 0 : Otherwise	Consumer Characteristic	0.811*	0.873*

Dollar amounts are in $100,000's. "Private" information is available to home banks but not external banks; "consumer characteristics" are assumed not to be available to lenders.

* Difference in means statistically significant at the 10% level.
** Income is not available in the credit bureaus but is self reported during application. It is classified as public or bureau information as EBs can use the self reported estimate.

Table 2: Two-Stage Estimates of Selection Model

	Home Bank Offer (S.E.)	External Bank Offer (S.E.)	Selection (S.E.)
	(I)	(II)	(III)
Constant	20.8412 ***	19.1332 ***	0.3145
	(2.0192)	(1.7932)	(0.4991)
Credit card balance to credit line	0.1113	0.1842 ***	-0.0329
	(0.0763)	(0.0669)	(0.0180)
Credit card balance to income	-0.1461	1.4859 ***	-0.0068
	(0.5612)	(0.5674)	(0.2105)
Mortgage owed to initial amount borrowed	-0.0025	0.1968	-0.0568
	(0.1925)	(0.1284)	(0.0410)
Home equity balance to credit line	0.3958	-1.3693 **	0.0381
	(0.8144)	(0.5920)	(0.1713)
Delinquency	0.1616	0.4536 **	-0.0112
	(0.2685)	(0.2068)	(0.0588)
Bankruptcy	0.1528	1.3664 ***	-0.2843 ***
	(0.5545)	(0.3735)	(0.1083)
Homeowner	-0.2059	0.1423	-0.0400
	(0.3736)	(0.2866)	(0.0801)
Log of income	-0.0469	-0.2441	0.0184
	(0.2020)	(0.1676)	(0.0480)
Log of liquid assets	-0.1163 *	-0.0831	0.0229
	(0.0696)	(0.0581)	(0.0155)
Log of net worth	-0.1835 ***	-0.0248	0.0368 ***
	(0.0648)	(0.0407)	(0.0121)
Not working	-0.7562	-0.2644	-0.1753
	(0.6916)	(0.5003)	(0.1426)
Retired	-2.6657 ***	0.0952	0.0641
	(0.5707)	(0.4730)	(0.1264)
Working but not self employed	-1.7421 ***	0.3400	0.1554 *
	(0.4388)	(0.3301)	(0.0924)
Age	0.0332 ***	0.0011	0.0101 ***
	(0.0128)	(0.0109)	(0.0027)
Years of schooling	-0.0759	-0.0835 *	-0.0223 *
	(0.0529)	(0.0484)	(0.0122)
Convenience user			0.0759
			(0.0647)
Shopping propensity			-0.1952 **
			(0.0773)
Average monthly payments to income			0.2893 **
			(0.1163)
Log of credit line			-0.1781 ***
			(0.0278)
$\sigma_{j\varepsilon}$	-1.4309 *	0.8915	
	(0.8123)	(0.9264)	
Sample size	861	1404	2265
Log likelihood			-1418.47
Adusted R-square	0.060	0.061	

Columns (I) and (II) contain least-squares estimates after adjusting for selection bias; column (III) contains the probit estimates of the selection equation.

*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

Table 3: Maximum Likelihood Estimates of Selection Model

	Home Bank Offer (S.E.)	External Bank Offer (S.E.)	Selection (S.E.)
	(I)	(II)	(III)
Constant	21.0358 ***	18.8073 ***	0.5591
	(2.2467)	(1.7866)	(0.5014)
Credit card balance to credit line	0.1164	0.1841 ***	-0.0381 *
	(0.1506)	(0.0674)	(0.0232)
Credit card balance to income	-0.1148	1.5171 **	0.1007
	(0.7498)	(0.6121)	(0.2381)
Mortgage owed to initial amount borrowed	0.0017	0.2076	-0.0509
	(0.3830)	(0.1957)	(0.0403)
Home equity balance to credit line	0.4118	-1.3599 **	0.0328
	(0.8402)	(0.6106)	(0.1768)
Delinquency	0.1617	0.4466 **	-0.0172
	(0.2877)	(0.2088)	(0.0590)
Bankruptcy	0.1959	1.3946 ***	-0.2776 ***
	(0.5335)	(0.4116)	(0.1080)
Homeowner	-0.1839	0.1587	-0.0490
	(0.4001)	(0.2989)	(0.0850)
Log of income	-0.0329	-0.2251	0.0045
	(0.2256)	(0.1712)	(0.0480)
Log of liquid assets	-0.1176 *	-0.0880	0.0239
	(0.0696)	(0.0587)	(0.0156)
Log of net worth	-0.1896 ***	-0.0301	0.0366 ***
	(0.0609)	(0.0422)	(0.0129)
Not working	-0.7362	-0.2300	-0.1874
	(0.7358)	(0.5040)	(0.1429)
Retired	-2.6673 ***	0.0814	0.0554
	(0.5689)	(0.4754)	(0.1276)
Working but not self employed	-1.7617 ***	0.3183	0.1437
	(0.4387)	(0.3183)	(0.0935)
Age	0.0316 **	-0.0005	0.0098 ***
	(0.0144)	(0.0105)	(0.0027)
Years of schooling	-0.0730	-0.0774	-0.0190
	(0.0562)	(0.0514)	(0.0124)
Convenience user			0.0674
			(0.0644)
Shopping propensity			-0.2076 ***
			(0.0732)
Average monthly payments to income			0.1779
			(0.1144)
Log of credit line			-0.18751 ***
			(0.0277)
σ_j	3.8240 ***	3.8250 ***	
	(0.2706)	(0.1027)	
ρ_j	-0.4368 **	0.3260 *	
	(0.1919)	(0.1737)	
Sample size	2265		
Log likelihood	-7571.3		

*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

Table 4: Ordered Probit Estimates of Delinquencies on Information Variables

	Full Sample		External Bank Sample	
	Delinquency (S.E.)	Marginal Effects (S.E.)	Delinquency (S.E.)	Marginal Effects (S.E.)
Constant	0.1231	0.006	0.2318	0.010
	(0.4565)		(0.5769)	
Credit card balance to credit line	0.0171 **	0.001	0.0572 ***	0.003
	(0.0087)		(0.0195)	
Credit card balance to income	0.4270 ***	0.020	0.6197 **	0.028
	(0.1397)		(0.2568)	
Mortgage owed to initial amount borrowed	-0.0085	0.000	0.0133	0.001
	(0.0554)		(0.0613)	
Home equity balance to credit line	0.1948	0.009	0.1412	0.006
	(0.2116)		(0.2609)	
Homeownership	-0.2871 ***	-0.013	-0.3186 **	-0.014
	(0.1065)		(0.1318)	
Log of income	0.0682	0.003	0.0906	0.004
	(0.0466)		(0.0602)	
Log of liquid assets	-0.0909 ***	-0.004	-0.1026 ***	-0.005
	(0.0200)		(0.0252)	
Log of net worth	-0.0294 **	-0.001	-0.0284 *	-0.001
	(0.0125)		(0.0147)	
Not working	0.0221	0.001	-0.0158	-0.001
	(0.1533)		(0.1812)	
Retired	-0.4446 **	-0.020	-0.6910 ***	-0.031
	(0.1796)		(0.2512)	
Working but not self employed	-0.0301	-0.001	-0.0886	-0.004
	(0.0958)		(0.1205)	
Age	-0.0051	0.000	-0.0035	0.000
	(0.0036)		(0.0045)	
Years of schooling	-0.0341 **	-0.002	-0.0551 *	-0.002
	(0.0166)		(0.0224)	
Bankruptcy	0.6337 ***	0.029	0.5761 ***	0.026
	(0.1212)		(0.1534)	
Threshold parameter				
μ_1	0.7355 ***		0.7614 ***	
Sample Size	2265		1404	
Chi-Square	268.06		207.42	

*** Significant at 1% level   ** Significant at 5% level   * Significant at 10% level

Table 5: Comparison of Interest Rates and Default Probabilities

	Home Bank	External Bank
Interest rate	14.75%	15.72%
Estimated probability of missing payment in last year	13.07%	15.59%
Estimated probability of non-payment by more than 2 months	4.00%	4.96%