# Information Asymmetries, Banking Markets, and Small Business Lending

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PROEFSCHRIFT

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## Preface

This Ph.D. dissertation consists of four essays on empirical banking that I wrote during my doctoral studies at CentER, Tilburg University. The purpose of the essays is to investigate the role of credit market imperfections in determining firms' borrowing incentives, firms' access to credit, and loan contract terms. Below I present a brief overview of the four chapters of the thesis.

*Chapter 1 – Distance, Bank Organisational Structure and Lending Decisions*
*(with Hans Degryse and Steven Ongena)*

This article surveys the extant literature on the effects of both a bank's organizational structure and the physical distance separating it from the borrower on lending decisions. The available evidence suggests that banks engage in spatial pricing, which can be rationalized by the existence of transportation costs and information asymmetries. Moreover, their ability to price-discriminate seems to be bounded by the reach of the lending technology of surrounding competitors. It is not entirely clear from an empirical viewpoint that small, decentralized banks have a comparative advantage in relationship lending. This advantage is motivated theoretically by the existence of agency and communication costs within a bank. However, differences in data and methodology may explain the inconclusive evidence.

*Chapter 2 – Rules versus Discretion in Loan Rate Setting (with Hans Degryse and Steven Ongena)*

Loan rates for seemingly identical borrowers often exhibit substantial dispersion. This paper investigates the determinants of the dispersion in interest rates on loans granted by banks to small and medium sized enterprises. We associate this dispersion with the loan officers' use of "discretion" in the loan rate setting process. We find that "discretion" is most important if: (i) loans are small and unsecured; (ii) firms are small and opaque; (iii) the firm operates in a large and highly concentrated banking market; and, (iv) the firm is distantly located from the lender. Consistent with the proliferation of information-technologies in the banking industry, we find a decreasing role for "discretion" over time in the provision of small credits to opaque firms. While widely used in the pricing of loans, "discretion" plays only a minor role in the decisions to grant loans.

This article has been presented at the 2008 European Finance Association meetings (Athens), 2008 FIRS Conference on Banking, Corporate Finance and Intermediation (Anchorage), 2008 Financial Economics Workshop on Banking and Financial Intermediation (Rimini), 2007 FDIC-JFSR Annual Bank Research Conference (Arlington), 2007 Conference on Banking Regulation, Integration and Stability (Mannheim), 2007 Federal Reserve Bank of Chicago's Conference on Bank Structure and Competition (Chicago), 2007 CEPR-ESSFM Meetings (Gerzensee), 2007 Conference on Small Business Banking and Financing: A Global Perspective (Cagliari), 2006 NAKE Research Day (Amsterdam), American University (Washington DC), Bank of Italy (Rome), Federal Reserve Board (Washington DC), Tilburg University (Tilburg), European University Institute (Florence), Kiel Institute of World Economics (Kiel), Instituto Superior de Economia e Gestão (Lisbon), Office of the Comptroller of the Currency (Washington DC), Universidad Carlos III (Madrid), and the University of Indiana (Bloomington).

For this paper I was awarded, by the 2009 Utah Winter Finance Conference, the Shmuel Kandel Award for outstanding PhD students in Financial Economics outside North America.

*Chapter 3 – Bank Concentration, Credit Quality and Loan Rates*

Studies that estimate the effect of bank market concentration on the supply of credit to firms typically find economically modest effects. This could stem from concentration affecting firms differentially, thereby causing the sample of borrowers to be endogenous. This paper finds that high bank concentration increases loan rates by 70 basis points, on average, when account is taken of the borrower pool selection process. This effect is three times larger than that obtained when the sample of borrowers is taken as given. The difference in estimates may be explained by an adverse shift in the qualitative composition of the borrower pool. Specifically, high concentration seems to both attract loan applications from lower-quality firms and induce banks to grant credit to these firms.

I have presented this article at the Federal Reserve Bank of Chicago (Chicago), Rotterdam School of Management (Rotterdam), Banco de Portugal (Lisbon), Universidade Católica Portuguesa (Lisbon), Universidade Nova de Lisboa (Lisbon), Federal Reserve Bank of Kansas City (Kansas City), Warwick Business School (Warwick), Copenhagen Business School (Copenhagen), University of New South Wales (Sydney), Sveriges Riksbank (Stockholm), and Tilburg University (Tilburg).

*Chapter 4 – Does Debtor Protection Really Protect Debtors? Evidence from the Small Business Credit Market (with Allen Berger and Fabiana Penas)*

This paper analyzes how different levels of debtor protection across U.S. states affect small firms' access to credit, as well as the price and non-price terms of their loans. We use a measure of debtor protection that has its maximum value when the borrower's home equity is lower than the state homestead exemption (debtor is fully protected), and is decreasing in the difference between the home equity and the homestead exemption (the amount that the creditor can seize). We find that the unlimited liability small businesses (sole proprietorships and most partnerships) have lower access to credit in states with more debtor-friendly bankruptcy laws. In addition, these businesses face harsher loan terms – they are more likely to pledge business collateral, have shorter maturities, pay higher rates, and borrow smaller amounts. For small limited liability companies (corporations and limited liability partnerships), we find only an increase in the loan rate, and a consequent decrease in loan size. Our results suggest that the credit market strongly penalizes unlimited liability small businesses located in states with debtor-friendly personal bankruptcy laws.

This article has been presented at the Free University (Amsterdam), Sveriges Riksbank (Stockholm), Tilburg University (Tilburg), Universidad Carlos III (Madrid), Universidad Torcuato Di Tella (Buenos Aires), Universidad de San Andrés (Buenos Aires), Kauffman Foundation-Federal Reserve Bank of Cleveland pre-conference and conference on Entrepreneurial Finance (Kansas City and Cleveland), 2008 Financial Management Association meetings (Dallas), University of Manheim (Manheim), and the 2009 American Finance Association meetings (San Francisco).

## Summary in Dutch

Dit proefschrift onderzoekt de rol van de kredietmarkt onvolkomenheden in de bepaling van de ondernemingen grondstoffenleningen prikkels, bedrijven toegang krijgen tot krediet en leningen bedingen. Het proefschrift bevat vier hoofdstukken. Het eerste hoofdstuk enquêtes de bestaande literatuur over de effecten van een bank op de organisatorische structuur en de fysieke afstand tot de kredietnemer op het uitlenen beslissingen. Het tweede hoofdstuk onderzoekt de determinanten van de spreiding van de rentetarieven op leningen van banken aan kleine en middelgrote ondernemingen. Associëren we dit dispersie met de lening officieren gebruik van "discretie" in het rentetarief, instelling proces. Het derde hoofdstuk analyseert het effect van de bank van marktconcentratie op de levering van de kredietverstrekking aan ondernemingen, alsook op de risico-samenstelling van de leningnemer zwembad. Het vierde hoofdstuk analyseert hoe de verschillende niveaus van bescherming schuldenaar over Amerikaanse staten beïnvloeden kleine bedrijven toegang tot krediet, alsmede de prijs en niet de prijs van hun leningen.

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A Ph.D. is a long haul full of obstacles and barriers, and some people simply made this journey seem considerably shorter and easier. First of all, I would like to thank Hans Degryse and Steven Ongena for their continuous support and guidance. They gave me the freedom to set my research path, and at the same time they were always there to point me the right direction. The two first chapters of the thesis benefited greatly from their co-authorship, the other chapters from their valuable comments, and the thesis as a whole, from their knowledge.

Second, I would like to thank Allen Berger, Martin Brown, and Fabiana Penas for being part of my dissertation committee, for providing very valuable feedback on my dissertation, and for being outstanding co-authors.

During my Ph.D., I have also benefited from the stimulating research environment and hospitality I encountered at the Sveriges Riksbank and Federal Reserve Board, both of which I visited on several occasions. I would like to thank Tor Jacobson and Kasper Roszbach for making my visits to the Riksbank possible and for the valuable discussions we had on research projects. While visiting the Federal Reserve Board I received valuable guidance from John Wolken about the Survey data that I use in all four chapters of the thesis.

This thesis has also benefited from very helpful comments from Sigbjørn Atle Berg, Robert Avery, Lamont Black, Diana Bonfim, John Boyd, Charles Calomiris, Elena Carletti, Mikael Carlsson, Sophie Claeys, João Cocco, Giancarlo Corsetti, Vicente Cuñat, Robert DeYoung, Marie Dutordoir, Emre Ergungor, Bjarne Florentsen, Thomas Gehrig, Giorgio Gobbi, Iftekhar Hasan, Robert Hauswald, Florian Heider, Giuliano Iannotta, Terhi Jokipii, William Keeton, Frederick Lehmann, José Liberti, Deborah Lucas, Helmut Lütkepohl, Paolo Emilio Mistrulli, Leonor Modesto, Judit Montoriol, Leonard Nakamura, Anna Naszodi, Lars Norden, Ricardo Nunes, Hernán Ortiz-Molina, Charlotte Ostergaard, Karen Pence, Jordan Rappaport, Jean-Charles Rochet, Kasper Roszbach, Scott Shane, Anand Srinivasan, Philip Strahan, Gregory Udell, and Lucy White. I would also like to thank my colleagues and friends at Tilburg University who have provided comments, encouragement, and technical advice: Thorsten Beck, Pedro Bom, Marco Da Rin, Vasso Ioannidou, Carlos Lourenço, Bertrand Melenberg, Viorel Roscovan, and Bas Werker.

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Geraldo Cerqueiro

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# Chapter 1

# Distance, Bank Organizational Structure, and Lending Decisions

## 1.1. Introduction

The last two decades have witnessed profound changes in the landscape of the banking industry, especially in the U.S. and Europe. Deregulation gave rise to an unprecedented wave of consolidation activity. At the same time, the relentless technological progress in information processing and communication abilities redefined the operational scope of financial intermediaries. A first order effect of technological development seems to have been an increase in the contestability of financial markets. In particular, the facility with which information can now be communicated across large distances resulted in an increase in the geographical reach of all potential financiers. Banks – whose lending activities traditionally relied on their superior ability to overcome informational asymmetries in the credit market – have been forced to revise their *modus operandi* in order to face these new challenges. Widely voiced concerns regarding the potential effects of these changes in the banking industry on the economic activity promptly soared. In particular, these voices questioned to what extent small firms – the engine of economic growth and those that most critically depend on bank financing – would be affected.

Among the various consequences of the complex reorganization in the banking industry, two of them are becoming particularly visible. First, banks are becoming larger and more hierarchically complex. Second, banks are expanding in their geographical span and consequently able to lend at larger distances. In this chapter we review the extant literature on the relation between a bank's organizational structure, its geographical span, and lending decisions. This is a natural step towards understanding the effects on the economic activity of the sea changes taking place in the banking industry, and the fact this topic has recently attracted great attention of researchers seems to cope with this view.

Despite the existence of a rich theoretical background to understand the relation between organizational structure, distance, and lending conditions, providing proper empirical tests of these theories has proved an extremely challenging task. One major difficulty is due to data limitations. Fortunately, substantial progress has been made in recent years in this respect.

The available evidence suggests that distance is an important factor in lending decisions. Specifically, the degree of local market power the lender possesses is inversely proportional to distance separating it from the borrower. Less obvious is the mechanism driving this effect. The theory suggests that both transportation costs and information asymmetries could induce banks to engage in spatial pricing, but the existing evidence is mixed with this respect. In particular, the available empirical does not allow one to safely single out any of the above explanations.

The role of organizational structure on lending decisions is also far from being a settled issue. Again, data limitations could be behind the inability of the empirical literature to reach a consensus. Although the bulk of the evidence indicates that small, decentralized banks are better in providing relationship loans, there are also some unsettled issues, which may reflect more than simply differences in empirical methodology or data. In particular, it is by no means clear where the competitive advantage of small banks in providing relationship loans stems from. This advantage could be due to larger organizations having higher internal agency costs, higher vertical and horizontal communication costs (across hierarchies and across distance), or to poor incentives of the credit staff to produce "soft" information.

Recent attention has also been drawn to the interrelation between organizational structure and distance as mutual determinants of a lending technology, which in turn influence lending conditions. The interaction between different lending technologies ultimately determines the pattern of competition in the banking market. The geographical reach of each organization not only is determined by its own choices, but as well by the choices made by the competing banks. In particular, it seems that a bank's geographical reach as well as its ability to price discriminate is negatively related to the reach of the competitors operating in the vicinity.

We organize the rest of the paper as follows. Section 2 reviews the literature on the relation between distance and lending decisions. Section 3 summarizes the literature on the relation between organizational structure and lending decisions. Section 4 concludes.

## 1.2. Distance and Lending Decisions

Economic theory has long recognized physical, or functional, distance as a source of inefficiency in credit markets, causing potentially relevant economic costs for both the banks granting credit and the firms seeking financing. Market imperfections arise because, for given physical locations of borrower and lender, distance creates an imbalance in the competitive environment in the credit market. In particular, distance shifts market power towards the bank that is closest located to the firm; banks located further away are at a competitive disadvantage, since establishing ties with far-away firms requires a higher effort. Not only are there distance-related pecuniary costs such as transportation costs, but there may also be extra efforts required from the bank to assess the creditworthiness of potential borrowers or to monitor firms' investments.

Recent structural changes in the banking industry stemming from technological progress and consolidation activity have resulted in a substantial increase in the geographical reach of banks. These changes have therefore developed renewed interest in the role of borrower location on lending behavior. A handful of empirical studies now analyze how physical distance separating a bank from its clients affects lending decisions, i.e. the availability and cost of credit for firms.

We start by reviewing the theoretical literature on spatial pricing. We discuss two broad channels through which distance affects lending decisions: transportation costs and asymmetry of information.[1] In the subsequent chapter we review the empirical evidence on spatial pricing and spatial rationing.

[1] In the subsequent theoretical exposition we disregard long-run dynamics by treating the number of banks (or the level of competition) as given. This assumption is implicit in most empirical studies we will analyze, as they employ samples spanning short time periods. Harsher competition should translate into lower loan rates, since it reduces the average distances between all possible combinations of firms and neighboring banks. On the other hand, an increase in the number of banks aggravates the adverse selection problem by enabling low-quality firms to obtain financing (Broecker 1990) and may result in a retrenchment towards relationship lending (Hauswald and Marquez 2006), resulting in higher loan rates.

### 1.2.1. Theory

#### *1.2.1.1. Transportation Costs*

Transportation costs may relate to time, effort and effective outlays born by a borrower who seeks to personally interact with a potential financier. The effect of transportation costs on pricing behavior has been formalized in the context of location or product differentiation models (see Hotelling 1929, Salop 1979, and Lederer and Hurter 1986). More recently, Chiappori, Perez-Castrillo and Verdier (1995) propose a spatial competition model of the banking sector (see Freixas and Rochet 1997 for a review). Provided that banks do not observe the location of the borrowers, spatial price discrimination will not occur, even if firms incur different transportation costs.[2] However, banks customarily know the addresses of their loan applicants and therefore banks can exploit the physical distance separating them from the firm. Greater distance and hence larger transportation costs result in stronger (local) monopoly power for the bank. Accordingly, a bank optimally charges higher loan rates to those borrowers that are located closest to its bank branch. Of course, the degree monopoly power depends on the locations of potential competitors. The rationale is that closer borrowers face higher transportation costs when visiting competing banks that are located further away than the lending bank. This allows the lending bank to increase the loan rate by an amount equivalent, in the limiting case, to the opportunity transportation cost faced by the borrower.

In the same way, banks may incur transportation costs related to their lending activities, in particular while screening applicants and monitoring borrowers. Banks could in principle pass along these costs to the firms by setting higher loan rates. However, the fact that total monitoring costs increases with the borrower-lender distance opens another window of opportunity for banks to engage in discriminatory pricing. Sussman and Zeira (1995) formalize this idea in a costly-state-verification framework and show that banks have local economies of scale with advantages for monitoring the closer they are to their clients. In other words, lenders can extract rents from closer borrowers because more distant competing banks take into account their own higher monitoring costs in their loan terms offers.

In short, spatial price discrimination models based on transportation costs entail the following empirical predictions: (i) a negative relationship between the loan rate and the borrower-lender distance, and (ii) a positive relationship between the loan rate and the borrower-closest competing bank distance.

#### *1.2.1.2. Asymmetric Information*

In the transportation-cost models analyzed, spatial discrimination simply takes place through loan pricing. If the severity of the asymmetric information problem intensifies with distance, then banks can strategically use their informational advantage to create a threat of adverse selection for their rivals, and thus soften competition. Hauswald and Marquez (2006) formalize this idea in a model where the quality of a bank's information-generation process is a decreasing function of the distance separating it from the borrower (see also Almazan 2002). Because banks receive more precise signals about close borrowers, competing banks face increasing adverse selection problems when approaching these locally captured firms. As a result, the informed relationship bank can charge higher loan rates to closer firms. An increase in distance between borrower and bank, however, curtails the bank's incentives to invest in information-generation activities.

[2] Notice that location is not exogenous in these models. See for instance Hoover (1936) for a spatial price discrimination model with fixed locations.

Consequently, distance weakens the bank's capability to extract rents from relationship borrowers, at the same time as it aggravates adverse selection problems for the lender with respect to transactional borrowers. Interestingly, the predictions in Hauswald and Marquez (2006) on loan pricing resemble those from transportation-cost models, i.e. loan rates decrease in the distance between the borrower and the relationship lender, but increase in the distance between the borrower and the competing transactional banks. As we will show later, the coinciding predictions on the role of distance on loan rates stemming from such dissimilar theoretical arguments poses serious identification challenges at the empirical level.

Spatial pricing models based on informational asymmetries also demonstrate that geographical credit rationing by banks can occur in equilibrium, where the underlying rationale is an adverse selection mechanism close in spirit to that in Stiglitz and Weiss (1981). In Hauswald and Marquez (2006), for example, more distant applicants are more likely to be credit rationed because of the winner's curse threat. A similar prediction is put forward by Carling and Lundberg (2005). As in Hauswald and Marquez (2006), they also postulate that the precision of the signal that a bank receives when assessing a borrower's default probability decreases with distance, and show that banks optimally turn down credit applications from some distantly located firms. Carling and Lundberg (2005) illustrate the idea that physical distance aggravates the information asymmetry problem with a figurative paradigm, the *Church Tower Principle* (CTP). According to the CTP, a bank is on the church tower, and its visual ability to observe the quality of the surrounding firms is constrained by the distance at which the firm is located from the tower.

### 1.2.2. Empirical Evidence

#### *1.2.2.1. Spatial Pricing*

Petersen and Rajan (2002) are the first to provide evidence of spatial loan pricing. They employ the 1993 National Survey of Small Business Finance (NSSBF) and find that a borrower located around the corner from the lender pays on average 126 basis points more than a borrower located 9 miles (the sample median) from the lender. While economically and statistically relevant, they don't control for the presence of other potential lenders in the vicinity. Moreover, Petersen and Rajan (2002) use predicted distance rather than actual distance in their regressions, which makes the results difficult to interpret. They calculate predicted distance by projecting a set of variables associated to the credit quality of the firm on observed distance. The underlying assumption is thus that more transparent firms have greater predicted distance. As a result, it is not clear to what extent their results reflect spatial loan pricing or simply that higher quality firms pay lower loan rates.

In a recent study, Degryse and Ongena (2005) provide more comprehensive evidence on the occurrence of spatial price discrimination in bank lending. They employ a dataset comprising the entire loan portfolio of an important Belgian bank that operates throughout Belgium. This dataset contains information on both the distance between the borrower and its lending bank and the distance between the borrower and other competing banks, as well as several measures of banking competition. In addition, the dataset covers a narrow period of time (1995-1997), making it suitable to test hypotheses generated by static spatial pricing models. They find that an increase in traveling distance from zero to the sample median (about 4 minutes) drops the expected loan rate by 14 basis points. In addition, they obtain a symmetric and qualitatively similar impact on the loan rate resulting from an analogous increase in the distance to the closest (quartile) competitor, a result that may reflect linear transportation costs.[3] From a variety of exercises, Degryse and Ongena (2005) confirm that transportation costs is the likely cause of the spatial price discrimination documented for Belgium.[4]

In an ensuing study, Agarwal and Hauswald (2006) exploit a novel dataset from a major U.S. bank to analyze the effect of borrower proximity on credit-market conditions. Their results suggest that a borrower located around the corner from the lender pays on average 195 basis points more than a borrower located 2.6 miles (the sample median) from the lender. In addition, an increase in a firm's traveling distance to the closest competing bank from zero to the sample median (0.55 miles) raises the loan rate by 55 basis points. Agarwal and Hauswald (2006) subsequently show that these results become statistically insignificant when they introduce a proxy for the bank's proprietary information about the borrower (the bank's internal credit score). Accordingly, they conclude that physical distance is simply a proxy for a lender's informational advantage, hence providing support for models of price discrimination based on information asymmetries.[5]

#### *1.2.2.2. Spatial Rationing*

In theoretical models founded on information asymmetries (Hauswald and Marquez 2006 and Carling and Lundberg 2005), geographical credit rationing may be the bank's optimal response to the deterioration of the quality of the information pertaining to distantly located firms. Nevertheless, the empirical evidence on the existence of geographical credit rationing is mixed. For instance, Petersen and Rajan (2002) find that applications from more distantly located firms are turned down more often in the U.S. and that this effect has sharply decreased over time. In contrast, Agarwal and Hauswald (2006) find that the effect of distance on the likelihood of credit denial nearly vanishes once they properly control in their regressions for the credit quality of the borrowers. Findings by Carling and Lundberg (2005) and by Uchida, Udell and Watanabe (2008) indicate the absence of distance related credit rationing in Sweden and Japan, respectively.

We offer three potential, not necessarily mutually exclusive, explanations for the lack of conclusive evidence on the incidence of spatial credit rationing. First, technological innovations may be breaking the "tyranny of distance" in small business lending. These innovations have granted small firms with increased access to transactions loans, for which physical distance does not matter. Second, transportation costs (that are fixed per loan), rather than informational asymmetries may be the explanation for the spatial price discrimination documented (as Degryse and Ongena 2005 argue). Third, we have disregarded so far the firm's incentives concerning the choice of a lender. Although the distance between borrowers and lenders has increased in the U.S., there is strong evidence that small firms still seek to establish ties with local financial institutions. This suggests that the empirical literature may have failed to detect spatial credit rationing due to a self-selection mechanism. In particular, those firms that are likely to be rationed credit on the basis of distance have incentives to seek relationship loans from local banks.

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[3] The cost of one traveling minute equals 3.5 basis points in Degryse and Ongena (2005) and about 5.4 basis points in Petersen and Rajan (2002) (we infer the average speed in the U.S. from Agarwal and Hauswald 2006).

[4] For instance, they find that borrowers located in densely populated (i.e. urban) areas experience discrimination twice as harshly, which is probably related to higher traveling times in urban areas due to traffic congestion. Recent evidence by Casolaro and Mistrulli (2007) seems to support this view. They find with an Italian dataset that spatial pricing is mainly confined to transactional loans.

[5] The bank's internal credit score itself could also be the avenue through which loan officers price discriminate, a possibility not addressed in their paper.

### 1.2.2.3. Distance and Collateral

Petersen and Rajan (2002) and Berger et al. (2005) find that collateralized loans are made, on average, at greater physical distance from the lender. However, they assume in their regressions that the causation effect goes from the collateral variable to the distance variable, hence disregarding a potential endogeneity problem.[6]

We believe that an empirical test of the effect of physical distance on collateral requirements would shed light on the nature of the mechanisms underlying the documented spatial pricing. For instance, if information asymmetries are driving the observed spatial pricing, as adverted in Agarwal and Hauswald (2006), then the likelihood that the loan is secured by collateral should increase with distance (*ceteris paribus*). In contrast, if collateral requirements are not related to distance, models based on transportation costs would be a more plausible explanation of spatial pricing (as in Degryse and Ongena 2005).[7]

We estimate the effect of the distance between borrower and lender (*Distance*) on the likelihood that the loan is secured by collateral (*Collateral*).[8] For this purpose we employ both the 1993 NSSBF and the Belgian dataset used by Degryse and Ongena (2005). By applying the two datasets we can retain differences between Belgium and U.S. in banking markets landscapes as a possible route to reconcile the conflicting views of Degryse and Ongena (2005) and Agarwal and Hauswald (2006).

First, we present the results for the 1993 NSSBF data set of estimating a logit regression of *Collateral* as a function of firm, loan characteristics and *Distance*.[9] Our findings, reported in Table 1, indicate that an increase in distance between lender and borrower from zero to the sample median raises the probability of the loan being secured by collateral by 2%. The effect is statistically significant at the 5% level but economically modest (as the sample median loan is secured by collateral). Second, we perform the same exercise using the Belgian sample. We report the results in Table 2. Employing a specification identical to that used in Degryse and Van Cayseele (2000) (Model (1) in Table III, p. 105) we find a negative, though both economically and statistically negligible effect of *Distance* on *Collateral*. We also acknowledge a substantial difference in fit between the two models (in terms of pseudo-$R^2$).

These results are not necessarily inconsistent with the view that different mechanisms may drive spatial pricing discrimination in loan markets in U.S. and Belgium. In particular, our findings do not contradict the finding in Degryse and Ongena (2005) that transportation costs cause the discrimination they document for Belgium, whereas asymmetries of information seem to be an important determinant of the spatial pricing discrimination observed for the U.S.

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[6] An important set of theoretical models motivates collateral as arising from information gaps between borrowers and lenders. In particular, collateral may offset problems of adverse selection (Bester 1985, Chan and Kanatas 1985, and Besanko and Thakor 1987) and moral hazard (Boot, Thakor and Udell 1991) in credit markets.

[7] A third possibility is addressed in Inderst and Mueller (2007). In their model the use of collateral is limited to loans granted by local lenders that have superior information over more distantly located competitors.

[8] This analysis implicitly assumes that the choice of a lending bank located at a given distance from the firm precedes the design of the loan contract. This is always the case when the firm has a pre-established relationship with the bank.

[9] We use a specification similar to that in Chakraborty and Hu (2006) (Model (1) in Table 2, p. 97), who also employ the 1993 NSSBF, with the following differences: (i) we use the variable Main Bank as a proxy for the scope of the bank-firm relationship rather than the number of financial services, (ii) we correct the age of the firm by the duration of the relationship between bank and firm, and (iii) we that add to the model the bank-firm distance, as well as a variable indicating whether the firm is located in a Metropolitan Statistical Area.

## 1.3. Organizational Structure and Lending Decisions

A recent body of literature draws attention to the relation between the organizational structure of a bank and its proclivity to provide credit to particular types of firms. This literature is founded on the view that relationship lending and transactions lending are intrinsically different lending technologies. As a result, a bank that favors relationship lending requires a different organizational form from one that specializes in arm's length lending (Berger and Udell 2002).

Under relationship lending, loan officers collect proprietary information over time through frequent and personal contacts with their clients, as well as with the local community. This information is "soft" in nature, being difficult to store and credibly communicate to others. A large bank, where multiple layers of management separate the agents who collect this "soft" information from the ultimate decision-makers, may have a competitive disadvantage in relationship lending (Berger and Udell 2002) and Stein 2002). In contrast, a complex organizational structure may give the bank an advantage in transactions-based lending, where the decisions are essentially based on automatisms that are fed on objective criteria, or "hard" information (e.g. balance sheet or income statement information).

Relationship lending allows a bank to overcome information asymmetries in credit markets (Boot 2000) and therefore it should primarily benefit small and opaque businesses. It is not surprising, as a result, that the recent organizational changes driven by consolidation in the banking industry (Berger et al. 1999) have risen widely expressed concerns of a severe cut-back in small business lending. At the same time, these concerns have sparked a renewed interest by scholars in the broader relation between the organizational design of banks and lending conditions.

We start by providing an overview of the theoretical literature that studies organizational design and delegation of authority in the context of the banking industry. We subsequently review the relevant empirical evidence in light of this theory.

### 1.3.1. Theory

The economics literature has recently drawn substantial attention to the organizational design of firms, focusing in particular on the distinctive features of centralized and decentralized systems. The comparative performance of the decentralized and centralized allocation systems is typically analyzed on the basis of communication and information processing they entail, as well as on the incentives these systems induce on individual agents. Decentralization involves the distribution of information processing responsibilities across agents and minimal communication requirements, resembling a market-based system consistent with self-interested behavior of agents. This implies, however, that an agent who is a delegated decision-making authority tends to act in its self-interest, rather than the interest of the organization; in other words, decentralization may give rise to internal agency costs. If these incentive problems cannot be contractually remedied *ex ante*, the choice between a centralized and a decentralized system follows from the balance between these internal agency costs and communication or information processing costs. In particular, a decentralized system is generally the preferred design when these agency costs are not too severe (Mookherjee 2006) or when the activity of the organization crucially depends on the agent's – i.e., the loan officer's – expertise (Berger and Udell 2002, Stein 2002).

The fact that information is critical to the activity of lending makes the banking sector especially interesting to analyze organizational theories. Following the recent consolidation activity, academics have increasingly focused their interest to the potential implications of the induced changes in the organizational structure of banks on small business lending.[10] There is a widely held view that small banks should be more inclined than their larger counterparts to lending to small and opaque firms. This result is due to the existence of organizational diseconomies that restrict the scope of large banks in their lending activities. While several theories have been proposed to motivate the existence of such organizational diseconomies, it seems that these diseconomies stem altogether from a common origin – the fact that small business lending and transactions-based lending are two inherently different activities (Boot 2000 and Berger and Udell 2002).

In small business lending, the bank bases largely its credit decisions on proprietary or "soft" information about the firm and its owner gathered through a multiplicity of contacts over time. This information allows the bank to assess the quality of the firm beyond what the financial statements of the firm (the "hard" information) might otherwise indicate. Consequently, "soft" information may confer the bank with a competitive advantage over banks that make their decisions merely on the basis of "hard" information, as they obtain a less precise signal of the creditworthiness of the firm. This "soft" information is, however, hardly verifiable by anyone else than the agent who produces it, and thus difficult to transmit to others or to store. Consequently, the inexistence of proper channels to communicate this "soft" information within a bank requires that internal adjustments be made at the organizational level. For instance, the bank should adopt a more general communication code as well as alternative channels of information transmission within the organization at the cost of specialization (Crémer, Garicano and Prat 2007). Put differently, the optimal organizational structure minimizes communication costs and expected information losses that result from both horizontal and vertical communication of subjective information.[11]

The subjective nature of "soft" information is essentially what makes small business lending different from transactions lending, and what restrains more centralized banks (e.g. a large bank holding company) from being as competent at relationship lending as decentralized banks (e.g. a small community bank). This point is demonstrated, for example by Stein (2002), who investigates how the organizational structure of a bank affects the incentives of loan officers to produce and use different types of information. Stein (2002) shows that loan officers in hierarchically complex organizations will have less incentive to collect "soft" information since they do not generally have decision making authority, and instead have to report that information to their superiors (see also Aghion and Tirole 1997). In contrast, a decentralized organization is more likely to reward research efforts of loan officers by ensuring that they will have access to funds that they can use to capitalize on that expertise. Of course, one can argue that "soft" information can be somewhat hardened and subsequently passed on "upwards".[12] The model in Stein (2002) suggests that in this case small banks may still be more efficient providers of relationship-based loans than large banks, since the incentives problem turns into a bureaucracy problem, i.e. loan officers reallocate excessively their effort from "field work" to report writing.

The prediction that a narrower gap between allocation and control promotes relationship lending is shared by Berger and Udell (2002). They address the key role that a loan officer plays as a repository of "soft" information within a bank and focus on the agency problems that this gives rise to. As suggested

[10] There is ample evidence of the importance of a bank relationship to small firms in terms of credit availability (Petersen and Rajan 1994), lower loan rates (Berger and Udell 1995 and Degryse and Van Cayseele 2000), reduced collateral requirements (Berger and Udell 1995) and intertemporal risk sharing (Petersen and Rajan 1995).

[11] See, for instance, Becker and Murphy (1992), Bolton and Dewatripont (1994), Radner (1993) and Garicano (2000).

[12] Petersen (2004) argues that the categorization of information into "hard" and "soft" is often too restrictive. He further suggests that "hard" and "soft" information are the extremes of a continuum along which information can be classified. An illustrative example of hardening "soft" information is a loan officer filling a report where he evaluates several attributes of an applicant (e.g. honesty and managerial competence).

before, these agency problems stem from the intangible nature of "soft" information and, in particular, from the difficulty in disseminating this information within an organization. This creates a trade-off in terms of the efficiency of a decentralized system. On the one hand, banks have to delegate more authority to their loan officers, since loan officers are in a unique position to personally contact with the firm, its owner and the local community, i.e. they have the greatest exposure to "soft" information. On the other hand, delegation may aggravate agency problems if the incentives of the loan officer are not properly aligned with those of the bank.[13] The implications arising from this trade-off have been extensively analyzed in the principal-agent theory. In particular, a bank that specializes in relationship loans should invest more in monitoring both loan officers and the performance of their loan portfolios (Udell 1989, Berger and Udell 2002).[14] Because these monitoring costs increase with the hierarchical complexity of the organization, small decentralized banks are endowed with another source of comparative advantage in small business lending.

So far we have neglected the fact that the competitive structure of credit markets (and hence lending conditions) is also shaped by differences in organizational structure across different competing banks. In other words, the organizational choices made by a bank's rivals bound its own scope concerning lending decisions. Degryse, Laeven and Ongena (2008) bridge this gap by investigating how differences in rival banks' organizational structures shape banking competition. They start by bringing into a theoretical model the evidence that banks engage in spatial price discrimination together with the view that organizational structure affects the nature of the lending technology. Their model extends the Hotelling (1929) location differentiation framework in that they allow a bank's organizational structure to act as a lending technology that determines a bank's geographical reach. Though they assume that the marginal cost associated to distance (transportation or monitoring costs) is identical across firms and banks for one visit, the required number of visits or the monitoring effort is determined by the lending technology. For instance, large, hierarchical organizations with automated decision-making mechanisms have an economic advantage at lending to distant firms since their technology is more cost-effective. Because these organizations rely to a larger extent on "hard" information, they will communicate less often and in impersonal ways with their borrowers, resulting in lower distance-related costs.

### 1.3.2. Empirical evidence

#### *1.3.2.1. Organizational structure and information use within a bank*

A recent stream of empirical studies the transmission of different types of information within an organization. Liberti and Mian (2008) investigate the effect of credit approval at higher hierarchical levels on the importance of "hard" and "soft" information in the credit approval decision. They use a dataset consisting of detailed information from the credit folders of a multinational bank in Argentina. The data contains objective elements as well as subjective assessments collected by the loan officer during the application process. This dataset also contains information on how far in the hierarchical ladder (and where) the application needs to travel before reaching the final credit decision. Consistent with organizational theories,

[13] These agency problems may result in the collusion between the loan officer and the firm (Tirole 1986), manipulation of "soft" information (Godbillon-Camus and Godlewski 2005, Ozbas 2005), excessive use of "discretion" in defining loan terms (Cerqueiro, Degryse and Ongena 2007), overlending or hiding a deteriorating condition of a borrower (Berger and Udell 2002).
[14] Godbillon-Camus and Godlewski (2005) use a principal-agent framework to study a loan officer's incentives to manipulate the signals conveyed about potential borrowers, which are based on "soft" information. They suggest that an adequate compensation scheme solves *ex ante* these agency problems. Ozbas (2005) analyze the optimal level of organizational integration when the agents' (i.e. loan officers') access to resources depends on the signals they communicate to their superiors.

Liberti and Mian (2008) find that "hard" information gains importance while "soft" information loses importance when going up the hierarchical ladder. They also find that these changes in "hard" and "soft" information sensitivity are particularly abrupt when the higher-level officer is located in a different branch. This is in line with the view that the subjective nature of "soft" information makes its communication across large distances difficult. Liberti and Mian (2008) also find that the decrease in sensitivity to "soft" information is less pronounced when information is assembled by more experienced loan officers. They cannot say, however, whether this result is due to a "reputation effect" or due to superior communication skills of more experienced loan officers (Ozbas 2005; see also Crémer, Garicano and Prat 2007).

Despite providing support to the view that communicating subjective information across hierarchies is costly, Liberti and Mian (2008) are unable to isolate the channel driving this effect. Their results strongly suggest that it is the physical distance (and not necessarily the hierarchical gap) generating the loss of credit sensitivity to "soft" information. Consistent with this view, Mian (2006) shows with data from Pakistan that the geographical distance between a foreign bank's headquarter and the local branches leads the bank to shy away from relationship lending. In contrast, Liberti (2004) provides support for the loan officers' incentives view in Stein (2002) by demonstrating that relationship managers who receive more authority put more effort into collecting "soft" information from their corporate clients.

#### *1.3.2.2. Organizational structure and information use across banks*

A considerable research effort has been recently devoted to test whether less hierarchical complex organizations are more efficient providers of relationship-based small business loans. The interest in this topic emerged primarily in response to the public concerns that the financial services industry consolidation trend might result in the reduction in the availability of credit to small firms (Berger et al. 1999). These concerns are founded on the fact that small businesses have crucially relied on banks to satisfy their credit needs (Cole, Wolken and Woodburn 1996, Berger and Udell 1998), and further reinforced by the evidence that large banks allocate smaller percentages of their assets to small business loans than do small banks (Berger and Udell 1996, DeYoung, Goldberg and White 1999, Keeton 1995, Peek and Rosengren 1996, Strahan and Weston 1996).

There is ample evidence that small banks are better able to collect and act on "soft" information (Scott 2004, Cole, Goldberg and White 2004, Berger et al. 2005, Uchida, Udell and Watanabe 2008, Casolaro and Mistrulli 2007). However, there is also some conflicting evidence. For example, Jayaratne and Wolken (1999) find that the probability that a small firm is credit rationed does not significantly depend on the presence of small banks in the market. Furthermore, Black and Strahan (2002) find that the liberalization of banking laws in the U.S. increased the rate of creation of new businesses, though it simultaneously reduced the number as well as the share of small banks.

The documented evidence provides insufficient indication that a bank's organizational structure affects credit availability to small businesses. In fact, the theory clearly states that it is organizational complexity rather than bank size shaping a bank's proclivity to make small-business loans. Studies that analyze the effect of organizational complexity on lending conditions to small firms also provide somewhat inconclusive evidence, which may be explained by the diversity of measures of organizational complexity employed. For instance, Strahan and Weston (1998) find that the organizational complexity of a holding company (measured as the total number of bank subsidiaries and the number of states in which it operates) is not significantly associated with its propensity to lend to small firms. In contrast, Keeton (1995) finds that banks with a large number of branches and banks owned by out-of-state holding companies devote lower proportions of their deposits to small businesses than do comparable banks. DeYoung, Goldberg and White (1999) control for the confounding effects of a bank's size and age and obtain similar results. Degryse, Laeven and Ongena (2008) demonstrate that the presence of larger and hierarchically organized rivals in the vicinity reduces the geographical reach of the lending bank and assuages spatial pricing.

## 1.4. Conclusion

A growing body of both theoretical and empirical literature studies the real effects of the recent changes at the organizational as well as operational level in the banking industry. We review the literature that focuses on the effects of both bank-firm distance and bank organizational structure on lending decisions.

There is strong evidence of spatial pricing by banks but it is still unclear what is the underlying mechanism driving it. Transportation costs and information asymmetries are two, non-mutually exclusive, explanations. Important differences in the datasets that have been used to test these theories may explain the dissimilar results obtained. The empirical evidence on spatial credit rationing is even more inconclusive. Moreover, it seems inconsistent with theories that rationalize spatial pricing in the context of models of asymmetric information.

Concerning organizational structure, it seems that small banks and less hierarchical complex organizations have an advantage in relationship lending. However, the empirical findings are not fully conclusive and suggest that this advantage may have decreased over time due to the expansion of transactions lending activities by large organizations. One major difficulty faced by empiricists appears to be the lack of precise measures of organizational complexity beyond bank size.

In short, despite notable research efforts, the complex net of relations linking distance, organizational structure and lending conditions is far from dismantled. As a result, the most likely conclusion springing from this paper is that further research is definitely warranted.

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## 1.6. Tables

**Table 1**

**Incidence of collateral in the 1993 NSSBF**

The table lists the coefficients and the standard errors from a logit regression where the dependent variable is one if the firm pledged collateral for the most recent loan. Besides the variables reported, each regression includes eight 2-digits SIC code dummies and three variables controlling for the type of organization of the firm. We refer to Chakraborty and Hu (2006) for a detailed description of the dataset and variables. The symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively.

| Variable | Coefficient | Standard Error |
|---|---|---|
| Log of length of relationship (years) | -0.27 *** | 0.08 |
| Main bank (0/1) | -0.27 * | 0.15 |
| Number of borrowing sources | 0.01 | 0.03 |
| Log of firm's age at start of relationship (years) | -0.24 | 0.21 |
| Log of total assets | 0.14 *** | 0.04 |
| Debt-to-assets ratio | 0.10 | 0.07 |
| Profit-to assets ratio | 0.02 | 0.02 |
| MSA (0/1) | -0.15 | 0.14 |
| Distance to lender (miles) | 0.08 ** | 0.04 |
| Number of Observations | 1,656 | |
| Pseudo-$R^2$ (%) | 4.83 | |

**Table 2**

**Incidence of collateral in the Belgian sample**

The table lists the coefficients and standard errors from a logit regression where the dependent variable is one if the firm pledged collateral for the most recent loan. Besides the variables reported, each regression includes 49 two-digit NACE industry dummies, eight regional dummies, two year dummies, four dummies for the revisibility of the loan, five dummies for the purpose of the loan and three dummies for the governance characteristics of the firm. We remit to Degryse and Van Cayseele (2000) for a detailed description of the dataset and variables. The symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively.

| Variable | Coefficient | Standard Error |
|---|---|---|
| Small firm (0/1) | 0.73 ** | 0.34 |
| Log of length of relationship (years) | 0.57 | 0.10 |
| Main bank (0/1) | -0.09 *** | 0.06 |
| Log of loan size | 0.47 *** | 0.08 |
| Log of repayment duration | 0.62 *** | 0.16 |
| Distance to lender (minutes) | -0.03 | 0.06 |
| Number of Observations | 15,044 | |
| Pseudo-$R^2$ (%) | 80.29 | |

# Chapter 2

# Rules versus Discretion in Loan Rate Setting

## 2.1. Introduction

Little is known about the procedures and processes through which banks price credit. The U.S. banking industry has experienced dramatic changes since the early nineties, due to deregulation and the increasing availability of information-intensive technologies. Common sense suggests that these changes should result in more standardized and transparent loan pricing practices by banks. However, even after one takes into account the differences in borrowers, lenders, and markets, loan rates still often exhibit substantial dispersion. This dispersion suggests that frictions in the credit market enable banks (i.e., through their loan officers) to price loans in a discretionary manner. The banks' use of "discretion" should affect aggregate welfare as well as its distribution across different market participants. Consequently, understanding the nature of "discretion" is crucial for any analysis of the credit market.

In this study we investigate the use of "discretion" by banks in the loan rate setting process. Specifically, we employ a heteroscedastic regression model to investigate what factors determine the dispersion in banks' loan rates to small and medium sized enterprises. We attribute this dispersion to the banks' exploitation of market imperfections and assess the relevance of firm and bank characteristics, as suggested by the theoretical literature, in explaining "discretion".

An example illustrates what we are after. Imagine a set of twins that applies for a bank loan. If the twins are fully identical in all respects (same sex, profession, street address, etc.) and the applications are made online through the same automated system, the twins should receive the same loan rate, as both the inputs in the credit application and the model processing these inputs are identical. Even if the twins differed in a few characteristics, the potential gap between the offered rates would be fully explained by the objective differences between them.

If instead the identical twins conduct their loan applications in person at a particular bank, they may not get the same loan rate, given there is an extra input in the pricing decision, i.e., the loan officer's judgment. This judgment may reflect a number of factors: experience, bargaining ability,[15] uncertainty regarding the costumer's prospects, and soft information. To a large extent, the loan officer's judgment could also be clouded by such eccentricities as the

[15] Guttentag (2003) for example emphasizes the relevance of these skills for the charged rates in the U.S. mortgage market: "If the loan officer tabs you as unknowledgeable and timid, you will probably pay an "overage" – a price above the price listed on the loan officer's price sheet. The lender and the loan officer usually share overages. If you are smart and forceful, on the other hand, you might get an underage – a price below the listed price."

color of the applicant's jacket or the loan officer's mood (which may not only depend on the weather conditions for example but also on many other personal factors). In any case, all the aforementioned factors share a common denominator that outlines our definition of "discretion": – they have an idiosyncratic nature and hence are not verifiable by third parties.

In this study we assess to what extent these judgmental factors, or "discretion", matter in the final loan-pricing decision. Hence, we want to investigate what factors determine the dispersion in the loan rates offered to many different sets of twins. We do so by empirically examining the determinants of the unexplained variance of a benchmark linear loan-pricing model. We interpret the higher predictive power of the model as evidence of the greater importance of "rules" in the loan rate setting process. Larger unexplained variance, on the other hand, is then associated with the prevalence of "discretion".

Our motivation for this analysis goes beyond the empirical regularity that contracted loan rates are typically difficult to predict (see e.g. Petersen and Rajan 1994, and Berger and Udell 1995). What is even more interesting is that the fit of the loan-pricing models seem to depend on the type of loans and borrowers in the sample that is being investigated. Degryse and Ongena (2005) for example estimate the same loan-pricing model for two independent sub-samples: one with small loans (below $5,000) and another with large loans (above $50,000). The fit of their regressions is strikingly different; the $R^2$'s are 1% for small loans and 67% for large loans, respectively.

The story about the twins and the different fits of the same loan-pricing models illustrate the adequacy of our methodology. "Rules" and "discretion" can be seen as the extremes of a continuum along which any loan-pricing model can be classified according to its level of standardization and the nature of its inputs. On the one extreme, "rules" corresponds to a standardized pricing model (e.g., a computer) that generates loan rates that can be predicted by verifiable characteristics of the applicant. On the other extreme, "discretion" refers to an arbitrary pricing technology, where loan rates reflect exclusively the loan officer's judgment. Consequently, "discretion" decreases our ability to predict observed loan rates for two interrelated reasons. First, loan rates are set on the basis of inputs that are only observed and understood by the loan officer (e.g., "these are serious people", or "that green hat is ridiculous"). Second, each pricing model – i.e., the relative weight of each input in the final loan rate – itself becomes arbitrary.

In a frictionless world there should be no room for "discretion" and loan rates should only vary with verifiable information. In contrast, economic theory predicts that the dispersion of loan rates, and hence "discretion", characterizes the equilibrium of credit markets under asymmetric and imperfect information. The extent to which loan rates reflect the prevalence of "rules" or "discretion" should depend on the severity of information asymmetries in the credit market. Moreover, "discretion" can also result from information search costs, switching costs, imperfectly competitive credit market structures, and regulatory constraints such as fixed or capped loan rates. These market imperfections determine the bargaining power banks have vis-à-vis firms and set the boundaries within which banks can engage in discretionary loan-pricing practices.

The estimates from our heteroscedastic regression models generate four new robust findings. First, the opaqueness and observable risk of borrowers are associated with a larger unexplained dispersion of loan rates. This result is in line with the mixed strategy loan pricing equilibrium in von Thadden (2004), where "discretion" is increasing in the severity of information asymmetries in the credit market. Moreover, this result also suggests that "discretion" is positively related to the switching costs firms face. Second, banks price larger loans according to more objective criteria or "rules". This finding illustrates that a firm's incentives to increase its search intensity constrains a bank's ability to price discriminate. Third, we find that "discretion" is most important in large and highly concentrated banking markets. Fourth, "discretion" increases with borrower-lender distance.

These findings are robust to arbitrary manipulations in our benchmark linear pricing model, and they are not driven by endogeneity of other loan contract terms, or by sample selection. Furthermore, we show that the information set we use to explain loan rates predicts quite accurately the outcome of the banks' loan granting decisions. In particular, our results suggest that, while being heavily used in loan pricing, "discretion" is far less present in the loan granting decision.

We employ four different datasets in our analysis. Our primary dataset is the 1993 Survey of Small Business Finances (SSBF), which we supplement with the 1998 and 2003 SSBF in order to identify potential changes over time in the use of "discretion". We find a decreasing role of "discretion" in small credits to opaque businesses over the period 1990-2005. This result is consistent with the proliferation in the banking industry of automated decision mechanisms in the U.S. Furthermore, we find evidence that "discretion" prevails in periods of high liquidity and that these risk-shifting incentives have become stronger over time.

To show the robustness of our results, we also study a dataset provided by an important Belgian bank. This dataset enables us to mitigate the concern that our results could be driven by the omission of relevant variables, since it contains <u>all</u> the information that was recorded and stored by the bank about each particular client. Moreover, the Belgian dataset allows us to include branch fixed-effects to control for potential heterogeneity across branches in lending technologies. Therefore we ensure that "discretion" will relate to the information observed only by the loan officer and to the arbitrariness in her pricing decisions.

Our study is the first to empirically analyze the determinants of discretionary pricing in the market for business loans. While loan rate dispersion itself has been widely documented before,[16] no study so far (to the best of our knowledge) has identified the actual sources of this dispersion. In fact, empirical research on price dispersion is limited to the product market (see Dahlby and West 1986, Hortaçsu and Syverson 2004, and Sorensen 2000). Price dispersion in the product market is motivated by costly consumer search, i.e. frictions on the demand side. In contrast to the product market, frictions in the credit market are present on both the demand side (firm uncertainty about the competitiveness of the loan offer) and the supply side (bank

[16] Heffernan (2002) finds that the margin between the highest and lowest lending rates for U.K. mortgages is relatively small (0.45 percentage points), compared with the market for personal loans, where there is a range of 8.17 percentage points. Hassink and Van Leuvensteijn (2007) find that lending rates in the Dutch mortgage market are highly dispersed both across lenders (1 percentage point) and within lenders (0.4 percentage points), even after controlling for borrowers' characteristics and regions. Martín, Saurina and Salas (2005) detect substantial and persistent unexplained dispersion of retail loan rates in Spain, across banks and products. Degryse and Ongena (2005) analyze data from a large Belgian bank and report substantial variation in loan rates at the branch level.

uncertainty about firm quality). Consequently, the credit market provides a richer environment to investigate how market imperfections translate into price dispersion.

The rest of the paper proceeds as follows. Section 2 provides the theoretical background, while Section 3 presents and motivates the methodology. Section 4 discusses the primary dataset and Section 5 presents our benchmark results. Section 6 provides the robustness tests. Section 7 studies temporal changes in our results and Section 8 concludes.

## 2.2. Theoretical Background

Loan rate dispersion is justified by the existence of market frictions as studied in the economics and financial intermediation literature. We choose to discuss the theoretical predictions on the determinants of loan rate dispersion in two separate subsections: information asymmetry and switching costs, and search costs.

### 2.2.1. Information Asymmetry and Switching Costs

The analysis of the Sharpe (1990) model by von Thadden (2004) yields a positive relation between the severity of the information asymmetry in the credit market and “discretion”. Our simulations of von Thadden’s mixed-strategy equilibrium show that his model predicts that the variance of loan rates:[17] (i) increases non-monotonically in the proportion of “good” firms in the market (the maximum variance corresponds to a proportion of about one-half in which case the bank has minimum information about the quality of the pool); (ii) increases in the difference in quality between the “good” and the “bad” firms; and, (iii) decreases in the average probability of loan repayment in the credit market.[18]

Bester (1988, 1993) provides a general economic analysis of the pricing implications of switching costs (see Klemperer 1995 for a review of this literature). The price emerging from the bargaining process between buyer and seller in these models is determined by the search and switching costs (the buyer’s “outside option”). Bester (1993) shows that *ceteris paribus* buyers with low switching costs face fixed prices, while buyers with high switching costs fall into a “haggling equilibrium” with negotiated prices. Wang (1995) demonstrates that bargaining may actually dominate the posting prices for a homogeneous product.

[17] Due to the difficulty in obtaining analytical solutions for the von Thadden (2004) model (see Black 2008), we evaluate it numerically. We start by simulating 300 loan rate offers by the informed bank and the uninformed bank, for given (randomized) values of the parameters that characterize the mixed strategy equilibrium in the von Thadden (2004) model. These parameters are: $\theta$ (proportion of “good” firms), $p_H - p_L$ (difference in repayment probabilities between the “good” and the “bad” firm), and $p$ (expected repayment probability in the credit market when no information about the firms is available). Then, we set the contracted loan rate to the minimum of the two rates offered and calculate the variance for the sample with the 300 contracted rates. We repeat the simulations 500 times for different randomized values of the above parameters. This procedure generates a sample of 500 observations with variation in the degree of dispersion in contracted loan rates that results from differences in the structural characteristics of the credit market. Using this sample, we regress the log of the variance in loan rates on the parameters $\theta$, $p_H - p_L$ , $p$, $p^2$, and on the proportion of loans that were granted by the informed bank. All results reported are statistically significant at the 1% level and the $R^2$ of the regression is 77.7%.

[18] Recent papers in Industrial Organization also model the impact of customer recognition on heterogeneity in product prices in an environment of dynamic competition. These models show that firms may set different prices to qualitatively identical new and old customers. The price difference depends on the market structure, the degree of consumer and firm patience, and the firm’s abilities to recognize new from existing consumers (see e.g. Villas-Boas 1999 or Fudenberg and Tirole 2000).

More opaque firms should face higher costs of switching lenders. These higher switching costs result from the greater informational advantage a lending bank has over its competitors. A bank typically obtains this informational advantage over the course of its relationship with the firm, during which the bank learns more about the firm's creditworthiness and prospects (Sharpe 1990, Rajan 1992 and Boot and Thakor 1994). On the one hand, stronger ties with a firm imply less uncertainty for a lender, and hence less "discretion". On the other hand, this informational advantage also translates into higher switching costs, yielding the opposite prediction.[19]

In contrast, switching costs should be lower for larger firms. Larger firms are generally regarded as more transparent to outsiders, because more information is publicly available on these firms. Furthermore, most large firms have their financial records audited, so that this hard financial information should provide a more precise and reliable indicator of its creditworthiness. Finally, large firms are more likely to engage multiple creditors, *ex ante* assuaging potential liquidity and holdup problems (Detragiache, Garella and Guiso 2000, von Thadden 1992, Ongena and Smith 2000). Consequently, banks dealing with large clients are constrained to price loans uniformly or based on "rules". Discretionary deviations from such a rule-based equilibrium result in either unprofitable deals (if loan rates are set too low) or a higher probability that the consumer chooses a competitor (if loan rates are set too high).

### 2.2.2. Search Costs

It is well established in the economics literature that the extent of price dispersion may be due to the costly consumer search of information (Stigler 1961, Salop and Stiglitz 1982). The search intensity, in turn, depends on the consumer's incentives such as the magnitude and frequency of the purchase. This intuitive mechanism has straightforward implications to the credit market. In particular, it implies that both the level and variance of loan rates should decrease in the size of the loan. On the one hand, a bank can only expect to grant a loan if the loan rate offered is sufficiently competitive vis-à-vis rival banks. On the other hand, banks may not persistently undercut the competitive spread without compromising profitability.

The search mechanism is similar to the presence of switching costs in generating a positive correspondence between loan rate dispersion and the magnitude of the underlying costs faced by the borrower. The main difference is that search costs may be driven mostly by incentives such as the size of the loan, whereas switching costs are mainly a product of firm specific characteristics such as firm size and the stock of private information about the firm the bank possesses. The magnitude of either the switching or search costs determines the degree of market power the bank has vis-à-vis its borrowers. In turn, market power translates into a higher dispersion of loan rates.

## 2.3. Econometric Methodology

In order to identify the determinants of the dispersion of loan rates, we employ the regression model with multiplicative heteroscedasticity proposed by Harvey (1976). The heteroscedastic

[19] The equilibrium in the von Thadden (2004) model incorporates this view. The winning rates offered by the informed bank are more dispersed than those of the uninformed bank (our earlier described simulations show).

version extends the linear regression model by allowing its residual variance to vary across different observations in the sample. We may think of the heteroscedastic regression model as comprising two equations – one to explain the mean of loan rates, and the other to explain the residual variance of loan rates. The two equations are, respectively:

$$y_i = \beta' X_i + u_i, \tag{1}$$

$$Log\,\sigma_i^2 = \gamma' Z_i. \tag{2}$$

We will refer throughout the paper to (1) as the "mean equation" or the "loan-pricing model", and to (2) as the "variance equation".[20] Our analysis will mainly focus on the variables in the variance equation, which determine the precision of the loan-pricing model. An important aspect of this methodology is that the parameters in the mean ($\beta$) and variance ($\gamma$) equations are uncorrelated.[21] This corollary allows us to treat the two equations separately in terms of variable selection and interpretation of the results.

The interpretation of the parameters of the variance equation ($\gamma$) is as follows. Pick one variable in $Z$, say loan size, and its respective parameter, $\gamma^{Size}$. A negative $\gamma^{Size}$ indicates that the residual variance is decreasing in loan size. In turn, a smaller residual variance is associated with a better fit (i.e., a higher $R^2$) of the mean equation. Consequently, a negative $\gamma^{Size}$ indicates that for larger loans there is less "discretion" in the loan rate setting process. In contrast, we interpret a positive $\gamma$ for any variable in $Z$ as evidence of more "discretion".

Next, we provide an example that should intuitively illustrate the inner workings of our methodology. Suppose we have detailed information on a sample of loan contracts, including observed characteristics of the loan. We run a regression of the loan rate on the prime rate, a dummy indicating whether the rate is variable (as opposed to fixed), and dummies controlling for the type of the loan.[22] Next, we rank the residuals by the size of the loan (from smallest to largest) and slice the data into twenty quantiles. Figure 1 displays box plots of the residuals of the regression for the twenty groups.

Simple visual inspection discloses two patterns. First, and as expected, loan rates are decreasing on loan size. Second, the dispersion of the residuals is also decreasing on loan size. This result indicates that the simple loan-pricing model (i.e. "rules") gains predictive power as we move towards windows containing larger loans. Recall that the results in Degryse and Ongena (2005) (their table VI, p. 256) we reported in the introduction were similar to this example. According to this evidence, it is reasonable to expect a negative sign for the parameter associated with the loan amount variable in the variance equation.

## 2.4. Sample Description

The primary dataset used in this study is the 1993 National Survey of Small Business Finances (SSBF), a survey conducted by the Federal Reserve Board and the Small Business

[20] We describe the estimation further in an Appendix.

[21] Harvey (1976) provides a technical explanation. The underlying principle is the same that explains why the consistency of the coefficients (i.e., the slopes) in a linear regression model is not affected by heteroscedasticity or autocorrelation in the error term.

[22] We describe our data in Section 2.4.

Administration that has been extensively used in empirical work (e.g., Berger, Miller, Petersen, Rajan and Stein 2005, Cole, Goldberg and White 2004, and Petersen and Rajan 2002). The 1993 SSBF collected data for the fiscal year 1993 for a nationally representative sample of 4,637 for profit, non-governmental, non-agricultural businesses with fewer than 500 employees. The dataset provides a detailed look at these firms – their characteristics and their use of credit and other financial services. We focus, in particular, on the firms' most recent borrowing experiences during the sample period (1990-1994), which include data on the characteristics of the borrower and of the lender, as well as the contracted loan terms.[23]

The 1993 SSBF is ideally suited for our purposes for several reasons. First, the sample is quite heterogeneous with respect to the types of borrowers and loan contracts. Despite its focus on small businesses, the sample also contains sizable loans and loans granted to reasonably large firms, both of which we presume to exhibit a more transactional nature. The coexistence of different types of borrowers and loans ensures a diversity of loan-pricing technologies in our sample. While this diversity is typically problematic in empirical work, the essence of our methodology is precisely to show how it translates into loan rate dispersion. In particular, we associate unexplained loan rate dispersion to a discretionary or judgmental pricing model. For that reason, we choose not to restrict the sample analyzed to particular categories of loans (e.g. lines of credit) or borrowers.

Second, because it has comprehensive information on loan contracts and firm characteristics, the SSBF permits us to exhaustively control for a significant share of the variation in loan rates that is explained by "rules". This point is particularly relevant since we interpret the magnitude of unexplained deviations from our loan-pricing model as a measure of the banks' use of "discretion" (in robustness we study a Belgian sample that contains all information that was recorded by a bank).

Finally, data is also available for the subsequently conducted surveys (SSBF 1998 and SSBF 2003). Since a consistent definition and a majority of identical questions are used across the three surveys, we are able to carry out a temporal analysis of our results over a relatively large time span (16 years).

### 2.4.1. Variable Selection for the Mean Equation

Table 1 presents the variables used in our study, along with their definitions and descriptive statistics. We now turn to a detailed description and motivation for each of these variables. Subsection 4.2 introduces the variable selection for the variance equation.

#### *2.4.1.1. Interest Rate Variables*

The dependent variable is the interest rate on the firm's most recent loan we label as the *Loan Rate*. On the right hand side, we include the variable *Prime Rate* to control for changes in the underlying cost of capital in the economy. Most firms in our sample pay a premium on top of

[23] We restrict our analysis to the sample of 1,695 firms that provided information on their most recent loans (about 36% of the total sample). We dropped 31 observations pertaining to firms that did not report all the required information and 39 observations related to loans granted by non-financial firms. We end up with a final sample of 1,625 observations.

the prime rate. However, 71 firms in our sample face loan rates equal to the current prime rate, and 91 firms enjoy loan rates below the prime rate.

#### *2.4.1.2. Loan Characteristics*

We employ the dummy variable *Floating* to control for differences in level between fixed and variable interest rates. *Ln(Loan Amount)* is the log of the amount of the loan in dollars.[24] The size of the loan provides a tacit measure of the bargaining power the firm has in setting loan terms (the loan rate, in particular), since the loan amount is strongly correlated with the firm's incentives to search for potentially better terms (Stigler 1961). *Ln(Loan Maturity)* is the log of the loan repayment duration and proxies for the term risk. *Collateral* is a dummy variable indicating whether the loan is secured by collateral. *Collateral* may represent the potential risk faced by the lender in the loan contract, as well as signal the quality of the firm (Bester 1985, Besanko and Thakor 1987).

#### *2.4.1.3. Firm/Owner Characteristics*

The dummies *Proprietorship*, *Partnership*, and *Corporation* (it includes both regular and S-type corporations) control for legal and governance aspects of the firm. *Minority* indicates whether or not the firm is held by members of a minority group (African-American, Asian or Native). Our motivation to include *Minority* follows from the evidence that minority groups tend to be more adverse to looking around for the best deals and to bargaining (Black, Boehm and DeGennaro 2003). Moreover, the variable *Minority* is intrinsically associated with higher credit risk, even when other observable risk factors are accounted for (Cavalluzzo, Cavalluzzo and Wolken 2002).

*Ln(Owner's Age)* is the log of the age of the firm's owner in years as of year-end 1993. Petersen and Rajan (1994) find that the reputation of the firm's owner is more important than that of the business in predicting loan rates. We correct *Ln(Owner's Age)* by the length of the firm-bank relationship to avoid spurious correlation between these two variables. Following Petersen and Rajan (1994) and Berger and Udell (1995), we interpret the age of the firm (owner) as the amount of public information available about the firm.[25]

#### *2.4.1.4. Accounting Information*

If financial statement lending was the dominant transactional technology employed by banks in the sample period 1990-1994 we analyze, then the firms' accounting figures should have a key role in explaining loan rates.[26] *Ln(Assets)* is the log of the book value of the firm's assets. We also include the following accounting identities for the fiscal year 1993, deflated by total assets: sales, profits, inventories, accounts receivable, accounts payable, total amount of loans and total debt. In addition, we include a variable that captures the firm's reliance on trade

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[24] In order to assuage scaling problems we take the logarithm of all continuous variables, except the financial ratios.
[25] We obtain similar results when we replace the age of the owner by the age of the firm.
[26] Financial statement lending was probably the dominant transactional technology in US in the early 1990s, right before the advent of Small Business Credit Scoring (SBCS). In fact, the largest provider of external models, Fair Isaac, introduced its first SBCS model only in 1995.

credit (*Trade Credit Use*). Petersen and Rajan (1994) suggest that trade credit use measures to what extent a firm is credit rationed.

#### *2.4.1.5. Credit History*

Previous studies find that the history of the principal (e.g., Berger, Frame and Miller 2005) is a very strong predictor of payment performance of small-business loans. *Bankrupt* indicates whether the firm or its principal owner has declared bankruptcy within the past seven years; *Owner (Firm) Delinquent* indicates whether the owner (firm) has been 60 or more days delinquent on personal (business) obligations within the past 3 years; and *Judgments* is a dummy that equals one if any judgments have been rendered against the principal owner within the past 3 years.[27] Finally, we include *IRS Problem* – a variable indicating whether the firm reported to have had serious problems with the Internal Revenue Service regulation or penalties during the last year.

#### *2.4.1.6. Relationship Characteristics*

Boot (2000) argues that relationship lending, ultimately a judgmental lending technology, is a multi-dimensional concept. Accordingly, we control in our pricing-model for three dimensions of the nature of the firm-bank relationship. (1) *Ln(Duration)* is the log of duration in years of the relationship the firm has had with the lender. There is ample evidence in the literature that the duration of the firm-bank relationship, a common measure of the stock of information the bank acquired, affects credit terms (see e.g. Berger and Udell 1995, and Petersen and Rajan 1994, 1995). (2) *Main Bank* indicates whether the lender is the firm's self-reported primary source of financial services, capturing the scope of the relationship. And (3) *Personal* is a dummy variable indicating whether the firm's most frequent method of conducting business with the lender is in person, or face-to-face.

#### *2.4.1.7. Competition/Location*

The variable *Concentrated* indicates whether the Herfindahl-Hirschman Index (HHI) in the deposits market of the MSA or county where the firm's headquarters office is located is greater than 1,800. The banking market structure should have both a direct and indirect effect on the distribution of loan rates. On the one hand, greater market concentration increases the banks' bargaining power with respect to borrowers. On the other hand, it should also influence the nature of the firm-bank relationship (Boot and Thakor 2000, Petersen and Rajan 1995).[28]

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[27] We further summarize the credit history of the owner and firm in the variable *Clean Record* – a dummy that equals one when all previous variables (*Bankrupt*, *Owner Delinquent*, *Firm Delinquent* and *Judgments*) equal zero. In the variance equation we use *Clean Record* in place of the above variables in order to identify an unambiguous effect of a firm's credit history (our measure of firm credit risk) on "discretion", and to conserve degrees of freedom. In the mean equation, though, we employ the variables *Bankrupt*, *Owner Delinquent*, *Firm Delinquent*, and *Judgments*.

[28] Elsas (2005) and Degryse and Ongena (2007) show that the incidence of relationship lending is non-monotonically related to the level of bank concentration. Despite the validity of the HHI as an indicator of market power being subject to criticism (e.g., Claessens and Laeven 2004), the HHI is extensively used in applied research (e.g., Petersen and Rajan 1995, Cetorelli and Strahan 2006) and in antitrust policy. In particular, markets with HHI greater than 1,800 are viewed by regulators as highly concentrated.

The variable *Ln(Distance)* is the log of the distance between the firm's main office and the lending institution's office. Degryse and Ongena (2005) demonstrate that banks engage in spatial price discrimination. Petersen and Rajan (2002) and Berger, Miller, Petersen, Rajan and Stein (2005) document that the lender-borrower relation becomes increasingly impersonal as their physical distance grows. *Personal* controls for the alternative transmission channel through which the firm-bank distance might affect loan rates. Finally, we include the variable *MSA*, which indicates whether the firm is located in an urban area.

#### *2.4.1.8. Other Control Variables*

We additionally include a set of time dummies (*Year dummies*), one-digit industry codes (*SIC*), census region (*Region*), a set of dummies for the type of the loan (*Loan type*) – line of credit, capital lease, mortgage, motor vehicle, equipment, and other type; and type of lending institution (*Lender type*) – commercial bank, savings bank, savings and loan association, credit union, finance company, insurance company, brokerage or mutual fund company, leasing company, and mortgage bank.

Variable Selection for the Variance equation

The variable selection for the variance equation is rooted in the theoretical discussion in Section 2. The corollary of this discussion is that "discretion" is ultimately a product of imperfections in the credit market, such as information asymmetries, search costs, and concentration in the banking market.[29]

The variables *Collateral*, *Minority*, *Corporation*, *Clean Record*, *IRS Problem,* and *Ln(Duration)* provide alternative measures of the firm's opacity *ex ante*. In contrast, *Ln(Distance)* measures how easy it is for the bank to monitor the firm, i.e., the firm's opacity *ex post*. The theory suggests a positive correlation between firm opaqueness and the importance of "discretion", which results from the informational advantage banks have over competitors. The equilibrium derived in von Thadden (2004) for example predicts that the variance of loan rates is an increasing function of the uncertainty pertaining to the quality of the pool of borrowers.

The loan amount should be a crucial input in the firm's decision of how much to invest in information acquisition, i.e., how much time devoted to "price-shop" (Stigler 1961). Because of this latent increase in competition among potential lenders, larger loans should be priced more homogeneously.

The variables *Ln(Owner's Age)* and *Ln(Duration)* capture, respectively, the amount of public and private information available to the bank about the firm. In principle, these variables should relate to more "discretion" in the loan-pricing process, since added information sharpens a bank's ability to price discriminate. However, banks may strategically avoid disclosing private information about their clients by setting loan rates merely on basis of publicly observable signals (Gan and Riddiough 2008). Consequently, the net effect of the strength of the bank-firm relationship on "discretion" is an empirical question.

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[29] As suggested before, we employ a large number of regressors in the mean equation, disregarding potential collinearity problems, for its role is to predict loan rates as accurately as possible. However, we do not include all possible variables in the variance equation to facilitate its readability and interpretation. The estimates of the parsimonious variance equation we present are further largely unaffected by the inclusion of other control variables.

Finally, the variables *MSA* and *Concentrated* control for differences in banking market size and structure. One would intuitively expect more “discretion” in more concentrated markets (Boot and Thakor 2000, Petersen and Rajan 1995). In addition, it seems also plausible that larger banking markets are characterized by a greater diversity of underwriting procedures and by higher search costs (Varian 1980 and Carlson and McAfee 1983). As a result, we expect both *MSA* and *Concentrated* to relate to more loan rate dispersion.

## 2.5. Empirical Results – SSBF 1993

We estimate the heteroscedastic linear regression model as shown in equations (1) and (2) to analyze the determinants of the dispersion of loan rates. The mean equation (1) specifies a linear model that predicts the observed loan rates. In the variance equation (2), we identify the factors affecting the residual variance of loan rates, i.e. the determinants of “discretion” (more unexplained variance) and “rules” (less unexplained variance).

While our interest lies mainly in the parameters of the variance equation, we also report the estimates of the mean equation. Columns I and II of Table 2 report the coefficients of the mean and variance equations, respectively. The dependent variable is the interest rate on the firm’s most recent loan, in basis points (bp).[30] In the mean equation we employ all variables described in Table 1 with the exception of *Clean Record*. In the variance equation we refine the variable selection as motivated in the previous section. We turn now to the discussion of our empirical results.

### 2.5.1. Mean Equation

The average firm in our sample obtains a loan rate of 8.42%.[31] Consistent with the results in Petersen and Rajan (1994 and 1995), we find that loan rates are relatively insensitive to changes in the cost of capital for banks.

Larger loans benefit from lower interest rates. This result probably reflects the borrowers’ efforts to get the best possible deals concerning large loans, as well as the dilution of contractual and operational fixed costs. Moreover, larger firms obtain more favorable rates. This result suggests that banks are able, on average, to extract larger rents or that they perceive higher risk in smaller, informationally opaque firms. Consistent with moral hazard theories we find that collateralized loans pay on average 31 bp more than unsecured loans.[32] All the effects mentioned are statistically significant at the 1% level.

Firms with healthier balance sheets and superior track records seem to enjoy lower loan rates, although the majority of the estimated coefficients are statistically insignificant. Regarding credit history, we emphasize that firms whose owners have been delinquent on personal obligations pay a premium of about 78 bp. This finding confirms that the history of

[30] Our results are virtually unaltered when we use the credit spread, defined as the loan rate minus the prime rate, as the dependent variable.

[31] Because we center all explanatory variables, the constants of the model have a direct interpretation – they represent the expected loan rate (mean equation) and the residual variance (variance equation) for the average firm in our sample.

[32] Some of the variables in the mean equation, namely those related to the non-price terms of the loan contract, raise endogeneity concerns. Our results do not change when we drop from the mean equation the variables *Ln(Loan Amount)*, *Collateral*, *Ln(Loan Maturity)*, and *Floating*.

the owner is a strong predictor of payment performance of small-business loans. Consistent with previous research (e.g., Cavalluzzo, Cavalluzzo and Wolken 2002), we find that firms owned by minority groups pay a premium of 33 bp.

The (unadjusted) $R^2$ of the loan-pricing model is 25%. This value is somewhat higher than what other studies obtain also employing data from the SSBF. For instance, Petersen and Rajan (1994) employ 1,389 observations from the NSSBF 1988 and obtain a $R^2$ of 14.5%; Brick and Palia (2007) employ a sample of lines of credit from the 1993 SSBF and obtain a $R^2$ of 11%, even though their pricing model contains 80 covariates. It seems unreasonable to 'blame' the poor fits of the empirical loan-pricing models entirely on an insufficient number of observations or covariates. For example, Degryse and Ongena (2005) estimate a pricing model using 83 covariates and a sample of 15,044 loans, and obtain an $R^2$ of 22%.

The distinctive aspect in our study is that we recognize the fit of the loan-pricing model to depend on certain borrower and loan contract characteristics. These characteristics reflect the nature of the lending technology adopted by the bank in the underwriting process and hence determine the extent of "discretion" used. As indicated before, Degryse and Ongena (2005) (their table VI, p. 256) provide evidence suggestive of this dependence by showing that the abovementioned $R^2$ of 22% encloses substantial heterogeneity across loans of different sizes. In particular, the $R^2$ of the same model increases to 67% when they use a subsample of large loans (above \$50,000) and decreases to 1% for the subsample of small loans (below \$5,000).

### 2.5.2. Variance Equation

We now explicitly investigate how the fit of the loan-pricing model depends on loan contract, borrower, and market structure characteristics. Positive coefficients in the variance equation indicate larger unexplained deviations (i.e., a poorer fit of the mean equation). In turn, we associate large deviations with the predominance of "discretion" in the loan-pricing process and small deviations with the prevalence of "rules".

The coefficient of *Ln(Loan Amount)* is negative and highly significant. This result is consistent with the difference in $R^2$ values reported in Degryse and Ongena (2005) and with the univariate findings in Figure 1. Larger loans incentivize firms to prospect the credit market for the best possible deal, as the potential savings in interest payments outweigh the costs of searching information and switching lenders. In turn, banks anticipate this latent increase in competition by employing more standardized criteria (i.e., "rules") in the underwriting process of large loans.[33]

The negative sign of *Corporation* matches the evidence that smaller firms are intrinsically more opaque from a bank's perspective, either because the information provided by small firms is less reliable or subject to faster depreciation.

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[33] This result could also indicate that larger banks rely more heavily on automated and standardized decision mechanisms (Akhavein, Frame and White 2005). Another possible explanation is that applications involving larger loans are generally appraised by higher hierarchical levels within the lending bank, levels that have less access to relevant soft information and hence can wield less "discretion" (Liberti and Mian forthcoming). However, in subsequent robustness tests we can dismiss these alternative explanations. In particular, we show that our results for *Ln(Loan Amount)* do not change when we control for the size of the lending institution nor when we use the sample from a Belgian bank in which the loan officers were responsible for all credit decisions.

The coefficients of *Minority* and *IRS Problem* are positive while the coefficients of *Collateral* and *Clean Record* are negative, all being statistically significant. All these variables proxy for the creditworthiness of the borrower. Consequently, this finding indicates that there is more "discretion" in loan pricing when borrowers are of doubtful quality.[34] This result is consistent with the market equilibrium analyzed in von Thadden (2004), which predicts a negative relation between the quality of the pool of borrowers and the dispersion of the loan rates. Moreover, observationally riskier firms that obtained credit probably underwent a more comprehensive screening process, endowing banks with more soft information about these firms. Soft information will tend to generate unexplained deviations from our loan pricing model and hence explain our results.

The negative estimate obtained for *Ln(Duration)* indicates a lower prevalence of "discretion" when there are strong ties between the firm and the lending bank. This result is inconsistent with the predictions in the von Thadden (2004) model and challenges conventional wisdom, since stronger ties increase hold-up costs and hence should lead to more "discretion".[35] However, the closeness of their relationship also determines a lender's ability to monitor the firm, through the nonborrowing side and the personal proximity of their relation, as well as the accuracy and relevance of the information that is available. For instance, Mester, Nakamura and Renault (2006), and Norden and Weber (2008) show that the information provided in checking accounts helps the bank to monitor commercial borrowers and to assess sudden changes in credit risks. As a result, we interpret this finding in line with our other measures of borrower opaqueness, i.e., as evidence that stronger ties between firm and bank mean less uncertainty for the bank concerning the firm's credit quality.[36]

The age of the firm (or its owner's) may measure the availability of public information about the firm. We obtain a positive and significant coefficient for *Ln(Owner's Age)*, suggesting that banks are able to discriminate loan prices by exploiting public information about borrowers.[37]

Concerning market structure, we obtain positive estimates for the variables *MSA* and *Concentrated*. Petersen and Rajan (1995) assert that higher levels of banking market concentration provide the necessary incentives for banks to engage in intertemporal risk sharing. In addition, the positive sign of *MSA* indicate that loans rates are more dispersed in larger markets (as predicted in Varian 1980, and Carlson and McAfee 1983). We also find that *Ln(Distance)* is associated with larger unpredicted deviations. Because distance decreases

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[34] *Collateral* could also be capturing unobserved variability in expected recovery rates. In particular, the negative coefficient of *Collateral* is in line with the view that recovery rates tend to vary more for unsecured loans than for secured loans (Schuermann 2004). We address the concern that our results might be driven by differences in expected recovery rates by re-estimating the model for the subsample of secured loans (1,177 observations). The results are similar to those we report in Table 2.

[35] We added in a separate model the variables *Main* and *Personal* to investigate whether the other dimensions of the firm-bank relationship had a similar impact on the residual variance. We obtained negative coefficients for these two variables and maintained a negative estimate for Duration, reinforcing the rather paradoxical result of a negative link between the strength of relationship and the importance of "discretion".

[36] The model in von Thadden (2004) also predicts that the variance of loan rates, besides decreasing in the quality of the pool of borrowers, also decreases in the uncertainty about the distribution of the borrowers' quality (specified in the model by the spread in success rates between high and low quality firms).

[37] Note that, if *Ln(Owner's Age)* provides a signal (either positive or negative) about the creditworthiness of the firm's owner and if banks use this public information to price loans, "good" firms will get lower rates while "bad" firms will get higher rates. Consequently, the unexplained variance increasing in *Ln(Owner's Age)* may indicate that banks use public information to price loans given to the "good" and "bad" types (that coexist in our sample).

a bank's ability to monitor the firm, this result is consistent with the view that distance represents an additional risk factor for the bank (DeYoung, Glennon and Nigro 2008).

### 2.5.3. Economic Significance of Estimates

We analyze the economic significance of the coefficients in the variance equation in terms of their effects on the $R^2$ of the mean equation.[38] The constant measures the residual variance of the loan-pricing model for the average firm in the sample. Its estimated value implies a mean deviation from the predicted loan rate of 77 bp, or an $R^2$ of 55% in the mean equation. The coefficient of *Ln(Loan Amount)* indicates that an increase in the loan amount from $25,000 (the 25th percentile) to $550,000 (the 75th percentile) induces a nearly six-fold increase in the $R^2$ of the pricing model. An increase in the distance separating the firm from the bank from 1 mile (the 25th percentile) to 13 miles (the 75th percentile) more than doubles the $R^2$ of the pricing model; however, going from 1 mile to 304 miles (the 95th percentile) increases the $R^2$ by a factor of four. The economic effects of the other continuous variables, *Ln(Duration)* and *Ln(Owner's age)*, are comparatively modest, ranging in magnitude close to the effects of the discrete variables (i.e., with an elasticity with respect to the $R^2$ smaller than one).

Another insightful exercise is to assess the dispersion of loan rates for different types of loans and borrowers. For instance, consider an unsecured loan of $25,000 granted to a single business (firm A).[39] Firm A's track record contains recent business delinquencies and it has done business with its lender for only the last three years. Suppose there exists also a corporation (firm B) that is granted a $550,000 secured loan. In contrast to firm A, firm B enjoys a clean legal record and it has had a relationship with the lender for 13 years. According to our estimates, the expected loan rates for firms A and B are 9.3% and 8.1%, respectively. In addition, our estimates translate into $R^2$s of the estimated pricing model of 1% for firm A and 81% for firm B. The residual deviations implied by these $R^2$s indicate that, with 95% confidence, firm A could face any loan rate in the range from 5.1% to 13.5%, whereas the range for firm B is substantially narrower: 6.3% to 9.9%. In short, these results illustrate the contrast between the intense use of "discretion" by the bank in the loan-pricing process (firm A) and a more standardized loan-pricing model (firm B).

### 2.5.4. Analysis of Extreme Residuals

Because we focus on the unexplained loan rate spreads paid by the firms, a pertinent question is to what extent the estimated firm-specific variances may reflect asymmetric, or one-sided, deviations. In particular, we seek to identify the factors associated with large upward and downward deviations from the "rules". For this purpose we propose to analyze separately positive and negative residuals. Our empirical strategy is as follows. We estimate a quantile regression of *Loan Rate* on the set of explanatory variables used in the loan-pricing model.[40]

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[38] Two assumptions are implicit in this analysis: we compute the changes in $R^2$ conditional on all covariates and on the sample (implying that we treat the total variance of loan rates as exogenous). Under these assumptions, the interpretation of the coefficients in the variance equation is straightforward: For a continuous (discrete) variable, it denotes the relative change in the $R^2$ resulting from a relative (discrete) change in the corresponding variable.

[39] In the subsequent analysis we set the continuous variables to their 25th or 75th percentiles, as explicitly mentioned or implied in the text. All unreferenced variables are set to their sample means.

[40] The quantile (or median) regression has the advantage over the linear (or mean) regression model that, while not affecting the residual variance, it is robust to skewness in the distribution of the residuals. For instance, if positive

Then, we generate the dummy variables *Rip-off* and *Bargain*, which indicate whether the estimated disturbance is larger or smaller than one standard deviation above or below the sample mean of the residuals (the estimated value is 17 bp). Finally, we estimate *logit* regressions of the variables *Rip-off* and *Bargain* on the same set of variables we employ in the variance analysis (see Column II in Table 2).

Table 3 displays the results. Consistent with our previous findings, *Ln(Loan Amount)* and *Corporation* decrease the probability of observing large deviations, in particular the probability of a rip-off. In contrast, the variables *Minority, IRS Problem* and *Ln(Distance)* increase the probability of both a bargain and a rip-off. *Minority* has a stronger effect on a downwards deviation, which is consistent with a bank's willingness to subsidize opaque firms (Petersen and Rajan 1995). Conversely, banks are substantially more likely to add a mark-up to a firm that has a fiscal delinquency in its track record. We are unable to draw conclusions on the remaining results, as they are particularly noisy and mixed.

### 2.5.5. Discontinuities in "Rules" versus "Discretion"

The application of "discretion" itself may be inherently discontinuous. For example, various loan and firm types may be assigned to different loan officers operating under unique pricing rules (see Liberti and Mian forthcoming). To test for the presence of such discontinuities we decompose each continuous variable into a linear spline with two breaks.[41] We then estimate a heteroscedastic regression using the splines in place of the original variables in the variance equation.

We find evidence of a pronounced discontinuity in the loan amount on "discretion". In particular, we obtain a sharp negative effect for small loans (below \$47,000), a moderate negative effect for large loans (above \$325,000), and surprisingly no effect for medium-sized loans (between \$47,000 and \$325,000). We conjecture that the strong negative effect for small loans reflects search efforts by the firms.

Our results also suggested that "discretion" decreases in importance over the duration of the relationship between the firm and the bank. We confirm this finding for short (less than 3 years) and long (more than 10 years) durations, but we find the opposite effect for medium lengths (between 3 and 10 years).[42] Concerning *Ln(Distance)*, our results indicate that the positive effect of this variable on "discretion" is confined to firms located further than two miles from the lender. Finally, we find no discontinuities regarding the age of the owner.

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deviations from the true pricing model are more sizeable than the negative ones, then a mean regression model will underestimate positive deviations and overestimate the negative ones.

[41] Each continuous variable is mapped into the following three mutually exclusive categories: "small" (if the value of the variable is in the lowest tercile), "large" (if the value is in the largest tercile) and "medium" (for intermediate values). Our results are qualitatively similar when we impose four breaks (yielding five distinct categories) instead of two.

[42] By allowing a greater number of intervals in the spline we actually see that the initial break occurs for relationships lasting between one and one-and-a-half years. In the medium term the loan officer may have achieved her maximum informational advantage. Internal mandated rotation and outside banks' observing the repeated lender – borrower interactions might ultimately weaken this informational advantage.

## 2.6. Robustness Tests

### 2.6.1. Specification Tests

Our main concern is that the variance results may be a product of our loan-pricing model being misspecified. We had access to the internal version of the 1993 SSBF, which is maintained by the Federal Reserve Board. The extra information in the confidential survey allowed us to conduct several important additional robustness tests. We report in advance that our previous results are virtually immune to the subsequent battery of tests.

First, we question to what extent our results may be simply due to bank heterogeneity (Stein 2002). As it is unfeasible to include a fixed effect for each lending institution in the SSBF, we resort to an alternative test. Specifically, in the mean equation we include 100 dummies that correspond to different bank size categories (in terms of gross total assets). Because each of these categories corresponds to a small cluster of banks that are similar in size, the inclusion of these dummies should control for potential differences in lending practices.

Second, we question the adequacy of both the information that we use to predict loan rates and the linearity assumption in our loan-pricing model. One major concern we have is the omission in our loan pricing model of a public measure of firm risk, such as the credit score. The confidential version of the 1993 SSBF contains the credit score percentile of the firm (as obtained from Dun & Bradstreet), which we employ in both the mean and variance equations. As expected, we find that lower credit scores are associated to more "discretion", while the other results remain unaltered. We then scrutinize the linearity assumption in our loan-pricing model by decomposing each of the continuous variables in the mean equation (i.e., loan size and maturity, age of firm's owner, credit score, assets, duration of relationship, and distance) into ten equally spaced splines. Moreover, we also perform a test similar in spirit to the Ramsey (1969)'s Reset Test.[43]

In order to examine further the relevance of the information we use in our loan pricing model we ask how our findings would change if we assumed that there were no "rules". That is, to the extent that our measure of "discretion" is by construction a product of omitted information (e.g., the "client's green hat" or the "client is nice" dummies), we next adopt the extreme view that all relevant variables are omitted. Column (2) of Table 4 displays the results for the variance equation when the mean equation includes only a constant term. These results are remarkably similar to those we presented in Table 2 (which we re-display in Column (1) of Table 4). Does this mean that the information we employ in our linear pricing model is inadequate?

To address this question we analyze the bank's decision to accept or reject a loan application. The objective of this exercise is twofold. First, we want to see to what extent our mean-equation variables can predict the bank's decision to grant a loan. Using all our mean-

[43] Specifically, we estimate the pricing model and obtain the fitted values (i.e., the predicted loan rates); then, we re-estimate the model including in the mean equation the quadratic and cubic terms of the fitted values. If the potential non-linearities in the model are biasing our results, then the introduction of these extra terms should significantly alter the estimates in the variance equation. The obtained estimates indicate that is not the case. Despite the non-linear terms being statistically significant in the mean equation, the results in the variance equation are virtually unaffected.

equation variables displayed in Table 2 except the loan characteristics, the estimated fraction of correct predictions by a probit model is 87%.[44] This result supports our view that the information we use in the pricing model is fairly adequate and comprehensive. Second, we want to assess how the extent of "discretion" in the accept/reject decision is affected by changes in the information set in the mean equation.

Columns (3) and (4) of Table 4 display the results of the heteroscedastic probit models of the bank's decision to accept or reject a loan application. Analogous to the loan pricing models in Columns (1) and (2), we compare a full fledged accept/reject model containing all explanatory variables, in Column (3), with a model containing only the constant term, in Column (4). In contrast to the similarity in results between the loan pricing models in Columns (1) and (2), the introduction of the variables in the mean equation causes most of the results in the variance equation to vanish. In fact, only three results survive in Column (3). Specifically, a bank is more likely to deviate from "rules" in its loan granting decision when: (i) the applicant has a poor track record (the firm is probably in the so-called "grey area"), (ii) the applicant is minority-owned (see Cavalluzzo, Cavalluzo and Wolken 2002), and (iii) the firm and the bank have a longer relationship.

Altogether the results in Table 4 suggest that the information we use in our models is used by lenders in their credit decisions. At the same time, they corroborate our view that the results of the variance equation in Table 2 reasonably reflect the use of "discretion" by loan officers in loan pricing.

### 2.6.2. Belgian Sample

We also use a dataset consisting of a large number of loans made by one important Belgian bank.[45] This dataset allows us to validate further our results against the sample design and limitations of the SSBF. Despite being less comprehensive than the SSBF in terms of firm-specific information, the Belgian dataset has at least three appealing features. First, it contains all the information stored by the bank about each particular borrower. This reassures us that "discretion" results from the loan officers' subjective assessments and pricing decisions rather than from an omitted variable problem in our model. Second, the Belgian dataset allows us to include branch fixed-effects in our regressions to control for branch heterogeneity within the single lending bank. Third, the potential differences in financial, geographical and cultural landscapes between the U.S. and Belgium provide an interesting challenge to the scope of our results.

We estimate a heteroscedastic regression model using all the information available in the Belgian dataset that we employed previously in the regressions with the SSBF sample (i.e., the variables described in Table 1). Due to data limitations in the Belgian sample, we are only able to explain the variance as function of the variables *Ln(Loan Amount)*, *Collateral*,

[44] We also use this probit model to test for the presence of sample selection bias. Presumably, a bank's lending decision could depend on the extent of "discretion" it expects to have vis-à-vis that particular applicant. We find no evidence of selection bias and the results of our variance equation remain unchanged. In the probit equation we drop all variables related to loan characteristics and replace the loan amount by the amount requested. The total number of observations is 1,916, distributed into 1,625 accepted loans and 291 credit denials.

[45] This dataset has been used in Degryse and Van Cayseele (2000), Degryse and Ongena (2005, 2007) and Degryse, Laeven and Ongena (2009). We refer to these papers for a detailed description of the dataset.

*Corporation, Ln(Duration)*, *Concentrated* and *Ln(Distance)*.[46] The results (not tabulated) confirm most of our previous findings: "Discretion" prevails when loans are small and unsecured, when the length of the firm-bank relationship is short, and when loans are granted to more distantly located firms. All referred effects are statistically significant at the 1% level.

## 2.7. Has "Discretion" Varied Over Time?

We now seek to detect temporal changes in the banks' loan-pricing behavior. In particular, we investigate whether the weight of "discretion", reflected in the greater unexplained dispersion of loan rates, has changed over time.

The literature fails to propose a clear-cut prediction about how the importance of "rules" and "discretion" may have evolved over the last two decades. It is widely recognized that the exponential increase in information processing capabilities has provided banks with innovative and low-cost tools to support their credit decisions. Less obvious is that the effective influence of these technologies in the banks' credit decisions has increased over time. For instance, Berger, Frame and Miller (2005) argue that the new technologies may act either as a substitute for or as a complement to existing lending technologies, such as the loan officer's judgment. Accordingly, one could expect an increasing or a decreasing role over time for "discretion".[47] In our subsequent empirical analysis, we seek to identify which of these effects dominates.

### 2.7.1. Panel Sample

We construct an augmented sample by merging the 1993 SSBF (1,625 observations, from 1990 to 1994), the 1998 SSBF (708 observations, from 1996 to 2000) and the 2003 SSBF (1,568 observations, from 2001 to 2005). The resulting sample spans 16 years, from 1990 to 2005. A consistent definition and a majority of identical questions used across all three surveys permits an analysis of the changes over time.[48] Table 5 reports sample statistics for each of the three samples. We opt to provide independent statistics for each sample as the unfolded panel allows us to assess major changes in the composition of the sample across surveys, as well as spot temporal correlations.[49]

[46] Unfortunately, the Belgian dataset does not provide the credit history of the firm, accounting information, information about the owner nor does it specify the financial services the bank provides to the firm. As a result, we cannot include in the variance equation the variables *Minority*, *Ln(Owner's Age)*, *Clean Record, IRS Problem* and *MSA*. In addition, in the Belgian sample *Ln(Distance)* is defined as the shortest traveling time to the lender (in minutes). The bank may have access to financial statements from a small subset of the firms in our sample – i.e., those listed in *Bel-first*. For that reason, we dropped those firms from our analysis.

[47] One could also argue that the proliferation of the internet led to a decrease in search costs and hence of "discretion". However, this may have not been the case initially (mid- to late-nineties), since internet banking is a rather recent phenomenon. Moreover, using data from the life-insurance market Brown and Goolsbee (2002) demonstrate that the internet initially may actually lead to an increase in price dispersion.

[48] *IRS Problem* is the only variable not present in the three surveys.

[49] In contrast to the 1993 and 2003 surveys, the renewals of lines of credit were excluded from the 1998 survey. This may explain the higher incidence of transactional lending in the 1998 sample, as suggested by the lower percentage of lines of credit, the lower fraction of loans granted by commercial banks (not tabulated), and by the relationship variables (shorter durations and higher incidence of impersonal relations). In addition, the higher loan rates and the smaller loan amounts in the 1998 survey may relate to the financial crisis surrounding this period. Our results are virtually unaffected when we remove the 1998 survey from our panel sample.

By comparing the 1993 SSBF to the 2003 SSBF we identify three clear trends in the data. First, there is an increase in loan maturity. Second, there is a steep decrease in the incidence of loans secured by collateral. Finally, the standard deviation of loan rates has increased over time, which is not to say that "discretion" has increased over time. In the next section we formally test for the presence of such a trend in the data.

### 2.7.2. Results

Table 6 displays the results from estimating a heteroscedastic regression model with the panel sample. We employ the same variables in the mean equation that we used in our cross-sectional analysis (see Table 1) plus a full set of year dummies to control for aggregate fluctuations. We just present the variance equation estimates to conserve on space. Column I employs a specification identical to the one we presented in Table 2. The panel results, apart from the drop in both magnitude and significance of *Clean Record* and *Ln(Duration)*, confirm our previous findings with the 1993 SSBF.

In Column II we add the temporal dimension to our analysis by including in the variance equation the variables *Prime Rate* and *Year*. *Prime Rate* controls for fluctuations in banks' risk shifting incentives. Consistent with recent findings by Jiménez, Ongena, Peydró and Saurina (2008) and Ioannidou, Ongena and Peydró (2007), the negative coefficient for *Prime Rate* indicates that banks tend to take more risks in periods of high liquidity (i.e., when interest rates are low).

The variable *Year* captures a time trend in the residual variance. We obtain a positive and statistically significant trend. However, this result may simply reflect structural changes in market conditions occurring during the period analyzed. We have in mind, in particular, the growing evidence that banks were increasingly lending to riskier (Berger, Frame and Miller 2005), more distantly located firms, and on a more transactional basis (Petersen and Rajan 2002). Our cross-sectional results (see Column II in Table 2) imply that these referred changes could explain *per se* an increase in the unexplained variance over time.

To account for potential changes in market conditions, we interact every variable in the variance equation with *Year*. Column III displays the results. Because we center all covariates, the variable *Year* captures a time trend in the residual variance for the average firm in the sample.[50] Its negative coefficient suggests a declining role for "discretion" over the sample period for the average firm, though the effect is not statistically significant. But the interaction terms reveal an interesting asymmetry this result masks. In particular, it seems that the negative time trend is more pronounced for small firms with weaker credit histories that obtain small loans, and nearly inexistent for large firms borrowing large amounts. For example, we obtain a statistically and economically significant decrease over time of the weight of "discretion" for a small firm that borrows $10,000 from a new lender. This result is consistent with the proliferation of credit scoring models for micro-loans (Berger, Frame and Miller 2005), and the findings in Brevoort (2006) and DeYoung, Frame, Glennon, McMillen and Nigro (2008). In contrast, we cannot reject the hypothesis that the role of "discretion" in

[50] Computing the marginal effect of *Year* for a median firm yields a similar result.

underwriting decisions concerning large loans and loans granted to large, transparent firms has remained steady over the period analyzed.[51]

Yet these interaction terms reveal another interesting phenomenon. The results in Column II suggested that there is more “discretion” in periods of low interest rates, a result consistent with risk-shifting behavior by banks. But it seems that these risk-shifting incentives have become stronger over time. In particular, our estimates suggest that prime rate has a negligible effect on the residual variance in the early part of our sample (i.e., around 1993), and a strong positive effect in the latter part of our sample (i.e., around 2003).

## 2.8. Conclusion

In this paper, we propose a heteroscedastic linear regression model to analyze the determinants of the unexplained dispersion of loan rates. Our variance analysis allows us to infer the nature of the lending technology that banks employ in their loan granting process. Larger unexplained deviations from the loan-pricing model are consistent with banks engaging in discretionary loan pricing (a judgmental and hence non-standardized technology). On the other hand, we interpret smaller deviations as the predominance of “rules” (a standardized lending technology). By parametrizing the unexplained variance of the loan-pricing model, we are able to identify the factors associated with “rules” and “discretion”. We believe this study is unique in that it combines within the same empirical framework a wide array of theoretical developments in the financial economics literature on the role of informational frictions on the credit market.

Consistent with theories based on costly search of information, we find that the weight of “discretion” in loan prices decreases in the size of the loan. In contrast, loan rate dispersion increase in various measures of the borrower opaqueness, in particular firm size, credit history and the bank’s effort to monitor the firm. We interpret this result as evidence that the switching costs faced by firms are an important source of market power for the lending bank. Our results also reveal that the weight of “discretion” increases with the size and level of concentration in the banking market, as well as with the borrower-lender distance.

We perform several robustness tests regarding the specification of the loan-pricing model, and compared our primary results (1993 SSBF) with those obtained in a dataset pertaining to a large Belgian bank. We found minor disparities, suggesting that our results are not sample-specific, driven by the omission of relevant information, nor driven by differences in banks’ technological and organizational structures. Finally, we construct a panel sample with the 1993, 1998 and 2003 SSBF and show that the significance of “discretion” decreased over the period analyzed (1990-2005) for small loans to opaque firms. Changes in market conditions rooted in the development of information and communication technologies seem to explain the decrease in loan rate dispersion during this period.

[51] These temporal results may be partially masked by structural changes in the legal environment in the U.S. banking industry, i.e., the 1999 Gramm-Leach-Bliley Act, that occurred during our sample period. We include an indicator variable for loans granted after 1999 in the variance equation (of the model in Column III). This inclusion reinforces our previous results as the negative trend for “discretion” becomes steeper. Interestingly, we find that the residual variance is 57% larger for loans granted after 1999, this effect being statistically significant at the 1% level.

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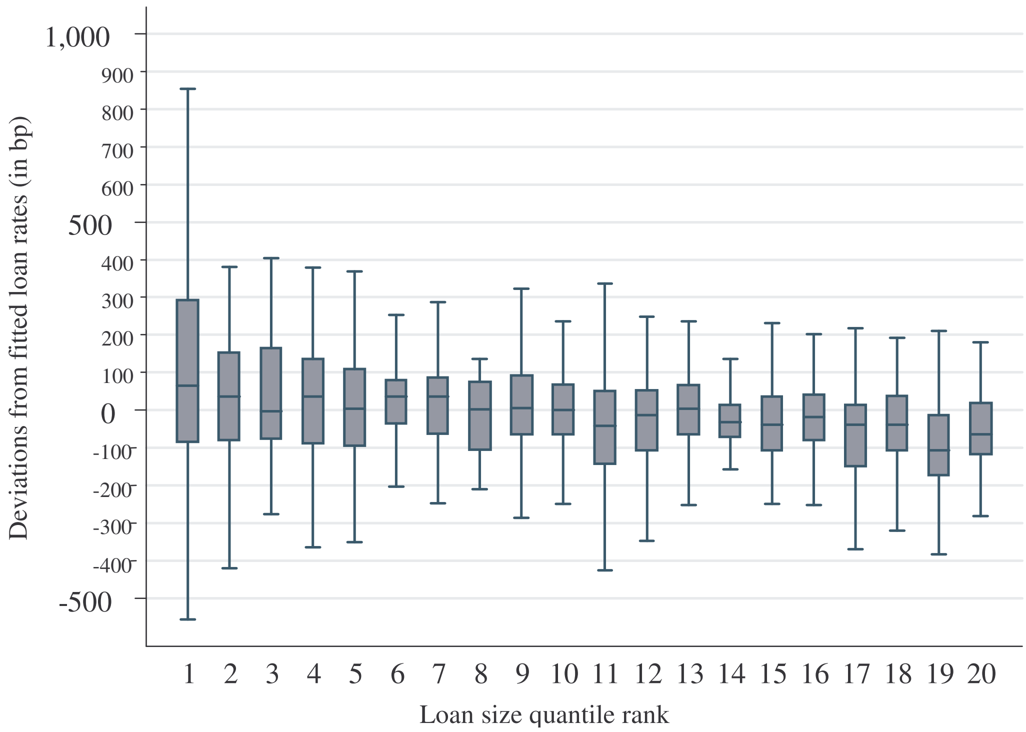
## 2.10. Tables and Figures

**Figure 1**
**Dispersion of residuals and loan size**

The figure displays box plots of the residuals from a regression of the loan rate on the prime rate, a dummy indicating whether the loan rate is variable, and five dummies for the loan type (see Table 1). The data are ranked by the loan size and sliced into twenty separate quantiles (1 corresponds to the smallest quantile and 20 to the largest). The dataset used is the 1993 SSBF.



## Table 1 – Descriptive Statistics, 1993 SSBF

All variables are obtained from the 1993 Survey of Small Business Finance, except the Prime Rate which we obtain from the Federal Reserve Economic Database. The table defines the variables employed in the empirical specifications and provides some sample statistics: mean, median (Med), standard deviation (S.d.), minimum (Min) and maximum (Max). The statistics take into account the 1993 SSBF sample weights. The number of observations is 1,625. Other variables used in our regressions (dummies): type of loan (5), one-digit SIC codes (9), year (4), census regions (8) and type of lender (8). We do not present descriptive statistics for these variables to conserve on space.

| Variable | Description | Mean | Med. | S.d. | Min | Max |
|---|---|---|---|---|---|---|
| *Interest Rate Variables* | | | | | | |
| Prime Rate | Prime rate (%) | 6.50 | 6.00 | 0.71 | 6.00 | 10.00 |
| *Loan Characteristics* | | | | | | |
| Loan Rate | Loan rate (%) [Dependent Variable] | 8.77 | 8.45 | 2.34 | 0.00 | 32.00 |
| Loan Amount | Loan size ($million) | 0.32 | 0.04 | 2.05 | 0.00 | 100.00 |
| Loan Maturity | Loan maturity (years) | 3.50 | 1.00 | 4.80 | 0.08 | 30.00 |
| Collateral | =1 if loan is collateralized | 0.70 | 1.00 | 0.46 | 0.00 | 1.00 |
| Floating | =1 if floating loan rate | 0.50 | 1.00 | 0.50 | 0.00 | 1.00 |
| *Firm/Owner Characteristics* | | | | | | |
| Proprietorship | =1 if firm is a proprietorship | 0.31 | 0.00 | 0.46 | 0.00 | 1.00 |
| Partnership | =1 if firm is a partnership | 0.08 | 0.00 | 0.28 | 0.00 | 1.00 |
| S-Corporation | =1 if firm is a S-corporation | 0.26 | 0.00 | 0.44 | 0.00 | 1.00 |
| Regular Corporation | =1 if firm is a regular corporation | 0.35 | 0.00 | 0.48 | 0.00 | 1.00 |
| Owner's Age | Age of firm's primary owner | 48.00 | 47.00 | 10.00 | 25.00 | 89.00 |
| Minority | =1 if firm is owned by minority race | 0.05 | 0.00 | 0.21 | 0.00 | 1.00 |
| *Accounting Information* | | | | | | |
| Assets | Total assets ($million) | 1.01 | 0.18 | 4.10 | 0.00 | 240.00 |
| Sales | = sales / assets | 4.50 | 2.70 | 7.00 | 0.00 | 92.00 |
| Profits | = profits / assets | 0.54 | 0.14 | 2.50 | -31.00 | 43.00 |
| Inventories | = inventories / assets | 0.19 | 0.06 | 0.26 | 0.00 | 1.00 |
| Accounts Receivable | = accounts receivable / assets | 0.18 | 0.10 | 0.22 | 0.00 | 1.10 |

**Table 1 (cont.)**

| Variable | Description | Mean | Med. | S.d. | Min | Max |
|---|---|---|---|---|---|---|
| Accounts Payable | = accounts payable / assets | 0.13 | 0.05 | 0.19 | 0.00 | 3.50 |
| Total Loans | = total loans / assets | 0.52 | 0.37 | 0.88 | 0.00 | 20.00 |
| Leverage | = total liabilities / assets | 0.70 | 0.56 | 0.94 | 0.00 | 21.00 |
| Trade Credit Use | % of purchases on trade credit | 56.00 | 75.00 | 41.00 | 0.00 | 100.00 |
| *Credit History* | | | | | | |
| Bankrupt | =1 if firm declared bankruptcy in past 7 years | 0.01 | 0.00 | 0.11 | 0.00 | 1.00 |
| Owner Delinquent | =1 if owner has been 60 or more days delinquent on personal obligations within past 3 years | 0.07 | 0.00 | 0.26 | 0.00 | 1.00 |
| Firm Delinquent | =1 if firm has been 60 or more days delinquent on business obligations within past 3 years | 0.17 | 0.00 | 0.37 | 0.00 | 1.00 |
| Judgments | =1 if any judgments have been rendered against the principal owner within the past 3 years | 0.03 | 0.00 | 0.17 | 0.00 | 1.00 |
| Clean Record | =1 if owner has clean record (the four previous variables equal zero) | 0.78 | 1.00 | 0.41 | 0.00 | 1.00 |
| IRS Problem | =1 if firm had IRS problems or penalties in the past year | 0.33 | 0.00 | 0.47 | 0.00 | 1.00 |
| *Relationship Characteristics* | | | | | | |
| Duration | Duration of relationship with the lender (years) | 7.80 | 5.00 | 7.70 | 0.00 | 53.00 |
| Main Bank | =1 if loan granted by primary bank | 0.72 | 1.00 | 0.45 | 0.00 | 1.00 |
| Personal | =1 if firm mainly conducts business with lender in person | 0.74 | 1.00 | 0.44 | 0.00 | 1.00 |
| *Competition/Location* | | | | | | |
| Concentrated | =1 if HHI>1800 (firm's headquarters office) | 0.54 | 1.00 | 0.50 | 0.00 | 1.00 |
| MSA | =1 if firm located in MSA | 0.73 | 1.00 | 0.44 | 0.00 | 1.00 |
| Distance | Distance to lender (miles) | 42.00 | 3.00 | 197.00 | 0.00 | 2608.00 |

**Table 2**

**Results of Heteroscedastic Regression with 1993 SSBF**

The table lists the coefficients and standard errors (S.e.) for the mean equation (Column I) and variance equation (Column II) from a heteroscedastic regression with *Loan Rate* (in basis points) as the dependent variable. The explanatory variables in both the mean and variance equation, which we define in Table 1, are demeaned. We obtain the estimates by Maximum Likelihood. The symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively. Some measures of fit are provided. $\chi^2$ ($k$) is the statistic for the joint test that all coefficients except the intercept are zero, for $k$ degrees of freedom. Pseudo-$R^2$ is defined as 1-Likelihood(just a constant)/Likelihood (full model). The VWLS (variance-weighted least squares) $R^2$ is obtained by using the inverse of the estimated variances in the heteroscedastic model as weights in the corresponding linear regression model.

| Variable | (I) Mean Equation | | (II) Variance Equation | |
|---|---|---|---|---|
| | $\beta$ | S.e. | $\gamma$ | S.e. |
| Constant | 842.2*** | 4.2 | 10.10*** | 0.04 |
| *Interest Rate Variables* | | | | |
| Prime Rate | 50.8*** | 7.0 | | |
| *Loan Characteristics* | | | | |
| Ln(Loan Amount) | -10.1*** | 3.4 | -0.27*** | 0.02 |
| Ln (Loan Maturity) | 0.2 | 4.4 | | |
| Collateral | 31.4*** | 9.2 | -0.18** | 0.08 |
| Floating Rate | -33.6*** | 8.8 | | |
| *Firm/Owner Characteristics* | | | | |
| Corporation | | | -0.24*** | 0.09 |
| Ln(Owner's Age) | 8.6 | 9.6 | 0.39*** | 0.13 |
| Minority | 32.6* | 17.1 | 0.34*** | 0.13 |
| *Accounting Information* | | | | |
| Ln(Assets) | -14.2*** | 3.7 | | |
| Sales | -1.3* | 0.8 | | |
| Profits | 2.0 | 2.1 | | |
| Inventories | -25.6 | 19.0 | | |
| Accounts Receivable | -13.3 | 19.5 | | |
| Accounts Payable | 15.3 | 29.2 | | |
| Total Loans | -4.6 | 17.4 | | |
| Total Debt | 16.3 | 16.2 | | |
| Trade Credit Use (%) | -0.1 | 0.1 | | |
| *Credit History* | | | | |
| Bankrupt | -2.6 | 30.7 | | |
| Owner Delinquent | 77.2*** | 20.3 | | |
| Firm Delinquent | 15.1 | 11.6 | | |
| Judgments | 24.4 | 23.0 | | |

**Table 2 (cont.)**

| Variable | I – Mean Equation | | II – Variance Equation | |
|---|---|---|---|---|
| | β | S.e. | γ | S.e. |
| Clean Record | | | -0.25*** | 0.09 |
| IRS Problem | 7.7 | 7.8 | 0.16** | 0.07 |
| *Relationship Characteristics* | | | | |
| Ln(Duration) | -2.4 | 5.2 | -0.12** | 0.05 |
| Main Bank | 15.7 | 10.1 | | |
| Personal | 5.5 | 8.5 | | |
| *Competition/Location* | | | | |
| Concentrated | 5.9 | 7.8 | 0.10 | 0.08 |
| MSA | 4.7 | 9.6 | 0.18** | 0.09 |
| Ln(Distance) | 3.2 | 2.8 | 0.10*** | 0.02 |
| *Other Controls* | | | | |
| Loan Type (5) | Yes** | | | |
| Firm Organization Type (3) | Yes** | | | |
| SIC (9) | Yes | | | |
| Year Dummies (4) | Yes** | | | |
| Regions (8) | Yes** | | | |
| Lender Type (8) | Yes*** | | | |
| Number of observations | 1,625 | | | |
| Number of parameters | 74 | | | |
| $\chi^2$-Statistic | 980.4 | | | |
| Pseudo-$R^2$ (%) | 4.46 | | | |
| VWLS $R^2$ (%) | 28.26 | | | |

## Table 3
## Analysis of Extreme Residuals

The table lists the marginal effects in percent (Mfx (%) from fitting a logit model to estimate the probabilities of observing a large positive residual (*Rip-off*) and a large negative residual (*Bargain*). The residuals originate from a quantile regression of *Loan Rate* on the set of variables defined in Table 1. *Rip-offs* (*Bargains*) correspond to residuals one standard deviation above (below) the sample mean. Bootstrapped standard errors (1000 replications) are provided. The symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively. The dataset used is the 1993 SSBF.

| **Variable** | **Prob. of Rip-off** | | **Prob. of Bargain** | |
|---|---|---|---|---|
| | **Mfx (%)** | **S.e.** | **Mfx (%)** | **S.e.** |
| *Loan Characteristics* | | | | |
| Ln(Loan Amount) | -2.2*** | 0.3 | -1.4*** | 0.3 |
| Collateral | -0.7 | 1.4 | 0.3 | 1.3 |
| *Firm/Owner Characteristics* | | | | |
| Corporation | -2.2 | 1.6 | -1.3 | 1.5 |
| Minority | 2.3 | 2.4 | 3.4 | 2.3 |
| Ln(Owner's Age) | -0.5 | 2.1 | 0.8 | 2.4 |
| *Credit History* | | | | |
| Clean Record | 1.0 | 1.4 | 0.0 | 1.4 |
| IRS Problem | 3.0** | 1.4 | 1.6 | 1.3 |
| *Relationship Characteristics* | | | | |
| Ln(Duration) | 0.4 | 0.8 | -1.6** | 0.8 |
| *Competition/Location* | | | | |
| Concentrated | -1.4 | 1.3 | -1.0 | 1.2 |
| MSA | 0.0 | 1.6 | -1.4 | 1.7 |
| Ln(Distance) | 0.9** | 0.4 | 1.1*** | 0.3 |
| Number of Observations | 1,625 | | 1,625 | |
| Pseudo-$R^2$ (%) | 7.3 | | 7.1 | |

## Table 4
## Banks' Use of Information in the Loan Granting and Loan Pricing Decisions

Columns (1) and (2) list the coefficients for the variance equation from heteroscedastic regression models with *Loan Rate* as the dependent variable. In model (1) the mean equation includes the full set of variables as in Table 2. The mean equation in model (2) contains only a constant term. Columns (3) and (4) display the coefficients for the variance equation from heteroscedastic probit models of the bank's decision to accept or reject the loan application. In model (3) the mean equation contains all variables employed in model (1), except the loan contract terms *Maturity*, *Collateral*, and *Floating Rate*. *Loan Amount* in model (3) refers to the amount requested in the application. Model (4) includes only a constant term in the mean equation. T-statistics are provided in parentheses. The symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively.

| **Dependent Variable** | **Loan Rate** | | **Accept/Reject** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Mean Equation* | *All Variables* | *Constant Only* | *All Variables* | *Constant Only* |
| *Variance Equation* | | | | |
| Ln(Loan Amount) | -0.27*** | -0.20*** | -0.06 | -0.09*** |
| | (-14.80) | (-10.90) | (-1.64) | (-4.33) |
| Collateral | -0.18** | -0.23*** | | |
| | (-2.22) | (-2.83) | | |
| Corporation | -0.24*** | -0.46*** | -0.14 | -0.15* |
| | (-2.77) | (-5.31) | (-0.85) | (-1.68) |
| Ln(Owner's Age) | 0.39*** | 0.20 | -0.04 | -0.17 |
| | (2.98) | (1.57) | (-0.12) | (-1.22) |
| Minority | 0.34*** | 0.35*** | 0.57** | 1.16*** |
| | (2.64) | (2.79) | (2.39) | (4.72) |
| Clean Record | -0.25*** | -0.39*** | -0.37** | -0.67*** |
| | (-2.90) | (-4.46) | (-2.48) | (-6.57) |
| IRS Problem | 0.16** | 0.16** | -0.28 | 0.28*** |
| | (2.14) | (2.16) | (-1.45) | (3.67) |
| Ln(Duration) | -0.12** | -0.08* | 0.31*** | -0.14*** |
| | (-2.46) | (-1.74) | (2.92) | (-3.11) |
| Concentrated | 0.10 | 0.08 | -0.07 | 0.05 |
| | (1.29) | (1.07) | (-0.48) | (0.65) |
| MSA | 0.18** | 0.14 | 0.01 | 0.18** |
| | (1.96) | (1.57) | (0.02) | (2.01) |
| Ln(Distance) | 0.10*** | 0.13*** | 0.06 | -0.05** |
| | (4.55) | (5.82) | (1.44) | (-2.41) |
| Constant | 10.10*** | 10.40*** | | |
| | (288.00) | (297.00) | | |
| Number of Observations | 1,625 | 1,625 | 1,916 | 1,916 |

## Table 5
## Descriptive Statistics – SSBF 1993, 1998 and 2003

The table provides some sample statistics (mean, median and standard deviation) for the 1993 SSBF, 1998 SSBF and 2003 SSBF. The number of observations is 1,625, 708 and 1,568, respectively. Table 1 defines the variables.

| Variable | Mean | | | Median | | | Standard Deviation | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1998 | 2003 | 1993 | 1998 | 2003 | 1993 | 1998 | 2003 |
| *Interest Rate Variables* | | | | | | | | | |
| Prime Rate | 6.50 | 8.20 | 4.50 | 6.00 | 8.30 | 4.30 | 0.71 | 0.33 | 0.82 |
| *Loan Characteristics* | | | | | | | | | |
| Loan Rate | 8.77 | 9.25 | 6.45 | 8.45 | 9.00 | 6.00 | 2.34 | 2.28 | 2.97 |
| Ln(Loan Amount) | 11.00 | 10.00 | 11.00 | 11.00 | 10.00 | 11.00 | 1.70 | 1.60 | 1.60 |
| Ln(Loan Maturity) | 0.64 | 0.98 | 1.30 | 0.00 | 1.30 | 1.40 | 1.10 | 1.20 | 0.77 |
| Collateral | 0.70 | 0.60 | 0.51 | 1.00 | 1.00 | 1.00 | 0.46 | 0.49 | 0.50 |
| Floating Rate | 0.50 | 0.29 | 0.44 | 1.00 | 0.00 | 0.00 | 0.50 | 0.45 | 0.50 |
| *Loan Type* | | | | | | | | | |
| Line of Credit | 0.53 | 0.29 | 0.57 | 1.00 | 0.00 | 1.00 | 0.50 | 0.45 | 0.49 |
| Capital Lease | 0.03 | 0.05 | 0.02 | 0.00 | 0.00 | 0.00 | 0.16 | 0.22 | 0.12 |
| Mortgage | 0.12 | 0.13 | 0.11 | 0.00 | 0.00 | 0.00 | 0.32 | 0.33 | 0.32 |
| Vehicle Loan | 0.10 | 0.20 | 0.13 | 0.00 | 0.00 | 0.00 | 0.30 | 0.40 | 0.34 |
| Equipment Loan | 0.10 | 0.17 | 0.10 | 0.00 | 0.00 | 0.00 | 0.30 | 0.37 | 0.30 |
| Other | 0.13 | 0.17 | 0.07 | 0.00 | 0.00 | 0.00 | 0.34 | 0.37 | 0.25 |
| *Firm/Owner Characteristics* | | | | | | | | | |
| Proprietorship | 0.31 | 0.38 | 0.32 | 0.00 | 0.00 | 0.00 | 0.46 | 0.49 | 0.47 |
| Partnership | 0.08 | 0.08 | 0.08 | 0.00 | 0.00 | 0.00 | 0.28 | 0.28 | 0.27 |
| S-Corporation | 0.26 | 0.29 | 0.38 | 0.00 | 0.00 | 0.00 | 0.44 | 0.46 | 0.49 |
| Corporation | 0.35 | 0.25 | 0.22 | 0.00 | 0.00 | 0.00 | 0.48 | 0.43 | 0.41 |
| Ln(Owner's Age) | 3.70 | 3.70 | 3.70 | 3.70 | 3.70 | 3.70 | 0.27 | 0.29 | 0.33 |
| Minority | 0.05 | 0.07 | 0.07 | 0.00 | 0.00 | 0.00 | 0.21 | 0.25 | 0.25 |
| *Accounting Information* | | | | | | | | | |
| Ln(Assets) | 12.00 | 12.00 | 12.00 | 12.00 | 12.00 | 12.00 | 1.80 | 1.90 | 1.80 |
| Sales | 4.50 | 237.00 | 5.60 | 2.70 | 2.70 | 2.80 | 7.00 | 3,378 | 16.00 |
| Profits | 0.54 | 217.00 | 1.10 | 0.14 | 0.23 | 0.19 | 2.50 | 3,175 | 5.60 |
| Inventories | 0.19 | 0.15 | 0.15 | 0.06 | 0.02 | 0.02 | 0.26 | 0.23 | 0.23 |
| Accounts Receivable | 0.18 | 0.18 | 0.18 | 0.10 | 0.06 | 0.06 | 0.22 | 0.24 | 0.24 |

**Table 5 (cont.)**

| Variable | Mean | | | Median | | | Standard Deviation | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1998 | 2003 | 1993 | 1998 | 2003 | 1993 | 1998 | 2003 |
| Accounts Payable | 0.13 | 0.28 | 0.12 | 0.05 | 0.03 | 0.02 | 0.19 | 2.40 | 0.28 |
| Total Loans | 0.52 | 2.40 | 0.85 | 0.37 | 0.38 | 0.40 | 0.88 | 21.00 | 3.10 |
| Leverage | 0.70 | 2.80 | 1.00 | 0.56 | 0.62 | 0.58 | 0.94 | 21.00 | 3.20 |
| Trade Credit Use (%) | 56.00 | 54.00 | 53.00 | 75.00 | 75.00 | 66.00 | 41.00 | 42.00 | 41.00 |
| *Credit history* | | | | | | | | | |
| Bankrupt | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.11 | 0.08 | 0.11 |
| Owner Delinquent | 0.07 | 0.12 | 0.10 | 0.00 | 0.00 | 0.00 | 0.26 | 0.33 | 0.30 |
| Firm Delinquent | 0.17 | 0.17 | 0.20 | 0.00 | 0.00 | 0.00 | 0.37 | 0.37 | 0.40 |
| Judgments | 0.03 | 0.02 | 0.03 | 0.00 | 0.00 | 0.00 | 0.17 | 0.15 | 0.16 |
| Clean Record | 0.78 | 0.78 | 0.74 | 1.00 | 1.00 | 1.00 | 0.41 | 0.42 | 0.44 |
| *Relationship Characteristics* | | | | | | | | | |
| Ln(Duration) | 1.80 | 1.40 | 1.90 | 1.80 | 1.30 | 1.90 | 0.83 | 0.91 | 0.88 |
| Main Bank | 0.72 | 0.54 | 0.66 | 1.00 | 1.00 | 1.00 | 0.45 | 0.50 | 0.47 |
| Personal | 0.74 | 0.61 | 0.68 | 1.00 | 1.00 | 1.00 | 0.44 | 0.49 | 0.47 |
| *Competition/Location* | | | | | | | | | |
| Concentrated | 0.54 | 0.51 | 0.47 | 1.00 | 1.00 | 0.00 | 0.50 | 0.50 | 0.50 |
| MSA | 0.73 | 0.74 | 0.74 | 1.00 | 1.00 | 1.00 | 0.44 | 0.44 | 0.44 |
| Ln(Distance) | 1.70 | 2.40 | 1.90 | 1.40 | 1.60 | 1.60 | 1.50 | 2.20 | 1.70 |

## Table 6
## Results of Heteroscedastic Regression with Panel Sample

The table lists the coefficients (Coeff.) and standard errors (S.e.) for the variance equation from a heteroscedastic regression of *Loan Rate* on the set of variables described in Table 1. We obtain the panel sample by merging the 1993, 1998 and 2003 SSBF samples. *Year* is the year in which the loan was granted. Table 1 defines the remaining variables. We obtain the estimates by Maximum Likelihood. The symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively. We provide some measures of fit. The Pseudo-$R^2$ is defined as 1-Likelihood(just a constant)/Likelihood (full model). The VWLS (variance-weighted least squares) $R^2$ is obtained by using the inverse of the estimated variances in the heteroscedastic model as weights in the corresponding regression model.

| Variable | Panel Sample (I) | | Panel Sample (II) | | Panel Sample (III) | |
|---|---|---|---|---|---|---|
| | Coeff. | S.e. | Coeff. | S.e. | Coeff. | S.e. |
| Constant | 10.45*** | 0.02 | 10.42*** | 0.02 | 10.4*** | 0.02 |
| *Loan Characteristics* | | | | | | |
| Ln(Loan Amount) | -0.20*** | 0.01 | -0.23*** | 0.01 | -0.22*** | 0.01 |
| Collateral | -0.39*** | 0.05 | -0.27*** | 0.05 | -0.30*** | 0.05 |
| *Firm/Owner Characteristics* | | | | | | |
| Corporation | -0.11** | 0.06 | -0.13** | 0.06 | -0.14** | 0.06 |
| Minority | 0.45*** | 0.08 | 0.46*** | 0.08 | 0.41*** | 0.09 |
| Ln(Owner's Age) | 0.15* | 0.08 | 0.10 | 0.08 | 0.12 | 0.08 |
| Clean Record | -0.05 | 0.05 | -0.09 | 0.05 | -0.07 | 0.05 |
| *Relationship Characteristics* | | | | | | |
| Ln(Duration) | 0.00 | 0.03 | -0.05 | 0.03 | -0.06** | 0.03 |
| *Competition/Location* | | | | | | |
| Concentrated | 0.15*** | 0.05 | 0.14*** | 0.05 | 0.12** | 0.05 |
| MSA | 0.23*** | 0.06 | 0.22*** | 0.06 | 0.24*** | 0.06 |
| Ln(Distance) | 0.15*** | 0.01 | 0.14*** | 0.01 | 0.13*** | 0.01 |
| *Temporal Variables* | | | | | | |
| Prime Rate | | | -0.06*** | 0.02 | -0.03 | 0.02 |
| Year (Time Trend) | | | 0.04*** | 0.01 | -0.08 | 0.08 |
| *Interaction Terms* | | | | | | |
| Year × Ln(Loan Amount) | | | | | 0.01*** | 0.00 |
| Year × Collateral | | | | | -0.03** | 0.01 |
| Year × Corporation | | | | | 0.01 | 0.01 |
| Year × Minority | | | | | 0.02 | 0.02 |
| Year × Ln(Owner's Age) | | | | | 0.00 | 0.02 |
| Year × Clean Record | | | | | 0.06*** | 0.01 |
| Year × Ln(Duration) | | | | | 0.01 | 0.01 |
| Year × Concentrated | | | | | 0.02** | 0.01 |
| Year × MSA | | | | | 0.03** | 0.01 |
| Year × Ln(Distance) | | | | | 0.01* | 0.00 |
| Year × Prime Rate | | | | | -0.01** | 0.01 |
| Number of observations (N) | 3,901 | | 3,901 | | 3,901 | |
| Number of parameters | 85 | | 87 | | 98 | |
| Pseudo-R2 (%) | 5.4 | | 5.6 | | 5.7 | |
| VWLS-R2 (%) | 49.8 | | 48.6 | | 46.7 | |

## 2.11. Appendix

The regression model with multiplicative heteroscedasticity is given by:

$$y_i = \beta' X_i + u_i, \tag{1}$$

$$Log\,\sigma_i^2 = \gamma' Z_i, \tag{2}$$

where (1) is the mean equation and (2) is the variance equation. The respective identifying assumptions are:

$$E\left(u_i \mid X_i\right) = 0, \tag{3}$$

$$E^2\left(u_i \mid Z_i\right) \equiv \sigma_i^2 = exp\left(\gamma' Z_i\right), \tag{4}$$

where $y$ is the dependent variable, $X$ a vector of explanatory variables in the mean equation, $u$ is a disturbance term, $\sigma^2$ the residual variance, and $Z$ a vector of explanatory variables in the variance equation. Under the normality assumption, the conditional distribution of $y_i$ is given by:

$$y_i \mid X_i, Z_i \xrightarrow{d} N\left(\beta' X_i, exp\left(\gamma' Z_i\right)\right), \tag{5}$$

As a result, we obtain Maximum-Likelihood estimates (MLE) in the heteroscedastic regression model by maximizing the following log-likelihood function with respect to $\beta$ and $\gamma$:

$$LogL = \frac{n}{2} log(2\pi) - \frac{1}{2}\sum_{i=1}^{n} \gamma' Z_i - -\frac{1}{2}\sum_{i=1}^{n} exp(-\gamma' Z_i)(y_i - \beta' X_i)^2. \tag{6}$$

Harvey (1976) demonstrates that this approach is analogous to estimating the mean equation (1), and taking the squared-residuals as the raw estimates of the individual variances, which are then used to estimate the variance equation (2). This two-step approach involves a substantial loss of efficiency vis-à-vis the MLE, however.

# Chapter 3

# Bank Concentration, Credit Quality and Loan Rates

## 3.1. Introduction

How bank concentration affects the real economy has been a lively topic of debate among academics. The conventional view is that concentration of market power in banking translates into reduced credit availability and higher loan prices. In turn, this might hamper investment and economic development (see, e.g. Jayaratne and Strahan 1996; Cetorelli and Gambera 2001; Black and Strahan 2002; Beck, Demirguc-Kunt and Maksimovic 2004). This view, which portrays the main concerns of regulators, has served to justify the first antitrust policies and has influenced subsequent regulation in banking.[1]

The importance of this topic is reflected in a substantial literature investigating how concentration in the banking sector affects credit market outcomes. Specifically, one influential stream of this literature investigates how concentration affects the interest rates that are charged on business loans. The evidence produced by these studies is somewhat mixed. Whereas the evidence generally points at a positive effect of concentration on loan rates, the magnitude of the estimated effects is generally small (Gilbert 1984, Berger 1995, Berger et al. 2004, and Degryse and Ongena 2008 provide comprehensive reviews).

A possible explanation for the lack of strong evidence of the effect of concentration on credit supply is that concentration may affect firms differentially, depending on their credit quality. While traditional industrial organization models (for example, Klein 1971) predict that banks in more concentrated markets uniformly charge higher rates to their customers, models that incorporate information asymmetries between lenders and borrowers have challenged this idea. Petersen and Rajan (1995), for instance, demonstrate that banks in highly concentrated markets are more likely to extend credit to lower-quality firms at discounted rates.

To the extent that the distribution of firms analyzed is likely to differ across data samples, studies can lead to different conclusions regarding the net effect of bank concentration on credit supply. But more importantly, if firms are differentially affected by concentration, then the distribution of the sample of firms analyzed (i.e., the borrowers) may itself be determined by the level of banking concentration. Consequently, these studies may have underestimated the effects of bank concentration because they disregard the potential effects of concentration on the *ex ante* incentives of firms and banks to sign a loan contract.

This paper uses data on the financing experiences of small firms to estimate the net effect of bank concentration on contracted loan rates. The estimated effect is thus "risk-adjusted"— in the sense that it takes into account the distribution of all potential borrowers, rather than the distribution of the actual borrowers only. The empirical model explicitly addresses the selection process that firms face until they become

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[1] The 1960 Bank Merger Act first recommended the consideration of competitive factors in the evaluation of bank mergers. In 1963, the US Supreme Court ruled that bank mergers were subject to the antitrust law. See Walter and Wescott (2008) for an historical perspective on antitrust banking.

borrowers. Specifically, the model encompasses the three following sequential stages: the firm's decision to apply for credit, the bank's decision about granting the loan, and the contracted loan rate. This framework differentiates the distinctive role that bank concentration may have across the different stages of the loan granting process. As a result, it allows one to disentangle the effect of concentration on the formation of the pool of borrowers from the net effect of concentration on loan rates.

The central findings of this paper are as follows. The average effect of high bank concentration on loan rates is 70 basis points (bp) when account is taken of the borrower pool selection process. This "risk-adjusted" effect is about three times larger than the result that is obtained when the sample of borrowers is treated as exogenous. The difference in estimates seems to reflect the deterioration in the average credit quality of the borrower pool in highly concentrated banking markets. This deterioration occurs through two separate channels. First, high concentration attracts loan applications from observationally riskier firms. Second, given a pool of applicants, banks in concentrated markets grant loans to observationally riskier applicants. Finally, the incidence of collateral does not seem to depend on the level of bank concentration.

While the results in this paper are consistent with the extant evidence that high bank concentration has (on average) a positive effect on loan rates, this study adds to the literature by measuring more precisely the effect of bank concentration on the supply of credit. In particular, this study demonstrates that focusing only on borrowers is of more limited economic interest because of selection bias with respect to the population distribution of loan supply functions. While those firms that are adversely affected by concentration will tend to be underrepresented in the credit market, benefited firms will tend to be overrepresented. As a result, one will tend to unambiguously underestimate the costs of bank concentration when focusing only on borrowers.

This paper also adds to the concurrent debate regarding the effect of bank concentration on the stability of the financial system. Specifically, the two following findings are of particular relevance to this debate. First, in concentrated markets firms pay substantially higher loan rates, which per se imply higher bankruptcy rates for borrowers. Second, the pool of borrowers is observationally riskier in concentrated markets. Both findings suggest that banks hold riskier loan portfolios in more concentrated markets (Boyd, De Nicoló and Jalal 2006; De Nicoló and Loukoianova 2006; Jimenez, Salas and Saurina 2006; Berger, Klapper and Turk-Ariss 2008). Note that while these studies use aggregate data on loan portfolio performance or bank failures, this study is the first (that I know of) to lend support to the "competition-stability" view with micro data.

Finally, this study brings together two important strands of literature that have matured independently. These strands focus on the perverse effects of bank concentration on the financial sector and on the real sector in the economy. However, in both cases these perverse effects are driven by the same mechanism—the fact that concentration changes the incentives of all credit market participants. This paper studies in greater detail the effects of these incentives, thereby contributing to a greater understanding of the economic costs associated with high bank concentration.

The remainder of this paper is structured as follows. Section 2 motivates the empirical tests. Section 3 outlines the econometric methodology. Section 4 describes the data and variables. Section 5 provides some univariate tests and Section 6 presents the multivariate results. Section 7 concludes.

## 3.2. Market concentration, loan rates and borrower sample

In principle, any sample of loan contracts is not a random sample of all potential credit market participants. There are at least two selection (or attrition) stages determining the sample of loan contracts. First, a firm must decide whether to apply for a bank loan. If banks in more concentrated markets charge higher loan rates, then this should discourage some firms from borrowing, for two reasons. First, if a firm has other sources of financing available, these sources become more attractive vis-à-vis bank loans. Second, the firm undertakes the investment only if the cost of financing does not exceed the maximum it can afford (i.e., the loan rate at which the expected NPV of the project equals zero). This notion is supported by the findings of Black and Strahan (2002), who show that fewer enterprises are created in more concentrated banking markets.

Second, the bank must decide whether or not to accept the loan application. This decision should depend on the availability of other investment opportunities and on the expected return on this particular investment. This expected return may, in turn, also depend on the level of bank concentration. In the Petersen and Rajan (1995) model, for instance, the return from lending to lower-quality firms is higher in concentrated markets, since a bank with market power can recoup the cost of lending over time.

The borrowing and lending decisions considered above are the outcome of rational choices made, respectively, by firms and banks. These choices act as selection mechanisms that shape the population of all potential credit market participants into a non-random sample of borrowers. This non-randomness may raise specification problems because the firm's application decision and the bank's decision to grant the loan could be driven by factors that cannot be observed empirically. If these unobserved factors also affect the contracted loan rates, then price-concentration regressions based on a sample of borrowers will result in biased estimates.

Financial intermediation theory has long recognized the importance in the credit market of unobserved factors. For instance, private information and implicit contracting arise endogenously during the firm-bank relationship in response to the information asymmetry problem (Boot 2000). The importance of these mechanisms was recently documented by Cerqueiro, Degryse and Ongena (2007), which shows that contracted loan rates to small and opaque businesses are explained mostly by unobservable factors. They also show that the importance of these factors (what they call "discretion") is higher in concentrated banking markets.

One factor that may be considered as (at least) partially unobservable is firm credit quality. Several theories argue that the level of bank concentration may have an effect on the quality of the borrower pool. For instance, Boyd and De Nicoló (2005) show how, in equilibrium, the risk of the banks' loan portfolios increases with the level of concentration.[2] This risk-shifting mechanism is based on the idea that banks, as concentration increases, charge higher loan rates to their customers. In turn, the higher loan rates exacerbate the agency problems in the credit market, since they induce firms to take more risk. In Petersen and Rajan (1995), the average credit quality of borrowers is also decreasing in the level of bank concentration. A monopoly bank can charge higher loan rates to old and locked-in customers. These rents enable the bank to extend credit to some low-quality firms that would not get credit in a competitive market.[3]

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[2] Several important studies predict a perverse link between competition and bank risk-taking (Broecker 1990; Keeley 1990; Riordan 1993; Allen and Gale 2004). These studies, however, ignore the risk-shifting incentives on the bank's asset side.

[3] Dewatripont and Maskin (1995) demonstrate that lenders in concentrated markets may optimally refinance bad projects. In their model, the lender cannot credibly commit not to refinance projects even when the projects are shown to be low quality, if sunk costs

As argued above, a price-concentration regression on a sample of borrowers may result in biased estimates, due to the presence of unobserved factors driving the firm's application decision and the bank's decision to grant the loan. To be more precise, in light of the above theories it will *underestimate* the true effect of concentration on loan rates. To see this, note that the problem of sample selection is that the sample of borrowers is not representative of the underlying population of all potential borrowers. The sample of borrowers will contain only those firms who found it optimal to borrow, given the market conditions they faced. If concentration is particularly costly for certain firms, then these firms will be under-represented in the borrower sample. On the other hand, firms that benefit from high concentration levels (e.g., the low credit-quality firms in Petersen and Rajan 1995) will be over-represented in the sample of borrowers. In short, the effect of concentration on loan rates will be likely underestimated because the sample of borrowers will contain those firms that are least affected by (or that could afford) the higher loan rates. The next section provides the econometric methodology.

## 3.3. Econometric methodology

Let $I_{1i}^*$ denote firm's $i$ net economic benefit of applying for a bank loan, and assume that $I_{1i}^*$ relates linearly to a set of explanatory variables ($Z_1$):

$$I_{1i}^* = Z_{1i}\delta_1 + v_{1i}, \tag{1}$$

where $v_1$ is a stochastic component. The individual-specific index function $Z_{1i}\delta_1$ measures the propensity of individual $i$ to apply for a bank loan. The borrowing decision should be related to the availability and expected return of investment projects. The rate of return takes into account the actual payoffs of the projects as well as the costs of financing these projects. Accordingly, besides depending on firm characteristics, $I_{1i}^*$ should also depend on the level of bank concentration. Although $I_{1i}^*$ is unobserved, firm's $i$ decision to apply for a bank loan is observed and given by:

$$I_{1i} = \begin{cases} 1 & \text{if } I_{1i}^* \geq 0 \\ 0 & \text{if } I_{1i}^* < 0. \end{cases} \tag{2}$$

If firm $i$ applies for a loan, then the bank must decide whether to accept or reject the application. Let $I_{2i}^*$ represent the bank's expected economic benefit of granting the loan to firm $i$, and assume

$$I_{2i}^* = Z_{2i}\delta_2 + v_{2i}, \tag{3}$$

where $Z_2$ is a vector containing characteristics of the applicant, and $v_2$ is an unobserved disturbance. The bank's lending decision should depend on the rents that the bank expects to extract in future deals with firm

were already incurred. *Ex ante*, this encourages entrepreneurs to undertake poor-quality projects. Consequently, also this model encompasses a positive link between high market concentration and a lower-quality pool of borrowers.

*i*. In Petersen and Rajan (1995), for example, these concession rents are increasing in the level of concentration.

As before, the outcome observed is the bank's decision to accept ($I_2 = 1$) or reject ($I_2 = 0$) the loan application, given by

$$I_{2i} = \begin{cases} 1 & \text{if } I_{1i}^* \geq 0, I_{2i}^* \geq 0 \\ 0 & \text{if } I_{1i}^* < 0. \end{cases} \tag{4}$$

Let $r_i$ denote the loan rate contracted between firm *i* and the bank, and let $r_i^*$ denote a latent loan rate defined over the entire population of firms. For the actual borrowers, the latent loan rate is the contracted loan rate. For the non-applicants, and for firms that were denied credit, $r_i^*$ measures the "shadow" loan rate— the rate that firm *i* would face if it obtained credit.

$$r_i = \begin{cases} r_i^* & \text{if } I_{1i}^* \geq 0, I_{2i}^* \geq 0 \\ \text{not observed} & \text{otherwise.} \end{cases} \tag{5}$$

Finally, assume that $r^*$ relates linearly to a set of exogenous covariates *X*:

$$r_i^* = \gamma' X_i + u_i, \tag{6}$$

where the *u* is the error term.

The structure of the model described above fits in the class of models that deals with self-selectivity (Maddala 1983) or incidental truncation (Wooldridge, 2002).[4] These terms refer to the non-randomness of the sample used in estimation. In the context of this paper, the non-randomness problem is due to the fact that any sample of borrowers is pre-determined by the incentives of a given firm or bank to sign a loan contract.

The error terms follow a trivariate normal distribution, with

$$cov(v_{1i}, v_{2i}, u_i) = \begin{bmatrix} 1 & \rho & \sigma_{1u} \\ \rho & 1 & \sigma_{2u} \\ \sigma_{1u} & \sigma_{2u} & \sigma_u^2 \end{bmatrix}. \tag{7}$$

The estimate for $\rho$ is small and insignificant, and therefore in the following exposition this parameter is restricted to zero. While not affecting the substantive results of this paper, the restriction that the errors

[4] Maddala (1983, pp. 278-283) provides several examples of applications in economics with multiple criteria for selectivity. This methodology has also been used in the Finance literature. For example, Cox and Japelli (1993), and Gropp, Scholz and White (1997) estimate households' demand for consumer liabilities conditional on being unconstrained in the credit market and holding positive debt. In addition, Chakravarty and Yilmazer (forthcoming) estimate the effect of the borrower-lender relationship on loan rates conditional on the firm's application decision and the bank's acceptance decision.

between the selection stages are uncorrelated allows the separate identification of the risk-shifting incentives of firms and banks.[5]

The reduced-form relation of interest is the expected loan rate for firm *i*, conditional on the firm's application decision and on the bank's decision about granting the loan. This conditional expectation is given by

$$E\left(r_i \mid X_i, I_{1i}^* \geq 0, I_{2i}^* \geq 0\right) = \gamma' X_i + \sigma_{1u}\lambda_{1i}\left(Z_{1i}\delta_{1i}\right) + \sigma_{2u}\lambda_{2i}\left(Z_{2i}\delta_{2i}\right), \tag{8}$$

where $\lambda_{1i}$ and $\lambda_{2i}$ are the inverse Mills ratios (IMRs). $\lambda_{1i}$ pertains to the firm's decision to apply for credit (equations 4 and 5), while $\lambda_{2i}$ pertains to the bank's decision about granting the loan (equations 6 and 7). The purpose of the IMRs is to correct the estimates obtained with the sample of borrowers for the sample selection design (Heckman 1979). Specifically, the IMRs "absorb" the effects due to the misalignment between the composition of the samples of borrowers and non-borrowers. As a result, the coefficients in $\gamma$ (equation 9) can be interpreted as measuring average effects for the population of all firms.[6]

I estimate the model with the two-step approach that was proposed by Heckman (1979), and is also known as *Heckit*. First, I estimate a probit model of the firm's decision to apply for a bank loan (equations 2 and 3), and use the estimate of $\delta_1$ to compute $\hat{\lambda}_1$ (the estimate of $\lambda_1$). Then, on the sample of applicants, I estimate a probit model of the bank's decision to grant the loan (equations 4 and 5), and use the estimate of $\delta_2$ to compute $\hat{\lambda}_2$. Finally, I estimate the loan-rate equation (8) using the sample of borrowers.[7]

## 3.4. Data and variables

### 3.4.1. Data

This study uses data from the 1993 National Survey of Small Business Finances (NSSBF), a survey conducted by the Federal Reserve Board and the Small Business Administration. The NSSBF focuses on the financing experiences of 4,637 small businesses (defined as firms with fewer than 500 employees) in operation in the US in 1993. The NSSBF does not use an equal-probability sample design. For instance, larger firms and firms owned by minorities were oversampled, and the sample weights thus crucially affect the interpretation of the survey data. All statistical and econometric analyses use the NSSBF weights to ensure that these data are representative of the population of small businesses.

The NSSBF collects balance sheet and income statement data of firms from their year-end 1992 financial statements. The survey contains not only financial and accounting information, but also detailed

[5] This restriction is supported by previous findings. For instance, using the 1993 NSSBF, Cole, Goldberg and White (2004), and Cavalluzzo, Cavalluzzo and Wolken (2002) estimate jointly the firm's application decision and the bank's acceptance decision, and find a low and insignificant correlation between the two equations.

[6] Note from its definition above that the IMR is inversely proportional to the firm's propensity to be selected into the sample of borrowers. This is the mechanism through which this methodology ensures the representativeness of the sample used in estimation. Firms that are over-represented receive less weight in estimation, while under-represented firms receive more weight in the estimation.

[7] In principle, this model can also be estimated by maximum-likelihood (ML). However, the two-step approach is far more popular in applied work, since the likelihood functions of models with partial observability typically have poor convergence properties. The fact that the model has two sequential selection equations makes estimation even more cumbersome. Another disadvantage of the ML approach is that it requires stronger distributional assumptions with respect to the joint distribution of the error terms (see Amemiya 1985 or Wooldridge 2002).

information about other firm characteristics, such as the organizational form, credit history, ownership, age, industry classification, demographic characteristics of the firm's owner, and the firm's use of financial services.

The NSSBF uniquely suits the purpose of this paper, since it covers a sample representative of small businesses. In particular, the NSSBF provides information not only about the actual borrowers, but also about firms that did not apply for bank credit— as well as those that did apply but were denied credit. This makes it possible to analyze the process through which firms are selected into the sample of borrowers, which should depend on the level of bank concentration.

The 1993 NSSBF is preferable to more recent surveys that are available (i.e., the 1998 and the 2003 SSBF), for two reasons. First, of the three surveys, the 1993 NSSBF is the one that has been most heavily used and tested in the empirical banking literature. Second, the measure of concentration in the banking market available in these surveys – the Herfindahl-Hirschmann Index (HHI) – is defined at the local (MSA or county) level. Previous studies argue that the HHI becomes a poor proxy for bank market power after deregulation in 1994 (e.g., Black and Strahan 2002; Cetorelli and Strahan 2006). The geographical scope of banking in the US changed in the mid-nineties, with regulatory changes and the massive adoption by banks of information-intensive technologies. In particular, after the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, it is less plausible that banking markets can be viewed as local.[8]

### 3.4.2. Variables

Variable definitions and model specifications are provided in Table 1, and some descriptive statistics appear in Table 2. There are 4,295 firms in the sample, which is representative of more than 4.5 million small businesses in the US.[9] Only 30% of the firms applied for a bank loan in the three years preceding the date of the survey. The dependent variable for the firm's application decision is *Applied*, and the corresponding explanatory variables are marked with an "X" in Column (1) of Table 1. The empirical specification for the bank's decision to accept or reject the loan application (*Accepted*) is described in Column (2). More than 80% of the loan applications were successful. As a result, the sample of actual borrowers is about one-fourth the size of the universe of firms. The empirical specification of the substantive equation (i.e. with *Loan Rate* as the dependent variable) is presented in Column (3).

As shown in Table 1, the equations for *Applied*, *Accepted*, and *Loan Rate* use different sets of explanatory variables. I start by describing the explanatory variables that are common to all three equations. The main variable is *Concentrated*. This is a dummy indicating whether the Herfindahl-Hirschman bank deposit index of banking market concentration (HHI) for the Metropolitan Statistical Area or county where the firm is located exceeds 1,800. The HHI is extensively used in empirical research as a measure of bank market power (e.g., Petersen and Rajan 1995; Cetorelli and Gambera 2001; Black and Strahan 2002; Cetorelli and Strahan 2006). Moreover, the deposit HHI is still the standard tool used by antitrust regulators to assess proposed bank mergers. In particular, a market is viewed as highly concentrated if its HHI is higher

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[8] Many important interstate banking restrictions were eradicated with the passage of the Act, and subsequent years were characterized by a massive wave of bank M&As in the US (Berger, Demsetz and Strahan 1999). Evidence on the adoption by US banks of small business credit scoring is provided in Akhavein, Frame and White (2005).

[9] From the original total of 4,637 observations in the NSSBF, I dropped all loan applications made to non-financial institutions (56 observations), firms that reported zero assets (4), and observations with missing data on other explanatory variables (4). Following Cole et al. (2004), I also dropped all loan applications made before 1993 (278 observations, and about 10% of all loan applications) to ensure that the date of the application does not precede the date of the financial data reported by the firm.

than 1,800. Mergers that will result in a concentration level exceeding 1,800 are normally challenged by the Department of Justice.

All equations contain the following characteristics of the firm and owner: the number of employees (*Employees*), the age of the firm (*Age*), governance dummies indicating whether the firm is family-owned (*Family*) and whether the firm is a sole proprietorship (*Proprietorship*), and a dummy indicating whether the firm and its owner have neither had delinquencies nor faced legal judgments in the past three years (*Clean Record*).[10] Larger firms and firms with longer track records are typically more transparent to outsiders, and may therefore have a greater set of financing options. Family-owned businesses may have easier access to funding from the family members who own the business. Sole proprietorships crucially differ from the other legal types in terms of liability. In particular, the owners of sole proprietorships are personally liable for the firm's debts, potentially expanding the range of assets that creditors can seize in the event of default (Berger, Cerqueiro and Penas 2008). But *ex ante,* this could inhibit owners of unlimited liability firms from engaging in formal loan agreements.

Following Berger and Udell (1995), I add three dummy variables to all of the equations, in order to control for industry effects. Each of these dummies equals one when the firm is in one of the following industries: construction, services or retail.

The regressions also include the following financial characteristics (deflated by total assets) of the firm: total value of accounts receivable, inventories, total debt and profits.[11] High accounts receivable and inventory balances enable firms to obtain credit in the form of asset-based loans and factoring loans, two widespread lending technologies in the US (Berger and Udell 2006). *Leverage* is an important measure of credit risk. Moreover, it should also influence (in a non-monotonic way) a firm's decision to apply for new bank loans. Specifically, moderately and highly leveraged firms alike should be less likely to apply for credit. More profitable firms tend to rely less heavily on bank credit, since they generate more internal funds.

I now turn to the variables that are specific to each equation. It is common practice in the empirical literature that uses the *Heckit* methodology to impose exclusion restrictions (i.e. to assume that one or more variables that affect the selection equations do not affect the substantive equation). In the application equation I thus include one group of variables (under the label *Financing Sources*) that is not in the loan-rate equation. These variables control for the availability of other financing sources: past injections of funds by the firm's owner (*Debt Owner*), trade credit (*TC Use*), and recent equity issuance (*New Equity*). Furthermore, firms that did not fulfill their trade credit obligations on time (*Late TC*), firms that were denied trade credit by their suppliers (*TC Denied*), and firms that unsuccessfully attempted to issue equity (*Failed Issuance*) should also exhibit a stronger demand for bank credit.

Both the bank's decision to accept a loan application and the contracted loan rate should depend on the nature of the relationship between the bank and the firm (Petersen and Rajan 1994; Berger and Udell 1995; Degryse and van Cayseele 2000). Accordingly, I include in equations 2 and 3 the variable *Main Bank*, which indicates whether the firm identified the lender as being its primary provider of financial services. Finally, the loan-rate equation includes the following variables: *Prime Rate*, to control for fluctuations in the bank's

[10] In estimation I use the natural logarithm of the firm's age in all equations. In addition, I use the natural logarithm of *Employees* in equations 2 and 3, and *Employees* plus its square in equation 1. The quadratic effect of *Employees* on the firm's decision to apply for credit is motivated by the predictions of life-cycle theories of small business financing (see Berger and Udell 1998). The results are similar when I use the natural logarithm of *Employees*.

[11] To minimize the influence of outliers, I winsorized the debt-to-assets ratio to the 99th percentile value and the profit-to-assets ratio to the 1st and 99th percentile values.

cost of capital; *Floating*, a dummy indicating whether the loan rate is variable (as opposed to fixed); and five dummies denoting the purpose of the loan.

Note that no exclusion restrictions were imposed on the bank's approval equation. It is difficult to ascertain, on theoretical grounds, which information banks employ in their decision about granting the loan and exclude from the loan-rate-setting process. As a matter of fact, any exclusion restriction may result in misspecification if the loan granting and pricing decisions are jointly determined.

## 3.5. Univariate tests

### 3.5.1. Subsample composition

Table 3 provides descriptive statistics (mean and standard errors) for each of the subsamples that are generated along the two credit-decision stages. The first stage is the firm's decision to apply for a bank loan, which splits the sample of all firms into two: *Non-Applicants* and *Applicants*. The second stage is the bank's decision about granting the loan, which divides the sample of *Applicants* into *Rejected Applicants* and *Borrowers*. For each selection stage, Table 3 also provides two-tailed mean (or proportion) comparison tests between the selected (*Applicants* and *Borrowers*) and non-selected (*Non-Applicants* and *Rejected Applicants*) groups of firms.

Firms seem more likely to apply for a bank loan if the local banking market is concentrated. Specifically, 53% of the applicants are located in concentrated markets, versus 47% for the non-applicants. This result is consistent with previous findings (e.g., Zarutskie 2006) that firms are more likely to hold bank debt in concentrated banking markets. However, note that this result could be driven by differences in firm characteristics across markets.

The pools of applicants and non-applicants differ along several other interesting dimensions. Firms that apply for bank loans are substantially larger and slightly younger. Family-owned businesses and sole proprietorships are also less likely to apply for credit. An important result is that the applicants have substantially higher debt-to-assets ratios and poorer track records than the non-applicants do. The applicants also seem to depend more heavily on external financing, such as trade credit and debt from the firm's owners. This difference reflects, perhaps, the incapacity of these firms to generate funds internally, an argument supported by their significantly lower profitability. Moreover, it seems that the applicants are more credit constrained than the non-applicants are. In particular, the applicants resort more often to expensive sources of funds (such as trade credit; Petersen and Rajan 1994), are more often late on their trade-credit obligations, and are more likely to be denied trade credit by suppliers. All of the differences referred to are statistically significant at the 1% level. Finally, firms that successfully raised equity in the past three years are less likely to apply for credit, while firms that attempted to do so, but failed, are more likely to apply.

The proportion of firms that are denied credit is lower in concentrated markets. As before, this result needs to be taken with caution. The reported difference could simply indicate that firms located in concentrated markets have higher credit quality.

As expected, banks are more likely to reject loan applications from observationally riskier and more opaque firms. Specifically, banks are less likely to turn down applications from firms that are that are substantially larger, older, less leveraged (as before, a difference of 15 points), and from firms with better track records. Moreover, loan applications from family-owned firms and sole proprietorships are more likely to be rejected, suggesting that these firms are seen by banks as more opaque. Somewhat surprisingly, the rejected applicants are, on average, as profitable as the firms that get credit. In contrast, the firms with more liquid assets are more likely to obtain loans. Finally, a firm that applies for a loan at its primary bank is far more likely to succeed, which confirms the importance of the scope of the firm-bank relationship (Degryse and van Cayseele 2000).

### 3.5.2. Market concentration and credit quality

The univariate tests show that, in concentrated banking markets, firms are more likely to apply for credit and banks are less likely to reject loan applications. The subsequent issue is then which type of firm drives the increase in the loan-application rate and benefits from the decrease in the loan-rejection rate that is observed in concentrated markets. As argued before, high levels of concentration should attract applications from observationally riskier firms and at the same time induce banks to grant credit to these firms.

I use "difference-in-differences" estimates to examine the effect of bank concentration on the credit quality of the borrower pool. Specifically, I test whether the difference in average credit quality between the *Applicants* and *Borrowers* (the treatment groups) and the *Non-Applicants* and *Rejected Applicants* (the respective control groups) depends on the level of concentration. The use of the control groups makes it possible to "difference out" potentially confounding factors and to isolate the causal effect of concentration. Consequently, the "difference-in-differences" estimates provide a direct test of whether high concentration encourages both lower-quality firms to apply for credit and banks to grant credit to such firms.

In the models that lend support to these hypotheses (e.g., Petersen and Rajan 1995), firm quality refers to default or bankruptcy risk. While credit risk is not fully observable, I use the firm's debt-to-assets and profits-to-assets ratios as proxies of bankruptcy risk. Previous research indicates that these variables are among the most important predictors of credit risk (Zmijewski 1984; Shumway 2001). In a recent study, Altman and Sabato (2007) show that leverage and profitability are also important predictors of credit risk for small- and medium-sized enterprises in the US.

Table 4 displays average firm leverage and profitability for the treatment groups and control groups, across concentrated and competitive banking markets.[12] The table provides also differences-of-means tests across the four groups and the difference-in-differences estimates in bold.

The first panel set (A) confirms the previous findings that the applicants are more leveraged and less profitable than the non-applicants. The difference-in-differences estimates show that these differences between applicants and non-applicants are (in absolute value) higher in concentrated markets. Specifically, going from competitive to concentrated banking markets increases the average leverage in the pool of applicants by 7 percentage points (pp) and decreases average profitability by 20 pp. These effects are statistically significant, and indicate that high levels of market concentration attract lower-quality firms to the credit market.

The second set of panels (B) refers to the sample of applicants. Consistent with the univariate tests, the rejected applicants are systematically more leveraged than the borrowers. The pattern is less clear for profitability. In competitive markets, profitable firms are more likely to obtain credit. In contrast, in concentrated markets average profitability is higher among the rejected applicants than among the borrowers

[12] Several firms in the sample display abnormally high debt-to-assets and profit-to-assets ratios. To avoid the influence of these potential outliers, I winsorized these two variables at the 95$^{th}$ percentile and the profit-to-assets ratio at the 5$^{th}$ percentile. The outcome of the difference-in-differences tests are qualitatively similar when the untruncated variables are used.

(the difference is not statistically significant, though). But again, the difference-in-differences estimates reveal a clear pattern. Going from competitive to concentrated banking markets induces banks to grant credit to firms that are, on average, more leveraged (11 pp) and substantially less profitable (40 pp). Both estimates are statistically significant at the 5% level or better. This result corroborates the view that high concentration induces banks to extend credit to lower-quality firms.

Overall, these difference-in-differences estimates indicate that high bank concentration decreases the credit quality of the pool of borrowers. This result concurs with recent studies that show that banks operating in concentrated markets hold riskier loan portfolios (e.g., Boyd, De Nicoló and Jalal 2006; De Nicoló and Loukoianova 2006; Jimenez, Salas and Saurina 2006; Berger, Klapper and Turk-Ariss 2008). Furthermore, it seems that this risk-shifting mechanism occurs at two different stages of the lending process. First, high levels of bank concentration attract applications from low-quality firms, decreasing the average credit quality of the applicant pool. Second, in concentrated markets banks grant credit to some low-quality firms, further decreasing the average credit quality of the actual borrower pool.

## 3.6. Multivariate results – Sample selection model

### 3.6.1. Selection equations

Table 5 displays the probit results for the firm's decision to apply for a bank loan in the three years preceding the survey. Firms located in concentrated banking markets are, on average, 6% more likely to apply for a bank loan. The univariate results suggest that these "new" applicants are low-quality firms that are decreasing the average credit quality in the pool of applicants.

The remaining results also agree with the findings in the univariate analysis. As predicted by life-cycle theories of small business financing (e.g., Berger and Udell 1998), the data strongly support a non-monotonic effect of firm size on the likelihood of a loan application. On average, small firms become more likely to apply for bank credit as they grow, but the effect reverses when they grow beyond two hundred employees. The first effect indicates that a firm gains access to intermediated debt finance as it grows. If it survives and continues to grow, it may then have access to public equity and debt markets, which explains the reversal.

Older firms are less likely to apply for credit. On the one hand, longer track records should also imply that the firm has greater access to these public finance markets. On the other hand, younger firms don't have access to internal funds, as they have not had the time to build up financial slack. The firm's actual leverage should be another important determinant of the firm's application decision. *Leverage* is allowed to have a non-monotonic effect on *Applied,* in order to account for differences across firms' debt positions vis-à-vis their target debt ratios. As expected, more moderately leveraged firms are more likely to apply for credit, while highly leveraged firms are less likely to apply.

A handful of variables measures the availability of alternative financing sources, and thus should control for the demand for bank credit. The results are generally consistent with the pecking-order argument in Myers (1984). For instance, sole proprietorships and family-owned businesses are less likely to apply for credit. These types of firms are typically more opaque to outsiders, implying that they should face higher costs of borrowing. These results therefore suggest that sole proprietorships and family-owned businesses rely more heavily on insider finance. Similarly, more profitable firms generate more internal funds, which may explain why they are also less likely to apply for credit. In turn, trade credit is considered to be an expensive source of funds (Smith 1987), and hence may be a sign of credit rationing (Petersen and Rajan 1994). Consistent with this view, firms that rely more heavily on trade credit are more likely to apply for bank loans. Finally, the positive coefficients of *Late TC* and *TC Denied* indicate that financially constrained firms display a stronger demand for bank credit.

Table 6 displays the probit results for the bank's decision to grant the loan, conditional upon an application being made. Again, the results are consistent with the univariate analysis. Holding all else constant, the probability of a loan approval in a concentrated market rises by about 5%. This result agrees with the positive effect of bank concentration on credit availability that was documented in Petersen and Rajan (1994) and Zarutskie (2006). The results in the previous section revealed that banks operating in concentrated markets extend credit to lower-quality firms, further diminishing the credit quality of the borrower pool. Consequently, the decrease in application rejections may capture the risk-shifting incentives of these "monopolistic" banks.

The remaining estimates suggest that higher quality and less informationally opaque firms are less likely to be denied credit. This includes larger firms, and those that are older and less leveraged, and those with no past delinquencies on record. In contrast, more profitable firms are not more successful in their credit applications. Finally, a loan application made to the firm's primary lender is about 8% more likely to succeed than an application made to any other bank that provides financial services to the firm.

### 3.6.2. Loan-rate equation

Table 7 presents the estimation results for the equation with the loan rate as the dependent variable. Column 1 displays the OLS estimates when the sample of borrowers is treated as exogenous. This model exemplifies the conventional methodology that has been used to estimate the price-concentration relation. Consequently, the results in Column 1 provide a convenient benchmark for comparing the results of the selection model.[13]

According to the OLS estimates, a firm in a concentrated market pays an average premium of about 24 bp over the loan rate to a similar firm in a competitive market. The magnitude of this effect lies well within the range of values found in the literature (see the review by Degryse and Ongena 2008), although the reported effect is not statistically significant.

Firms that are larger and older pay significantly lower loan rates. For instance, a firm with a single employee (the $5^{th}$ percentile) pays a premium of 55 bp, compared with a firm with 32 employees (the $95^{th}$ percentile). Similarly, an increase in the firm's age from three years (the $5^{th}$ percentile) to 37 years (the $95^{th}$ percentile) reduces the loan rate by 63 bp. Firms with higher proportions of liquid assets (such as accounts receivable and inventories), less leveraged firms, and more profitable firms, all enjoy lower rates. A 1 bp increase in the prime rate raises the contracted loan rate by 0.5 bp. This sluggishness in loan-rate adjustments has been documented extensively in the literature (e.g., Berger and Udell 1992; Petersen and Rajan 1994; Degryse and Ongena 2005). The remaining estimates display the expected sign, although most are not statistically significant. Previous research shows that loan rates are typically difficult to predict due to the importance of non-observable factors (Cerqueiro, Degryse and Ongena 2007).

Column 2 displays the results for the sample selection model. The sample selection model differs from the OLS model in Column 1 in that it includes the correction terms ***Lambda1*** and ***Lambda2***. ***Lambda1*** is the

[13] Using the terminology of the "difference-in-differences" approach, the OLS model provides "control results", while the selection model provides the "treatment results". This paper focuses on the difference between these two results, which is interpreted as stemming from shifts in the qualitative distribution of borrowers across different market structures.

inverse Mills ratio (IMR) computed from the firm's decision to apply for credit (Table 5), and *Lambda2* is the IMR from the bank's decision about granting the loan (Table 6). Both IMRs display positive coefficients, indicating that the correlation between the residuals in the selection equations and the residual in the loan-rate equation is positive. This correlation may capture private information, such as signals about firm quality (Li and Prabhala 2008). But more importantly, the inclusion of the IMRs switches the population of interest from "borrowers" to "all small businesses". It thereby internalizes the potential risk-shifting incentives that are induced by concentration.

The regression in Column 2 provides a risk-adjusted effect of concentration on loan rates. This risk-adjusted effect is 69 bp— almost three times larger than the OLS estimate and statistically significant at the 5% level. The difference between the risk-adjusted effect and the OLS estimate is about 45bp. This difference refers to the effect of concentration on loan rates that is mediated through the structural shift in the borrower pool composition. Note that this finding is consistent with the arguments fleshed out in Section 2 and with the univariate results. The OLS estimate is obtained for a sample that is not representative of the population of all potential applicants in two ways. First, in concentrated markets there are some lower-quality firms benefiting from low loan rates, a group that is overrepresented. Second, some higher-quality firms that exit the credit market as a result of the high loan rates are underrepresented in the sample. The risk-adjusted effect uses information about all firms and therefore corrects the OLS estimates for these sources of sample bias.

Many of the remaining estimates in Column 2 also differ substantially from the OLS estimates. However, these coefficients are estimated rather imprecisely, which is probably due to the collinearity that comes from adding *Lambda1* and *Lambda2* to the loan-rate equation. Specifically, this is because most variables used to compute the IMRs are also present in the loan-rate equation.[14] One way to ameliorate the collinearity problem would involve imposing additional exclusion restrictions. However, this solution is attractive only if the restrictions are based on economic theory. To the extent that the bank's decision about granting the loan and the loan rate offered could be jointly determined, any exclusion restriction on the second selection stage could potentially bias the results in the loan-rate equation.

### 3.6.3. Additional tests

The previous analysis relies crucially on the HHI being a good measure of local credit-market concentration. Most firms in the survey borrow from banks that are located close to them. The median distance to the lender is three miles, and 90% of the borrowers are within 34 miles of their lending bank. Still, some firms borrow at considerable distance. For these firms the local deposit HHI may not be a relevant measure of credit-market concentration. I rerun the model for the subsample of firms that are located within 15 miles of their lenders. According to this definition of local market, 82% of the borrowers borrow locally. Concerning the non-borrowers, only the firms that are located within 15 miles of their primary banks are considered. About 90% of all firms in the sample have local primary lenders.

As shown in Table 8, the results are quite similar to those reported in Table 7.[15] The fit of the selection model is still substantially better than that of the OLS regression. The difference between the risk-adjusted

[14] To further assess the collinearity problem, I regressed the IMRs on all the other explanatory variables in the loan-rate equation. The $R^2$s of these regressions are, respectively, 0.74 for *Lambda1*, and 0.92 for *Lambda2*, suggesting that the collinearity problems were mostly driven by the second selection equation. This result is not surprising, since no exclusion restrictions were imposed on the second selection equation.

[15] For brevity I do not report the results for the selection equations. These results are similar to those presented in Tables 5 and 6.

effect and the OLS estimate for *Concentrated* becomes even greater (77 – 17 = 60 bp), reinforcing the previous results.

The second test concerns the potential role of other contract terms, such as collateral. It is possible that banks operating in concentrated markets reduce their exposure to the lower-quality borrowers by increasing collateral requirements. If this is the case, then the earlier finding that borrowers operating in concentrated markets are of lower quality does not necessarily imply higher expected losses for the bank or increased failure risk. However, as shown below, this view is not supported in the data.

I conduct a number of tests based on a dummy variable that indicates whether the loan is secured by collateral. The proportion of secured loans is 68.6%. Although this proportion is slightly higher in concentrated markets (69.3%) than in competitive markets (67.8%), the difference is statistically insignificant (the test for the difference yields a p-value of 0.63). I complement this test with multivariate analysis. Specifically, I estimate a probit model of the dummy collateral on the same explanatory variables used in the loan-rate equation (results not reported). The estimates show that the probability that a loan is secured by collateral is slightly lower in concentrated markets, although the coefficient is not statistically significant (the coefficient has a p-value of 0.74). Finally, as a validation test, I estimate the two specifications displayed in Table 7 separately for the subsamples of unsecured loans and secured loans. The results are remarkably similar across the two subsamples, and similar to the results in Table 7.

## 3.7. Conclusion

An extensive literature tests empirically the effect of banking market concentration on the loan rates charged to firms. This is an important area of research, with vital policy implications for regulators, since antitrust authorities use extensively the same price-concentration equations to assess the economic impact of mergers (e.g., Baker and Rubinfeld 1999). This paper argues that this literature may have underestimated the effects of concentration on the supply of credit, since these studies often disregard the possibility that the composition of the borrower sample may itself be shaped by the level of concentration.

This paper uses a sample selection model to estimate the effect of concentration on the contracted loan rates, taking into account the borrower pool-formation process. The estimated risk-adjusted effect of concentration on loan rates is about 70 bp. This effect is nearly three times greater than the effect obtained with a benchmark OLS regression.

The difference in results may be explained by an adverse shift in the qualitative composition of the borrower pool in concentrated markets. This paper provides evidence consistent with this argument, as high concentration decreases the average credit quality of the pool of borrowers. In particular, it seems that high concentration attracts applications from lower-quality firms, and at the same time induces banks to extend credit to lower-quality firms. Moreover, this apparent increase in risk exposure by banks is not offset by an adjustment in collateral requirements. As a result, this study offers evidence based on micro-data that is consistent with the risk-shifting paradigm in Boyd and De Nicoló (2005).

Overall, the results suggest that high concentration in banking markets has a detrimental effect on the economy. High concentration seems to distort the incentives of all credit-market participants, leading to both a less efficient allocation of credit in the economy and a potential increase in the instability of the financial sector.

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## 3.9. Tables

**Table 1 – Variable definitions and model specifications**

The table defines the variables and the empirical specifications of the three equations of the model. Equation (1) refers to the firm's decision to apply for a bank loan in the three years preceding the date of the survey. Equation (2) refers to the bank's decision to accept the loan application conditional on the fact that the firm applied for a loan. Equation (3) models the contracted loan rate conditional on (1) and (2). For each equation, "Y" identifies the dependent variable and "X" denotes an explanatory variable. The dataset is the 1993 National Survey of Small Business Finances (NSSBF).

| Variable | Description | Used in equation | | |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| *Endogenous Variables* | | | | |
| Applied | = 1 if firm applied for a bank loan in the 3 years preceding the survey; = 0 otherwise | Y | | |
| Accepted | = 1 if the loan application was approved; = 0 otherwise | | Y | |
| Loan Rate | Contracted loan rate (in basis points) | | | Y |
| *Market Structure* | | | | |
| Concentrated | = 1 if HHI of bank deposit concentration is ≥ 1,800; = 0 otherwise | X | X | X |
| *Firm Characteristics* | | | | |
| Employees | Number of employees | X | X | X |
| Age | Firm age (in years) | X | X | X |
| Family | = 1 if the firm is family-owned; = 0 otherwise | X | X | X |
| Proprietorship | = 1 if the firm is a sole proprietorship; = 0 otherwise | X | X | X |
| Clean Record | = 1 if in the past 3 years neither the firm nor the owner were at least 60 days delinquent on personal or business obligations and no judgments were rendered against the principal owner, and if the owner did not declare bankruptcy in the past 7 years; = 0 otherwise | X | X | X |
| *Industry Characteristics* | | | | |

| Variable | Description | Used in equation | | |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| Construction | = 1 if in construction industry; = 0 otherwise | X | X | X |
| Services | = 1 if in services industry; = 0 otherwise | X | X | X |
| Retail | = 1 if in retail industry; = 0 otherwise | X | X | X |
| Other Industries | = 1 if in other industries (base case); = 0 otherwise | | | |
| *Firm Financials* | | | | |
| Accts. Receivable | Receivables and trade notes (% of assets) | X | X | X |
| Inventories | Inventory value (% of assets) | X | X | X |
| Leverage | Total liabilities (% of assets) | X | X | X |
| Profits | Profits (% of assets) | X | X | X |
| *Financing Sources* | | | | |
| Debt Owner | Principal owed to the owner of the firm (% of assets) | X | | |
| TC Use | Percentage of purchases made on TC | X | | |
| Late TC | Frequency of late payments on TC. Range: 0 (never) – 5 (always) | X | | |
| TC Denied | = 1 if any request by the firm for TC was denied by suppliers; = 0 otherwise | X | | |
| New Equity | = 1 if the firm raised equity in the 3 years preceding the survey; = 0 otherwise | X | | |
| Failed Issuance | = 1 if the firm was unsuccessful in its attempt to raise equity; = 0 otherwise | X | | |
| *Relationship Variables* | | | | |
| Main Bank | =1 if the loan application was made to the firm's self-reported primary bank; = 0 otherwise | | X | X |
| *Loan Characteristics* | | | | |
| Loan Type | Six dummies for the following loan types: Line of credit (the base case), Capital Lease, Mortgage, Motor Vehicle, Equipment, and Other types | | X | X |
| Floating | =1 if the loan rate is variable; = 0 otherwise | | | X |
| Prime Rate | Prime rate (in bp) | | | X |

## Table 2
## Descriptive statistics (all firms)

The table provides some descriptive statistics – mean, standard deviation (Std Dev), minimum (Min), the 25th, 50th, and 75th percentiles (P25, P50, and P75, respectively), maximum (Max), and the number of observations (# Obs) – for the variables defined in Table 1. The dataset is the 1993 National Survey of Small Business Finances (NSSBF). All statistics reported take into account the weighting employed in collecting the NSSBF data.

| Variable | Mean | Std Dev | Min | P25 | P50 | P75 | Max | # Obs |
|---|---|---|---|---|---|---|---|---|
| *Endogenous Variables* | | | | | | | | |
| Applied (0/1) | 0.30 | 0.46 | 0 | 0 | 0 | 1 | 1 | 4,295 |
| Accepted (0/1) | 0.83 | 0.37 | 0 | 1 | 1 | 1 | 1 | 1,670 |
| Loan Rate (bp) | 866 | 240 | 0 | 750 | 825 | 950 | 3,200 | 1,443 |
| *Market Structure* | | | | | | | | |
| Concentrated (0/1) | 0.48 | 0.50 | 0 | 0 | 0 | 1 | 1 | 4,295 |
| *Firm Characteristics* | | | | | | | | |
| Employees | 8.50 | 23 | 0.50 | 1.50 | 3 | 6.50 | 495 | 4,295 |
| Age (years) | 14 | 12 | 0 | 6 | 11 | 19 | 216 | 4,295 |
| Family (0/1) | 0.85 | 0.35 | 0 | 1 | 1 | 1 | 1 | 4,295 |
| Proprietorship (0/1) | 0.43 | 0.50 | 0 | 0 | 0 | 1 | 1 | 4,295 |
| Clean Record (0/1) | 0.73 | 0.44 | 0 | 0 | 1 | 1 | 1 | 4,295 |
| *Industry Characteristics* | | | | | | | | |
| Construction (0/1) | 0.14 | 0.34 | 0 | 0 | 0 | 0 | 1 | 4,295 |
| Services (0/1) | 0.22 | 0.41 | 0 | 0 | 0 | 0 | 1 | 4,295 |
| Retail (0/1) | 0.38 | 0.48 | 0 | 0 | 0 | 1 | 1 | 4,295 |
| Other Industries (0/1) | | | | | | | | |
| *Firm Financials* | | | | | | | | |

| Variable | Mean | Std Dev | Min | P25 | P50 | P75 | Max | # Obs |
|---|---|---|---|---|---|---|---|---|
| Accts. Receivable | 0.16 | 0.22 | 0 | 0 | 0.05 | 0.26 | 1 | 4,295 |
| Inventories | 0.17 | 0.25 | 0 | 0 | 0.03 | 0.27 | 1 | 4,295 |
| Leverage | 0.59 | 0.54 | 0 | 0.22 | 0.47 | 0.79 | 3.10 | 4,295 |
| Profits | 0.89 | 2.60 | -4.60 | 0 | 0.22 | 1 | 15 | 4,295 |
| *Financing Sources* | | | | | | | | |
| Debt Owner | 0.08 | 0.27 | 0 | 0 | 0 | 0 | 1.70 | 4,295 |
| TC Use (0-1) | 0.45 | 0.42 | 0 | 0 | 0.45 | 0.90 | 1 | 4,295 |
| Late TC (0-5) | 0.86 | 1.30 | 0 | 0 | 0 | 2 | 5 | 4,295 |
| TC Denied (0/1) | 0.06 | 0.23 | 0 | 0 | 0 | 0 | 1 | 4,295 |
| New Equity (0/1) | 0.01 | 0.08 | 0 | 0 | 0 | 0 | 1 | 4,295 |
| Failed Issuance (0/1) | 0.01 | 0.10 | 0 | 0 | 0 | 0 | 1 | 4,295 |
| *Relationship Variables* | | | | | | | | |
| Main Bank (0/1) | 0.67 | 0.47 | 0 | 0 | 1 | 1 | 1 | 1,665 |
| *Loan Characteristics* | | | | | | | | |
| Floating (0/1) | 0.51 | 0.50 | 0 | 0 | 1 | 1 | 1 | 1,443 |
| Prime Rate (bp) | 643 | 62.1 | 600 | 600 | 600 | 699 | 850 | 1,443 |

## Table 3
## Descriptive statistics for subsamples

The table provides descriptive statistics – mean and standard deviation (Std Dev) – for each of the subsamples that are generated along the two sequential credit decision stages. The first two subsamples contain the firms that applied for a bank loan (*Applicants*) and firms that did not apply for a bank loan (*Non-Applicants*); then the subsample of *Applicants* is further split into *Rejected Applicants* (firms that were denied credit) and *Borrowers* (firms that were granted credit). The table also provides group mean or proportion comparison tests (Diff ) between *Applicants* and *Non-Applicants*, and between *Borrowers* and *Rejected Applicants*. *, ** and *** denote significance at the 10, 5 and 1% levels, respectively. The dataset is the 1993 National Survey of Small Business Finances (NSSBF). The statistics reported take into account the weighting employed in collecting the NSSBF data.

| Variable | Non-Applicants | | Applicants | | Diff | Rejected Applicants | | Borrowers | | Diff |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | Mean | Std Dev | | Mean | Std Dev | Mean | Std Dev | |
| *Endogenous Variables* | | | | | | | | | | |
| Applied (0/1) | 0 | 0 | 1 | 0 | | 1 | 0 | 1 | 0 | |
| Accepted (0/1) | | | 0.83 | 0.37 | | 0 | 0 | 1 | 0 | |
| Loan Rate (bp) | | | | | | | | 866 | 240 | |
| *Market Structure* | | | | | | | | | | |
| Concentrated (0/1) | 0.47 | 0.50 | 0.53 | 0.50 | 0.06*** | 0.48 | 0.50 | 0.54 | 0.50 | 0.06* |
| *Firm Characteristics* | | | | | | | | | | |
| Employees | 5.80 | 16 | 15 | 33 | 9.20*** | 7.80 | 17 | 16 | 35 | 8.20*** |
| Age (years) | 15 | 13 | 13 | 11 | -2.00*** | 9.40 | 7.50 | 14 | 12 | 4.60*** |
| Family (0/1) | 0.87 | 0.33 | 0.81 | 0.39 | -0.06*** | 0.86 | 0.35 | 0.81 | 0.40 | -0.05* |
| Proprietorship (0/1) | 0.49 | 0.50 | 0.31 | 0.46 | -0.18*** | 0.41 | 0.49 | 0.29 | 0.46 | -0.12*** |
| Clean Record (0/1) | 0.75 | 0.43 | 0.70 | 0.46 | -0.05*** | 0.47 | 0.50 | 0.74 | 0.44 | 0.27*** |
| *Industry Characteristics* | | | | | | | | | | |
| Construction (0/1) | 0.13 | 0.34 | 0.15 | 0.36 | 0.02* | 0.18 | 0.38 | 0.15 | 0.35 | -0.03 |
| Services (0/1) | 0.21 | 0.41 | 0.22 | 0.41 | 0.01 | 0.22 | 0.41 | 0.22 | 0.41 | 0.00 |
| Retail (0/1) | 0.40 | 0.49 | 0.31 | 0.46 | -0.09*** | 0.30 | 0.46 | 0.31 | 0.46 | 0.01 |

| Variable | Non-Applicants | | Applicants | | Diff | Rejected Applicants | | Borrowers | | Diff |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | Mean | Std Dev | | Mean | Std Dev | Mean | Std Dev | |
| Other Industries (0/1) | 0.26 | 0.44 | 0.32 | 0.47 | 0.06* | 0.30 | 0.46 | 0.32 | 0.47 | 0.02 |
| *Firm Financials* | | | | | | | | | | |
| Accts. Receivable | 0.15 | 0.23 | 0.18 | 0.22 | 0.03*** | 0.15 | 0.21 | 0.18 | 0.22 | 0.03* |
| Inventories | 0.16 | 0.25 | 0.19 | 0.26 | 0.03*** | 0.16 | 0.23 | 0.20 | 0.27 | 0.04** |
| Leverage | 0.55 | 0.53 | 0.70 | 0.55 | 0.15*** | 0.82 | 0.58 | 0.67 | 0.53 | -0.15*** |
| Profits | 1 | 2.80 | 0.56 | 2 | -0.44*** | 0.56 | 2.20 | 0.56 | 1.90 | 0.00 |
| *Financing Sources* | | | | | | | | | | |
| Debt Owner | 0.07 | 0.26 | 0.11 | 0.28 | 0.04*** | | | | | |
| TC Use (0-1) | 0.41 | 0.42 | 0.55 | 0.41 | 0.14*** | | | | | |
| Late TC (0-5) | 0.73 | 1.20 | 1.20 | 1.40 | 0.47*** | | | | | |
| TC Denied (0/1) | 0.05 | 0.21 | 0.08 | 0.28 | 0.04*** | | | | | |
| New Equity (0/1) | 0.01 | 0.07 | 0.01 | 0.11 | 0.01** | | | | | |
| Failed Issuance (0/1) | 0.01 | 0.08 | 0.02 | 0.14 | 0.01*** | | | | | |
| *Relationship Variables* | | | | | | | | | | |
| Main Bank (0/1) | | | | | | 0.51 | 0.50 | 0.71 | 0.46 | 0.20*** |
| *Loan Characteristics* | | | | | | | | | | |
| Floating (0/1) | | | | | | | | 0.51 | 0.50 | |
| Prime Rate (bp) | | | | | | | | 643 | 62.10 | |
| Number of observations | 2,625 | | 1,665 | | | 217 | | 1,447 | | |

## Table 4
## Market concentration and credit quality

The table displays the average leverage (debt-to-assets ratio) and average profitability (profits-to-assets ratio) for firms located in concentrated markets (HHI≥1,800) and competitive markets (HHI<1,800), for the four subsamples of firms that are generated along the two sequential credit decision stages. The four subsamples: for all firms (Panel A), firms that applied for a bank loan (*Applicants*) and firms that did not apply for a bank loan (*Non-Applicants*), and, for the subsample of applicants (Panel B), firms that were granted credit (*Borrowers*) and firms that were denied credit (*Rejected Applicants*). The table also provides T-tests for differences between groups (*Difference*) and F-tests for differences between pairs of groups (*Diff-in-Diff*). The dataset is the 1993 National Survey of Small Business Finances (NSSBF). The statistics take into account the sample weights, implying that all of the statistics are representative of the population of US small businesses. $^{*}$, $^{**}$ and $^{***}$ denote significance at the 10, 5 and 1% levels, respectively.

*A) All Firms (N = 4,295)*

| | *Average Leverage* | | |
|---|---|---|---|
| | Concentrated Markets | Competitive Markets | Diff / **Diff-in-Diff** |
| Applicants | 0.67 | 0.63 | 0.04 |
| Non-Applicants | 0.50 | 0.53 | -0.03$^{**}$ |
| Diff / **Diff-in-Diff** | 0.17$^{***}$ | 0.10$^{***}$ | **0.07**$^{***}$ |

| | *Average Profitability* | | |
|---|---|---|---|
| | Concentrated Markets | Competitive Markets | Diff / **Diff-in-Diff** |
| Applicants | 0.37 | 0.59 | -0.22$^{***}$ |
| Non-Applicants | 0.79 | 0.81 | -0.02 |
| Diff / **Diff-in-Diff** | -0.42$^{***}$ | -0.22$^{***}$ | **-0.20**$^{**}$ |

*B) Applicants (N = 1,670)*

| | *Average Leverage* | | |
|---|---|---|---|
| | Concentrated Markets | Competitive Markets | Diff / **Diff-in-Diff** |
| Borrowers | 0.66 | 0.60 | 0.06$^{***}$ |
| Rejected Applicants | 0.73 | 0.78 | -0.05 |
| Diff / **Diff-in-Diff** | -0.07$^{**}$ | -0.18$^{***}$ | **0.11**$^{**}$ |

| | *Average Profitability* | | |
|---|---|---|---|
| | Concentrated Markets | Competitive Markets | Diff / **Diff-in-Diff** |
| Borrowers | 0.36 | 0.65 | -0.29$^{***}$ |
| Rejected Applicants | 0.48 | 0.37 | 0.11 |
| Diff / **Diff-in-Diff** | -0.12 | 0.28$^{***}$ | **-0.40**$^{***}$ |

## Table 5
## The firm's decision to apply for a loan

The table lists Probit coefficients, robust standard errors (S.e.), and marginal effects (Mfx) calculated at the mean of the explanatory variables. The dependent variable is *Applied*, a dummy that equals one if the firm applied for a bank loan in the three years preceding the survey. The definitions of the explanatory variables are provided in Table 1. Besides the reported variables, the regression includes three industry dummies. Data are from the 1993 National Survey of Small Business Finances (NSSBF). The estimation takes into account the weighting employed in collecting the NSSBF data. $^{*}$, $^{**}$ and $^{***}$ denote significance at the 10, 5, and 1% levels, respectively.

| Variable | Coefficient | S.e. | Mfx (%) |
|---|---|---|---|
| Constant | -0.93*** | 0.15 | |
| *Market Structure* | | | |
| Concentrated (0/1) | 0.19*** | 0.05 | 6.3 |
| *Firm Characteristics* | | | |
| Employees (×100) | 1.86*** | 0.14 | 62.5 |
| $(\text{Employees}\times 100)^2$ | -0.46*** | 0.04 | -15.4 |
| Ln(1+Age) | -0.09*** | 0.04 | -3.2 |
| Family (0/1) | -0.04 | 0.08 | -1.5 |
| Proprietorship (0/1) | -0.14** | 0.06 | -4.7 |
| Clean Record (0/1) | -0.002 | 0.07 | -0.1 |
| *Firm Financials* | | | |
| Accts. Receivable | 0.10 | 0.12 | 3.3 |
| Inventories | 0.10 | 0.12 | 3.3 |
| Leverage | 0.80*** | 0.13 | 27.1 |
| $(\text{Leverage})^2$ | -0.24*** | 0.05 | -8.1 |
| Profits | -0.03*** | 0.01 | -1.1 |
| *Financing Sources* | | | |
| Debt Owner | 0.09 | 0.10 | 3.0 |
| TC Use (0-1) | 0.24*** | 0.07 | 8.0 |
| Late TC (0-5) | 0.07*** | 0.02 | 2.4 |
| TC Denied (0/1) | 0.17 | 0.11 | 6.0 |
| New Equity (0/1) | 0.15 | 0.25 | 5.4 |
| Failed Issuance (0/1) | 0.27 | 0.25 | 9.9 |
| Number of Observations | | 4,295 | |
| F-statistic | | 22.21*** | |

## Table 6
## The bank's decision to accept the loan application

The table lists Probit coefficients, robust standard errors (S.e.), and marginal effects (Mfx) calculated at the mean of the explanatory variables. The dependent variable is *Accepted*, a dummy that equals one if the firm bank accepted the firm's most recent loan application. The definitions of the explanatory variables are provided in Table 1. Besides the reported variables, the regression includes five loan-type dummies and three industry dummies. Data are from the 1993 National Survey of Small Business Finances (NSSBF). The estimation takes into account the weighting employed in collecting the NSSBF data. $^{*}$, $^{**}$ and $^{***}$ denote significance at the 10, 5, and 1% levels, respectively.

| **Variable** | **Coefficient** | **S.e.** | **Mfx (%)** |
|---|---|---|---|
| Constant | -0.47 | 0.31 | |
| *Market Structure* | | | |
| Concentrated (0/1) | 0.19$^{*}$ | 0.11 | 4.0 |
| *Firm Characteristics* | | | |
| Ln(Employees) | 0.11$^{**}$ | 0.05 | 2.2 |
| Ln(1+Age) | 0.36$^{***}$ | 0.09 | 7.5 |
| Family (0/1) | -0.20 | 0.16 | -3.9 |
| Proprietorship (0/1) | -0.12 | 0.15 | -2.7 |
| Clean Record (0/1) | 0.60$^{***}$ | 0.12 | 14.2 |
| *Firm Financials* | | | |
| Accts. Receivable | 0.39 | 0.27 | 8.2 |
| Inventories | 0.46 | 0.26 | 9.7 |
| Leverage | -0.23$^{**}$ | 0.10 | -4.9 |
| Profits | 0.03 | 0.03 | 0.7 |
| *Relationship Variables* | | | |
| Main Bank (0/1) | 0.38$^{***}$ | 0.12 | 8.5 |
| Number of Observations | | 1,665 | |
| F-statistic | | 5.71$^{***}$ | |

## Table 7
## The determinants of loan rates

The table lists the coefficients (Coeff.) and robust standard errors (S.e.) of regressions with the rate on the firm's most recent loan (in basis points) as the dependent variable. The definitions of the explanatory variables are provided in Table 1. All models are estimated by ordinary least-squares. *Lambda**1*** and *Lambda**2*** are the Inverse Mill's Ratios as obtained from the two selection equations (respectively, the firm's decision to apply for a bank loan (Table 5) and the bank's decision to accept the loan application (Table 6). Besides the reported variables, all regressions include five loan-type dummies and three industry dummies. Data are from the 1993 National Survey of Small Business Finances (NSSBF). The estimation takes into account the weighting employed in collecting the NSSBF data. $^{*}$, $^{**}$ and $^{***}$ denote significance at the 10, 5 and 1% levels, respectively.

| **Variable** | **(1) Benchmark** | | **(2) Selection Model** | |
|---|---|---|---|---|
| | **Coeff.** | **S.e.** | **Coeff.** | **S.e.** |
| Constant | 646$^{***}$ | 110 | 134 | 226 |
| *Market Structure* | | | | |
| Concentrated (0/1) | 24 | 17 | 69$^{**}$ | 30 |
| *Firm Characteristics* | | | | |
| Ln(Employees) | -16$^{***}$ | 6 | 12 | 16 |
| Ln(1+Age) | -25$^{**}$ | 12 | 29 | 28 |
| Family (0/1) | 12 | 23 | -17 | 26 |
| Proprietorship (0/1) | 39$^{*}$ | 23 | 7 | 24 |
| Clean Record (0/1) | -18 | 23 | 89$^{*}$ | 50 |
| *Firm Financials* | | | | |
| Accts. Receivable | -54 | 36 | 20 | 39 |
| Inventories | -86$^{***}$ | 34 | 7 | 45 |
| Leverage | 16 | 18 | -16 | 28 |
| Profits | -2 | 4 | 1 | 4 |
| *Relationship Variables* | | | | |
| Main Bank (0/1) | -18 | 24 | 49 | 34 |
| *Loan Characteristics* | | | | |
| Floating (0/1) | -41$^{**}$ | 17 | -38$^{**}$ | 16 |
| Prime Rate (bp) | 49$^{***}$ | 14 | 45$^{***}$ | 14 |
| *Selection Terms* | | | | |
| Lambda**1** (Applied) | | | 92$^{*}$ | 54 |
| Lambda**2** (Accepted) | | | 538$^{**}$ | 276 |
| Observations | 1,443 | | 1,443 | |
| F-statistic | 3.74$^{***}$ | | 3.56$^{***}$ | |
| $R^2$ (%) | 12.80 | | 14.50 | |

## Table 8
## The determinants of loan rates (local banks only)

The table lists the coefficients (Coeff.) and robust standard errors (S.e.) of regressions with the rate on the firm's most recent loan (in basis points) as the dependent variable. The sample contains only firms located within 15 miles of their primary bank (for the non-borrowers) or located within 15 miles of their lender (for the borrowers). The definitions of the explanatory variables are provided in Table 1. All models are estimated by ordinary least-squares. *Lambda**1*** and *Lambda**2*** are the Inverse Mill's Ratios as obtained from the two selection equations (respectively, the firm's decision to apply for a bank loan and the bank's decision to accept the loan application). Besides the reported variables, all regressions include five loan-type dummies and three industry dummies. Data are from the 1993 National Survey of Small Business Finances (NSSBF). The estimation takes into account the weighting employed in collecting the NSSBF data. $^{*}$, $^{**}$ and $^{***}$ denote significance at the 10, 5 and 1% levels, respectively.

| Variable | (1) Benchmark | | (2) Selection Model | |
|---|---|---|---|---|
| | Coeff. | S.e. | Coeff. | S.e. |
| Constant | 710$^{***}$ | 122 | 109 | 265 |
| *Market Structure* | | | | |
| Concentrated (0/1) | 17 | 16 | 77$^{**}$ | 39 |
| *Firm Characteristics* | | | | |
| Ln(Employees) | -22$^{***}$ | 6 | 3 | 15 |
| Ln(1+Age) | -23$^{*}$ | 13 | 40 | 32 |
| Family (0/1) | 1 | 18 | -9 | 20 |
| Proprietorship (0/1) | 65$^{**}$ | 26 | 5 | 31 |
| Clean Record (0/1) | -33 | 24 | 95$^{*}$ | 58 |
| *Firm Financials* | | | | |
| Accts. Receivable | -25 | 37 | 59 | 44 |
| Inventories | -72$^{**}$ | 32 | 44 | 59 |
| Leverage | 19 | 18 | -32 | 37 |
| Profits | -5 | 4 | -2 | 4 |
| *Relationship Variables* | | | | |
| Main Bank (0/1) | -33 | 27 | 56 | 38 |
| *Loan Characteristics* | | | | |
| Floating (0/1) | -46$^{***}$ | 16 | -41$^{**}$ | 16 |
| Prime Rate (bp) | 47$^{***}$ | 15 | 43$^{***}$ | 15 |
| *Selection Terms* | | | | |
| Lambda**1** (Applied) | | | 82 | 56 |
| Lambda**2** (Accepted) | | | 621$^{*}$ | 332 |
| Observations | 1,134 | | 1,134 | |
| F-statistic | 3.38$^{***}$ | | 3.34$^{***}$ | |
| $R^2$ (%) | 14.40 | | 16.80 | |

# Chapter 4

# Does Debtor Protection Really Protect Debtors? Evidence from the Small Business Credit Market

## 4.1. Introduction

Recent research points to the important role of creditor protection in determining the size and breadth of capital markets (La Porta et al. 1997 and 1998, Djankov et al. 2003, Djankov et al. 2007, and Davydenko and Franks 2008). Poor creditor protection decreases firms' opportunities for external financing, which, in turn, hampers economic growth (King and Levine 1993). While most of the recent empirical literature has focused on lending to large companies, the effect of creditor protection on bank lending to small businesses is largely unexplored. This is in spite the fact that small businesses constitute a crucial sector of the U.S. economy, contributing about half of private non-farm GDP and employment.[1]

We try to fill this void by exploiting the differences in U.S. personal bankruptcy law across states. We study the effect of weak creditors' rights to seize borrowers' assets that are embedded in debtor protection laws on small firms' access to credit, and the price and non-price terms of their loans. While personal bankruptcy law is designed for consumers, it also affects unlimited liability firms (sole proprietorships and most partnerships) whose owners are legally liable for the firm's debts. To a lesser extent, it could also affect small limited liability firms (corporations and limited liability partnerships), as long as lenders require the owners of these firms to personally guarantee their loans or these firms could transfer assets to their owners.

Although federal law governs personal bankruptcy in the U.S., the states are allowed to adopt their own bankruptcy exemption levels. Debtors who file for personal bankruptcy under Chapter 7 (discussed below) must turn over any assets they own above a predetermined exemption level, but their future earnings are exempt from the obligation to repay, the so-called "fresh start" principle. A higher exemption level therefore provides partial wealth insurance to debtors, reducing the assets that the lender can seize in case of bankruptcy.

Our focus is on the *ex ante* incentives introduced by bankruptcy exemptions. Exemptions should affect both the demand for and the supply of credit. As argued by Gropp, Scholz, and White (1997), wealth insurance makes risk-averse borrowers better off, increasing the demand for credit. However on the supply side, because banks anticipate that exemptions increase the probability of default and the expected loss given default on a loan, higher exemption levels should lead to a retraction in credit supply. This retraction should then translate into harsher loan contract terms, such as higher rates, smaller credit amounts, and/or shorter

[1] The Small Business Administration reports that, of the 116.3 million nonfarm private sector workers in 2005, small firms with fewer than 500 workers employed 58.6 million while large firms employed 57.7 million.

maturity, and may result in credit rationing (Stiglitz and Weiss 1981). To some degree, the higher exemption levels may be offset by the pledging of collateral, given that the exemptions do not apply to secured assets.

We investigate these issues using both public and confidential data from the 1993, 1998, and 2003 Surveys of Small Business Finances (SSBF). The Surveys contain detailed information on whether and when the firm obtained credit, the contract features of the most recent loan obtained by the firm if credit was granted, as well as detailed firm and owner characteristics. We supplement these data with state-level control variables that may be correlated with state exemptions, allowing us to better identify the effect of the exemptions. We employ two main measures of debtor protection. The first measure is the homestead exemption in the state in which the firm is located. This is the maximum home equity value that a debtor can exempt when filing for personal bankruptcy. The second, our preferred measure, is a borrower-specific variable that also takes into account the value of the home equity of the firm owner. This measure has its maximum value when the home equity amount is lower than the exemption (the debtor's home equity is fully protected), and is decreasing in the difference between the home equity value and the exemption (the amount of home equity that the creditor can seize). Because it measures the value in home equity that is shielded from creditors under the bankruptcy law, this measure delves directly into the agency problems associated with the bankruptcy law.

We report several empirical results. First, we find that increased debtor protection is associated with a significantly higher probability that an unlimited liability firm is denied credit or is discouraged from borrowing. This effect is economically significant –the probability of being denied or discouraged from borrowing increases by about 12 percentage points for a median firm located in a state with the highest exemption level (the debtor's home equity is fully protected) compared to a firm located in a state with zero exemption (the debtor's home equity is unprotected). Supporting this result, we also find that the pool of unlimited liability borrowers is significantly less risky (i.e., has higher credit scores) than unlimited liability non-borrowers in high exemption states, while these two groups do not show any significant difference in terms of credit score in low exemption states.

Second, we find that high levels of debtor protection are associated with considerably deteriorated non-price terms for the unlimited liability companies that do receive credit. Specifically, these firms receive lower loan amounts, have significantly shorter maturities, and are significantly more likely to pledge business collateral in high exemption states.

Third, for the limited liability firms, our results show significantly weaker effects. Specifically, we find some evidence of a small reduction in access to credit and increase in interest rates for this group of firms.

We should note that our results hold after controlling for other state-level characteristics, type of lender, and potential selection effects, leading us to conclude that exemptions have an adverse effect on the supply of credit to unlimited liability firms.

These results have important policy implications. High levels of debtor protection seem to distort the legal purposes of the unlimited liability company form, since debtors are in practice not fully personally liable for their firm's debts. The institutional framework may therefore prevent some of these small firms from pre-committing to harsh penalties, limiting their access to credit.

We note that the main problems with debtor protection highlighted in our paper do not seem to have been addressed by the reform of the personal bankruptcy law that was passed in 2005. To prevent borrowers from abusing the bankruptcy laws and using them to clear debts they can afford to pay, the new law makes it more difficult for high-income people to file for Chapter 7.[2] However, our results suggest that the personal bankruptcy law adversely affects the credit availability and credit terms especially for firm owners with low home equity. The new law does not introduce any significant changes for this particular group of borrowers.

The paper proceeds as follows. Section II gives a very brief literature review and Section III details the institutional background of bankruptcy law in the U.S. Section IV describes the data set and the variables used in the analysis, Section V addresses the empirical methodology, and Section VI presents the results. Section VII concludes.

## 4.2. Literature Review

Our paper contributes to the growing literature on the effect of creditor protection on the functioning of credit markets. Esty and Megginson (2003) and Esty (2004) study how the strength and enforcement of creditors' rights affect the size and composition of loan syndicates. Giannetti (2003) finds that better creditor protection makes it easier for firms investing in intangible assets to obtain loans and for firms operating in volatile sectors to obtain long-term debt. Bae and Ghoyal (2004) and Qian and Strahan (2007) find that strong property rights and more creditor protection lead to better loan contract terms.[3]

Our paper is also related to the literature focusing on how differences in bankruptcy exemption levels affect household credit. For example, Fay, Hurst, and White (2002) find that the probability of filing for bankruptcy increases with the financial benefit of filing (i.e., the debt discharged minus the value of non-exempt assets). Consistent with this result, Gropp, Scholz, and White (1997) find that state bankruptcy exemptions have a positive effect on the probability that households will be turned down for credit or discouraged from borrowing. They also find that generous exemptions redistribute credit from low-asset borrowers towards borrowers with high assets. Finally, Berkowitz and Hynes (1999) and Lin and White (2001) study whether exemptions affect secured lending, specifically mortgages. Their results are mixed. While Berkowitz and Hynes (1999) find that exemptions have neither increased mortgage rates nor the probability of being denied a mortgage, Lin and White (2001) find that applicants for mortgages are more likely to be turned down when exemptions are high.

However, to the best of our knowledge, Berkowitz and White (2004) is the only study analyzing the effect on small business bank lending of weak creditor rights embedded in debtor protection laws. Although they also exploit the U.S. variation across states in exemption levels, our study differs from theirs in several important ways.

First, while Berkowitz and White (2004) only use the 1993 Survey of Small Business Finances (SSBF), we also use the 1998 and 2003 SSBF. Using the last two waves has two advantages. While in the 1993 SSBF the legal form of the firm is not always specified, the two latter surveys clearly distinguish the unlimited liability firms from the limited liability firms. But the most important benefit is that, unlike the 1993 SSBF, the two later survey waves contain information about the wealth of the firm's principal owner – the home equity value and the remaining net worth. This allows us to control for wealth effects, and to develop a measure of debtor protection that is borrower-specific and takes into account both the homestead exemption level and the debtor's home equity value.

[2] We address this issue in more detail in Section III.
[3] In a related vein, there is a literature that focuses on the effect of the legal framework on private equity contracts (Lerner and Schoar 2005, Kaplan, Martel, and Stromberg 2007, Hasan and Wang 2008, Bottazzi, Da Rin, and Hellmann forthcoming).

Second, while Berkowitz and White (2004) analyze the effect of the exemptions level on credit availability, loan rates, and loan amounts, we also investigate how exemptions affect the incidence of different types of collateral, the maturity of the loan, and the qualitative composition of the pool of borrowers.

Third, we control for the costs that banks must incur when foreclosing on a property. These costs vary significantly across states. In fact, Pence (2006) shows that higher foreclosure costs are associated with lower mortgage loan sizes, suggesting that this variable can have important effects on credit availability and on contract terms. Because exemptions may be correlated with high foreclosure costs, controlling for these costs allows us to better identify the exemptions effect.

Fourth, we use a credit score measure from an independent credit bureau (Dun & Bradstreet) that enables us to better control for firm credit quality. The availability of more survey waves and more detailed borrower specific information may altogether explain why our findings, compared to Berkowitz and White (2004), point to a sharper contrast between the effect of exemptions on unlimited liability companies and their effect on limited liability firms.

Finally, we show that our results reflect an adverse shift of credit supply in response to higher debtor protection, rather than a potential increase in the demand for credit by the riskier types. This increase in demand would be consistent with the recent evidence that high exemptions foster entrepreneurship (Fan and White 2003, Armour and Cumming 2008).

## 4.3. Bankruptcy Law

There are two different personal bankruptcy procedures in the U.S. – Chapter 7 and Chapter 13 – and, during our sample period, debtors were allowed to choose between them.[4] When an individual files for bankruptcy, all collection efforts by creditors terminate. Under Chapter 13, the debtors' wealth is exempted, but they must propose a repayment plan. This plan typically involves using a proportion of the debtor's future earnings over a five-year period to repay debt. Repayment plans must give creditors the same amount they would receive under Chapter 7, but no more.

Under Chapter 7, all of the debtor's future earnings are exempt from the obligation to repay – the "fresh start" principle.[5] However, debtors must turn over any unsecured assets they own above a predetermined exemption level (the secured debts cannot be discharged). While the "fresh start" is mandated by Federal law, and applies all over the U.S., in 1978 Congress gave the states the right to adopt their own bankruptcy exemptions. The wealth exemptions vary widely across states as a result.

After our sample period, on October 17, 2005, a new bankruptcy law became effective. The purpose of the new law is mainly to reduce fraud and abuse in the bankruptcy system by high-income agents. Under the new law, fewer people are allowed to file under Chapter 7; more are forced to file under Chapter 13. Specifically, people whose income is above the state's median income and that can afford to pay 25 percent of their unsecured debt are no longer allowed to file for Chapter 7. Also, if a borrower's income is below the state's median, but the borrower can pay 25 percent of the unsecured debt, the Court may require the borrower to file for Chapter 13 instead of Chapter 7.[6]

[4] See White (2007) for a comprehensive exposition of personal bankruptcy law in the U.S.
[5] In 2005, about 75% of bankruptcy filings occurred under Chapter 7.
[6] The reform had two main purposes. The first was to deter high-income debtors from filing under Chapter 7. The second was to raise the costs of filing for bankruptcy. See White (2009).

There are generally two types of exemptions: for equity in owner-occupied residences (the homestead exemption), and for various other types of personal assets (the personal property exemption). The personal property may include assets as diverse as: the bible, other books, musical instruments, burial plots, family portraits, clothing, wedding rings, other jewelry, furniture, guns, pets, cattle, crops, motor vehicles, health aids, and food. Furthermore, the types of personal assets specified in the law vary considerably across states and are difficult to compare. Consequently, we confine our analysis to the homestead exemptions. [7]

Table 1 displays the homestead exemptions by state for 1993, 1998, and 2003.[8] The homestead exemptions vary widely across states, ranging from zero (e.g., Delaware and Maryland) to unlimited (e.g., Florida and Texas).[9] In contrast to this variation, the states have made relatively few changes in their exemption levels over our sample period. Most of the changes in the exemption levels that occurred during our sample period simply reflect nominal adjustments. The median homestead exemption increased at an annual rate of 1.9%, from $30,000 in 1993 to 36,900 in 2003. These median exemptions actually match the Federal Bankruptcy Exemptions. The Federal Exemptions are adjusted at every three-year interval to reflect changes in the inflation rate (measured with the Consumer Price Index).

## 4.4. Data and Variables

We use both public and confidential data from the 1993, 1998 and 2003 Surveys of Small Business Finances (SSBF) to study the effects of bankruptcy law on small business credit. For the descriptive statistics we include data from the three waves. However in our multivariate analysis, we restrict our sample to the 1998 and 2003 SSBF because one of our key variables, the home equity of the firm's owner, and one important control variable, the owner's net worth, are not available for the 1993 Survey. Because a consistent definition and a majority of questions are identical across the two surveys, we merge the surveys into a single dataset that spans 10 years (1996-2005).[10] Each survey contains a different sample of firms, and therefore we cannot follow firms over time.

The SSBF contains detailed information on the financing experiences of a representative sample of for-profit, non-financial, non-governmental and non-agricultural businesses with less than 500 employees operating in the U.S. at the date of the survey. The survey asks respondents about their borrowing experiences within the preceding three years – whether they applied for or whether they were discouraged from applying for credit, and whether the credit application was successful. For the successful applications, the respondents then report the terms of the loan contract – the rate, size and maturity of the loan, and collateral requirements.

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[7] In many states, the law leaves unspecified the value of some assets. As a result, any attempt to quantify the personal property exemptions would likely result in a noisy measure of creditor protection. Consistent with these arguments, Berkowitz and White (2004) find no effect of their measure of personal property exemptions on any of the credit variables they analyze.

[8] Some states allow their residents to choose between the state and the federal exemptions. In these cases, we selected the option which grants the claimant with the highest exemption level. In some states, married couples are allowed to double the amount of the exemption for home equity when filing for bankruptcy together (called "doubling"). We have doubled all amounts except in those cases where bankruptcy law explicitly prohibits "doubling." We obtain the state-level homestead exemptions from Elias, Renauer, and Leonard (several editions).

[9] The homestead exemptions are never truly unlimited. Those exemptions that do not contain a dollar limit contain a limit on the physical size of the lot, which depends on whether the property is located in a rural or urban area (see Berkowitz and Hynes 1999).

[10] The data covers 1996 to 2005, rather than just the stated survey years of 1998 and 2003 because the questions were asked in years subsequent to the stated survey years, and refer to recent applications and loan experiences that may have taken place in any of several years for each survey.

The survey also provides detailed information about the firm and the owner, such as the credit history (including the Dun & Bradstreet credit scores, which are based on business information), firm income statement and balance sheet information, and geographic location, industry, and ownership characteristics. In addition, the survey asks firms about the nature of the relationships they have with their financial providers – e.g., the duration of their relationships and the types of financial services purchased.

Of the 7,415 observations in our regressions, 4,579 correspond to limited liability firms, and 2,836 to unlimited liability firms.[11] The unlimited liability group includes sole proprietorships and most partnerships, while the limited liability group contains corporations (both regular and S-type), as well as the limited liability partnerships.

Table 2 lists the variables and provides summary statistics (means, standard deviations, and number of observations) for the unlimited liability and limited liability firms.

### 4.4.1. Dependent variables

We employ six dependent variables in our analysis. We follow Gropp, Scholz, and White (1997) and Berkowitz and White (2004) to build our measure of availability of credit. The variable *Discouraged/Denied* is a dummy variable equal to one if the most recent credit application was denied or if the manager was ever discouraged from applying for credit in the three preceding years, 0 otherwise. Our descriptive statistics show that the limited liability and the unlimited liability firms faced a similar discouraged/denial rate of 23%.

Because not all firms report a most recent borrowing experience (the ones that are discouraged from borrowing, denied a loan, or simply do not apply), we only observe the remaining dependent variables, i.e., the terms of the loan contract, for one-third of the firms in the sample. These variables include a dummy indicating whether personal real estate collateral was pledged, a dummy indicating whether business collateral was pledged, the loan maturity (when specified),[12] the loan interest rate, and the size of the loan. Business collateral includes the following firm assets: inventory, accounts receivable, equipment, vehicles, securities, deposits, real estate, and other unspecified assets.

We analyze personal real estate collateral separately from business collateral because the homestead exemptions may affect these two types of collateral differently. The pledging of collateral blunts the effects of increased debtor protection. However, there are at least two reasons why this effect may dominate for business collateral, but not necessarily for personal real estate collateral. First, banks may face higher costs of seizing real estate collateral in high exemption states.[13] Second, it is more costly for risk-averse owners to pledge their real estate as collateral when the real estate is protected by the bankruptcy law (i.e., by pledging their home, they give up the wealth insurance provided by the exemptions). While the first effect is supply-

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[11] In the case of the descriptive statistics, of the 11,936 observations, 7,362 correspond to limited liability firms and 4,574 to unlimited liability firms. We dropped all observations with missing data on any of the variables used in our empirical specifications and observations on firms that reported zero assets. To ensure accurate representation of the population of small businesses, the SSBF uses a stratified random sample design, with stratification based on census area, rural/urban location, employment size, and ethnicity of the owner. In all our statistical and econometric analyses, we use the sampling weights that make the sample representative of all small businesses in the U.S.

[12] We additionally lose 145 observations in the maturity regressions because some loans have an unspecified term.

[13] In the context of the bankruptcy law, a property foreclosure requires the approval of the bankruptcy trustee, increasing the delay and imposing higher transactions costs. Because high exemptions increase the probability that a borrower that may also have unsecured loans files for bankruptcy, exemptions may increase the expected foreclosure costs for the bank. Lin and White (2001) find empirical evidence from the mortgage market that supports this argument.

driven and the second is demand-driven, both effects imply that, in equilibrium, higher exemptions may be associated with a lower incidence of personal real estate collateral.

The descriptive statistics show that on average unlimited liability firms were more likely to pledge personal real estate collateral, but less likely to pledge business collateral than their limited liability counterparts. In addition, the unlimited liability firms borrowed substantially smaller amounts and paid higher rates, but benefited on average from longer maturities.

### 4.4.2. State-level variables

Our main variable of interest is the homestead exemption: the maximum home equity value that a debtor can exempt when filing for personal bankruptcy under Chapter 7. We collect the homestead exemption for each state from Elias, Renauer, and Leonard several editions. As explained in Section III, the homestead exemptions vary widely across states, but there is little time variation over our sample period. Most of the changes in the exemption levels during our sample period simply reflect nominal adjustments to inflation. A recent study on the political determinants of exemption laws by Hynes, Malani and Posner (2004) finds that the only significant determinant of the post-1975 variation in exemption laws is the state exemption level in the 1920s, indicating that inertia appears to be part of the explanation. These findings suggest that endogeneity of the homestead exemptions should not be a concern during our sample period.

A related concern is that the exemption variable may be correlated with other state-level characteristics such as other institutional differences, or differences in state economic conditions that could affect the (unobserved) characteristics of the pool of applicants. We therefore employ two additional state-level variables. First, we include a dummy equal to one for the 21 states where lenders must go through the courts to foreclose on a property (*Judicial foreclosure*), 0 otherwise.[14] This variable controls for the higher costs of the judicial foreclosure procedure, which takes on average five months longer than the non-judicial alternative, and imposes higher transaction costs (Wood 1997). According to Pence (2006), the judicial procedure can increase costs as much as 10% of the loan balance. She also shows that higher foreclosure costs are associated with lower mortgage loan sizes, suggesting that this variable can have important effects on credit availability and on contract terms. Second, in order to control for economic differences across states that may affect the quality of the pool of applicants, we also include the state median income (*State median income*), which we obtain from the U.S. Census Bureau.

### 4.4.3. Firm-level controls

We include several characteristics of the firm and of the firm's principal owner. *Home equity* is the market value of the primary residence of the firm's owner minus the outstanding mortgage balance. We impute a value of zero for *Home equity* when business owners do not own their home (this is the case for 7% of the firms). *Net worth* is the total net worth, excluding the primary home and the value of the firm, of the firm's owner. These variables are only available for the 1998 and 2003 SSBF.

We also include a dummy variable indicating whether an African-American owns at least 50% of the firm (*African-American*), the number of employees (*Log*(*1+Employees*)), a dummy indicating whether a family owns at least 50% of the firm (*Family owned*), and the firm's age (*Log*(*1+Firm's age*)). To control for the firm's financial health, we include the ratios of debt to assets (*Debt/assets ratio*), profits to assets

[14] We are grateful to Karen Pence for providing the foreclosure data.

(*Profits/assets ratio*), tangible assets (includes land, building, and equipment) to total assets (*Tangible assets*). Because these ratios have sometimes implausibly large values, we winsorized (trimmed) the debt to assets ratio at the 95$^{th}$ percentile and the profits to assets ratio at the 5$^{th}$ and 95$^{th}$ percentiles.

Previous research (e.g., Kallberg and Udell 2003) suggests that the third-party mercantile ratings are strong predictors of default risk in small business lending. Accordingly, we also include the credit score percentile of the firm, as obtained from Dun & Bradstreet (*Firm credit score*). The credit score is based on business information and should provide a good estimate of the credit quality of the firm.[15]

### 4.4.4. Relationship controls

There is ample evidence in the literature on the importance of the nature of the relationship between the firm and its lender in the small business credit market.[16] We include a dummy that equals one if the firm has a checking account with the lending institution (*Checking account*), the duration in years of the relationship the firm has had with the lender (*Log*(*1+Duration*)), the number of financial institutions from which the firm borrows (*Number of lenders*), and the distance in miles separating the firm from the bank (*Log*(*1+Distance*)).

### 4.4.5. Market-level controls

All regressions include a set of dummies for the type of the lending institution, which we aggregate into the three following categories: depository, non-depository financial, and non-depository non-financial. These dummies should control for differences across states in the banking industry.

To further control for the geographic and local market conditions, we include the Herfindahl-Hirschman bank deposit index of banking market concentration (*HHI deposit market*), and a dummy that indicates whether the firm is located in a metropolitan statistical area (*Firm in MSA*). The inclusion of the MSA variable is particularly relevant, since one should expect a large discrepancy between rural and urban areas in terms of the value of the real estate property.

### 4.4.6. Other controls

All regressions include also a set of time dummies and one-digit industry codes (not shown in the tables). In all regressions with the loan contract terms as dependent variables, we also include a dummy indicating whether it is a floating rate loan, and a set of dummies for the type of the loan – line of credit, capital lease, mortgage, motor vehicle, equipment, and other type. These variables should have an important role in ensuring proper identification. For instance, there is evidence that lines of credit (which typically have higher rates and shorter maturity) are more relationship-driven than the other types of loans (Berger and Udell 1995). Moreover, relationship lending should play a more important role in markets with higher exemptions, where agency problems are more severe. By controlling for the type of the loan, we rule out that the effect of

[15] If these credit scores already incorporate the exemptions as a risk factor, then our regression models might fail to identify the effect of the exemptions on the credit market variables. We investigated further the nature of these credit scores by regressing the credit scores on the remaining characteristics of the firm and owner, and on the homestead exemptions. We found that the exemptions are not systematically related to the credit scores.

[16] Petersen and Rajan (1994, 1995), Berger and Udell (1995), Cole (1998), Angelini, Di Salvo, and Ferri (1998), Harhoff and Körting (1998), Degryse and Van Cayseele (2000) analyse the effect of firm-creditor relationships on credit availability and collateral requirements. Petersen and Rajan (1994), Berger and Udell (1995), Angelini, Di Salvo, and Ferri (1998), Degryse and Cayseele (2000) and Brick and Palia (2007) focus on the effect of relationships on interest rates. Mester, Nakamura, and Renault (2007) and Norden and Weber (2008) show that checking account information helps banks monitor borrowers.

the exemptions on the credit terms could simply reflect an adjustment in the banks' loan portfolio composition.

## 4.5. Empirical Methodology

Our main prediction is that high levels of debtor protection should adversely affect the small businesses in the credit market, and that this effect should be stronger for the unlimited liability firms. We expect, in particular, to obtain empirical support for the following set of predictions. First, increased debtor protection, all else equal, should reduce credit availability, as greater debtor protection induces or exacerbates agency problems between the firm and its potential lenders. In particular, it should increase the likelihood that an unlimited liability firm is either denied credit or discouraged from applying for credit. Moreover, this reduction in credit availability should also translate into lower loan amounts. We test these predictions with the following empirical models, which we estimate separately for unlimited liability and limited liability firms:

$$P(Discouraged/Denied) = \alpha_1\, Debtor\ Protection + \beta_1 X + \varepsilon_1, \tag{1}$$

$$Ln(Loan\ Amount) = \alpha_2\, Debtor\ Protection + \beta_2 X + \varepsilon_2, \tag{2}$$

where the vector $X$ includes a constant term plus the control variables defined in the previous section (see Table 2), and $\varepsilon_1$ and $\varepsilon_2$ are the residual terms. We estimate equation (1) with a probit model and equation (2) via OLS.

Second, the terms of credit – interest rates and maturity – are expected to become harsher (higher rates, shorter maturities) as the level of debtor protection increases. These predictions translate into the following two regressions, which we estimate separately for the unlimited liability and limited liability firms:

$$Loan\ Rate = \alpha_3\, Debtor\ Protection + \beta_3 X + \varepsilon_3, \tag{3}$$

$$Ln(1{+}Loan\ Maturity) = \alpha_4\, Debtor\ Protection + \beta_4 X + \varepsilon_4. \tag{4}$$

Third, higher debtor protection should have differential effects on the incidence of personal real estate collateral and business collateral. As discussed above, the effect of debtor protection on the incidence of personal real estate collateral is ambiguous. In contrast, the pledging of business collateral unequivocally blunts the effects of increased debtor protection. Consequently, higher debtor protection should increase the incidence of business collateral for unlimited liability firms that receive loans. The two corresponding empirical equations are given by:

$$P(Pers.\ real\ estate\ collateral) = \alpha_5\, Debtor\ Protection + \beta_5 X + \varepsilon_5, \tag{5}$$

$$P(Bus.\ assets\ collateral) = \alpha_6\, Debtor\ Protection + \beta_6 X + \varepsilon_6, \tag{6}$$

which we estimate using probit models, and we do them separately for the unlimited liability and limited liability firms. Given the above discussion, for the unlimited liability group we expect a positive $\alpha_6$ and an undetermined sign for $\alpha_5$.

To test for our hypotheses, we use two specifications with two different measures of debtor protection. In the first specification, we control for the borrower's home equity, and we use as our measure of debtor protection a logarithmic transformation of the homestead exemption in the state where the firm is located:

$$Debtor\ Protection_1 = Ln(1 + Homestead\ Exemption).$$

For states with unlimited homestead exemptions, we set *Homestead Exemption* equal to the maximum homestead exemption across all states in the same year. These are the results we report in Columns 1 and 3 in Tables 5-10. But we also check for the robustness of our results by assigning a value of $1 million to the states with unlimited exceptions. We do not report these other specifications which show similar results.

The second specification uses our preferred measure (*adjusted exemption*). This measure is borrower-specific, and recognizes that the homestead exemption fully protects a debtor only to the extent that the value of the debtor's home equity is less than or equal to the exemption level. The adjusted exemption is given by:

$$Debtor\ Protection_2 = -\ Ln(1 + Max\{Home\ equity - Homestead\ Exemption, 0\}),$$

where *Home equity* is the home equity value of the firm's owner. This measure of debtor protection has its maximum value when the borrower's home equity is lower than the state homestead exemption (the debtor's home equity is fully protected), and is decreasing in the difference between the home equity and the homestead exemption (the amount that the creditor can seize). To see this more clearly, it is important to note that the argument in the logarithmic function (i.e., the *Max* function) is an *inverse* measure of debtor protection. The minus sign that precedes the logarithmic function reverses the sign, so that our measure becomes a direct measure of debtor protection.

In our empirical analysis, when we report the economic impact of going from a state with unlimited exemptions to a state with zero exemptions, we focus primarily on our preferred measure, and we report it for the median home equity value in our sample.

## 4.6. Results

### 4.6.1. Univariate tests

Table 3 reports the means of all dependent and independent variables for high exemption states and low exemption states, and for both types of firms (unlimited and limited liability). For this table, we consider as low exemption states the ones at or below the $10^{th}$ percentile of the homestead exemptions each year (the critical value equals $10,000 throughout the entire sample). We consider high exemption states the ones with unlimited exemptions and the ones at or above the $90^{th}$ percentile (the critical value is $100,000 in the 1993 and 1998 SSBF, and $150,000 in the 2003 SSBF). The difference-of-means tests show that the percentage of firms that were denied or discouraged from borrowing does not differ significantly between high and low exemption states for either type of firm. With respect to the contract terms, the only significant differences between high exemption and low exemption states are for the measures of collateral pledged for unlimited liability firms. Specifically, the percentage of unlimited liability firms that pledge business collateral is significantly higher in high exemption states as expected, and the percentage of unlimited liability firms that pledge personal real estate collateral is significantly lower.

With respect to the state-level controls, the difference-of-means tests indicate that high exemption states have a significantly higher state median income and are significantly less likely to require lenders to go through the courts to foreclosure property, suggesting that it is important to control for these state-level differences.

We then investigate how the exemptions affect the credit quality of the pool of borrowers. We use the credit score information from Dun & Bradstreet that is available for all firms, whether borrowers or not, and we perform several differences-of-means tests for the unlimited liability and limited liability firms. The results are reported in Table 4. Panel A shows that while the pool of unlimited liability *borrowers* in high exemption states has significantly higher credit scores than the pool of non-borrowers, this difference is not observed in low exemption states. Moreover, this pattern is not present in the case of limited liability companies (Panel B). These results suggest that in high exemption states, a selection mechanism based on credit quality is shaping the pool of the unlimited liability borrowers. This is consistent with an increase in credit quality requirements by banks in response to the adverse incentives created by high exemptions on the unlimited liability firms' owners.[17] They also highlight the importance of controlling for risk characteristics, both to analyze the probability of being discouraged/denied and the determinants of the contract terms. We therefore turn to a multivariate analysis in the next subsection.

### 4.6.2. Multivariate analysis

We next examine the effect of exemptions on the availability of credit and on the contract terms after controlling for state-level, market-level and firm and owner characteristics (including the credit score of the firm, the owner's net worth, and the owner's home equity).

#### *4.6.2.1. Credit availability*

We begin by investigating whether debtor protection affects the probability of firms being denied credit or discouraged from borrowing. Table 5 reports the results of probit regressions, using our two measures of debtor protection. Columns 1-2 report the results for the unlimited liability companies and Columns 3-4 give the findings for the limited liability companies. In Columns 1 and 3, we use the level of the homestead exemption as our main explanatory variable, while controlling for the home equity value of the firm's owner. In Columns 2 and 4, we use our borrower-specific measure of debtor protection that takes into account both the exemptions and the owner's home equity. As expected, for unlimited liability firms, we find a strong positive effect of both measures of debtor protection on the probability of being discouraged/denied. In particular, our adjusted measure indicates that for the median home equity in our sample,[18] the probability of an unlimited liability firm being denied credit or discouraged from borrowing increases 12 percentage points

[17] However, note that *all* unlimited liability firms (borrowers and non-borrowers) have substantially higher scores when they are located in high exemption states. This could be due to a survival effect – i.e., some poor credit quality firms cannot obtain credit and go out of business.
[18] The median home equity equals $80,000 for the unlimited liability firms and $140,000 for the limited liability firms.

if the firm is located in a state with unlimited rather than zero homestead exemptions.[19] This is consistent with our previous result that the pool of unlimited liability borrowers being significantly safer in high exemption states. For the limited liability firms, we only find a significant effect in the case of our adjusted measure. The economic impact is only 5 percentage points, less than half the one we obtain for the unlimited liability companies. This confirms our hypothesis that unlimited liability firms are more adversely affected in their access to credit when the level of debtor protection is high.

Many of our control variables turn out to be significant with the expected sign for both types of firms. A better credit score and higher net worth decrease the probability of denial/discouraged. Also, a longer relationship with the bank increases the availability of credit, consistent with the findings in Cole (1998). In addition, if the company has higher leverage or if it is majority-owned by an African-American, the probability of being credit rationed increases. These results are consistent with Cavaluzzo, Cavaluzzo, and Wolken (2002) who also find that denial rates are significantly higher for firms owned by African-Americans. Finally, if the firm has a larger number of lenders, denial rates are higher, which could be explained by lower quality firms seeking additional financing in other institutions when they are credit-constrained with their primary lender.

Table 6 reports the results on loan size. In line with the previous result, we find a strong negative effect of both measures of debtor protection on the size of the loan for the unlimited liability firms. Specifically, our adjusted measure shows that for the median home equity in our sample, the size of the loan falls by 24 percent if the firm is located in a state with unlimited rather than zero homestead exemptions. We do not find any significant effect for the limited liability firms. With respect to control variables, the results also show a strong positive effect of net worth on the size of the loan for both types of firms.

In short, the findings for discouraged/denied and loan size altogether suggest that increased debtor protection has a strong pervasive effect on credit availability for unlimited liability businesses.

#### *4.6.2.2. Other contract terms*

We now investigate the effect of debtor protection on the contract terms. Tables 7 to 10 report reduced-form regressions for the different contract terms, both for limited liability and unlimited liability companies.

Table 7 reports results for the loan rates. We find a positive effect of greater debtor protection on loan rates for both the unlimited liability and limited liability firms. Although the estimated economic impacts are remarkably similar for both types of firms, the effect is only statistically significant for our first specification and for the limited liability group. As explained above, high exemptions may also affect small limited liability firms, because the owners of these firms may guarantee the firms' loans or because these firms could transfer assets to the owners.

Table 8 reports the results for loan maturity. As expected, high exemptions significantly reduce the maturity of the loans for unlimited liability companies, though the effect is only statistically significant for our adjusted measure. Specifically, according to our adjusted measure, maturity falls by 19 percent if the firm is located in unlimited exemption states rather than zero exemption states, suggesting that banks respond to high exemptions not only by increasing the demand for business collateral, but also by reducing

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[19] We also investigate the effect of debtor protection on the probability that a firm is *denied* credit. The results (not reported) are significant for our adjusted measure, indicating that moving the exemption level from zero to unlimited increases this probability by 6 percentage points.

maturity (Diamond 2004). This result is consistent with the findings of Qian and Strahan (2007), who find that that weak creditor protection reduces maturity of loans to large companies.

Finally, we turn to the results on the different types of collateral. Table 9 reports the results on the probability of pledging personal real estate collateral. For limited liability firms, we do not find any effect of our measures of debtor protection on the probability of pledging personal real estate collateral. For unlimited liability companies, our adjusted measure indicates that greater debtor protection is associated with a lower probability of pledging personal real estate collateral. One possible explanation is that banks in high exemption states face higher costs of seizing personal real estate collateral. However, a demand-side explanation is also possible. For risk-averse owners of unlimited liability companies, pledging personal real estate collateral is more costly in high exemption states because by doing so, they lose the wealth insurance that these states provide. However, we should note that our first specification (column 1) suggests that this result is not driven by exemptions (which are not significant), but rather by variations in home equity. More home equity (which reduces our adjusted measure of debtor protection when debtors are not fully protected) is associated with a larger probability of pledging this type of collateral. This result may reflect the simple fact that the probability of pledging personal real estate is a positive function of the borrower's availability of such of collateral (i.e., the amount of home equity).

However, we still expect that high debtor protection increases the likelihood that firms pledge business collateral, since collateral blunts the effect of the exemptions. We therefore run the corresponding probit models and we report the results in Table 10. As expected, both our measures show that the probability of pledging business collateral increases with the exemptions level for unlimited liability firms. Specifically, our adjusted measure indicates that for the median home equity value in our sample, the probability of an unlimited liability firm pledging business collateral increases 13 percentage points if the firm is located in a state with unlimited rather than zero homestead exemptions. We note that this effect is economically significant and that in contrast, we find no effect for limited liability firms. This provides further evidence that exemptions impose harsher lending terms for unlimited liability firms in high exemption states.

## 4.7. Robustness

We have shown that increased debtor protection increases unlimited liability firms' discouragement/denial rates and deteriorates the price and non-price terms of their loans when they receive credit. These results suggest that debtor protection results in a reduction of credit supply to unlimited liability businesses. However, up to now our empirical strategy does not allow us to rule out that our findings may be partially driven by an increase in the demand for credit by these firms. An increase in demand for credit could result from the wealth insurance provided by increased debtor protection (Gropp, Scholz, and White 1997) and from the fact that debtor protection fosters entrepreneurship (Fan and White 2003, Armour and Cumming 2008). Because start-ups are typically riskier, and if our observable measures fail to fully capture this risk component, then our results could be partially explained by debtor protection increasing the average risk of the pool of applicants.

Because we also have information on the firm's decision to apply for a loan, we can estimate sample selection models for all our credit market variables. In this way we can formally test whether our prior findings may be driven by the pool of firms that demand credit in high exemption states being unobservably riskier. The selection equation is the firm's decision to apply for a bank loan. This equation should absorb potential shifts in the demand for credit, allowing us to interpret our results for the credit market variables as supply-driven (Gropp, Scholz, and White 1997). In fact, the results of the sample selection models for our debtor protection measures are similar to those we show in Tables 5-10, and hence we choose not to report them. These extra tests confirm our previous conclusion that banks respond adversely to increased debtor protection by reducing credit availability and tightening lending standards.

## 4.8. Conclusion

We study the effect of debtor protection on small firms' access to credit, and on the price and non-price terms of bank lending to these companies. Our empirical strategy exploits the variation across states of U.S. personal bankruptcy law.

We find robust evidence of a strong adverse effect of high levels of debtor protection on unlimited liability firms. Specifically, for these firms the probability of being denied credit or being discouraged from borrowing increases by 12 percentage points if the firm is located in a state with unlimited rather than zero homestead exemptions. Consistent with this result, the pool of unlimited liability borrowers has on average significantly better credit scores than the pool of non-borrowers in high exemption states (while there is no significant difference between these two pools of firms in low exemption states), suggesting that lenders restrict credit to these firms. Moreover, for the unlimited liability companies that do receive credit, non-price terms are considerably less favorable in high exemption states. Specifically, both loan amounts and maturity fall significantly. We also note that while less personal real estate collateral is pledged in these circumstances, the incidence of business collateral is significantly higher. For limited liability firms, we find that higher debtor protection leads to a smaller reduction in credit availability, and to higher interest rates.

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## 4.10. Tables

**Table 1 – Bankruptcy exemptions by state in 1993, 1998, and 2003**

The source is Elias, Renauer, and Leonard (1993, 1998, and 2004). [F] Indicates that the Federal exemption was selected; [D] Indicates that the exemption was doubled. In some states married couples are allowed to double the amount of the exemption for home equity when filing for bankruptcy together (called "doubling"). We have doubled all amounts except in those cases where bankruptcy law explicitly prohibits "doubling."

| State | Homestead exemptions ($) | | |
|---|---|---|---|
| | 1993 | 1998 | 2003 |
| Alabama [D] | 10,000 | 10,000 | 10,000 |
| Alaska | 54,000 | 62,000 | 67,500 |
| Arizona | 100,000 | 100,000 | 100,000 |
| Arkansas | Unlimited | Unlimited | Unlimited |
| California [D] | 75,000 | 75,000 | 75,000 |
| Colorado [D] | 60,000 | 60,000 | 90,000 |
| Connecticut [D] | 150,000 | 150,000 | 150,000 |
| D.C. [F, D] | 30,000 | 32,300 | 36,900 |
| Delaware | 0 | 0 | 0 |
| Florida | Unlimited | Unlimited | Unlimited |
| Georgia [D] | 10,000 | 10,000 | 20,000 |
| Hawaii [F, D] | 30,000 | 32,300 | 36,900 |
| Idaho | 50,000 | 50,000 | 50,000 |
| Illinois [D] | 15,000 | 15,000 | 15,000 |
| Indiana [D] | 15,000 | 15,000 | 15,000 |
| Iowa | Unlimited | Unlimited | Unlimited |
| Kansas | Unlimited | Unlimited | Unlimited |
| Kentucky [D] | 10,000 | 10,000 | 10,000 |
| Louisiana | 15,000 | 25,000 | 25,000 |
| Maine [D] | 25,000 | 25,000 | 70,000 |
| Maryland | 0 | 0 | 0 |
| Massachusetts | 100,000 | 100,000 | 500,000 |
| Michigan [F, D] | 30,000 | 32,300 | 36,900 |
| Minnesota | Unlimited | Unlimited | Unlimited |
| Mississippi [D] | 150,000 | 150,000 | 150,000 |
| Missouri | 8,000 | 8,000 | 15,000 |
| Montana [D] | 80,000 | 120,000 | 200,000 |
| Nebraska | 20,000 | 12,500 | 12,500 |
| Nevada | 95,000 | 125,000 | 200,000 |
| New Hampshire [D] | 60,000 | 60,000 | 200,000 |
| New Jersey [F, D] | 30,000 | 32,300 | 36,900 |
| New Mexico [D] | 60,000 | 60,000 | 60,000 |
| New York [D] | 20,000 | 20,000 | 20,000 |
| North Carolina [D] | 20,000 | 20,000 | 20,000 |
| North Dakota | 80,000 | 80,000 | 80,000 |
| Ohio [D] | 10,000 | 10,000 | 10,000 |
| Oklahoma | Unlimited | Unlimited | Unlimited |
| Oregon [D] | 33,000 | 33,000 | 33,000 |
| Pennsylvania [F, D] | 30,000 | 32,300 | 36,900 |
| Rhode Island | 30,000 | 32,300 | 200,000 |
| South Carolina [F, D] | 30,000 | 32,300 | 36,900 |
| South Dakota | Unlimited | Unlimited | Unlimited |
| Tennessee [D] | 7,500 | 7,500 | 7,500 |
| Texas | Unlimited | Unlimited | Unlimited |
| Utah [D] | 10,000 | 40,000 | 40,000 |
| Vermont [D] | 60,000 | 150,000 | 150,000 |
| Virginia [D] | 10,000 | 10,000 | 10,000 |
| Washington | 60,000 | 40,000 | 40,000 |
| West Virginia [D] | 15,000 | 30,000 | 50,000 |
| Wisconsin | 40,000 | 40,000 | 40,000 |
| Wyoming [D] | 20,000 | 20,000 | 20,000 |
| Median | 30,000 | 32,300 | 36,900 |

## Table 2 – Descriptive statistics for unlimited liability and limited liability firms

The table displays summary statistics – means (Mean), standard deviations (Std. dev.), and number of observations (N. obs.) – for unlimited liability and limited liability firms. The unlimited liability group includes sole proprietorships and partnerships with this legal form. The limited liability group contains all corporations (both regular and S-type), plus the sole proprietorships and partnerships that have a limited liability form. The dataset comprises the 1993, 1998, and 2003 SSBF. The firm owner's home equity and net worth are not available for the 1993 SSBF.

| Variable | Unlimited liability | | | Limited liability | | |
|---|---|---|---|---|---|---|
| | Mean | Std. dev. | N. obs. | Mean | Std. dev. | N. obs. |
| *Dependent variables* | | | | | | |
| Discouraged/Denied (0/1) | 0.23 | 0.42 | 4,574 | 0.23 | 0.42 | 7,362 |
| Collateral – Personal real estate (0/1) | 0.15 | 0.36 | 989 | 0.11 | 0.31 | 3,194 |
| Collateral – Business assets (0/1) | 0.41 | 0.49 | 989 | 0.52 | 0.50 | 3,194 |
| Loan maturity (years) | 4.90 | 6.20 | 943 | 3.80 | 5.10 | 3,095 |
| Loan rate (%) | 8.60 | 3.20 | 989 | 7.50 | 2.90 | 3,194 |
| Loan size ($000) | 132.31 | 1,199.02 | 989 | 380.10 | 1,804.61 | 3,194 |
| *State-level variables* | | | | | | |
| Homestead exemption ($000) | 92.37 | 121.46 | 4,574 | 91.85 | 130.15 | 7,362 |
| Judicial foreclosure | 0.40 | 0.49 | 4,574 | 0.47 | 0.50 | 7,362 |
| State median income ($000) | 40.44 | 6.74 | 4,574 | 40.52 | 6.93 | 7,362 |
| *Firm-level controls* | | | | | | |
| Home equity ($000) | 144.54 | 353.95 | 2,836 | 232.36 | 734.80 | 4,579 |
| Net worth ($000,000) | 0.36 | 1.80 | 2,836 | 0.96 | 10.00 | 4,579 |
| African-American (0/1) | 0.04 | 0.20 | 4,574 | 0.03 | 0.16 | 7,362 |
| Number of employees | 3.90 | 9.90 | 4,574 | 14.00 | 30.00 | 7,362 |
| Family owned (0/1) | 0.95 | 0.23 | 4,574 | 0.82 | 0.39 | 7,362 |
| Firm's age (years) | 14.00 | 11.00 | 4,574 | 14.00 | 11.00 | 7,362 |
| Debt/assets ratio | 0.31 | 0.45 | 4,574 | 0.46 | 0.50 | 7,362 |
| Profits/assets ratio | 1.20 | 1.80 | 4,574 | 0.72 | 1.50 | 7,362 |
| Tangible assets | 0.41 | 0.36 | 4,574 | 0.34 | 0.32 | 7,362 |
| Firm credit score (0-1) | 0.50 | 0.27 | 4,574 | 0.54 | 0.30 | 7,362 |
| *Relationship controls* | | | | | | |
| Checking account (0/1) | 0.84 | 0.37 | 4,574 | 0.83 | 0.38 | 7,362 |
| Duration of relationship (years) | 8.90 | 8.80 | 4,574 | 8.40 | 8.90 | 7,362 |
| Number of lenders | 2.00 | 1.30 | 4,574 | 2.50 | 1.60 | 7,362 |
| Distance (miles) | 37.00 | 204.00 | 4,574 | 47.00 | 272.00 | 7,362 |
| *Market-level controls* | | | | | | |
| HHI deposit market (0-1) | 0.21 | 0.12 | 4,574 | 0.19 | 0.10 | 7,362 |
| Firm in MSA (0/1) | 0.76 | 0.43 | 4,574 | 0.83 | 0.37 | 7,362 |

## Table 3 – Descriptive statistics for unlimited liability vs. limited liability firms, and for high vs. low homestead exemptions

Low exemptions refer to the homestead exemptions that are for each year at or below the 10th percentile, which equals $10,000 throughout the entire sample. High exemptions refer to the unlimited exemptions and to the homestead exemptions that are for each year at or above the 90th percentile. The 90th percentile of the homestead exemptions is $100,000 in the 1993 and 1998 SSBF, and $150,000 in the 2003 SSBF. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The dataset comprises the 1993, 1998, and 2003 SSBF.

| Variable | Unlimited liability | | | | | Limited liability | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Low exemption* | | *High exemption* | | Difference | *Low exemption* | | *High exemption* | | Difference |
| | Mean | Std. dev. | Mean | Std. dev. | *Low-High* | Mean | Std. dev. | Mean | Std. dev. | *Low-High* |
| *Dependent variables* | | | | | | | | | | |
| Discouraged/Denied (0/1) | 0.23 | 0.42 | 0.26 | 0.44 | -0.03 | 0.23 | 0.42 | 0.23 | 0.42 | 0.00 |
| Collateral–Personal real estate (0/1) | 0.13 | 0.34 | 0.09 | 0.29 | 0.04*** | 0.10 | 0.30 | 0.09 | 0.29 | 0.01* |
| Collateral–Business assets (0/1) | 0.37 | 0.48 | 0.46 | 0.50 | -0.09*** | 0.55 | 0.50 | 0.56 | 0.50 | -0.01 |
| Loan maturity (years) | 4.70 | 5.30 | 4.50 | 6.40 | 0.20 | 3.90 | 4.80 | 3.90 | 5.80 | 0.00 |
| Loan rate | 8.40 | 3.00 | 8.70 | 2.90 | -0.30 | 7.60 | 2.60 | 7.80 | 2.70 | -0.20 |
| Loan size ($000) | 144.20 | 531.11 | 156.98 | 1,797.54 | -12.78 | 286.20 | 1,470.51 | 395.30 | 1,860.50 | -109.10 |
| *State-level controls* | | | | | | | | | | |
| Judicial foreclosure | 0.47 | 0.50 | 0.26 | 0.44 | 0.21*** | 0.47 | 0.50 | 0.39 | 0.49 | 0.08*** |
| State median income | 39.20 | 7.06 | 38.47 | 6.74 | 0.73** | 40.14 | 7.56 | 38.66 | 7.13 | 1.48*** |
| *Firm-level controls* | | | | | | | | | | |
| Home equity ($000) [c] | 120.36 | 181.39 | 129.78 | 389.35 | -9.42 | 185.07 | 361.56 | 204.52 | 318.43 | -19.45 |
| Net worth ($000) | 0.33 | 0.96 | 0.39 | 2.90 | -0.06 | 0.70 | 2.30 | 0.88 | 6.00 | -0.18 |
| African-American (0/1) | 0.07 | 0.25 | 0.04 | 0.18 | 0.03*** | 0.04 | 0.20 | 0.02 | 0.14 | 0.02** |
| Number of employees | 3.80 | 9.20 | 3.60 | 9.00 | 0.20 | 14.00 | 29.00 | 13.00 | 29.00 | 1.00 |
| Family owned (0/1) | 0.95 | 0.22 | 0.95 | 0.22 | 0.00 | 0.82 | 0.38 | 0.81 | 0.39 | 0.01 |
| Firm's age (years) | 14.00 | 11.00 | 14.00 | 12.00 | 0.00 | 14.00 | 12.00 | 13.00 | 11.00 | 1.00** |
| Debt/assets ratio | 0.29 | 0.41 | 0.34 | 0.46 | -0.05*** | 0.41 | 0.47 | 0.50 | 0.51 | -0.09*** |
| Profits/assets ratio | 1.20 | 1.80 | 1.20 | 1.70 | 0.00 | 0.63 | 1.40 | 0.74 | 1.50 | -0.11** |
| Tangible assets | 0.41 | 0.35 | 0.42 | 0.34 | -0.01 | 0.35 | 0.32 | 0.34 | 0.32 | 0.01 |
| Firm credit score (1-100) | 0.47 | 0.27 | 0.49 | 0.26 | -0.02 | 0.54 | 0.30 | 0.53 | 0.29 | 0.01 |
| *Relationship controls* | | | | | | | | | | |
| Checking account (0/1) | 0.84 | 0.37 | 0.84 | 0.37 | 0.00 | 0.83 | 0.38 | 0.82 | 0.38 | 0.01 |
| Duration of relationship (years) | 9.10 | 8.80 | 8.50 | 8.50 | 0.60 | 8.40 | 9.30 | 7.90 | 8.50 | 0.50 |
| Number of lenders | 1.90 | 1.30 | 2.00 | 1.30 | -0.10* | 2.60 | 1.60 | 2.60 | 1.60 | 0.00 |
| Distance to lender (miles) | 32.00 | 159.00 | 39.00 | 213.00 | -7.00 | 31.00 | 154.00 | 52.00 | 241.00 | -21.00*** |
| *Market-level controls* | | | | | | | | | | |
| HHI deposit market (0-1) | 0.20 | 0.40 | 0.22 | 0.41 | -0.02 | 0.18 | 0.38 | 0.19 | 0.39 | -0.01 |
| Firm in MSA (0/1) | 0.71 | 0.45 | 0.77 | 0.42 | -0.06*** | 0.81 | 0.39 | 0.85 | 0.36 | -0.04 |

## Table 4 – The effect of the homestead exemptions on credit quality

The table displays the average firm credit scores for borrowers and non-borrowers, in high versus low exemption states, for the unlimited liability and limited liability firms. Low exemptions refer to the homestead exemptions that are for each year at or below the 10th percentile, which equals $10,000 throughout the entire sample. High exemptions refer to the unlimited exemptions and to the homestead exemptions that are for each year at or above the 90th percentile. The 90th percentile of the homestead exemptions is $100,000 in the 1993 and 1998 SSBF, and $150,000 in the 2003 SSBF. Standard errors are provided in parentheses. All statistics take into account the sample weights, implying that all the statistics are representative of the population of U.S. small businesses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Subsamples | (A)<br>All firms | (B)<br>Borrowers | (C)<br>Non-borrowers | Difference<br>(C) - (B) |
|---|---|---|---|---|
| *A) Unlimited liability* | | | | |
| (I) All firms | 49.58<br>(0.46)<br>N=4,574 | 50.42<br>(1.08)<br>N=989 | 49.36<br>(0.51)<br>N=3,585 | -1.07 |
| (II) Low exemptions | 46.65<br>(1.24)<br>N=676 | 46.34<br>(2.71)<br>N=152 | 46.74<br>(1.39)<br>N=524 | 0.40 |
| (III) High exemptions | 49.33<br>(0.78)<br>N=1,528 | 52.64<br>(1.71)<br>N=315 | 48.50<br>(0.88)<br>N=1,213 | -4.14** |
| Difference (III) - (II) | 2.68* | 6.30** | 1.76 | |
| *B) Limited liability* | | | | |
| (I) All firms | 53.71<br>(0.49)<br>N=7,362 | 54.20<br>(0.83)<br>N=3,194 | 53.46<br>(0.60)<br>N=4,168 | -0.74 |
| (II) Low exemptions | 54.39<br>(1.16)<br>N=1,318 | 53.43<br>(1.90)<br>N=579 | 54.92<br>(1.45)<br>N=739 | 1.49 |
| (III) High exemptions | 52.50<br>(0.88)<br>N=2,193 | 54.00<br>(1.58)<br>N=951 | 51.70<br>(1.06)<br>N=1,242 | -2.30 |
| Difference (III) - (II) | -1.89 | 0.56 | -3.22* | |

## Table 5 – The effect of the homestead exemptions on the likelihood of Discouraged/Denied

The table lists the coefficients from a probit regression of *Discouraged/Denied* on the set of variables reported. The model also includes (estimates not shown) year dummies, one-digit SIC dummies, and lender type dummies. In the first specification, *Log(1+Exemption)*, we impute for the unlimited exemptions the maximum homestead exemption in the same period. *Adjusted exemption* is given by: *-Log(1+max{z,0})*, where *z* is the equity of the residence of the firm's owner minus the homestead exemption. The row "Δ Exemptions (0-Unlimited)" refers to the predicted change in probability of the dependent variable that results from changing the exemption level from zero to unlimited. The effect was calculated at the mean value of the other independent variables. For the first specification (columns 1 and 3) we set the unlimited exemption to the maximum exemption level in the 1998 SSBF ($200,000). For the specification that uses the adjusted exemptions (columns 2 and 4), we set the value of the home equity to its sample median (equals $80,000 for the unlimited liability firms, and $140,000 for the limited liability firms). The dataset comprises the 1998 and 2003 SSBF. Robust t-statistics (standard errors are clustered at the state level) are provided in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Variable | Unlimited liability | | Limited liability | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(1+Exemption) | 0.02* | | 0.01 | |
| | (1.64) | | (0.51) | |
| Log(1+Home equity) | -0.05*** | | -0.04*** | |
| | (-6.78) | | (-4.84) | |
| Adjusted exemption | | 0.04*** | | 0.02** |
| | | (6.71) | | (0.01) |
| Δ Exemptions (0-Unlimited) | 0.07 | 0.12 | 0.02 | 0.05 |
| *State level controls* | | | | |
| Judicial foreclosure | -0.15 | -0.12 | 0.03 | 0.03 |
| | (-1.41) | (-1.11) | (0.32) | (0.31) |
| State median income | 0.22 | 0.42 | 0.52 | 0.65** |
| | (0.51) | (1.08) | (1.60) | (1.98) |
| *Firm-level controls* | | | | |
| Log(1+Net worth) | -2.03*** | -1.97*** | -1.64*** | -1.76*** |
| | (-3.12) | (-2.71) | (-4.30) | (-4.40) |
| African-American | 0.64*** | 0.65*** | 0.64*** | 0.65*** |
| | (5.00) | (5.20) | (4.05) | (4.29) |
| Owner education | -0.12*** | -0.12*** | -0.07** | -0.07** |
| | (-3.42) | (-3.64) | (-2.19) | (-2.15) |
| Log(1+Employees) | 0.03 | 0.03 | -0.09** | -0.10** |
| | (0.48) | (0.42) | (-2.35) | (-2.54) |
| Family owned | 0.14 | 0.10 | 0.10 | 0.10 |
| | (0.87) | (0.68) | (1.34) | (1.29) |
| Log(1+Firm's age) | -0.05 | -0.06 | -0.08* | -0.09* |
| | (-1.04) | (-1.25) | (-1.78) | (-1.92) |
| Debt/assets ratio | 0.32*** | 0.32*** | 0.36*** | 0.36*** |
| | (4.82) | (4.56) | (4.61) | (4.55) |
| Profits/assets ratio | -0.03 | -0.03 | -0.06*** | -0.06*** |
| | (-1.48) | (-1.52) | (-2.86) | (-2.86) |
| Tangible assets | -0.01 | -0.04 | 0.25** | 0.25** |
| | (-0.08) | (-0.46) | (2.24) | (2.29) |
| Firm credit score | -0.91*** | -0.96*** | -1.06*** | -1.07*** |
| | (-7.75) | (-8.21) | (-11.28) | (-10.68) |
| *Relationship controls* | | | | |
| Checking account | -0.06 | -0.06 | -0.33*** | -0.32*** |
| | (-0.58) | (-0.57) | (-2.79) | (-2.67) |
| Log(1+Duration) | -0.15*** | -0.15*** | -0.09*** | -0.09*** |
| | (-2.89) | (-2.85) | (-2.60) | (-2.68) |
| Number of lenders | 0.19*** | 0.20*** | 0.11*** | 0.11*** |
| | (5.10) | (5.13) | (5.76) | (5.72) |
| Log(1+Distance) | 0.05* | 0.05* | 0.00 | 0.00 |
| | (1.84) | (1.80) | (-0.15) | (-0.19) |
| *Market-level controls* | | | | |
| HHI deposit market | -0.64 | -0.64 | 0.50 | 0.45 |
| | (-1.55) | (-1.62) | (1.38) | (1.18) |
| Firm in MSA | 0.01 | 0.01 | 0.28*** | 0.26*** |
| | (0.07) | (0.10) | (3.27) | (3.08) |
| Observations | 2,830 | 2,830 | 4,540 | 4,540 |
| Pseudo $R^2$ (%) | 17.83 | 17.52 | 18.57 | 17.87 |

## Table 6 – The effect of the homestead exemptions on Loan size

The table lists the coefficients from a linear regression of *Log(Loan size)* on the set of variables reported. The model also includes (estimates not shown) year dummies, one-digit SIC dummies, loan type dummies, lender type dummies, and a dummy for whether it is a floating rate loan. In the first specification, *Log(1+Exemption)*, we impute for the unlimited exemptions the maximum homestead exemption in the same period. *Adjusted exemption* is given by: *-Log(1+max{z,0})*, where *z* is the equity of the residence of the firm's owner minus the homestead exemption. The row "Δ Exemptions (0-Unlimited)" refers to the estimated change of the dependent variable that results from changing the exemption level from zero to unlimited. For the first specification (columns 1 and 3) we set the unlimited exemption to the maximum exemption level in the 1998 SSBF ($200,000). For the specification that uses the adjusted exemptions (columns 2 and 4), we set the value of the home equity to its sample median (equals $80,000 for the unlimited liability firms, and $140,000 for the limited liability firms). The dataset comprises the 1998 and 2003 SSBF. Robust t-statistics (standard errors are clustered at the state level) are provided in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Variable | Unlimited liability | | Limited liability | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(1+Exemption) | -0.05** | | 0.02 | |
| | (-2.35) | | (0.91) | |
| Log(1+Home equity) | 0.04*** | | 0.03** | |
| | (2.85) | | (2.39) | |
| Adjusted exemption | | -0.02* | | -0.01 |
| | | (-1.89) | | (-1.53) |
| Δ Exemptions (0-Unlimited) | -0.59 | -0.24 | 0.22 | -0.13 |
| *State level controls* | | | | |
| Judicial foreclosure | -0.08 | -0.04 | 0.08 | 0.06 |
| | (-0.67) | (-0.43) | (0.91) | (0.85) |
| State median income | 0.84** | 0.90** | 0.30 | 0.09 |
| | (1.97) | (2.14) | (0.88) | (0.26) |
| *Firm-level controls* | | | | |
| Log(1+Net worth) | 1.58*** | 1.62*** | 1.19*** | 1.21*** |
| | (2.99) | (3.09) | (7.64) | (8.15) |
| African-American | -0.03 | 0.01 | 0.22 | 0.15 |
| | (-0.11) | (0.05) | (0.94) | (0.64) |
| Owner education | 0.11*** | 0.11*** | 0.04 | 0.04 |
| | (2.71) | (2.85) | (1.10) | (1.16) |
| Log(1+Employees) | 0.40*** | 0.39*** | 0.53*** | 0.53*** |
| | (4.29) | (4.20) | (11.93) | (11.53) |
| Family owned | -0.75*** | -0.76*** | -0.18* | -0.18* |
| | (-4.01) | (-4.13) | (-1.76) | (-1.79) |
| Log(1+Firm's age) | 0.16** | 0.17** | 0.04 | 0.05 |
| | (2.01) | (2.04) | (0.66) | (0.70) |
| Debt/assets ratio | 0.13 | 0.15 | -0.02 | -0.02 |
| | (1.23) | (1.37) | (-0.19) | (-0.19) |
| Profits/assets ratio | -0.14*** | -0.14*** | -0.10*** | -0.10*** |
| | (-3.73) | (-3.66) | (-3.59) | (-3.65) |
| Tangible assets | -0.12 | -0.12 | 0.00 | 0.00 |
| | (-0.85) | (-0.84) | (0.00) | (-0.01) |
| Firm credit score | -0.12 | -0.11 | 0.55*** | 0.56*** |
| | (-0.59) | (-0.50) | (3.82) | (3.90) |
| *Relationship controls* | | | | |
| Checking account | -0.08 | -0.11 | 0.27** | 0.27** |
| | (-0.72) | (-1.04) | (2.29) | (2.18) |
| Log(1+Duration) | -0.07 | -0.06 | -0.08** | -0.08** |
| | (-0.83) | (-0.70) | (-2.05) | (-1.97) |
| Number of lenders | 0.02 | 0.02 | 0.05* | 0.05** |
| | (0.35) | (0.33) | (1.90) | (1.95) |
| Log(1+Distance) | 0.04 | 0.04 | 0.05* | 0.05** |
| | (0.94) | (1.00) | (1.78) | (1.96) |
| *Market-level controls* | | | | |
| HHI deposit market | -0.25 | -0.26 | -0.31 | -0.28 |
| | (-0.63) | (-0.66) | (-0.91) | (-0.8) |
| Firm in MSA | 0.22 | 0.23 | 0.10 | 0.12 |
| | (1.44) | (1.59) | (1.09) | (1.24) |
| Observations | 562 | 562 | 1,920 | 1,920 |
| Pseudo $R^2$ (%) | 49.46 | 48.96 | 46.87 | 46.67 |

## Table 7 – The effect of the homestead exemptions on Loan rate

The table lists the coefficients from a linear regression of *Loan rate* on the set of variables reported. The model also includes (estimates not shown) year dummies, one-digit SIC dummies, loan type dummies, lender type dummies, and a dummy for whether it is a floating rate loan. In the first specification, *Log(1+Exemption)*, we impute for the unlimited exemptions the maximum homestead exemption in the same period. *Adjusted exemption* is given by: *-Log(1+max{z,0})*, where *z* is the equity of the residence of the firm's owner minus the homestead exemption. The row "Δ Exemptions (0-Unlimited)" refers to the estimated change of the dependent variable that results from changing the exemption level from zero to unlimited. For the first specification (columns 1 and 3) we set the unlimited exemption to the maximum exemption level in the 1998 SSBF ($200,000). For the specification that uses the adjusted exemptions (columns 2 and 4), we set the value of the home equity to its sample median (equals $80,000 for the unlimited liability firms, and $140,000 for the limited liability firms). The dataset comprises the 1998 and 2003 SSBF. Robust t-statistics (standard errors are clustered at the state level) are provided in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Variable | Unlimited liability | | Limited liability | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(1+Exemption) | 0.09 | | 0.10*** | |
| | (1.49) | | (3.94) | |
| Log(1+Home equity) | -0.09* | | -0.01 | |
| | (-1.66) | | (-0.36) | |
| Adjusted exemption | | 0.03 | | 0.02 |
| | | (1.06) | | (1.26) |
| Δ Exemptions (0-Unlimited) | 1.15 | 0.38 | 1.19 | 0.27 |
| *State level controls* | | | | |
| Judicial foreclosure | -0.01 | -0.08 | -0.13 | -0.23 |
| | (-0.02) | (-0.23) | (-0.72) | (-1.21) |
| State median income | 0.03 | -0.18 | -0.35 | -0.63 |
| | (0.02) | (-0.13) | (-0.54) | (-0.89) |
| *Firm-level controls* | | | | |
| Log(1+Net worth) | -0.74 | -0.93* | -1.22*** | -1.15*** |
| | (-1.57) | (-1.69) | (-3.91) | (-3.69) |
| African-American | 2.02 | 1.92 | 1.39 | 1.23 |
| | (1.49) | (1.42) | (1.26) | (1.09) |
| Owner education | -0.21** | -0.23** | -0.11 | -0.11 |
| | (-2.51) | (-2.45) | (-0.95) | (-0.96) |
| Log(1+Employees) | -0.07 | -0.08 | -0.40*** | -0.39*** |
| | (-0.44) | (-0.46) | (-6.27) | (-6.11) |
| Family owned | 0.70 | 0.74 | -0.27 | -0.29 |
| | (1.49) | (1.47) | (-0.99) | (-1.08) |
| Log(1+Firm's age) | -0.42** | -0.47** | 0.03 | 0.04 |
| | (-2.07) | (-2.30) | (0.23) | (0.38) |
| Debt/assets ratio | 0.83** | 0.78** | -0.08 | -0.08 |
| | (2.53) | (2.36) | (-0.42) | (-0.44) |
| Profits/assets ratio | 0.21* | 0.21* | -0.01 | -0.01 |
| | (1.70) | (1.72) | (-0.09) | (-0.07) |
| Tangible assets | -0.14 | -0.13 | 0.00 | -0.05 |
| | (-0.25) | (-0.25) | (-0.01) | (-0.16) |
| Firm credit score | -0.35 | -0.41 | -0.64* | -0.63 |
| | (-0.68) | (-0.93) | (-1.64) | (-1.58) |
| *Relationship controls* | | | | |
| Checking account | 0.44 | 0.49 | 0.11 | 0.08 |
| | (0.97) | (1.07) | (0.48) | (0.33) |
| Log(1+Duration) | -0.14 | -0.15 | -0.01 | 0.00 |
| | (-0.86) | (-0.95) | (-0.20) | (-0.06) |
| Number of lenders | 0.09 | 0.09 | 0.04 | 0.04 |
| | (0.81) | (0.85) | (0.91) | (0.83) |
| Log(1+Distance) | -0.10 | -0.11 | 0.10 | 0.10 |
| | (-0.94) | (-1.05) | (1.00) | (1.03) |
| *Market-level controls* | | | | |
| HHI deposit market | 0.62 | 0.67 | 1.66* | 1.72* |
| | (0.46) | (0.49) | (1.84) | (1.90) |
| Firm in MSA | -0.07 | -0.12 | 0.13 | 0.17 |
| | (-0.20) | (-0.31) | (0.66) | (0.83) |
| Observations | 562 | 562 | 1,920 | 1,920 |
| Pseudo $R^2$ (%) | 35.31 | 34.45 | 30.6 | 30.32 |

## Table 8 – The effect of the homestead exemptions on Loan maturity

The table lists the coefficients from a linear regression of *Log(1+Loan maturity)* on the set of variables reported. The model also includes (estimates not shown) year dummies, one-digit SIC dummies, loan type dummies, lender type dummies, and a dummy for whether it is a floating rate loan. In the first specification, *Log(1+Exemption)*, we impute for the unlimited exemptions the maximum homestead exemption in the same period. *Adjusted exemption* is given by: *-Log(1+max{z,0})*, where *z* is the equity of the residence of the firm's owner minus the homestead exemption. The row "Δ Exemptions (0-Unlimited)" refers to the estimated change of the dependent variable that results from changing the exemption level from zero to unlimited. For the first specification (columns 1 and 3) we set the unlimited exemption to the maximum exemption level in the 1998 SSBF ($200,000). For the specification that uses the adjusted exemptions (columns 2 and 4), we set the value of the home equity to its sample median (equals $80,000 for the unlimited liability firms, and $140,000 for the limited liability firms). The dataset comprises the 1998 and 2003 SSBF. Robust t-statistics (standard errors are clustered at the state level) are provided in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Variable | Unlimited liability | | Limited liability | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(1+Exemption) | -0.02 | | 0.02*** | |
| | (-1.42) | | (2.56) | |
| Log(1+Home equity) | 0.02** | | 0.00 | |
| | (1.98) | | (0.15) | |
| Adjusted exemption | | -0.02*** | | 0.00 |
| | | (-3.44) | | (0.50) |
| Δ Exemptions (0-Unlimited) | -0.27 | -0.19 | 0.25 | 0.02 |
| *State level controls* | | | | |
| Judicial foreclosure | 0.11* | 0.12** | 0.11*** | 0.08** |
| | (1.79) | (2.16) | (2.78) | (2.05) |
| State median income | 0.40 | 0.36 | 0.23 | 0.14 |
| | (1.56) | (1.56) | (1.32) | (0.75) |
| *Firm-level controls* | | | | |
| Log(1+Net worth) | -0.05 | -0.07 | -0.14*** | -0.13*** |
| | (-0.21) | (-0.31) | (-2.78) | (-2.66) |
| African-American | 0.06 | 0.06 | 0.14 | 0.10 |
| | (0.56) | (0.56) | (1.37) | (0.97) |
| Owner education | -0.06 | -0.06 | -0.02 | -0.02 |
| | (-1.60) | (-1.62) | (-0.95) | (-0.97) |
| Log(1+Employees) | 0.07* | 0.07 | 0.03 | 0.03 |
| | (1.72) | (1.62) | (1.47) | (1.48) |
| Family owned | 0.22* | 0.21* | 0.07 | 0.07 |
| | (1.77) | (1.67) | (1.55) | (1.46) |
| Log(1+Firm's age) | 0.02 | 0.02 | 0.01 | 0.01 |
| | (0.56) | (0.52) | (0.30) | (0.38) |
| Debt/assets ratio | 0.06 | 0.06 | 0.01 | 0.01 |
| | (0.76) | (0.83) | (0.33) | (0.35) |
| Profits/assets ratio | -0.04 | -0.03 | 0.00 | 0.00 |
| | (-1.45) | (-1.28) | (0.01) | (0.05) |
| Tangible assets | 0.15 | 0.16* | 0.27*** | 0.26*** |
| | (1.51) | (1.63) | (4.71) | (4.45) |
| Firm credit score | -0.05 | -0.03 | 0.06 | 0.07 |
| | (-0.46) | (-0.36) | (0.76) | (0.80) |
| *Relationship controls* | | | | |
| Checking account | -0.12 | -0.15 | -0.12** | -0.12** |
| | (-1.23) | (-1.45) | (-2.03) | (-1.96) |
| Log(1+Duration) | -0.01 | 0.00 | -0.07*** | -0.07*** |
| | (-0.12) | (0.05) | (-3.17) | (-2.99) |
| Number of lenders | 0.00 | 0.00 | -0.03** | -0.03** |
| | (0.12) | (0.14) | (-2.43) | (-2.43) |
| Log(1+Distance) | 0.02 | 0.02 | 0.01 | 0.01 |
| | (1.11) | (1.06) | (0.62) | (0.69) |
| *Market-level controls* | | | | |
| HHI deposit market | 0.31 | 0.32 | 0.11 | 0.13 |
| | (1.15) | (1.16) | (0.50) | (0.57) |
| Firm in MSA | 0.19** | 0.19** | 0.02 | 0.03 |
| | (2.27) | (2.37) | (0.29) | (0.45) |
| Observations | 516 | 516 | 1,821 | 1,821 |
| Pseudo $R^2$ (%) | 47.88 | 48.18 | 41.61 | 41.32 |

## Table 9 - The effect of the homestead exemptions on the likelihood of Personal real estate collateral

The table lists the coefficients from a probit regression of *Collateral – Personal real estate* on the set of variables reported. The model also includes (estimates not shown) year dummies, one-digit SIC dummies, loan type dummies, and lender type dummies. In the first specification, *Log(1+Exemption)*, we impute for the unlimited exemptions the maximum homestead exemption in the same period. *Adjusted exemption* is given by: *-Log(1+max{z,0})*, where *z* is the equity of the residence of the firm's owner minus the homestead exemption. The row "Δ Exemptions (0-Unlimited)" refers to the predicted change in probability of the dependent variable that results from changing the exemption level from zero to unlimited. The effect was calculated at the mean value of the other independent variables. For the first specification (columns 1 and 3) we set the unlimited exemption to the maximum exemption level in the 1998 SSBF ($200,000). For the specification that uses the adjusted exemptions (columns 2 and 4), we set the value of the home equity to its sample median (equals $80,000 for the unlimited liability firms, and $140,000 for the limited liability firms). The dataset comprises the 1993 and 2003 SSBF. Robust t-statistics (standard errors are clustered at the state level) are provided in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Variable | Unlimited liability | | Limited liability | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(1+Exemption) | -0.06 | | -0.02 | |
| | (-1.24) | | (-0.44) | |
| Log(1+Home equity) | 0.03* | | 0.00 | |
| | (1.65) | | (-0.02) | |
| Adjusted exemption | | -0.04** | | -0.01 |
| | | (-2.47) | | (-1.31) |
| Δ Exemptions (0-Unlimited) | -0.11 | -0.07 | -0.03 | -0.02 |
| *State level controls* | | | | |
| Judicial foreclosure | -0.30 | -0.28* | -0.06 | -0.05 |
| | (-1.61) | (-1.75) | (-0.40) | (-0.36) |
| State median income | 1.17 | 1.14* | 0.43 | 0.35 |
| | (1.60) | (1.73) | (0.63) | (0.53) |
| *Firm-level controls* | | | | |
| Log(1+Net worth) | 0.01 | -0.16 | -0.99*** | -1.11*** |
| | (0.02) | (-0.27) | (-2.72) | (-3.04) |
| African-American | 0.08 | 0.13 | -0.16 | -0.12 |
| | (0.18) | (0.33) | (-0.42) | (-0.34) |
| Owner education | 0.03* | 0.03 | -0.07 | -0.07 |
| | (1.67) | (0.29) | (-1.25) | (-1.23) |
| Log(1+Employees) | -0.37*** | -0.37*** | 0.01 | 0.00 |
| | (-2.58) | (-2.72) | (0.13) | (0.04) |
| Family owned | 0.00 | 0.00 | 0.29** | 0.30** |
| | (0.35) | (0.00) | (1.96) | (1.99) |
| Log(1+Firm's age) | 0.18 | 0.15 | 0.05 | 0.04 |
| | (-0.1) | (1.48) | (0.66) | (0.58) |
| Debt/assets ratio | -0.02 | 0.00 | 0.37*** | 0.37*** |
| | (0.13) | (-0.02) | (3.08) | (3.12) |
| Profits/assets ratio | 0.01 | 0.01 | 0.02 | 0.01 |
| | (0.14) | (0.12) | (0.37) | (0.35) |
| Tangible assets | 0.04 | 0.07 | -0.24* | -0.22 |
| | (-0.84) | (0.24) | (-1.64) | (-1.50) |
| Firm credit score | -0.25* | -0.30 | -0.18 | -0.20 |
| | (-1.78) | (-1.02) | (-0.94) | (-1.04) |
| *Relationship controls* | | | | |
| Checking account | -0.48 | -0.55** | -0.38** | -0.37** |
| | (0.33) | (-2.02) | (-2.45) | (-2.38) |
| Log(1+Duration) | 0.03 | 0.04 | 0.02 | 0.02 |
| | (-0.52) | (0.50) | (0.35) | (0.32) |
| Number of lenders | -0.03 | -0.02 | 0.02 | 0.02 |
| | (0.00) | (-0.33) | (0.46) | (0.55) |
| Log(1+Distance) | -0.01 | -0.02 | -0.05* | -0.05* |
| | (-0.31) | (-0.56) | (-1.70) | (-1.63) |
| *Market-level controls* | | | | |
| HHI deposit market | -1.11 | -1.07 | 0.14 | 0.16 |
| | (-1.51) | (-1.53) | (0.24) | (0.29) |
| Firm in MSA | 0.01 | 0.01 | -0.08 | -0.08 |
| | (0.05) | (0.04) | (-0.37) | (-0.38) |
| Observations | 562 | 562 | 1,920 | 1,920 |
| Pseudo $R^2$ (%) | 24.96 | 25.60 | 15.21 | 15.38 |

## Table 10 - The effect of the homestead exemptions on the likelihood of Business collateral

The table lists the coefficients from a probit regression of *Collateral - Business assets* on the set of variables reported. The model also includes (estimates not shown) year dummies, one-digit SIC dummies, loan type dummies, and lender type dummies. In the first specification, *Log(1+Exemption)*, we impute for the unlimited exemptions the maximum homestead exemption in the same period. *Adjusted exemption* is given by: *-Log(1+max{z,0})*, where *z* is the equity of the residence of the firm's owner minus the homestead exemption. The row "Δ Exemptions (0-Unlimited)" refers to the predicted change in probability of the dependent variable that results from changing the exemption level from zero to unlimited. The effect was calculated at the mean value of the other independent variables. For the first specification (columns 1 and 3) we set the unlimited exemption to the maximum exemption level in the 1998 SSBF ($200,000). For the specification that uses the adjusted exemptions (columns 2 and 4), we set the value of the home equity to its sample median (equals $80,000 for the unlimited liability firms, and $140,000 for the limited liability firms). The dataset comprises the 1998 and 2003 SSBF. Robust t-statistics (standard errors are clustered at the state level) are provided in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Variable | Unlimited liability | | Limited liability | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(1+Exemption) | 0.09*** | | -0.01 | |
| | (2.57) | | (-0.41) | |
| Log(1+Home equity) | 0.01 | | 0.01 | |
| | (0.26) | | (0.72) | |
| Adjusted exemption | | 0.03** | | -0.00 |
| | | (2.25) | | (-0.02) |
| Δ Exemptions (0-Unlimited) | 0.33 | 0.13 | -0.05 | -0.00 |
| *State level controls* | | | | |
| Judicial foreclosure | 0.08 | 0.02 | -0.18* | -0.16 |
| | (0.56) | (0.16) | (-1.78) | (-1.52) |
| State median income | 0.53 | 0.45 | -0.46 | -0.40 |
| | (0.76) | (0.68) | (-1.18) | (-0.98) |
| *Firm-level controls* | | | | |
| Log(1+Net worth) | 0.14 | 0.26 | 0.05 | 0.08 |
| | (0.46) | (0.86) | (0.26) | (0.38) |
| African-American | -0.94* | -1.01** | 0.16 | 0.16 |
| | (-1.93) | (-2.06) | (0.55) | (0.54) |
| Owner education | -0.02 | 0.00 | 0.03 | 0.03 |
| | (-0.18) | (0.00) | (0.68) | (0.71) |
| Log(1+Employees) | 0.11 | 0.12 | 0.13*** | 0.13*** |
| | (1.13) | (1.15) | (3.2) | (3.23) |
| Family owned | 0.03 | 0.02 | -0.20* | -0.20* |
| | (0.09) | (0.06) | (-1.72) | (-1.71) |
| Log(1+Firm's age) | 0.14 | 0.18* | 0.05 | 0.05 |
| | (1.53) | (1.91) | (0.87) | (0.87) |
| Debt/assets ratio | 0.03 | 0.01 | 0.04 | 0.04 |
| | (0.18) | (0.07) | (0.35) | (0.32) |
| Profits/assets ratio | -0.08 | -0.09 | -0.07* | -0.07* |
| | (-1.19) | (-1.35) | (-1.69) | (-1.71) |
| Tangible assets | -0.03 | -0.02 | 0.31* | 0.31* |
| | (-0.13) | (-0.09) | (1.76) | (1.75) |
| Firm credit score | -0.57*** | -0.50** | -0.16 | -0.15 |
| | (-2.82) | (-2.40) | (-1.09) | (-1.01) |
| *Relationship controls* | | | | |
| Checking account | -0.18 | -0.11 | 0.30** | 0.30** |
| | (-1.04) | (-0.62) | (2.14) | (2.12) |
| Log(1+Duration) | -0.16** | -0.19*** | 0.00 | 0.00 |
| | (-2.15) | (-2.80) | (-0.01) | (0.00) |
| Number of lenders | -0.01 | -0.01 | 0.07*** | 0.07*** |
| | (-0.13) | (-0.24) | (2.93) | (2.93) |
| Log(1+Distance) | -0.02 | -0.01 | -0.02 | -0.02 |
| | (-0.36) | (-0.2) | (-0.65) | (-0.68) |
| *Market-level controls* | | | | |
| HHI deposit market | 0.43 | 0.42 | 0.17 | 0.17 |
| | (0.82) | (0.81) | (0.33) | (0.33) |
| Firm in MSA | -0.17 | -0.16 | -0.08 | -0.09 |
| | (-1.06) | (-0.98) | (-0.58) | (-0.61) |
| Observations | 562 | 562 | 1,920 | 1,920 |
| Pseudo $R^2$ (%) | 20.9 | 20.96 | 13.03 | 12.96 |