A Reexamination of the Role of "Relationships" in the Loan Granting Process

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Abstract

We reexamine the role of relationships in the overall loan granting process. A practical implication emerging from classical studies on the role of relationships in credit rationing is that good relationships between borrower and lender should, in fact, work to lower the interest rate charged to the borrower. We test this implication in our paper using a robust sample selection methodology that accounts for the entire fabric of the loan granting process, including a borrower's decision to apply to the bank for a loan (or not), whether a bank approves the application for a loan (or not), and the loan rate it chooses for the borrower – all within a unified framework. Our model also explicitly includes the analysis of discouraged borrowers (i.e., those who do not apply for loans because they believe they will be rejected), which is an issue not tackled in the extant literature. We find that relationships matter only in the first and second decision stages of the loan process, i.e., in a borrower's decision whether to apply for a loan and in the loan approval/rejection decision by the financial institution. Relationships, however, are not important in determining the loan rate associated with the approved loan once the sample selection bias in the loan process is appropriately accounted for. Our conclusions are robust to the nature of loans (collateralized or otherwise) and borrowers (small businesses or individual families).

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"Finally, you have the most sophisticated of all marketing tools: Person-to-person relationships….You know your customers personally by taking care of a variety of banking transactions for them on a daily or weekly basis and, for many, you know them through community activities as well. More than likely, you know when they get married, when they move, when they are having children, when their children are ready for college, when their kids graduate and when retirement is around the corner. No computer model has been developed that can compete with this kind of knowledge."

***Community Banker*, June 2001**

1. Introduction

The goal of this paper is to further our understanding of how "relationships" work in the loan granting process. In a seminal paper, Stiglitz and Weiss (1981) were the first to show how the problem of asymmetric information between a borrower and a potential lender could impede the flow of credit to an otherwise qualified borrower. Subsequent researchers [see Elyasiani and Goldberg (2004) for a review] have argued that lenders could overcome the informational asymmetry by collecting soft information about the borrower through the building and sustenance of a relationship (as the above quote from the *Community Banker* magazine suggests) and using such information in credit approval/rejection decisions, thereby lowering the cost of capital for the lender.

In the wake of Stiglitz and Weiss's intuitive conclusions, an impressive body of empirical research has blossomed over the past decade, documenting the role of relationships in the rationing both for small business loans as well as consumer-oriented loans.[1] The common empirical framework underlying these studies has been to show that a credit rationing proxy -- usually the loan rate or credit availability -- is significantly correlated with relationship proxies after incorporating appropriate control variables measuring borrower (and loan) characteristics. These studies investigate whether relationships are significant determinants of credit availability in loans associated with small businesses and individual families. However, as Elyasiani and Goldberg (2004) aver, evidence of the role of relationships on credit availability is mixed. For instance, while earlier studies, such as Peterson and Rajan (1994) and Berger and Udell (1995), found that relationships have a negative significant effect on the loan rate, later studies did not find that relationships are significant determinants of credit availability or loan rate (Blackwell and Winters, 1997 and Cole, Goldberg and White, 2004). Our study contributes to the literature by reexamining whether credit approval increases and interest rates decrease in good relationships with the

[1] See, for example, Cole (1998); Cole, Goldberg, and White (2004); Duca (1998); Petersen and Rajan (1994, 1995, 2002); Berger and Udell (1995, 1998, 2002); Berger, Klapper, and Udell (2001); Lehman and Neuberger (2001); and Chakravarty and Scott (1999).

lending institution.[2] To do so, we take a closer look at the overall loan granting process, which, arguably, can be described by the following decisions:

- **[The Application Decision]** a borrower's decision whether to apply to the lender (usually a bank) for a loan (or not),
- **[The Credit Approval Decision]** whether a bank approves the application for a loan (or not), and
- **[The Loan Rate Setting Decision]** the loan rate the bank chooses for the borrower,

all of which are endogenously determined. In particular, the bank's Credit Approval Decision is observable only if the borrower decides to apply for a loan, and the Loan Rate Setting Decision is observable only if the borrower decides to apply for a loan and the bank approves the loan application. Therefore, any empirical study that individually estimates any of the above stages (in isolation of the other stages), typically either the Credit Approval Decision [see, for example, Cole (1998), Chakravarty and Scott (1999)], or the Rate Setting Decision [see, for example, Petersen and Rajan (1994) and Berger and Udell (1995)] would, in essence, be estimating a misspecified model with its accompanying issues of biased parameter estimates. We circumvent such issues by employing a robust sample selection approach (discussed in detail later) that accounts for the double selectivity in the loan process as described above. Overall, our analysis underscores the inherently distinct role possibly played by relationships in distinct areas of the loan process – an intuition hitherto not explored in the extant literature.

The benefit of using our particular estimation technique is two-fold. First, it allows us to model discouraged borrowers (in the Application Decision) and the potential role of relationships in their decision to self-ration – another neglected issue in the literature. To examine the effect of relationships on credit availability for small businesses and individual borrowers, it is important to understand the role of relationships on the decision to apply for a loan as well as to approve the loan or to determine the loan rate. Decisions to not apply for credit as a result of weak relationships with lending institutions would adversely impact the well-being of businesses and families in the long-run.

Second, our estimation technique allows us to investigate the financial institution's Credit Approval and Loan Rate Setting Decisions as part of a multistage process. We are, therefore, able to tease out the potentially distinct roles of relationship measures in the various stages of the loan process. In order to estimate the effectiveness of programs targeted towards enhancing relationships between banks and

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[2] The literature on the role of relationship-banking highlights the differences in lending by small and large banks to small borrowers (see, for example, Cole et al., 2004, and Berger, Miller, Petersen, and Rajan, 2004). We do not investigate the impact of the size of the lending institution on the loan granting process. Instead, we use standard measures of relationships, which include the length of association between borrower and lender, used in the literature cited above, as well as the number of asset accounts and loans with a lender, and the total number of financial institutions that the borrower has dealings with.

consumers who have historically weaker relationships with lending institutions, it is important to understand the distinct role of relationships in the different stages of a loan process.

The bulk of bank-borrower relationship research involves small business loans [see, for example, Petersen and Rajan (1994, 1995), Berger and Udell (1995), Cole (1998), and Cole et al., 2004)]. Therefore, we too focus our analysis on the role of relationships in small business lending using the most recent (i.e., 1998) version of data from the National Survey of Small Business Finances (NSSBF). The uniqueness of the NSSBF data lies in its detailed business-level information, including directly observing credit-constrained and discouraged small business borrowers. Consistent with the discussion above, we empirically examine the role of relationship measures on 1) the probability of applying for a loan; 2) the probability of approving/rejecting a loan applicant for a loan; and 3) the loan rate, all determined within a unified framework. Our relationship proxies are all standard measures and include the length of association between borrower and lender, the number of asset accounts and loans with a lender, and the total number of financial institutions that the borrower has dealings with. We initially focus our attention on the most recent loans of the small businesses in our dataset.

Upon estimating our model, we find that relationship measures are most important in increasing the probability of applying for a loan and lowering the probability of being rejected for a loan. Apart from relationship effects, the financial characteristics of a small business, such as current sales and total assets and liabilities, also have a powerful effect in explaining a discouraged and/or credit-constrained borrower. Having identified that relationship measures play an important role in the overall loan approval/denial process, we go a step further in determining the role of relationships in loan rate decisions. Considering only those small businesses in our data that had outstanding loans (i.e., without accounting for the sample selection bias) we find that relationship measures have significant power in explaining loan rates when only relationship measures are included in the second stage estimation. Upon inclusion of other relevant borrower characteristics, the power of relationship measures, while becoming less important, still remains significant. The statistical significance of relationship variables, however, disappears altogether when the selection bias is appropriately corrected for; i.e., relationship measures have no power in explaining the loan rate. Still, other characteristics of small business borrowers, such as current sales and accounts receivable turnover, continue to have a significant effect on the loan rate.

To ensure that our findings are not a function of borrower type, we also confront our empirical model with a unique data set related to loans taken out by American families. To the extent that small business loans may be inherently distinct from loans made to individual families, both in terms of loan amounts and borrower transparency, it is not necessarily clear if the conclusions drawn about small business loans will crossover into the realm of individual loans. It has also been suggested that the approval process for consumer loans and the determination of loan rates are fairly standardized and reliant on the credit information on potential borrowers available from the three major credit bureaus in the United States. This would argue for a reduced role of relationships on the loan approval/rejection process for individual families. However, our extensive interactions with bank loan officers indicate that relationships still have an important role to play in their loan granting decisions, which suggests our empirical model is relevant in the consumer loan market as well.[3] The importance of relationships in the consumer loan market is also underscored by the existence of specific programs targeted toward (typically low income) families with no current relationships with banks in order to foster such relationships. Examples of such programs include offering Individual Development Accounts (IDAs) to low-income families and mortgage loans made through Neighbor Works Home Ownership Centers established through partnerships between various States, non-profit organizations and financial institutions in order to develop and nurture fledgling relationships between consumers and banks.[4]

Additionally, the relationship proxies used in this paper are more comprehensive than the factors used to determine individuals' credit scores, which usually include information on how applicants pay their bills, the amount they owe, and the amount of their available credit. By contrast, our relationship proxies include information available only to the potential lender, or the applicant's main bank, such as the number of the asset accounts held by the applicant at that particular lending institution. Furthermore, the data on individual loans include information on the self-reported credit history of the applicant. We use this information to tease out the potentially differential effect of relationships after controlling for the applicant's past credit history.

To examine the potential role of relationships in lending to individual consumers and families, we use data from the 1995, 1998 and 2001 versions of the Survey of Consumer Finances (SCF) compiled by the Federal Reserve Board, which also allows us to directly observe discouraged and credit-constrained borrowers. This allows us to draw an explicit connection between credit rationing and borrower characteristics vis-à-vis the borrowers' personal relationships with their banks. We focus on mortgage loans taken out by families since such loans arguably represent the most important consumer loan. In many ways, however, our choice of mortgage loans represents the toughest test of our model in the consumer loan arena because of the collateralized nature of such loans, where the impact of relationships may be relatively small to begin with.

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[3] For example, Wells Fargo has a mortgage loan called "Jumbo Relationship ARM" for consumers interested in purchasing bigger homes with an adjustable-rate loan. On the application of this loan, it is actually emphasized that "the stronger your banking relationship with Wells Fargo, the deeper your potential discounts will be." For further details, go to https://www.wellsfargorelo.com/relo/jumbo.wfm.

[4] The Michigan IDA Partnership, an initiative of the Council of Michigan Foundations and the State Family Independence Agency, is one of these programs (see also http://www.cmif.org/IDA/idabanks.htm). For details on program design of a typical Neighbor Works Home Ownership Center in Long Island, NY, see "In the Region/Long Island: Helping New Buyers Cope With High Housing Cost," published in the New York Times, 09/09/2001.

Using a large sample of families, we are able to confirm that relationships impact only the availability of consumer oriented loans and that, once the sample selection bias is appropriately accounted for, loan rates of consumer oriented loans are not impacted by relationships. Apart from relationship effects, the characteristics of a borrower such as her age, income, assets, liabilities, and credit history have powerful effects in explaining a discouraged and/or a credit-constrained borrower. Similar to small business loans, we find that relationship measures have significant power in explaining mortgage loan rates when only relationship measures are included in the second stage estimation. Upon inclusion of other relevant borrower characteristics, however, relationship measures become less important (but still remain significant), and the statistical significance of the relationship variables disappears altogether when the selection bias is appropriately corrected for. However, other characteristics of borrowers, such as total assets, liabilities, and whether the borrower shops for credit or not, continue to have a significant effect on the determination of mortgage loan rates.

In sum, relationships, while playing an important role in loan approval, do not actually play any significant role in the lowering of loan rates. This finding demonstrates the importance of examining the role of relationships across the distinct stages of a loan granting process and is robust across the small business and consumer loan markets.

The remainder of this paper is structured as follows. Section 2 discusses the methodology and constructs the empirical framework. Section 3 describes the data, and Section 4 defines the variables used in the analysis. Section 5 presents the findings of our empirical analysis for small businesses loans and compares our findings with the extant small business borrower-lender relationship literature. Section 6 investigates the role of relationships for individual families' mortgage loans. Section 7 concludes our study.

2. The Empirical Model

In this section we present the modeling of relationships as it pertains to the overall lending process. The basic assumption on which the formalization below rests is that the lending process is comprised of a three-stage decision. First, the borrower decides whether or not to apply for a loan. Second, there is a screening process by which the loan applicant is either rejected or approved for the loan. Finally, the loan interest rate is set by the lender. Since the credit approval decision is observable only if the borrower decides to apply for a loan and the loan interest rate is observable only when the applicant decides to apply for a loan **and** the lender approves the application, we have a double selectivity model described by the following three equations:

Assume a borrower *i* is not discouraged from applying for a loan if

The Application Equation

$$y_{1i}^* = x_{1i}\beta_1 + \varepsilon_{1i} > 0, \qquad (1)$$

and is not credit-constrained if

The Credit Approval Equation

$$y_{2i}^* = x_{2i}\beta_2 + \varepsilon_{2i} > 0\,, \qquad (2)$$

where y_{1i}^* and y_{2i}^* are latent variables representing the borrower's decision to apply to the lender for a loan and the lender's decision to approve the loan, respectively; x_{1i} and x_{2i} are vectors of independent variables; β_1 and β_2 are vectors of parameters; ε_{1i} and ε_{2i} are error terms with standard deviations σ_1 and σ_2, respectively and, without loss of generality, σ_1=σ_2=1. The borrower applies for a loan ($y_{1i} = 1$) if $y_{1i}^* > 0$, and does not apply for a loan ($y_{1i} = 0$), otherwise. Also, the borrower is not credit-constrained ($y_{2i} = 1$) if $y_{2i}^* > 0$, and is credit-constrained or refused a loan ($y_{2i} = 0$), otherwise. Essentially, we observe y_{2i} only if $y_{1i} = 1$. That is, if the borrower decides not to apply for a loan, i.e., $y_{1i} = 0$, then we do not observe whether she is, or isn't, approved for a loan.

The loan rate for borrower *i* is represented by the following equation:

The Loan Rate Equation

$$y_{3i} = x_{3i}\beta_3 + \varepsilon_{3i}\,, \qquad (3)$$

where y_{3i} is the observable loan rate; x_{3i} is a vector of independent variables; β_3 a vector of parameters; and ε_{3i} is an error term with the standard deviation σ_3. The loan rate is observed only when the borrower is not discouraged from applying for a loan <u>and</u> is approved for a loan conditional on applying: i.e., $y_{1i} = y_{2i} = 1$.

The error terms are assumed to be independently and identically distributed across the sample with a joint normal distribution: [5]

$$\begin{pmatrix}\varepsilon_1\\ \varepsilon_2\\ \varepsilon_3\end{pmatrix} \sim N\left[\begin{pmatrix}0\\0\\0\end{pmatrix},\begin{pmatrix}1 & \rho & \sigma_{13}\\ & 1 & \sigma_{23}\\ & & \sigma_3^2\end{pmatrix}\right]. \qquad (4)$$

We employ a two-stage selection estimator used by Ham (1982) to obtain the consistent estimates

[5] Extant research has shown that the estimated parameters may be sensitive to the distributional assumptions made in the selection models. It has been suggested that approaches based on semiparametric and nonparametric estimators may be more appropriate. However, it is almost impossible to apply these methods to our specific question. See Greene (2003, page 789) for a discussion of these methods and the inherent difficulties in estimating them.

of the Loan Rate Equation. The crucial issue in correcting for bias with the double selection rule is the expectation of the loan rate conditional on $y_{1i}^* > 0$ and $y_{2i}^* > 0$. This conditional expectation can be expressed as

$$E(y_{3i} \mid y_{1i}^* > 0, y_{2i}^* > 0) = x_{3i}\beta_3 + E(\varepsilon_{3i} \mid \varepsilon_{1i} > -x_{1i}\beta_1, \varepsilon_{2i} > -x_{2i}\beta_2)$$
$$= x_{3i}\beta_3 + \sigma_{13}\lambda_{1i} + \sigma_{23}\lambda_{2i} \qquad (5)$$

where

$$\lambda_{1i} = \frac{\phi(x_{1i}\beta_1)\Phi(\frac{x_{2i}\beta_2 - \rho x_{1i}\beta_1}{(1-\rho^2)^{1/2}})}{F(x_{1i}\beta_1, x_{2i}\beta_2, \rho)} \text{ and } \lambda_{2i} = \frac{\phi(x_{2i}\beta_2)\Phi(\frac{x_{1i}\beta_1 - \rho x_{2i}\beta_2}{(1-\rho^2)^{1/2}})}{F(x_{1i}\beta_1, x_{2i}\beta_2, \rho)} \qquad (6)$$

and $\phi(.)$ and $\Phi(.)$ are the univariate standard normal density and the distribution functions, respectively, and F(.) is the bivariate standard normal distribution function. If σ_{13} and σ_{23} are not both equal to zero, the expectation in Equation (5) is not equal to $x_{3i}\beta_3$ and the resultant least squares estimation of Equation (5) on the censored sample will lead to the same sort of specification error bias that Heckman (1976) described in his single selection rule case.

We follow the same estimation procedure as Heckman (1976). That is, we first estimate the parameters of the selection Equations (1) and (2) by maximizing the following likelihood function:

$$L = \sum_{\substack{y_{1i}=1 \\ y_{2i}=1}} \ln\{F(x_{1i}\beta_1, x_{2i}\beta_2, \rho)\} + \sum_{\substack{y_{1i}=1 \\ y_{2i}=0}} \ln\{F(x_{1i}\beta_1, -x_{2i}\beta_2, -\rho)\} + \sum_{y_{1i}=0} \ln\{1-\Phi(x_{1i}\beta_1)\}, \quad (7)$$

where the first term on the right hand side of Equation (7) denotes the likelihood of a borrower applying and being approved for the loan, the second term denotes the likelihood of a borrower applying and being rejected for a loan, and the third term denotes a borrower not applying for a loan (i.e., self rationing).[6]

We then use the parameter estimates of β_1, β_2 and ρ to form consistent estimates $\hat{\lambda}_{1i}$ and $\hat{\lambda}_{21}$ of λ_{1i} and λ_{21} in Equation (6). As shown in Ham (1982), a least squares estimation of Equation (5) provides consistent estimators of parameters β_3, σ_{13} and σ_{23}. However, the least square estimation does not account for the fact that $\hat{\lambda}_{1i}$ and $\hat{\lambda}_{21}$ are estimators of λ_{1i} and λ_{21} and includes some of the same variables

[6] Also, see Wyand and van Praag (1981) and Meng and Schmidt (1985) for the likelihood function of a bivariate probit model when one of the dependent variables in the second stage is only partially observed.

in x_{3i} . Therefore, the standard errors of the parameter estimates may be inconsistent. We therefore use a bootstrapping method to obtain consistent standard errors.[7]

When estimating the above model, we also need to ensure that the system of equations is properly identified. To guarantee that the parameters of any specific equation in our model can be estimated (i.e., to overcome the identification problem), we need to impose appropriate exclusion restrictions on the variables included in the Application, Credit Approval, and Loan Rate Setting Equations, respectively. To do so, we need i) a variable in the bank's Credit Approval Equation not included in the borrower's Application Equation; ii) a variable in the borrower's Application Equation not included in the Credit Approval Equation; and iii) an additional variable in the bank's Credit Approval Equation and the borrower's Application Equation not included in the Loan Rate Setting Equation (see, for example, Maddala, 1983 pp. 280). We discuss (and justify), in Section 5, the variables that are excluded from the Application, Credit Approval and Loan Rate Setting Equations in order to ensure model identification.

3. Data

We use the 1998 version of the National Survey of Small Business Finances (NSSBF), sponsored by the Federal Reserve Board and the U.S. Small Business Administration, for a large part of our analysis. In particular, the NSSBF survey includes a nationally representative sample of 3,561 small businesses operating in the U.S. The survey provides detailed information on each firm's credit history including the firm's most recent borrowing experience, income statement and balance sheet, firm characteristics including organizational form, and characteristics of the firm's primary owner.

The NSSBF is uniquely suited to the study of credit rationing because discouraged and credit-constrained borrowers are identified directly. Specifically, a discouraged small business borrower is one who does not hold a loan at the time of the interview and responded "yes" to the question: "During the last three years, were there times when the firm needed credit, but did not apply because it thought the application would be turned down?" A credit-constrained small business borrower is one who applied for a new loan and whose application was denied. We have 403 borrowers who were discouraged from

[7] Specifically, we generate 250 random samples with replacement from the original sample. For each of these random samples, we estimate Equation (7) and use the estimates of β_1 , β_2 and ρ to calculate $\hat{\lambda}_{1i}$ and $\hat{\lambda}_{2i}$. We then use $\hat{\lambda}_{1i}$ and $\hat{\lambda}_{2i}$ as independent variables in Equation (5) to estimate the remaining unknown coefficient, β_3 , as well as the sample selection terms, σ_{13} and σ_{23} . We repeat this process 250 times, compute the standard deviations of these coefficients for each of those cases, and report them as the corresponding standard errors of the coefficients in Model 3 in Tables IV and VI.

applying for a loan and 706 borrowers who were not discouraged from applying.[8] Of these 706 borrowers, 140 were turned down (and do not hold a loan at the time of the interview) and therefore were credit-constrained, and the remaining 566 were approved for a loan (and hold a loan at the time of the interview).

In addition to the small business data set, we use the Survey of Consumer Finances (SCF) to potentially tease out the distinct role played by relationship measures in the overall loan process in consumer lending. The SCF data are a triennial survey of U.S. families sponsored by the Board of Governors of the Federal Reserve System with the cooperation of the U.S. Department of Treasury.[9] The survey is designed to provide detailed information on the assets, liabilities and income of U.S. families at of the time of interview.[10] Specifically, we use the 1995, 1998 and 2001 SCF survey data that include 4,299, 4,305 and 4,442 households, respectively.

Similar to the NSSBF, the SCF data are uniquely suited to the study of credit rationing because the discouraged and credit-constrained households are identified directly. A discouraged borrower is a household who answered “yes” to the question: “Was there any time in the past five years that you (or your spouse) thought of applying for credit at a particular place but changed your mind because you thought you might be turned down?” Those discouraged households that do not hold a mortgage loan (and do not own a home) at the time of the interview are identified as discouraged borrowers for the current analysis, i.e., mortgage loan. There are at least two reasons why we focus exclusively on mortgage loans within the SCF dataset. First, mortgage loans are the largest, and therefore the most significant, loans taken out by individuals and families by far. Second, these loans have the additional advantage of possessing the most detailed information among all consumer loans within the SCF data set. For instance, we can tell when a mortgage loan originated as well as other related details (more so than other consumer loans where a lot of the pertinent information is either missing or just not available), making it a natural candidate for the current analysis from an operational standpoint.

[8] Small businesses that were not discouraged, but did not apply for a loan in the past three years, are excluded from the sample because they did not need credit. Businesses that have relationships lasting longer than 35 years with their main bank and that were owned by the current owners longer than 35 years are also excluded from the sample.

[9] The term “family” used here is comparable to the U.S. Census Bureau’s definition of “household,” which includes the possibility of a family of one individual.

[10] To ensure that the survey picks up attributes both broadly distributed in the population as well as those concentrated in a relatively small part of the population, the SCF employs a dual-frame sample design consisting of both a standard geographically-based random sample and a special oversampling of relatively wealthy families. This design has been unchanged since 1989. Other details about the 1995, 1998 and 2001 SCF data collection process, including summary statistics on the data itself, are provided in Kennickell, Starr-McCluer, and Surette (2000) and Aizcorbe, Kennickell, and Moore (2003).

We define a credit-constrained household as one who answered "yes" to the question: "In the past five years has a particular lender or creditor turned down any request that you (and your spouse) made for credit or have you been unable to get as much credit as you applied for?" Those credit-constrained households that do not hold a mortgage loan (and do not own a home) are assumed to be credit-constrained for a mortgage loan.[11]

In the final analysis, after combining data from the 1995, 1998 and 2001 versions of the SCF, we have 1,050 families who were discouraged from applying for a mortgage loan and 3,175 families who were not discouraged from applying.[12] Since the wording of the questionnaires and the underlying measurements are highly comparable in these years, we combined them in our analysis and included 1995 and 1998 year dummies in our estimation to control for aggregate economic effects that may be specific to the 1995 and 1998 survey years.[13] Out of 3,175 families that applied for a mortgage loan, 323 were turned down and therefore were credit-constrained. The remaining 2,852 families were approved for a mortgage loan (non-constrained) over a five-year period from their respective interview dates.

4. Defining the Variables in the Small Business Data

4.1 Defining relationship factors

The underlying intuition provided by Stiglitz and Weiss (1981) is that the informational asymmetry between borrower and lender originates from moral hazard and adverse selection effects, causing lenders to refuse loans to some among an observationally identical population of potential borrowers. It is, therefore, argued that, through the observation of certain variables related to the interaction over time between a potential borrower and a lender, the latter is better able to make a determination about a potential borrower's ability to repay the loan. Consistent with Petersen and Rajan (1994), we label these interaction terms as relationships. Our choice of relationship variables is guided by the extant literature related to small business and individual borrowers [see, for example, Petersen and Rajan (1994, 2002), Berger and Udell (1995), Cole (1998) and Chakravarty and Scott (1999)].

The relationship variables included are, respectively, LENGTH, defined as the duration (in years)

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[11] From the group of credit-constrained families, we exclude those who reapplied for credit and received the desired amount. Households that have a relationship lasting longer than 35 years with their main bank are excluded from the sample. Also, households that have an association with more than 15 financial institutions are excluded from the sample. These households are mostly business owners, and it is hard to differentiate personal finances and loans from their business loans.

[12] Households that were not discouraged but did not apply for credit in the past five years are excluded from the sample for mortgage loan analysis.

[13] All dollar values are converted to 2001 dollars using The Consumer Price Index Research Series Using Current Methods (CPI-U-RS).

that the firm has conducted business with the potential lending institution; ACTIVITY and LOAN, defined as the number of asset accounts (checking and savings) and loans with the potential lending financial institution, respectively. We also include NOFININ, defined as the number of financial institutions that a small business has association with – either through asset accounts or through loans.

In sum, our relationship variables -- LENGTH, ACTIVITY, LOAN and NOFININ -- measure the strength of relationships with financial institutions and, especially, with the main bank. In individually examining the role of relationships in either credit availability or the determination of loan rates, the extant literature has reported that the same relationship proxies generally either increase credit availability or decrease loan rates. Consistent with this reported evidence -- and within our unified framework of examining loan application, loan approval and loan rate setting -- we would expect to find that these relationship proxies are associated with higher probabilities of applying and being approved for a loan and negatively associated with loan rates, once their role in the Application and Decision stages are controlled for.

4.2 Other factors affecting credit rationing

Berger and Udell (1995) and Cole (1998) have argued about the importance of accounting for the potentially confounding effect of firm age, which previous studies have shown to be highly correlated with the relationship-length variable discussed above. Additionally, Diamond (1991) argues that the age of a firm should influence whether it receives credit, simply because a firm in business for a longer period of time has generated enough reputational capital through its ability to survive the critical start-up period. We, therefore, include AGEF, defined as the number of years that the current owners owned the business, as a public information proxy.

We control for borrower riskiness with the traditional borrower-specific measures of riskiness that include size, creditworthiness and leverage. We proxy for size and creditworthiness with sales for the previous fiscal year (SALESF), total business assets (ASSETSF), profits (PROFIT) and accounts receivable turnover (ARTURN). We proxy for leverage with business liability (DEBTF) and accounts payable turnover (APTURN).

We also include control variables that measure the governance and industry characteristics of small businesses. The legal form of the business is reflected in the dummy variables for (non-Subchapter S) corporation (CORP), Subchapter S Corporation (SUBS), partnership (PART), and proprietorship (PROP). We include a dummy variable indicating whether or not 50 percent or more of the business is owned by a single family (CONC50). The industry characteristics are measured by dummy variables for construction (CONSTR), services (SERVICES), retail (RETAIL) and other industries (OTHERIND). The governance and industry characteristics are included to proxy for risk of credit for lenders. Finally, we include dummy variables to measure the education level of the current owner for those with high school or less education (HIGHSCH), college degree (COLLEGE) and post-college degrees (POSTCOLLGE). These variables are included because they might have an effect on applying for a loan. Table I presents a formal description of the variables used in the empirical estimation.

4.3 Comparing across discouraged, credit-constrained, and non-constrained small businesses

Table II presents summary statistics for the variables introduced above for discouraged, credit-constrained, and non-constrained small businesses in the 1998 NSSBF data.

First, we compare the discouraged and credit-constrained small businesses. The discouraged businesses have a significantly longer relationship (LENGTH) with their potential lenders (7.08 years versus 5.94 years) and been under the current management longer (11.50 years versus 9.96). In addition, the number of financial institutions that a discouraged borrower has association with (NOFININ) is lower (2.11 versus 2.92). Among financial variables measuring borrower size, creditworthiness and leverage, total sales and assets are lower for the discouraged borrowers relative to constrained borrowers. However, the total debt (DEBTF) and profit (PROFIT) of discouraged borrowers are lower, but not significantly different, from those of the constrained borrowers. Most of the governance and industry-specific characteristics of discouraged borrowers are not significantly different from those of the credit-constrained borrowers.

Second, we compare credit-constrained and non-constrained small business borrowers. Differences between credit-constrained and non-constrained borrowers are larger than the differences between discouraged and credit-constrained borrowers. Compared to non-constrained borrowers, credit-constrained borrowers have significantly shorter relationships (LENGTH) [5.94 years versus 7.25 years], fewer activities (ACTIVITY) [0.94 versus 1.20], and loans (LOANS) [0.44 versus 1.22] with their potential lenders. The number of financial institutions that a credit-constrained borrower has association with (NOFININ) is also lower (2.92 versus 3.43). Among the financial variables measuring borrower characteristics, there are significant differences between the credit-constrained and non-constrained businesses. For instance, the number of years under current management is lower for credit-constrained businesses. Also, the total sales of non-constrained businesses are almost six times as much as the credit-constrained businesses, and their total assets are about four times greater. The debt of non-constrained businesses is about six times greater than that of credit-constrained businesses. Finally, non-constrained businesses are more likely to be corporations and less likely to be sole proprietorships; they are less likely to be majority (i.e., at least 50 percent) owned by a single person or family; they are less likely to be in the retailing and service industries and more likely to be managed by a college graduate, compared to their credit-constrained counterparts.[14]

Overall, there are significant differences in characteristics between small business borrowers (a) who were discouraged from applying for a loan, (b) who applied for credit but were constrained (turned down for a loan), and (c) who applied and obtained the loan.

5. Multivariate Analysis

5.1 Estimating the two-stage selection: applying and being approved for a loan

In this section, we begin estimating our empirical model described in Section 2. We wish to emphasize that whether or not a given small business borrower is credit-constrained is not observable if the borrower is discouraged from applying for a loan (i.e., if the borrower self-rations). Any empirical estimation methodology that ignores this bias is not fully utilizing the information in the data, leading to unreliable parameter estimates. We, therefore, estimate the likelihood of being constrained, given by Equation (7), by appropriately correcting for this sample selection bias. We also note that since we are testing for an overall validation of our hypothesis in the realm of small business loans, we choose not to partition the loans on any dimensions, such as whether they were collateralized or not, focusing instead on all valid small business loans in the data.[15]

The results are represented in Table III. The independent variables, capturing bank-borrower relationships and borrower characteristics including governance and industry characteristics, have been discussed in Section 3.[16] As noted in Section 2, exclusion restrictions on the variables are included in the Application and Credit Approval Equations. Thus, for example, the Application Equation excludes CONC50, while the Credit Approval Equation excludes NOFININ, COLLEGE and POSTCOLLEGE. These appear to be valid restrictions because bank loan officers do not directly observe the number of financial institutions that a borrower has association with and the education level of the borrower. Also,

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[14] For those small businesses holding a loan, the average loan rate is equal to 402.99 basis points where the loan rate is defined as the interest rate on the latest loan minus the rate on 3-month Treasury Bills during the month the loan was taken out.

[15] Berger and Udell (1995), for example, focus solely on small business lines of credit as a rejoinder to the findings (or the lack thereof) by Petersen and Rajan (1994) who, using a sample of small business loans (that include lines of credit as well as other types of small business loans) from the 1989 version of the NSSBF data set, find no statistical association between the duration of the bank borrower relationship and loan pricing. By contrast, Berger and Udell examine a subset of these loans, namely the lines of credit, and show that small business borrowers, with longer banking relationships, pay lower interest rates.

[16] We add one and take the natural logarithm of the variables SALESF, ASSETSF and DEBTF. For instance, ASSETSF is operationalized as Ln (1+ASSETSF) to ensure we do not lose observations with zero assets. Similar adjustments are made to the two other variables.

majority (i.e., at least 50 percent) ownership by a single owner should not affect the decision by an applicant to apply for a loan, once the legal organization of the business and other governance characteristics are controlled for.[17]

The marginal effects of independent variables included in Equation (7) are also provided in Table III. The marginal effects of each independent variable are calculated while holding all other explanatory variables at their respective sample means.

The role of relationships in applying for a loan. Among the relationship proxies, ACTIVITY, LOAN, and NOFININ significantly affect the likelihood of applying for a loan. For instance, an increase by one unit in asset accounts and loans with the bank increases the probability of applying for a loan by 6.8 and 6.0 percentage points, respectively, and an increase (by one) in the number of financial institutions that the borrower has association with increases the probability of applying for a loan by 5.6 percentage points. Among the financial variables, the coefficients for the natural log of both SALESF and ASSETSF are positive and the coefficient for the natural log of DEBTF is negative. A 10 percent increase in sales and assets, on average, increases the probability of applying for a loan by 0.38 and 0.18 percentage points, respectively. The remaining governance and industry characteristics do not appear to affect the probability of applying for a loan.

The role of relationships in being approved for a loan. Among relationship variables, the coefficients for ACTIVITY and LOAN are positive and significant. Conditional on applying for a loan, an increase by one unit in asset accounts and loans with the bank raises the probability of being approved by 5.4 and 6.5 percentage points. Conditional on applying for a loan, SALESF and ASSETSF have significant positive effects on the probability of being approved for a loan. The industry type of the business also affects the probability of being approved for a loan. Compared to other types of industries, those in construction, services, and retailing are less likely to be approved for a loan.

In sum, the results of a two-stage selection model show that relationship variables are significant predictors of being discouraged from applying for a loan and being approved for a loan. We now turn to the role of relationships in determining the loan rate.

5.2 Estimating the loan rate

Using only small businesses holding a loan to estimate the role of relationships on loan rates leads to inconsistent estimates if the probability of applying and being approved for a loan are correlated with the error term and the independent variables including relationship variables. Our empirical model takes into account this sample selection bias in estimating the role of relationships on loan rates. To do so, we

[17] NOFININ significantly enters the borrower's application decision and, therefore, helps in identifying the model. Unfortunately, CONC50 does not have a significant effect on being approved for a loan. For robustness, we have estimated our model after excluding other explanatory variables. Excluding variables other than NOFININ, COLLEGE, POSTCOLLEGE and CONC50, and estimating Equation (7), did not materially alter our results.

first calculate $\hat{\lambda}_{1i}$ and $\hat{\lambda}_{2i}$ in Equation (6) using the estimates of β_{1i} β_{2i}, and ρ. Then we estimate Equation (5) using the sample of those businesses that obtained a loan in the past 3 years. The estimation results are given in Table IV, which also provides estimation results without correcting for selection bias. We also need an additional variable, included in the Application and the Credit Approval Equation but not included in the estimation of the loan rate, in order to ensure that the model is identified. Accordingly, the loan rate regression excludes the variables signifying the number of financial institutions that the borrower has association with (NOFININ), the legal organization of the business (CORP, SUBS, PART), and the education level of the owner (COLLEGE and POSTCOLLEGE) as independent variables. We argue that excluding the legal organization of the business from the Loan Rate Equation is a valid exclusion restriction because the legal organization should not directly affect the profit of the bank and should, therefore, not affect the loan rate. Also, the number of institutions that a borrower has association with and the education level of the owner are not directly observed by the bank. We have, however, checked for the robustness of our results by excluding other independent variables from the regression. Our results remain qualitatively unchanged.

When only relationship proxies are included in the estimation (Model 1), LENGTH and LOAN have a negative, and significant, effect on the loan rate – which is what we would expect. Specifically, a one year increase in relationship length decreases the mortgage loan rate by 3.34 basis points and an increase in the number of loans with the primary lender (by a unit) decreases the rate by 31.41 basis points. However, when financial variables and governance and industry characteristics are added in the estimation (Model 2), the relationship proxies collectively reduce in statistical significance relative to Model 1 but are still able to explain the reduction in loan rates. This finding is very similar to the results reported by Berger and Udell (1995). In their analysis of loan rates on non-collateralized loans, both LENGTH and AGEF are negative while AGEF is not statistically significant.[18]

Model 3 corrects for the sample selection bias discussed previously. Once this is done, the relationship variables lose their power entirely to explain the loan rate. Among the financial variables, small businesses with higher levels of SALESF and ARTURN have lower rates. Other financial, governance, and industry characteristics do not significantly affect the loan rate. Also, one of the

[18] In the empirical analysis, we use the LENGTH and AGEF in levels. Berger and Udell (1995) use the natural log of LENGTH and AGEF. We run robustness checks by including the natural log of LENGTH and AGEF in the estimation of our model. Our findings remain unchanged. Also, as discussed in Berger and Udell (1995), LENGTH and AGEF are correlated with each other. However, there is an important distinction between them. AGEF measures information that is revealed to the loan market whereas LENGTH measures private information revealed to the lender. When AGEF is dropped from the estimation of our model, the importance of LENGTH increases in all three stages of the loan process.

selections terms, λ_Apply, is significant, suggesting that there might be a sample selection problem in estimating the Loan Rate Equation using only those borrowers carrying loans.[19]

We also examine whether the relationships play a more important role for the loan processes of the smallest businesses. In our sample, 745 small businesses have less than \$400,000 of total assets. About half of those businesses (354) were discouraged from applying for a loan. Of those businesses applying for a loan, 276 of them were extended a loan and 115 were rejected. This indicates that most of those firms in our original sample that were discouraged from applying for a loan, or those that were credit-constrained, were the smallest firms. This is an important finding in light of policymakers' (and some academics') concerns about some small businesses being squeezed out of the credit markets. Our research is able to precisely identify the size of such small businesses, and the estimation results, in fact, show that relationships play a more important role in the loan granting processes of those firms with assets below \$400,000.[20] For example, a unit increase in the number of loans increases the probability of approval by almost 20 percent. Also, the relationship length with the business' primary lending institution seems to have a significant effect on the loan rate. However, even this effect disappears entirely when we appropriately control for sample selection.

In sum, it is clear that relationships are only important in the selection stage of a loan process and play no significant role in the loan rate determination stage of the process.

5.3 Comparison of our findings to extant research

Petersen and Rajan (1994) use the 1989 version of the National Survey of Small Business Finances data to show a "small" effect of relationships on the loan rates charged by lenders. They obtain this result by regressing the interest rate quoted on a firm's most recent loan on proxies capturing the underlying cost of capital, as well as loan- and firm-specific characteristics that may influence the rate and, most importantly, relationship measures. They also separately examine the role of relationships on the availability of credit and find "stronger" effects of relationships on their proxy for credit availability. In spirit, this finding is similar to what we uncover using business loan data. However, there are several important differences between their approach and ours.

First, unlike our data, Petersen and Rajan's data do not allow them to observe credit availability directly. The authors are therefore forced to find indirect proxies for credit availability. They initially use the firm's debt ratio as a proxy for credit availability but acknowledge its inherent problems as a suitable

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[19] That is, conditional on the observable characteristics of the businesses, it appears that there is negative selectivity: those businesses predicted to be more likely to apply for loans have lower loan rates than their otherwise identical counterparts.

[20] We do not formally present the results of our analysis for the smallest businesses. The estimation results are available on request.

proxy due to the fact that changes in debt ratio can occur either due to changes in the demand for credit or by the changes in the supply of credit, thereby giving rise to a potential simultaneous equation bias when used as a dependent variable. They then use the percentage of trade credits repaid late as a separate (and improved) measure of credit availability. However, the assumption on which such a measure is a valid proxy for credit availability is that the discount offered for early payment (typically 2 percent or less) is a strong enough incentive to pay off bills early. In the relatively low interest rate climate of the last decade, it is unclear if such incentives are taken seriously by vendors. Furthermore, if the repayments are allowed to be stretched beyond the due date (as they frequently are) then such a measure is an inappropriate proxy for credit availability.

Second, Petersen and Rajan (and Berger and Udell, 1995) separately estimate the role of relationships on loan rate and credit availability. But conversations with bank officials and other theoretical considerations point unambiguously to the fact that the two decisions, credit availability and the determination of the loan rate, are inextricably woven together as part of the same loan process and should not be considered as distinct.

In contrast, we examine the entire loan granting process using data from the small business loan market (and, in what follows, also from the consumer loan market). In every instance, our finding is that it is the availability of credit, rather than the pricing of credit that is significantly correlated with the relationship proxies. While our finding is similar in spirit to Petersen and Rajan (1994), we wish to underscore that it flows out of data where credit availability is directly observed and that the empirical estimation process explicitly accounts for the various stages of the loan process within a robust and unified framework.

6. The Role of Relationships in Consumer Loans: A Robustness Check

In the previous section, we established the differential role played by relationship measures in small business loans. Is it possible that the results we have documented above are specific to the type of borrower, i.e., small businesses? Alternatively, could the role of relationships be fundamentally different for small businesses than it is for individuals and families?[21] It is a fact that the magnitude of a loan is

[21] We know that small businesses keep more meticulous accounting records, which are usually managed professionally. By contrast, families maintain records more informally and may not use the help of a professional accountant. As a result, the financial picture of a small business is likely to be more transparent than that of an average family. The implication is that small businesses should probably have relatively lower informational asymmetry than individual families. By the same token, however, financial intermediaries can access an individual's credit information from the three major credit bureaus (Equifax, Experian and TransUnion) and have a reasonably comprehensive picture of the loan applicant -- something not possible with small businesses. In the net, therefore, it is not clear if there is a clear path to extrapolate to consumer loans from our findings with small business loans.

generally higher for a small business than it is for a loan made to a family. For example, an average small business loan in the 1998 NSSBF data was for $508,697 while the average mortgage loan (arguably the most significant consumer loan) made to a family in the 1998 SCF data was for $105,271.

It can be reasonably asked if consumer mortgage loans are the best candidate consumer loans to analyze in order to understand the potential impact of relationships on loans. After all, mortgage loans are collateralized loans where the effect of relationships may be limited. Berger and Udell (1995), in striving to clarify the relative lack of importance of relationship measures in explaining small business loan rates reported in Petersen and Rajan (1994), essentially make a similar point. It could, therefore, be argued that mortgage loans taken out by families and individuals may not be the best venue to look for relationship effects. While we do not quibble with this argument, our point is very simply that since the purpose of this section is primarily to gauge the robustness of our earlier findings in a different loan arena, the possibility that consumer mortgage loans may have somewhat of a tenuous connection with relationships will actually work to our advantage if we can still show the same trend in such loans as we did in our earlier analysis of small business loans. We therefore expand the scope of our investigation to include consumer loans using the SCF data described in Section 3.

To allow direct comparison of our findings with small business loans, we use the same relationship variables, LENGTH, ACTIVITY, LOAN and NOFININ to investigate the role of relationships in individual lending. We control for borrower riskiness with the traditional borrower-specific measures of riskiness that include size, leverage and creditworthiness. We proxy for size with family assets (ASSETS) and total family income (INCOME). We proxy for leverage by family liability (DEBT). For homeowners, we exclude the value of the home from ASSETS and the amount of any outstanding mortgage loans from DEBT. We proxy for borrower creditworthiness with three variables: BADHISTORY, a dummy variable taking the value 1 if the individual (or any member of the household) had problems over the previous year, in making existing loan payments, and zero otherwise; WELFARE, a dummy variable taking the value 1 if the household received public assistance over the preceding year and zero otherwise; CUREMP, a variable measuring the number of years that the head of the household had worked in his current employment. We also control for other characteristics of borrowers, such as race, marital status, gender, the number of children and also whether the borrower does a great amount of shopping for credit or not, and whether the borrower is willing to take financial risk for higher returns or not. Once again, Table I presents the description of variables used in the empirical estimation. Our control variables, encapsulating the financial and demographic characteristics of the household, closely match a large extant literature investigating the role of discrimination on mortgage loan approval/rejection decisions [see, for example, Munnell, Tootell, Browne, McEneaney (1996), Bostic (1996), and Ladd (1998)].

Upon comparing across discouraged, credit-constrained and non-constrained families in the 1995, 1998 and 2001 versions of the SCF data, we find similar patterns as those reported in the context of small businesses in Table II.[22] For instance, relative to credit-constrained families, the discouraged families have significantly fewer relationships (through LENGTH, ACTIVITY, LOAN and NOFININ). Discouraged families are more likely to be older, with lower total annual income and a higher proportion of liabilities. Finally, discouraged families are less likely to be married, less likely to be of Caucasian origin, and less likely to be willing to take financial risks. They are also more likely to have had credit-related problems in the past, be on welfare, be headed by single females, and have more children.

And comparing between credit-constrained and non-constrained families (with regard to mortgage loans only), we find that the credit-constrained families have significantly shorter relationship measures in all four relationship dimensions. Additionally, the total income of non-constrained families is almost three times as much, total liabilities about twice as much, and their total assets are about eight times as much as of those of the credit-constrained families. Finally, the non-constrained families are more likely to be older, married, of Caucasian origin, and have more children; they are more likely to shop for credit and have longer tenure at their current employment and less likely to have had credit-related problems, have been on welfare, or be headed by single females, relative to their credit-constrained counterparts. In short, we see a smooth transitive association between discouraged, credit-constrained, and non-constrained borrowers.

6.1 Estimating the two-stage selection: applying and being approved for a mortgage loan

The results of the two-stage estimation for mortgage loans are represented in Table V. The Application Equation excludes CUREMP, while the Credit Approval Equation excludes WELFARE. These appear to be valid restrictions because bank loan officers do not directly observe whether or not an applicant receives income from welfare. Also, the number of years the applicant worked in the current job should not affect the decision by an applicant to apply for a loan. [23]

The role of relationships in applying for a mortgage loan. All the relationship proxies significantly affect the likelihood of applying for a mortgage loan. For example, a one year increase in relationship length increases the probability of applying for a mortgage loan by 0.6 percentage points. Similarly, an increase by one unit in asset accounts and loans with the bank increases the probability of applying for a mortgage loan by 2.1 and 3.9 percentage points, respectively, and an increase (by one) in the number of financial institutions that the family has association with increases the probability of

[22] We do not formally present these univariate results. They are available from the authors on request.
[23] CUREMP and WELFARE significantly enter the bank's approval decision and the borrower's application decision, respectively and, therefore, help in identifying the model. For robustness, we have estimated our model after excluding other explanatory variables. Excluding variables other than CUREMP and WELFARE and estimating Equation (7) did not materially alter our results.

applying for a mortgage loan by 3.3 percentage points. Also, AGE has a significantly positive effect. A one year increase in the age of the household head increases the probability of applying for a mortgage loan by 0.2 percentage points.

Among financial variables, the coefficients for both INCOME and ASSETS are positive and the coefficient for DEBT is negative. Among variables measuring borrower creditworthiness, BADHISTORY and WELFARE, are negative. Having a bad credit record in the recent past decreases the probability of applying for a mortgage loan by 12.8 percentage points and receiving income from public assistance decreases the probability by 8.7 percentage points.

The role of relationships in being approved for a mortgage loan. Among relationship variables, the coefficients for LENGTH, LOAN and NOFININ are positive and significant. Conditional on applying for a mortgage loan, a one unit increase in relationship length increases the probability of being approved for a mortgage loan by 0.3 percentage points, an increase of one unit in loans with the bank increases the probability by 1.8 percentage points, and an increase by one unit in the number of financial institutions that the family has association with increases the probability by 2.0 percentage points. AGE and ASSETS have significantly positive effects on the probability of being approved for a mortgage loan, while DEBT has a significantly negative effect. The marginal effect of BADHISTORY, conditional on the probability of being approved for a mortgage loan, is relatively smaller than its effect on the probability of applying for a mortgage loan. Those with bad credit histories are 4.5 percent less likely to be approved for a mortgage loan. CUREMP is positive, showing that an extra year of employment increases the conditional probability of being approved for a mortgage loan by 0.3 percentage points.

6.2 Estimating the mortgage loan rate

The estimation results are given in Table VI, which also provides estimation results without correcting for the selection bias.[24] The loan rate regressions include an additional independent variable that is appropriate in a mortgage rate regression: the average annual prime rate prevailing in the year of origin of the mortgage loan, MRATE.[25]

When only relationship proxies, the average prime mortgage rate, and the length of the loan are included in the estimation (Model 1), LENGTH, ACTIVITY and NOFININ have a negative and

[24] The mortgage loan rate regression, however, excludes the number of children as an independent variable in order to satisfy the exclusion restriction. Excluding the number of children from the Loan Rate Equation is a valid exclusion restriction because the number of children should not directly affect the profit of the bank and, therefore, should not affect the mortgage loan rate. We have, however, checked the robustness of our results by excluding other independent variables from the regression. Our results remain qualitatively unchanged.

[25] The significance of the selection terms, λ_Apply and λ_Approved, do not change when we do not include MRATE, or use the difference between the mortgage rate and MRATE as the dependent variable, in the estimation of Equation (5).

significant effect on the loan rate. Specifically, a one unit increase in relationship length decreases the mortgage loan rate by 0.71 basis points,, an increase in the number of accounts with the primary lender decreases the mortgage rate by 4.65 basis points, and an increase in the number of institutions that the family has an association with decreases the loan rate by 5.70 basis points. However, when financial variables and family demographics are added in the estimation (Model 2), the relationship variables, while collectively losing a lot of power relative to Model 1, still remain a significantly negative determinant of loan rates (in particular, through NOFININ). This is consistent with what has been reported in the literature. The implication is that relationship measures significantly (and negatively) impact loan rates even after controlling for all relevant measures impacting loan rates that are documented in the literature.

Model 3 corrects for the sample selection bias discussed before. In so doing, the relationship variables lose their power entirely to explain the mortgage loan rate. Among financial variables, households with higher levels of ASSETS and lower levels of DEBT have lower mortgage rates. After accounting for the effect of BADHISTORY on the probability of applying and being approved for a loan, BADHISTORY has no effect on the loan rate, showing that having a bad credit history actually affects only whether the family applies and gets the loan or not. The coefficient of SHOP is robust to correcting for the selection bias. Families who shop around for credit have a mortgage rate that is 11.05 basis points lower than those who do not shop. Furthermore, the estimated coefficients show that a single basis point increase in the prime mortgage rate increases the actual mortgage rate by 0.40 basis points. Compared to 2001, the mortgage loan rates were 15.82 and 17.61 basis points higher in 1995 and 1998, respectively. Finally, the selections terms, λ_Apply and λ_Approved, are significant, implying that there is a sample selection problem in estimating the Loan Rate Equation using only those families carrying mortgage loans.

7. Discussion and Conclusion

We reexamine the role of relationships in credit rationing. While an impressive body of empirical research exists investigating the role of relationships in lowering the probability of being credit-constrained or lowering the interest rate on the borrower's most recent loan, the overall evidence on the role of relationships on credit availability is mixed.

We use an estimation technique that accounts for the fact that the overall loan granting process is a multistage process involving a borrower's decision to apply to the bank for a loan (or not), whether a bank approves the application for a loan (or not), and the loan rate it chooses for the borrower. More importantly, we argue that all three stages of the process are endogenously determined, so that any model that ignores this potential endogeneity runs the risk of being biased and inconsistent. Also, the multistage nature of the loan granting process raises the intriguing question of whether relationships are equally important in all stages of the loan granting process. That is, we examine if relationships have a distinct role in the different stages of the loan process. Our empirical model is also able to explicitly account for discouraged borrowers (i.e., those who do not apply for loans because they believe they will be rejected) – an issue not tackled in the extant literature.

Using the NSSBF data, which allows us to observe credit-constrained and discouraged small businesses directly, we examine the role of relationship measures on the probability of applying for a small business loan; the probability of approving/rejecting a loan applicant for a loan; and determining the loan rate, within a unified framework. We find that relationships matter only in the first and second stages of the loan process, i.e., a borrower's decision whether to apply for a loan and the loan approval/rejection decision by the financial institution. Once the sample selection bias is appropriately controlled for, relationships are not important in determining the loan rate associated with the approved loan. While our analysis is performed on small business loans, we go further in examining if our results, and conclusions therefrom, are robust to the loan arena. Specifically, we also examine the potential role of relationships in mortgage loans taken out by individuals and families using the SCF data, with the caveat that it is likely, given the collateralized nature of mortgage loans and the fact that banks can easily access the individual applicant's credit history from the three national credit rating agencies, that the role of relationships in the consumer mortgage loan process may be tenuous to begin with. Yet, here too we find results similar to those reported with small business loans, thereby establishing that our findings, and the resultant conclusions, are robust to the loan arena as well as to the nature (collateralized versus non-collateralized) of the loan itself.

A practical implication of our findings is that relationships, in fact, do not affect loan pricing. It is only at the prior approval/rejection stage that relationships appear to play a significant role. An intuitive explanation for our finding might lie in the way lending institutions may view loans in general. If relationships reduce a lender's expected cost from making the loan, while simultaneously increasing the informational monopoly that it enjoys over the borrower, then the lender may not feel obligated to pass on the cost savings to the borrower. If this is the case, then rates will indeed not be affected by good relationships, which is what we observe. Additionally, in the increasingly competitive loan markets of the nineties and over the beginning of the new century, consumers (be it individuals, families or small businesses) have shown no loyalty towards the original lenders of their loans, choosing instead to be wooed away (through refinancing) by another lender with competitive incentives including no closing costs and various cash rewards. In fact, this spate of refinancing over most of the past decade has made lending institutions, in particular, suffer significant losses. And as the original lenders of these loans have lost money (through premature repayments of these loans), they may not have felt the burden of adjusting loan rates downwards due to strong relationships.[26]

[26] Conversations with bank loan officers also reveal that, down in the mortgage loan trenches, loan officers have relatively little discretion (about 25 basis points) in choosing the rate, because of fair lending laws and bank policy. But, at the same time, loan officers do enjoy more discretion in deciding whether to accept or reject the application, and that any pre-existing relationship does play a role at the margin.

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Table I
Variable Description

This table describes the variables used in the estimation of the model. Data are from the National Survey of Small Business Finances (NSSBF) and Survey of Consumer Finances (SCF).

NNSBF	SCF	Description
Relationship Variables		
LENGTH	LENGTH	Duration (in years) the borrower (family or small business) has done business with the potential lending institution
ACTIVITY	ACTIVITY	Total number of asset accounts with a borrower's potential lending financial institution
LOAN	LOAN	Number of loans with a borrower's potential lending financial institution
NOFININ	NOFININ	Number of financial institutions that a borrower has association with – either through asset accounts or through loans.
	Borrower Characteristics:	
	AGE	Age of the head of the household
	INCOME	Total household income from earned form all sources
	ASSETS	Total household financial and nonfinancial assets
	DEBT	Total household liabilities
	BADHISTORY	=1 if the individual (or any member of the household), over the previous year, had problems in making existing loan payments.
	WELFARE	=1 if the household received public assistance over the preceding year.
	CUREMP	Number of years that the head of the household had worked in his current employment.
	SHOP	=1 if the borrower does a great amount of shopping for credit.
	RISKY	=1 if the borrower is willing to take above average financial risk for higher returns.
	Demographic Characteristics:	
	MARRIED	=1 if the head of the household is a married male.
	FEMALE	=1 if the head of the household is a single female.
	WHITE	=1 if the head of the household head is of Caucasian origin.
	CHILDREN	Number of children living in the household
Loan Characteristics		
SMRATE		The interest rate on the latest loan minus the rate on 3-month Treasury Bills during the month the loan was taken out.
	HMRATE	Mortgage loan rate
	MRATE	Average annual prime rate prevailing in the year of origin of the loan.
Financial Characteristics		
AGEF		The number of years current owners owned the business
ASSETSF		Total assets
DEBTF		Total liabilities
SALESF		Sales for previous fiscal year
PROFIT		Profit
ARTURN		Accounts receivable turnover in days
APTURN		Accounts payable turnover in days
Governance Characteristics		
CORP		=1 if firm is a non-Subchapter S corporation.
SUBS		=1 if firm is a Subchapter S corporation.
PART		=1 if firm is a partnership.
PROP		=1 if firm is a proprietorship.
CONC50		=1 if at least 50% ownership is in one family.
HIGHSCH		=1 if the current owner has a high school degree or less education.
COLLEGE		=1 if the current owner has a college degree.
POSTCOLEGE		=1 if the current owner has post college degree.
Industry Characteristics		
CONSTR		= if the firm is in construction industry.
SERVICES		=1 if the firm is in service industry.
RETAIL		=1 if the firm is in retail industry.
OTHERIND		=1 if the firm is in other industries.

Table II

Univariate Statistics for Discouraged, Credit-constrained and Non-constrained Small Businesses

Data are from the 1998 National Survey of Small Business Finances (NSSBF). All variables are defined in Table I. The results are for 1,109 small businesses. The means appear first with the standard errors in parenthesis. Credit-constrained (non-constrained) small businesses include those businesses that applied, and were denied (approved for) a loan in the last three years. Out of 1,109 businesses, 706 applied and 566 were approved for a loan.

	Not applied for a loan		Applied for a loan			
			Credit-constrained		Non-constrained	
Relationship Variables						
LENGTH	7.08	(6.50)	5.94	(5.24)[*]	7.25	(6.48)[b]
ACTIVITY	0.99	(0.52)	0.94	(0.57)	1.20	(0.63)[a]
LOAN	0.48	(0.73)	0.44	(0.76)	1.22	(1.01)[a]
NOFININ	2.11	(1.35)	2.92	(1.44)[***]	3.43	(1.97)[a]
Financial Characteristics						
AGEF	11.50	(7.77)	9.96	(6.97)[**]	13.85	(8.44)[a]
SALESF	556,263	(1,988,101)	974,980	(3,580,230)[*]	5,828,888	(16,337,429)[a]
ASSETSF	267,016	(1,029,763)	675,741	(3,020,854)[**]	2,698,680	(6,951,878)[a]
DEBTF	237,098	(909,448)	329,832	(941,395)	1,850,666	(5,095,016)[a]
PROFIT	70,900	(507,821)	281,662	(2,530,633)	890,063	(5,330,495)
ARTURN	50.42	(451.06)	38.75	(139.10)	34.63	(58.18)
APTURN	99.99	(861.12)	62.39	(156.54)	45.02	(272.97)
Governance Characteristics						
CORP	0.213	(0.410)	0.157	(0.365)	0.336	(0.473)[a]
SUBS	0.231	(0.422)	0.293	(0.457)	0.346	(0.476)
PART	0.065	(0.246)	0.086	(0.281)	0.078	(0.268)
PROP	0.491	(0.501)	0.464	(0.501)	0.240	(0.428)[a]
CONC50	0.898	(0.303)	0.893	(0.310)	0.788	(0.409)[a]
HIGHSCH	0.551	(0.498)	0.586	(0.494)	0.403	(0.491)
COLLEGE	0.273	(0.446)	0.229	(0.421)	0.385	(0.487)[a]
POSTCOLEGE	0.176	(0.381)	0.186	(0.390)	0.212	(0.409)
Industry Characteristics						
CONSTR	0.097	(0.296)	0.150	(0.358)[*]	0.117	(0.321)
SERVICES	0.452	(0.498)	0.464	(0.501)	0.348	(0.477)[b]
RETAIL	0.203	(0.403)	0.200	(0.401)	0.161	(0.368)[a]
OTHERIND	0.248	(0.432)	0.186	(0.390)	0.375	(0.484)
SMRATE					402.99	(217.25)
N	403		140		566	

[***] indicates that the difference in the means of discouraged and credit-constrained group is significant at the .01 level, [**] indicates that the difference in the means of discouraged and credit-constrained group is significant at the .05 level and [*] indicates that the difference in the means of discouraged and credit-constrained group is significant at the .10 level. [a] indicates that the difference in the means of credit-constrained and non-constrained group is significant at the .01 level and [c] indicates that the difference in the means of credit-constrained and non-constrained group is significant at the .1 level.

Table III

Regression Results for Applying and Being Approved for a Small Business Loan

The dependent variables in the regressions are the probability of applying for a loan and being approved for a loan. The independent variables are defined in Table I. Data are from the 1998 National Survey of Small Business Finances (NSSBF). The results are for 1,109 small businesses, 706 applied and 566 were approved for a loan. "Coeff" represents the coefficient estimates and "SE" represents the consistent standard errors. "Marginal" and "Conditional" represent marginal effects of the variables on the probability of applying for a loan and the conditional effect of the variables on the probability of being approved for a loan, respectively. Both marginal and conditional effects are computed holding all other variables at their sample averages. The marginal and conditional effects for SALESF, ASSETSF, and DEBTF show the effect of a 100 percent increase in these variables.

	Applied for a loan			**Approved for a loan**		
	Coeff	**SE**	**Marginal**	**Coeff**	**SE**	**Conditional**
LENGTH	-0.010	0.007	-0.003	-0.002	0.011	0.000
ACTIVITY	0.249	0.085***	0.068	0.360	0.098***	0.054
LOAN	0.217	0.069***	0.060	0.406	0.120***	0.065
NOFININ	0.204	0.043***	0.056			
AGEF	-0.006	0.006	-0.002	0.013	0.010	0.003
ln (SALESF)	0.138	0.037***	0.038	0.145	0.057***	0.019
ln (ASSETSF)	0.065	0.027**	0.018	0.073	0.035**	0.010
ln (DEBTF)	-0.027	0.015*	-0.007	0.003	0.021	0.002
PROFIT/100000	0.004	0.002	0.001	0.000	0.002	0.000
ARTURN/100	-0.008	0.013	-0.002	-0.069	0.064	-0.013
APTURN/100	-0.017	0.012	-0.005	-0.024	0.022	-0.004
CORP	-0.179	0.133	-0.051	-0.024	0.180	0.008
SUBS	-0.011	0.122	-0.003	-0.063	0.150	-0.012
PART	0.133	0.169	0.035	-0.085	0.249	-0.027
CONC50				-0.179	0.187	-0.032
COLLEGE	0.114	0.154	0.006			
POSTCOLEGE	-0.031	0.110	0.010			
CONSTR	-0.179	0.129	0.030	-0.497	0.221**	-0.137
SERVICES	0.022	0.121	-0.009	-0.295	0.158*	-0.058
RETAIL	0.035	0.141	-0.052	-0.422	0.175**	-0.083
CONSTANT	-2.600	0.346***		-2.719	0.884***	
rho	0.635	0.419				
LogL	-864.9					

*** indicates that the coefficient is significant at the .01 level, ** indicates that the coefficient is significant at the .05 level and * indicates that the coefficient is significant at the .1 level.

Table IV
Regression Results for Small Business Loans

The dependent variable is the difference between the interest rate on the latest loan minus the rate on 3-month Treasury Bills during the month the loan was taken out. The independent variables are defined in Table I. Data are from the 1998 National Survey of Small Business Finances (NSSBF). "Coeff" represents the coefficient estimates and "SE" represents the consistent standard errors. The results are for 566 small businesses in our data that indicated having been approved for a loan in the last three years.

	Model 1		**Model 2**		**Model 3**	
	Coeff	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
LENGTH	-3.34	1.16***	-2.54	1.25**	-1.80	1.51
ACTIVITY	-8.74	15.65	-6.43	15.45	-10.74	21.61
LOAN	-31.41	8.76***	4.94	9.06	-1.55	13.89
AGEF			-1.47	1.11	-0.86	1.25
ln (SALESF)			-24.59	9.50**	-30.91	11.82***
ln (ASSETSF)			4.73	8.95	-0.38	9.55
ln (DEBTF)			-4.50	5.35	-2.59	5.83
PROFIT/100000			0.07	0.14	0.02	0.27
ARTURN/100			-26.76	15.09*	-28.64	17.75*
APTURN/100			0.41	1.34	0.62	11.04
CONC50			16.12	20.71	12.42	21.76
CONSTR			18.92	22.73	8.50	28.91
SERVICES			8.56	20.91	1.62	24.49
RETAIL			-17.24	26.38	-14.78	32.00
λ_Apply					-150.05	86.71*
λ_Approved					12.54	109.06
CONSTANT	475.97	25.15***	769.16	87.78***	947.02	202.71***
R2	0.034		0.103		0.111	

*** indicates that the coefficient is significant at the .01 level, ** indicates that the coefficient is significant at the .05 level and * indicates that the coefficient is significant at the .1 level

Table V

Regression Results for Applying and Being Approved for a Mortgage Loan

The dependent variables in the regressions are the probability of applying for a mortgage loan and being approved for a mortgage loan. The independent variables are defined in Table I. Data are from the 1995, 1998 and 2001 versions of the Survey of Consumer Finances (SCF). The results are for 4,225 families. Out of 4,225 families, 3,175 applied and 2,852 were approved for a mortgage loan. "Coeff" represents the coefficient estimates and "SE" represents the consistent standard errors. "Marginal" and "Conditional" represent marginal effects of the variables on the probability of applying for a mortgage loan and the conditional effect of the variables on the probability of being approved for a mortgage loan, respectively. Both marginal and conditional effects are computed holding all other variables at their sample averages. The marginal and conditional effects for INCOME, ASSETS, and DEBT show the effect of a 100 percent increase in these variables.

	Applied for mortgage loan			Approved for mortgage loan		
	Coeff	**SE**	**Marginal**	**Coeff**	**SE**	**Conditional**
LENGTH	0.032	0.005***	0.006	0.025	0.007***	0.003
ACTIVITY	0.113	0.028***	0.021	-0.032	0.033	-0.002
LOAN	0.212	0.047***	0.039	0.161	0.061***	0.018
NOFININ	0.181	0.024***	0.033	0.180	0.037***	0.020
AGE	0.009	0.003***	0.002	0.020	0.004***	0.002
Ln(INCOME)	0.239	0.045***	0.044	0.103	0.065	0.012
Ln(ASSETS)	0.070	0.020***	0.013	0.148	0.040***	0.015
Ln(DEBT)	-0.014	0.008*	-0.003	-0.038	0.012***	-0.004
BADHISTORY	-0.559	0.073***	-0.128	-0.288	0.124**	-0.045
WELFARE	-0.391	0.120***	-0.087			
CUREMP				0.029	0.008***	0.003
SHOP	0.049	0.059	0.009	0.115	0.083	0.012
RISKY	0.045	0.065	0.008	-0.114	0.089	-0.011
MARRIED	0.381	0.085***	0.077	0.259	0.124**	0.033
FEMALE	0.034	0.093	0.006	0.083	0.130	0.008
WHITE	0.455	0.066***	0.098	0.194	0.110*	0.028
CHILDREN	0.021	0.026	0.004	0.146	0.046***	0.015
YEAR95	0.151	0.070**	0.027	0.244	0.101**	0.024
YEAR98	0.029	0.071	0.005	-0.079	0.096	-0.008
CONSTANT	-4.471	0.421***		-3.396	0.718***	
rho	-0.570	0.138***				
LogL	-1775.0					

*** indicates that the coefficient is significant at the .01 level, ** indicates that the coefficient is significant at the .05 level and * indicates that the coefficient is significant at the .1 level.

Table VI
Regression Results for Mortgage Rates

The dependent variable is the interest rates on the first mortgage loan. The independent variables are defined in Table I. Data are from the 1995, 1998 and 2001 versions of the Survey of Consumer Finances (SCF). The results are for 2,852 families in our data who have indicated having an outstanding mortgage loan. "Coeff" represents the coefficient estimates and "SE" represents the consistent standard errors.

	Model 1		**Model 2**		**Model 3**	
	Coeff	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
LENGTH	-0.71	0.24***	-0.36	0.26	-0.07	0.27
ACTIVITY	-4.65	1.39***	-2.02	1.33	-0.26	1.53
LOAN	-0.77	2.44	0.32	2.41	1.96	2.59
NOFININ	-5.70	0.81***	-2.16	0.83***	-1.20	0.94
AGE			-0.08	0.23	-0.15	0.23
Ln (INCOME)			-5.24	2.66**	-3.32	2.77
Ln (ASSETS)			-7.82	1.84***	-7.71	2.06***
Ln(DEBT)			1.07	0.40***	1.23	0.42***
BADHISTORY			18.58	10.83*	3.28	11.68
WELFARE			3.04	57.11	-33.38	64.88
CUREMP			0.17	0.22	-0.01	0.23
SHOP			-10.51	4.22**	-11.05	4.60***
RISKY			-4.66	4.17	-1.88	4.73
MARRIED			-1.45	7.12	3.87	8.02
FEMALE			-2.40	9.32	-4.93	9.71
WHITE			-11.24	7.98	0.06	9.73
MRATE	0.41	0.04***	0.40	0.04***	0.40	0.04***
λ_Apply					115.72	46.24**
λ_Approved					-109.17	51.80**
YEAR95	19.95	5.78***	15.55	5.72***	15.82	5.81***
YEAR98	18.07	4.97***	16.15	4.84***	17.61	5.19***
CONSTANT	465.11	32.28***	620.30	40.01***	565.65	46.21***
R2	0.034		0.135		0.139	

*** indicates that the coefficient is significant at the .01 level, ** indicates that the coefficient is significant at the .05 level and * indicates that the coefficient is significant at the .1 level.