Financing Small Firms: Lender Relationships and Information Spillovers

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Introduction

Small and medium enterprises (SMEs) play a key role in the world economy. Not only do they account for a considerable share of output and employment,[1] but they are also widely considered as the primary engine of economic growth and the major contributors to innovation.

At the heart of a healthy and vibrant small firms sector lies an efficient transfer of funds to firms with good investment opportunities. To innovate and expand, these firms require an efficient intermediation, based on a good understanding of the risks and returns. Unfortunately, such an evaluation of the risks and rewards is difficult to perform given the severe information asymmetries that exist between the providers of external capital and the often privately-owned small firms. As a result, the access of SMEs to external finance is often limited to intermediaries that have competitive advantages in providing capital to these opaque firms. By far, the most important outside providers of capital for SMEs are financial intermediaries such as commercial banks and finance companies, and the firms' suppliers of inputs. Together, they represent an average 85% of all outside debt and equity, and 95% of outside debt of non-farm, non-financial small firms in the US (Berger and Udell 1998).[2]

This thesis empirically investigates possible reasons that award financial intermediaries and suppliers such a central role in the financing of small firms. Chapter 3 addresses a question that lies at the heart of the modern theory of financial intermediation. This literature builds on the existence of market frictions such as information asymmetries and agency costs to explain how institutional creditors may overcome these problems by producing information about the firms and using it on the credit decisions. As described in the literature review (Chapter 1), the most recent devel-

[1]For example, in the US small firms - i.e. firms with fewer than 500 employees - account for around fifty percent of output and employment in the US (Office of Advocacy, SBA report to the president, 2006).

[2]Outside debt and equity refers to all debt or equity that is not provided by any of the owners of the firms, their relatives or their friends, and that likewise does not come from retained earnings.

opments in this field recognize that one important source of competitive advantage of banks[3] in lending to small firms lies on their ability to collect 'soft' information, i.e. primarily subjective and qualitative information about the firms' (or their owners') repayment capacity. While numerous studies have showed evidence of financial institutions collecting proprietary information and using it in their credit decisions, few of them have ever tried to disentangle empirically whether this proprietary information (or part of it) is soft or hard, or what is the relative importance of each of these sources in the lending decision. Chapter 3 fills these gaps, by focusing on the importance of soft information in the decision to grant a loan or not. As a follow-up, Chapter 4 studies the role of soft information in the setting of the terms of the loans provided by the intermediaries.

The main empirical obstacle that we encounter in Chapters 3 and 4 is the unavailability of measures of soft information. By definition, soft information cannot be summarized unequivocally in a quantitative measure, thus making the empirical research on the importance of soft information especially challenging. In both chapters, I deal with this problem by taking an indirect approach. Using a very detailed database on the financing practices of small businesses, conducted for the Board of Governors of the Federal Reserve System (and described in depth in Chapter 2), I first identify the banks that have the possibility to incorporate soft information about their potential borrowers in their credit decisions. This identification is carried out in Section 3.3.1. Then, I identify a number of variables containing relevant 'hard' facts about the firms' credit quality that could be available to all banks - those in possession of soft information and those without soft information - and that are important determinants of the credit decisions made by banks. Finally, I determine whether the access to soft information changes the relative importance that banks assign to these previously identified variables in their credit decisions. The premise is the following: if soft information matters, then the access to soft information should render these

[3] Throughout the text, I will use the terms "bank" and "financial institution" as synonyms.

public ‘hard’ variables redundant and hence the importance given to these variables should be reduced when banks have access to soft information.

The variables identified as the ones containing relevant publicly available ‘hard’ information about the firms’ credit quality are different depending on the lender’s decision under analysis. In Chapter 3, where the binary credit-granting decision is under scrutiny, these ‘hard’ variables refer to the outside reputation of the firms, as earned through other credit relationships. It has been often argued that the reputation may determine the access of firms to credit (Diamond 1989). Hence, I use two proxies for outside reputation: the existence of a default by the owner or its principal owner, and the average percentage of purchases on credit that are paid after their due date. I analyze the relative importance set to these variables according to the information sets available to the lenders in Sections 3.3.3 and 3.6, the former being actually the core section of Chapter 3. I find that banks that do not have soft information about a firm are significantly less likely to grant a loan if the firm has a negative reputation, with respect to a caeteris paribus firm with a positive reputation. In contrast, institutions that have access to soft information are significantly less sensitive to changes in the firms’ outside reputation.

Figure 1 contains a schematic representation of the main findings of Chapter 3, as obtained from the analysis of Section 3.3.3. The horizontal axis represents a widely available external measure of the firm’s reputation, as measured (in reverse form) by the average proportion of purchases on credit paid after the due date.[4] The four lines represent the estimated probability with which a bank grants a loan to an average firm with different levels of reputation, all else equal. Each of the lines differs only on the type of information available for the banks: no private information, only soft information, only hard information, or both types of private information. The strong reaction of the privately uninformed banks to the outside reputation of the firms is represented by the very steep slope of the dotted line. Once the bank gathers

[4] The graph represents the estimated probabilities of obtaining a bank loan for the average firm on the model estimated in the second column of Table 11. Refer to the figure for more information.

private information, soft or hard, about the firm's quality, the slope is smoothed. In particular, the slope for soft information availability is less steep than the slope for no information availability. In fact, the difference in slope is statistically significant. Hence, soft information does seem to be an important determinant of the small firms' access to credit.

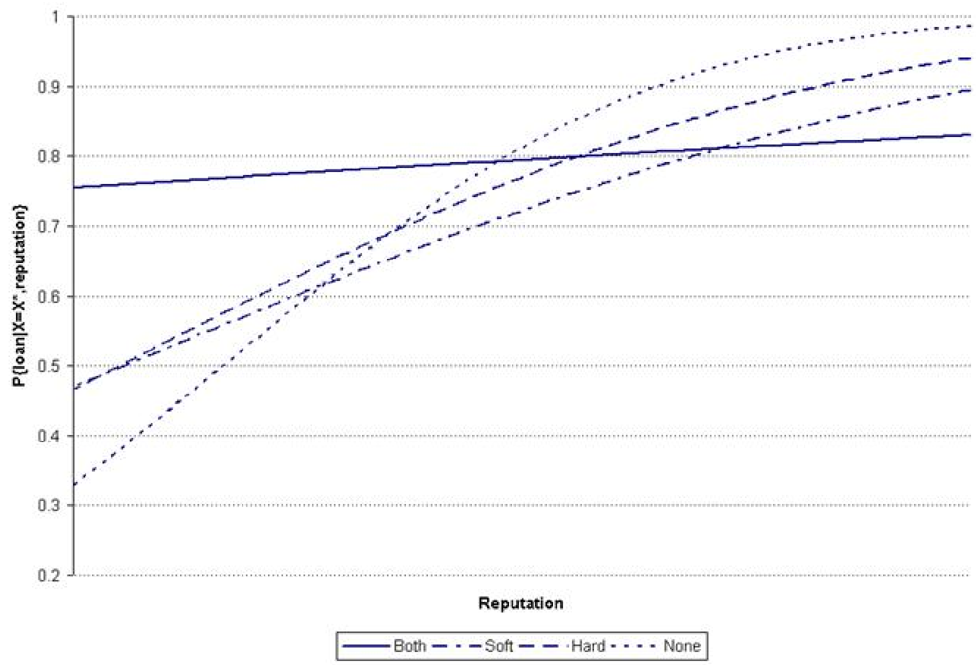

Figure 1: Information availability and small firm lending

This figure represents the estimated probability of obtaining a bank loan for an average firm under different information availabilities of the lender, and as a function of the outside reputation of the firm. The estimated probabilities are calculated from the model of Column 2 in Table 11. Hence, the (reverse) measure of reputation used regards the proportion of purchases on credit that the firm pays after the due date; a bank is considered to have soft information about the firm if it leads a personal relationship with the firm's owner or manager; and a bank is considered to have private hard information about the firm if they both have lead a relationship of more than one year.

The findings of Chapter 3 naturally introduce the question of whether soft information may also play a role on the determination of the loan terms used in small firm lending. Chapter 4 therefore presents an extension of the analysis of Chapter 3 to the determination of interest rates and collateral requirements, and explores whether there may be cases in which banks give preferential treatment (lower interest rate, lower probability of asking to post collateral) to 'character' loans - that is, the loans based primarily on soft information. As explained before, the approach used in this chapter is similar to the one in Chapter 3. Hence, having already identified in that chapter the banks that could use soft information and those that couldn't, we are left with the task of identifying widely available 'hard' variables likely to affect the interest rate and the collateral requirements, respectively.

When dealing with the interest rate set for the loans in Section 4.2, I select a home ownership binary variable as the publicly observed measure that is likely to affect the bank's cost of lending to a given firm - and hence the interest rate charged. On the other hand, in Section 4.3 I use a binary variable containing previous defaults as the measure that may affect the likelihood of the bank of requiring the firm to post collateral. A complete econometric argumentation of why these variables are chosen is present, respectively, in Sections 4.2.1 and 4.3.1. Then, as before, I compare how the availability of soft information changes the behavior of banks regarding these measures with respect to the non-availability of such information.

The analyses in Chapter 4 require a slightly different methodological approach than those of Chapter 3 due to the fact that interest rates and collateral requirements can only be observed on the sample of firms that were granted a loan. As pointed out by Stiglitz and Weiss in their seminal 1981 paper, in an asymmetric information framework prices do not always adjust to clear the markets. This means that some firms may be rationed from the credit rather than charged a higher interest rate. Translated in econometric terms, this means that the pool of firms that we observe may present a selection bias, since the variables that are likely to affect the interest rate charged or the availability of collateral requirements also affect the likelihood of being in the observed sample. To deal with this problem, I augment the analyses with a simple Heckman selection-robust estimation procedure. The selection-robust estimations for the interest rate are found in Section 4.2.3, and the corresponding estimations for collateral are found in Section 4.3.3. Notably, the estimations obtained through this procedure are very stable throughout different specifications, both for the interest rate and for the collateral requirements.

The results regarding the importance of soft information on the setting of the interest rates can be summarized in Figure 2. The horizontal axis represents a measure of the bank's cost to lend to the borrower (high when the owner of the firm does not have a house, low otherwise). The vertical axis, on the other hand, contains the estimated average interest rate charged to the borrower, all else equal except for the cost of lending to the borrower and the information available to the lender. Each of the lines represent the estimated interest rate whenever the financial institution granting the loan has soft / hard / both / no information about its customer.[5] As can be seen in the upper line of the graph, the banks that do not have any private information about the firms are most likely to react to the cost of lending and set significantly higher rates whenever the cost of lending increases. However, the availability of any kind of private information - soft or hard - about the firm makes this reaction much smoother.

Regarding the collateral requirements, the main findings may be summarized in Figure 3. This figure represents the estimated probabilities of each firm to be required to post collateral, depending on the information available to their lenders, and as a function of their reputation.[6] The negatively-sloped lines in the figure represent the lower probability of asking to post collateral for firms that have obtained a good reputation in previous credit relationships. From the figure we can observe that the availability of soft information seems to *increase*, rather than decrease, the probability of requiring the firm to post collateral, and that this is especially true whenever the firm has a negative reputation. One interpretation of these findings is that banks

[5]The graphed coefficients correspond to the model estimated in the third column of Table 23. For more information, refer to the graph.

[6]The model I use to predict the probabilities is that in the third column of Table 27. For more information, refer to the figure.

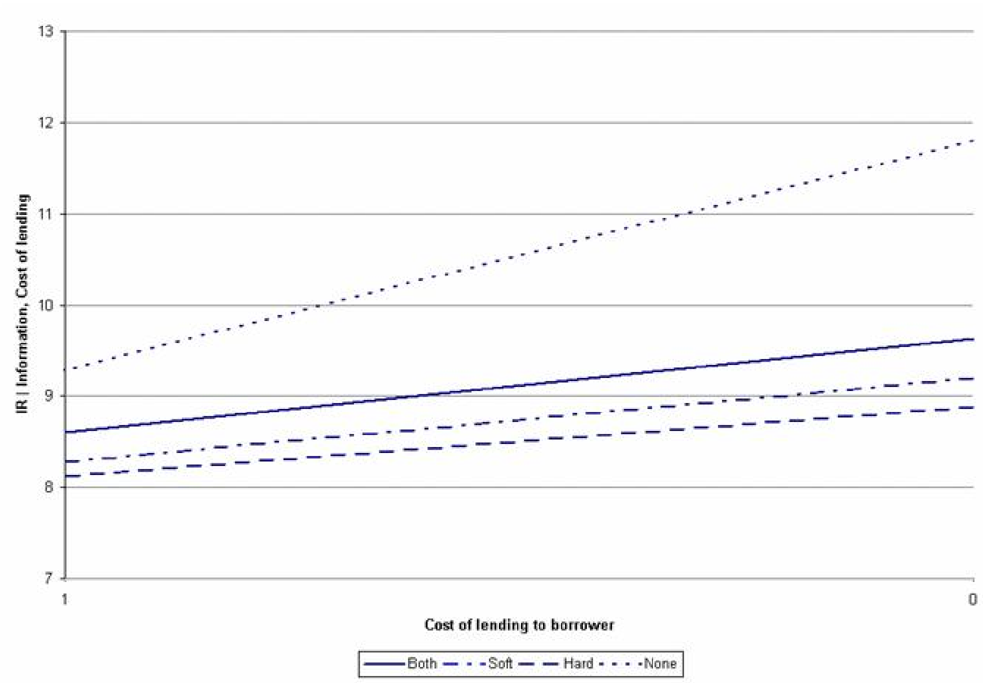

Figure 2: Information availability and interest rates

This figure represents how the interest rate changes when the lender has access to different information sources about the borrower, as a function of the cost, from the bank's point of view, of lending to the borrower. The graphed coefficients correspond to the model estimated in the third column of Table 23. The horizontal axis represents the home ownership of the principal owner of the firm. Clearly, the latter variable can only take the extreme values of 0 or 1 , and the continuous lines show only the general tendency of banks to charge a lower interest rate whenever the owner of the business has a home.

lending on a 'character' base (i.e. based on soft information) use collateral relatively more in order to manage the potentially higher risks due to soft information-based lending.

The findings of Chapters 3 and 4 can be jointly interpreted in the following way. We may identify four types of lending: (1) 'Relationship' lending, or lending when the bank has access to both soft and hard private information about the borrower, (2) 'Character' lending, or lending based mostly on soft information, (3) 'Hard information' lending, or lending when the bank has access to private hard information about the firm, and (4) 'Transaction' lending, or lending when the bank lacks any kind of private information. Character lending tends to be generous regarding the access to credit for firms that do not have an outstanding credit history. Should a faulty firm apply for credit to a transaction institution, its probability of success would drop by an average 10%. Yet, character-based lending tends to be significantly more prone to ask for the posting of collateral. I interpret this as character banks managing the risk of lending based on potentially subjective considerations. On the other hand, 'transaction' lending is very vulnerable to changes in the reputation of the borrowers, and hence could be very likely to deny credit to a firm with a low outside reputation. However, a firm that gets access to credit through a transaction institution is roughly equally likely to be asked to post collateral than a relationship institution. In other words, the selection (or screening) of firms based on transaction criteria occurs during the first stage of the lending process. The greatest benefits are observed for relationship lending, where firms have a stable access to credit - independently of their outside reputation - and enjoy a significantly lower probability of having to post collateral. Finally, regarding the interest rate, I find that the availability of any kind of private information significantly lowers the interest rate charged.

As was clear from the previous paragraphs, both Chapter 3 and 4 deal with relationship lending. In a sense, relationship lending involves the creation of an internal reputation. That is, a financial institution would normally be willing to provide financing to the firms that, in the course of their relationship, provide soft or hard evidence of financial soundness or repayment capacity according to the bank's own criteria. In other words, firms that have a good internal standing with the banks - or a good internal reputation - would have better access to the credit offered by the bank. It takes time, though, to create such an internal reputation. Small firms that seek financing for the first time with a given bank can obviously not rely on their -inexistent- internal reputation within that bank. In these situations, it is reasonable to believe that banks should develop other ways of screening among a pool of ex-ante indistinguishable opaque borrowers, avoiding to select the 'lemons' as in Akerlof (1970). One such possibility would be to screen borrowers according to their credit history with their input suppliers. Because many small firms have more unrestricted access to trade credit relative to bank credit, this plausible and intuitive possibility has been frequently mentioned in the literature (Biais and Gollier 1997, Burkart, Ellingsen and Giannetti 2006). However, as discussed in Chapter 1, empirical tests about this possibility are at best very scarce. Chapter 5 therefore fills this gap by providing empirical evidence that the reputation obtained through the credit relationship with the input suppliers may affect the likelihood of firms to obtain bank credit.

The main obstacle present in the analysis of Chapter 5 is the correct identification of causality from trade credit to bank credit. I deal with the problem by exploiting the richness of the cross-sectional database described in Chapter 2, together with an instrumental variables approach and a set of relevant instruments (which is duly discussed in Chapter 5). The main result is that trade credit is indeed a valuable and credible signal of reputation for banks that are otherwise uninformed about the credit quality of their potential borrowers. The results highlight an important role of suppliers for the future access of small firms to finance, analogous to the role that banks themselves play for the access of firms to the public credit markets (James 1987). In other words, and making reference to the title of the thesis, there seem to be important "information spillovers" from suppliers to banks.

The results of the last chapter may be also interpreted at the light of the results of the previous two. Once again, the availability of private information about the firms is highlighted. Whenever the financial institution has access to any kind of private information about the firms' credit quality, potential benefits of having a good outside reputation disappear. Likewise, the potential costs of having a bad outside reputation disappear whenever the financial institutions have access to private information.

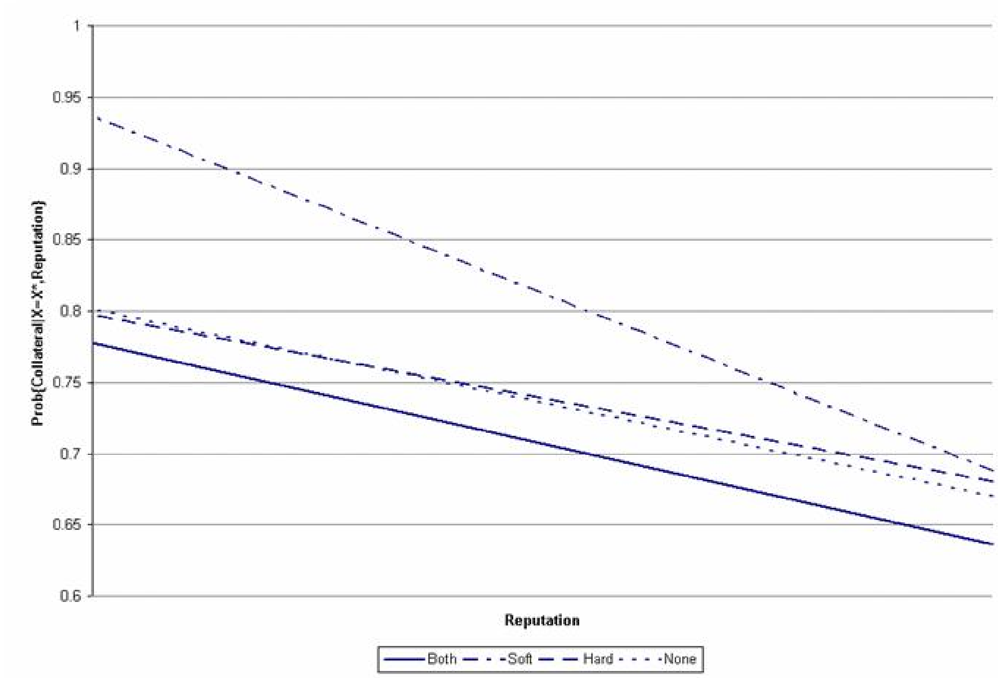

Figure 3: Information availability and collateral requirements

This figure represents the estimated probability of requiring the posting of collateral for an average firm under different information availabilities of the lender, and as a function of the outside reputation of the firm. The model used to predict the probabilities is that in the third column of Table 27. The (reverse) measure of reputation used is the existence of a previous default. Hence, in the sample we may only observe the extreme cases. Therefore, to construct this figure, first the probabilities of default are estimated, respectively, for firms that have not defaulted and for firms that have defaulted (under each of the four different information sets), and then extrapolated for the rest of the values by connecting the two extremes. The resulting negatively-sloped line represents the general tendency of banks to require collateral with a higher probability to those firms that have experienced default.

1 Related literature

The articles in this thesis pertain to the broad topic of small firm financing. The financing of such businesses is especially challenging due to the severe informational opacity that outside investors face.[7] Unlike most large firms, the contracts between the majority of small businesses and their employees, suppliers, and customers are kept private. Moreover, most of the small businesses are privately held and are not obliged to audit their financial statements or share them with potential outside investors. As a result of this informational opacity, the asymmetries of information between insiders and outsiders can be extreme. Hence, outside providers of funds in the form of either debt or equity have developed a number of specialized technologies to help overcome these problems. Such technologies usually involve screening or selecting the best potential borrowers, monitoring them, and/or contracting with them in order to control the credit risk.[8]

1.1 Relationship lending: Theoretical contributions

One lending technology that is especially suitable for the financing of small and opaque firms is what has been called in the literature as "relationship lending". Several authors have provided formal definitions for relationship lending, all of which involve an interaction between the borrower and the lender that allows the lender to extract valuable proprietary information about the borrower. Probably the most complete definition of the term has been given by Boot (2000), who defines relationship lending as " the provision of financial services by a financial intermediary that (i) invests in obtaining customer-specific information, often proprietary in nature; and (ii) evaluates the profitability of these investments through multiple interactions with the same customer over time and/or across products." Similarly, Ongena and Smith

[7]Berger and Udell (1998) provide a comprehensive review of small business finance. Other contributions to the topic appear in the August 1998 issue of the Journal of Banking and Finance.

[8]Berger and Udell (2006) provide both a framework for analyzing and a description of the most common lending technologies for small firms.

(2000) define relationship lending as "the connection between a bank and customer that goes beyond the execution of simple, anonymous, financial transactions [that may allow] the transfer of proprietary information, a commitment to continue doing business together through financially tough times, or the offer or delivery of services at prices different from costs;" while Freixas (2005) describes it as "the investment in providing financial services that will allow to repeatedly deal with the same customer [, where] the standard investment is the one made by the bank in obtaining borrower-specific information."

The above definitions reveal why relationship lending is especially relevant in the framework of small business financing. The informational wedge between borrowers and lenders is more acute in this context. Lacking financial statements and other sources of public data, these firms cannot generally access the public debt or equity markets. Hence, these firms rely almost completely on the private markets for external financing. By establishing an intertemporal relationship with their borrowers and so gathering information, financial intermediaries are able to make their credit decisions based upon this otherwise inaccessible input.

The literature on relationship lending has its roots at the heart of the modern theory of financial intermediation. Early theoretical works in this field provide a justification for the existence itself of financial intermediaries given their role as institutions which might facilitate the resolution of information asymmetries between lenders and borrowers (Leland and Pyle 1977, Bryant 1980, Diamond 1984, Ramakrishnan and Thakor 1984, Diamond 1991).[9] These theories develop on the basic premise that there exist informational asymmetries between borrowers and lenders, and explain how financial intermediaries are able to overcome them by screening, monitoring, or contracting with firms. More recent theoretical works go one step forward and concentrate on describing the further benefits (apart from overcoming information

[9]The other justification for the existence of financial institutions is their ability to provide liquidity. See Bhattacharya and Thakor (1993) for a survey of the contemporary literature of financial intermediation. A much more extensive and thoughtful analysis can be found in Freixas and Rochet (1997).

asymmetries) and identifying the potential costs of relationship lending. Among the further benefits of relationship lending we point out the disclosure of sensitive information that would otherwise remain proprietary to the firm (Bhattacharaya and Chiesa 1995), higher contracting flexibility with respect to other types of contracts due to the possibility of renegotiating (Boot, Greenbaum and Thakor 1993), reduction of conflicts of interest and agency costs through an increased control of the firm (Berlin and Mester 1992), the possibility of making an optimal use of collateral due to the monitoring capacities of banks (Rajan and Winton 1995), and provision of credible certification of payment ability (Diamond 1991). The costs of relationship lending, on the other hand, include a potential lack of toughness in the enforcement of the contracts, or the "soft budget constraint problem" (Dewatripont and Maskin 1995), and a possible informational monopoly obtained by relationship banks that leads to higher costs of lending for the clients who are locked in the relationship (Sharpe 1990, Rajan 1992).[10]

1.2 Relationship lending: Empirical contributions

Following the trends of the theoretical literature, the empirical literature on relationship lending has also followed two main routes. The first group, which includes the earliest developments in this arena, concentrates on investigating the role of banks as information producers. The pioneering work of James (1987) finds that there is a positive effect on stock prices following the announcement of a bank loan agreement or renewal, while there is no similar effect following the announcement of a private bond placement. The results suggest that bank loan announcements contain positive information about the value of the firm, and highlight the role of banks as information producers. Numerous studies have since refined the findings of James. For example, Lummer and McConnell (1989) find that it is actually bank loan renewals, and not

[10] The previous lines draw on Boot (2000). Other surveys of the relationship lending literature are present in Ongena and Smith (2000) and, more recently, Elyasiani and Goldberg (2004).

first-time loan agreements, what drives the effects found by James. This implies that it is the information accumulated by banks in the course of their relationships with firms what matters to investors. On the same lines, Slovin, Sushka, and Poloncek (1993) find a negative effect on the stock prices of firms having a relationship with the insolvent Continental Illinois in 1984, as well as a further stock price increase following the announcement of the rescue by the FDIC. More recently, Schenone (2004) and Kutsana et al (2007) find a smaller IPO underpricing whenever the issuer had a pre-existing banking relationship.

The second set of empirical papers has focused on identifying the main benefits and/or costs of such information production by relationship lenders. This growing stream of literature takes the role of financial intermediaries as information accumulators as given, and studies the effects of such relationships (measured, for example, through proxies of the duration of the relationship, breadth of the services offered by the bank, or bank or firm self-assessments) on the availability of credit and on loan terms obtained by borrowers. There is an overall international consensus that the existence of a banking relationship increases the firm's access to credit (Hoshi, Kashyap and Scharfstein 1991, Petersen and Rajan 1994, Angelini, Salvo and Ferri 1999, Cole 1998, Elsas and Krahnen 1998) and decreases the collateral requirements (Berger and Udell 1995, Harhoff and Koerting 1998, Degryse and Cayseele 2000, Chakraborty and Hu 2006). Regarding the pricing of the interest rates, the evidence is mixed. For example, in the US case, Petersen and Rajan (1994) find no significant effect of the duration of relationships on interest rate. Using the same data set, but restricting the sample only to lines of credit and excluding general loans, Berger and Udell (1995) find that interest rates decrease with the length of the relationship. Dennis, Nandy and Sharpe (2000) use a different empirical approach that recognizes the endogenous relationship between interest rates and collateral (among other variables), as well as a different sample, and find that interest rates tend to increase with the relationship. This mixed evidence has led economists to question whether the competitive environment of the banking sector may determine the relative importance of relationship lending and hence affect credit availability and loan pricing (Petersen and Rajan 1995, Angelini et al. 1999, Degryse and Ongena 2005, Elsas 2005, Montoriol 2006). The evidence, however, is still inconclusive.[11]

The theoretical and empirical articles cited above have been centered mainly on the private debt markets for bank loans. The focus on bank loans is especially relevant in the context of small business finance, given that the vast majority of small firms have access only to these markets for external finance (Berger and Udell 1998). Accordingly, the term "relationship banking" is often used as a substitute for "relationship lending". Nevertheless, the concept of relationship lending - or even, as suggested by Boot (2000), "relationship intermediation" - is applicable at a much wider scope (Berger and Udell 2002). For example, a relatively limited number of small firms can also access the private equity markets for external financing. The target firms for such investments in private equity are usually high-growth firms that may reward equity investors with hefty returns, and that lack enough tangible assets that can be posted as collateral for debt financing (Gompers 1995, Fenn, Liang and Prowse 1997). In this context, relationship lending exists in the form of the general partner usually sitting on the firm's board of directors, and constantly monitoring the firm's activities (Gompers and Lerner 1999, Smith and Smith 2004). Similarly, brokers such as investment bankers may engage in a form of relationship lending when performing the due diligence and henceforth interacting continuously with the firm and absorbing the credit risk involved in the underwriting of securities. As a final example, relationship lending may also arise in the public markets for debt, where the lead underwriter contracts closely with the firm (Dennis and Mullineaux 2000). The focus of this thesis goes in line with the trend and is centered around relationship banking, as the interest is placed in the majority of small firms that have access to

[11]For an extensive review of this empirical literature refer to Ongena and Smith (2000) or, more recently, Montoriol (2006).

bank loans (Berger and Udell 1998, Berger and Udell 2002).

1.3 Soft information

Chapter 3 of this thesis is closely related to the first stream of empirical literature on relationship banking, as it deals with the role of banks as information gatherers. Yet, it follows the most recent developments in the theoretical literature, which acknowledge that there are two basic types of information that may be collected by financial intermediaries through a relationship (Petersen 2004). On the one hand, through repeated interaction lenders may access a wide range of quantitative and objective information about the firm, such as data about the firm's cash flows and sales cycles, debt levels, and default histories. Such information has been called "hard" information. To the extent that institutions other than banks (for example, rating agencies) may collect hard information and transmit it to the public markets in the form of a numerical rating, the real source of added value in lending relationships is the accumulation of "soft" information. This is typically qualitative and subjective information that cannot be easily summarized as a number, and cannot easily be verified by third parties. Soft information refers to factors such as the honesty and the ability of the manager, and subjective evaluations about the quality and feasibility of future projects. The empirical literature on soft vs. hard information in relationship lending has focused on analyzing - implicitly or explicitly - whether Stein (2002) is right by claiming that small banks are at a comparative advantage relative to large banks in evaluating investment projects that involve soft information, whereas large banks fare better when information about investment projects can be easily "hardened". A number of empirical findings seem to confirm Stein's conjecture. First, some studies find that mergers reduce lending to small businesses (Peek and Rosengren 1998, Berger, Saunders, Scalise and Udell 1998, Sapienza 2002). Second, small banks tend to invest proportionally more to opaque small businesses than large banks (Nakamura 1994, Strahan and Weston 1998). Third, larger banks are more prone to lend based on financial data, while small banks are more relationship-oriented (Cole, Goldberg and White 2004, Berger, Miller, Petersen, Rajan and Stein 2005). Fourth, larger banks tend to operate at larger distances and in less personal ways with their lenders (Berger, Miller, Petersen, Rajan and Stein 2005). Collectively, all these findings point towards the direction suggested by Stein (2002), but still do not provide formal evidence for his theory. However, Liberti (2003,2005) explicitly analyzes the relative use of soft and hard information in different organizational structures using a very complete dataset on the lending practices of one Argentinean bank. Results from both papers provide a more direct support for the theory.

Chapter 3 deviates from the organizational structure framework of Stein. Instead, in this chapter I go back to the central assumption that holds that soft information is crucial for small business lending, test it empirically in a large sample of small firms, and compare its relative importance with respect to hard private information. In this sense, the most related work is Liberti (2005). However, his work is based on one single bank's lending practices, while the results of Chapter 3 are more general to the extent that they deal with the lending practices of a number of different banks. On the other hand, while Liberti uses direct measures of soft information - i.e., "hardened" soft information, I consider an indirect approach to soft information that makes the hardening process unnecessary.

In Chapter 4 I go one step further and examine the relative role of soft and hard information on the loan terms required in small business lending - in particular, on the price and collateral requirements. In this sense, this paper belongs to the second stream of literature of empirical relationship lending, which analyzes the benefits and costs of relationship lending. The novelty is the analysis of the importance of soft vs. hard information availability in this second stage of the lending process, which has been notably absent in the previous literature.

1.4 Trade credit literature

In Chapter 5, I deviate from the relationship lending literature and examine an alternative way in which small firms could access the private debt markets: certification by their input suppliers. The idea that input suppliers can provide certification of payment ability to firms stems from the observation that, long before small firms may access any kind of institutional credit, most small firms are offered the possibility to delay the payment of their inputs through what is known as 'trade credit' (Petersen and Rajan 1997, Berger and Udell 1998). It is natural, then, to claim that the supplier-firm relationship could provide financial institutions with a good idea of the repayment ability of the business.

In fact, some explanations for the puzzling fact that non-financial firms are willing to lend to other firms, without being substituted by specialized financial institutions, also describe how bank credit rationing could be reduced whenever a firm has access to trade credit. These are the so-called 'informational advantage' theories of trade credit.[12] Suppliers, they hypothesize, are more able than banks to infer the credit quality of opaque businesses for several reasons. First, suppliers could face lower costs than financial institutions for searching for the most adequate borrowers, as borrowers are their clients (Ferris 1981). Second, the nature of suppliers' business allows these firms to have an information advantage, either because their customers are more homogeneous than the banks' customers - they usually belong to the same industry as the supplier itself (Emery 1984, Mian and Smith 1992, Jain 2001), or because they must constantly visit their clients' premises that allows them to have more timely information about their clients' situation (Ferris 1981, Biais and Gollier 1997). Third, because suppliers deliver in kind, instead of cash which may be easily diverted for non-productive activities, they automatically learn about the firm's intentions to

[12] There are, of course, several other theories for the existence of trade credit. The works of Petersen and Rajan (1997), Cuñat (2001) and, more recently, Burkart, Ellingsen and Giannetti (2006) offer quite extensive surveys of the literature of trade credit.

produce (Burkart and Ellingsen 2004).[13]

The information advantage theories of trade credit, coupled with the observation that banks tend to investigate the nature of the trade credit relationship before making their credit decisions (Biais and Gollier 1997, Kallberg and Udell 2003, Greenbaum and Thakor 1995), lead to the plausible hypothesis that indeed, banks could seek some certification about the firm's credit quality through their relationships with suppliers. However, there have been few studies that investigate the issue empirically in a direct manner. Nevertheless, a number of recent findings do tend to point towards this direction. For example, Petersen and Rajan (1997) find that firms use trade credit relatively more when credit from financial institutions is not available, suggesting that there could indeed be some information advantage of suppliers over banks that allows them to lend whenever banks are not willing to do so. More recently, Burkart, Ellingsen, and Giannetti (2006) find that firms that use trade credit tend to borrow from a larger number of banks, utilize more distant banks, and have shorter relationships with their banks, possibly indicating that trade credit users have relatively easy access to less informed sources of finance and hence of the certification hypothesis. However, the findings in this paper can only be interpreted as evidence for the certification hypothesis if any confounding effect is eliminated and a direct link between trade credit use and credit availability is found. For a direct evidence of the certification hypothesis, we should discard the possibility of unobserved heterogeneity, i.e. an association between no access to trade credit and low quality borrowers that cannot access informed finance either. To the extent that firms that borrow from multiple sources and haven't been able to establish a banking relationship with an informed bank have been associated with having a lower credit quality (Elsas 2005), this possibility cannot be excluded ex ante.

One paper that contains more direct evidence for the link between trade credit and

[13] In fact, insofar as they are anchored in an asymmetric information framework, the explanations of Biais and Gollier (1997), Jain (2001) and Burkart and Ellingsen (2004), these explanations are akin to the justifications of the existence of financial institutions.

bank finance is Cook (1999). In an examination of the post-soviet Russian banking system, she finds that users of trade credit are more likely to obtain bank loans than non-users of trade credit. Her results are robust to confounding stories of unobserved heterogeneity and reverse causality. In this sense, Chapter 5 is most directly linked to this paper. Yet, both the sample and the methodology differs largely with respect to her study. On the one hand, the economy under scrutiny in Chapter 5 is the US. On the other hand, in this chapter I rely on an instrumental variable approach rather than on propensity score and GMM estimations to discard unobserved heterogeneity and inverse causality.

Chapter 5 also differs from Cook's approach in that I investigate more thoroughly the mechanism through which trade credit could serve as a signal for credit quality. Specifically, as in Cook, I explore the certification hypothesis *à la* Biais and Gollier (1997), studying whether the simple presence of suppliers offering credit could affect the availability of bank finance. Yet, thinking that the mere presence of suppliers may convey banks a valuable signal of credit quality is probably too simplistic and naïve: knowing that banks behave in this manner, firms could simply collude and provide trade financing to others only to be able to access the market for bank loans later on.[14] Therefore, in this chapter I go one step forward relative to Cook's approach, and investigate whether it is rather the reputation obtained through the credit relationship what really matters to banks. The approach makes sense to the extent that a crucial variable included in the reports of credit rating agencies is the credit history of the firm regarding its relationships with suppliers (Kallberg and Udell 2003). Moreover, by following this broader approach we are not limiting the study to become a test for the informational advantage theories of trade credit. Instead, trade credit can be justified through any of the existing theories: Cost advantages in lending due to the bundling of the credit offer together with the selling activity (Nadiri 1969, Emery 1984); reduction of transactions costs due to the uncertainty in the timing of

[14]In fact, Biais and Gollier (1997) rely on the assumption of non collusion between the firm and its suppliers to base their conclusions.

the arrival of new supplies (Ferris 1981) or in the reduction of the tax bill (Brick and Fung 1984); advantage in screening among borrowers by price discrimination, through the offer of payments in cash or in credit (Smith 1987); signalling product quality by enabling customers to return products with which they are unsatisfied (Smith 1987, Lee and Stowe 1993); advantage in salvaging collateral due to its higher value to suppliers than to financial institutions (Frank and Maksimovic 2004); advantage in repayment enforcement due to the threat of cutting future supplies (Cunat 2007); informational theories of trade credit. Whatever the motive for extending trade credit, the relationship between the supplier and the firm could still convey very useful information to financial intermediaries about the firm's credit quality.

In this sense, this chapter is also related to the idea of signaling quality through reputation, which has been around for decades in the economic literature. In fact, based on the more modern approach of the information asymmetries (rather than transactions costs) framework, the early works of Klein and Leffler (1981) and Shapiro (1982,1983) proposed reputation as a solution of the 'lemons' problem in general buyer-seller setups. Later on, Diamond (1989) introduced a reputation acquisition model for the financial markets for debt. In this paper, I provide evidence for this acquisition of reputation at a smaller scale, i.e. when firms pass from non-institutional trade credit to more formal sources of institutional lending. Similarly, Chapter 5 also relates to the growing literature of the value of information exchange by lenders (Jappelli and Pagano 1993, Jappelli and Pagano 2002), by providing evidence that the trade credit reports are of utmost importance for small and opaque firms to access institutional credit.

2 Data

2.1 Source of data

The main source of data for this study is the Survey of Small Business Finances (SSBF), conducted for the Board of Governors of the Federal Reserve System during 1999 and 2000. The target population is the set of all US for-profit, nonfarm, nonsubsidiary firms with fewer than 500 employees that were in operation as of year-end 1998. The resulting sample, drawn with a two stage stratified sampling scheme, consists of 3,561 firms satisfying the criteria of the SSBF.

The survey's focus on small firms is ideal for the analysis of this thesis for several reasons. First, the vast majority of these firms are private. The average ownership share of the principal owner is 80%, the median is 100%, and for only 5% of the firms does the principal owner possess less than a 30% stake of the firm. Consequently there is a small role for outside equity for the firms in the sample, and information about this type of firms is likely to be scarce and difficult to obtain. Moreover, only 12% of these firms used some type of financial statements or accounting records to respond the survey. This suggests that there is not much hard information available about these firms. In these cases, banks must rely on other sources of information in order to make their lending decision. The analysis of the use of soft information that is performed in Chapters 3 and 4 is ideally made in a setup where private information availability is crucial, as in the case of opaque firms.

Another reason why the sample is the ideal setup for the analysis of this thesis is that by far the most important external sources of finance for these firms are trade and bank credit. More than two-thirds of the firms in the sample (68%) use trade credit, and a similar number of firms (64%) used some kind of bank financing. Thus, if trade credit plays a role in bank lending (as we study in Chapter 5), the effect is likely to be present in this environment.

Finally, the great detail available in the sample makes it very suitable for the analysis of this thesis. The survey contains a description of the firms' general characteristics (size, age, industry, location, ownership structure, etc.), demographics of the owners, and a considerable amount of financial information. Among the financial information, there is an inventory of all loans, mortgages, and leases, selected balance sheet and income statement items as of year-end 1998, recent credit history of the firm and its owners, information about all the financial service suppliers of the firms, the use of trade credit, and the firms' experience in the last three years in applying for a new loan or line of credit. For many of the analyses in this thesis, I focus on the firms' most recent application for a new loan.

2.2 Construction of the sample

From the original SSBF sample, I exclude all the firms in the financial and government sectors, as well as firms with a negative amount of assets in their balance sheet.[15] Out of the remaining sample, only 900 applied for at least one new loan in the three years previous to the survey date. However, 39 of these applied for a loan to friends or family, to a government agency, or to other business firms. Since we are interested in institutional lending, I drop these 39 firms to get the final sample of 861 firms that asked for a loan to a financial institution.

The loan application for these 861 firms could have happened anytime three years before the survey date. However, most of the financial information of the firm (in particular, the balance sheet and financial statement) refers to fiscal year 1998. As it will become apparent later, some analyses require us to identify whether the application for the loan occurred before, during, or after 1998. Fortunately, this information is available in the survey: Out of these 861 firms, 429 applied for its most recent loan after, 269 during, and 163 before 1998. Eliminating the firms that applied before 1998 for a bank loan leaves us therefore with a subsample of 698 firms.

[15]The balance sheet items must satisfy the following relationship *Total Assets = Total Liabilities + Total Equity*. The survey designers forced this relationship to hold for all firms, calculating one of the items as a function of the other two. As a result, a few firms reported negative assets.

Some of the analyses in Chapter 5 can only be done on the subsample of users of trade credit. 195 firms out of the total of 861 that applied for a loan are non-users of trade credit. This leaves us with 666 firms that used trade credit and applied for a loan to a financial institution. Out of these 666 firms, 132 asked for a loan before, 203 during, and 331 after 1998.

The analyses in Chapter 4 refer to the approved loan applications. Out of the 861 firms that applied for at least one new loan to a financial institution, 639 were granted the credits for all of their loan applications. These firms are the target sample for these analyses. Out of these 639 firms, 312 were granted the credit after, 196 during, and 131 before 1998. As in the previous cases, some analyses will require the elimination of the firms that got the loan before 1998, leaving us with a sample of 508 firms.

To obtain the exact number of observations used in each of the regression analyses of the following chapters, we should take into account that some observations are lost in the process due to missing variables. To see the precise construction of each of the samples for each analysis, refer to the Appendix.

2.3 Variables

For all of the firms in the basic selected sample of 861 firms, there is information on whether the bank granted the most recent request for a loan or not.[16] With this information, I construct a binary variable to measure the response of banks towards the firm's most recent application for credit, i.e., whether the loan was granted or not. This variable will measure how the credit-granting decision of banks changes depending on the information availability of the lenders, and on the relationship between the firm and its suppliers. It will be the dependent variable in the analyses of Chapters 3 and 5.

The survey also contains information for the terms obtained for all the approved

[16] The question in the survey asks explicitly whether the recent loan was approved or denied *by the financial institution*. In other words, this variable measures the financial institution's reaction to the loan application, and not the supply and demand equilibrium outcome.

loans (interest rate charged, collateral requirements, maturity, etc.). These variables are the focus of the analyses of Chapter 4.

There are several firm characteristics that may explain the variation in the firms' credit quality and consequently, the variability of the application outcomes. I include measures for what bank analysts traditionally refer to as the "five C's of credit": Capital, capacity, character, collateral, and conditions.[17] The firm's size, age, profitability, liquidity, leverage, and sales growth are measures of its capital and repayment capacity. Some governance characteristics (for example, whether the firm has limited liability, whether it is owner managed, etc.) are measures of the firms' character. An indicator for home ownership by the principal owner of the firm is a measure for availability of collateral and, to the extent that the firm has unlimited liability, of repayment capacity. Finally, the firm's industry, its location (i.e. the geographical region and whether it is in a Metropolitan Statistical Area or not), the concentration of the banking credit market, and the year of the loan application determine the conditions that could affect the credit-granting decisions of banks.

The decision of granting the loan or not can also be related to characteristics of the particular financial institution to which the firm asked recently for a loan. It could be, for example, that venture capitalists are in general less risk averse than commercial bankers, and all else equal they could be more willing to lend to an informationally 'opaque' firm.[18] On the other hand, a bank that has had a long relationship with the firms, or that conducts a personal relationship with its clients, could have more information about the firms than a transaction bank, or a large bank that does most of its business electronically (Leland and Pyle 1977, Diamond 1984, Fama 1985, Diamond 1991). Among other information, the survey has questions about: (1) The type of lender (commercial bank, insurance company, venture capitalist, etc.); (2) The number of years that the lender has conducted a business relationship with the

[17] Greenbaum and Thakor (1995).

[18] Standard utility theory would suggest that risk aversion decreases with wealth. Venture capitalists have typically very large pools of money to invest.

firm; (3) The most frequent method of conducting business with the firm (in person, by phone, electronically, etc.); (4) Whether the firm considers the lender its primary financial services provider.[19] These characteristics are important determinants of the loan outcomes, so it is necessary to take them into account in the subsequent analysis.

Similarly, the type of loan for which the firm applied recently may also determine the decision of banks regarding the application. Obtaining for example a line of credit could be more difficult than obtaining a loan for equipment or a vehicle, because the equipment or vehicle themselves are the collateral for these loan. I also take into account these factors in the analysis.

Trade credit plays a central role in this study. There are several variables in the survey that illustrate the nature of the credit relationship between the firm and its suppliers, and that I consequently include in my analyses: (1) Whether the firm is a trade credit user or not; (2) Whether any supplier has denied trade credit to the firm in the past; (3) The percentage of purchases made on trade credit by each bank; (4) The fraction of the purchases made during 1998 that the firm paid after the due date; (5) The number of suppliers that offer trade credit to the firm (6) The length of the net period, and, if it applies, the length of the discount period and the size of the discount of the most important supplier. Variables (1) to (4) will become the focus of the analyses in Chapter 5. Variable (4) will also play an important role in the determination of the type of information used by banks. As it shall become clear from the text, variables (5) and (6) will be used as instruments in some of the regression analyses.

Finally, other important determinants of the loan outcomes are the owner characteristics. In particular, the principal owner's race could affect the lender's decision to grant the loan or not, and even its pricing. More importantly, the owner's personal credit history could well determine the loan outcomes. I also include these variables in the analyses.

[19]Another important determinant for the lending outcome would be the size of the lender institution. Unfortunately, the public version of the dataset does not contain this information.

The precise definition of all of the variables used throughout this study can be found in the Appendix.

2.4 Summary statistics

In this chapter, I give a first overview of the data used in all of the subsequent analyses, i.e the firms that recently applied for a loan to a financial institution. I start by discussing the distribution of these firms.

2.4.1 General characteristics of the sample

Column 1 of Table 1 shows the mean and standard deviation of selected variables for the firms' characteristics. We may observe that the firms in our target sample are indeed small, with an average worth of only $2.6 million. In fact, as can be deduced from the histogram displayed in Figure 4, 50% of the sample firms have assets that are worth less than $0.25 million. They are also, in general, 'growth' firms: Their average return on assets is 1.02, and less than 25% of the sample has negative ROA, while their mean year-to-year sales growth is 40%, and the median is in around 9.6%. The average firm in our target sample is slightly larger and than the mean firm of the complete SSBF sample, which has assets of $1.5 million and an average ROA of 1.4 (figures not reported in the table). The smallest firms are generally not included in our target sample as they do not usually rely on institutional credit for their fund-raising activities.[20] On the other hand, the average firm in the sample is 13 years old, and the median firm age is 10 years. The age of the firms in our sample does not differ much from the average age of the complete SSBF sample of 14.5 years. The complete histogram of the age of firms can be seen in Figure 5.

Two-thirds of the firms in the sample of 861 firms that obtained a bank loan have limited liability, and 87.5% of the firms are owner managed. In the complete

[20]Smallest firms tend to rely more on insider finance, angel finance and trade credit (Berger and Udell 1998).

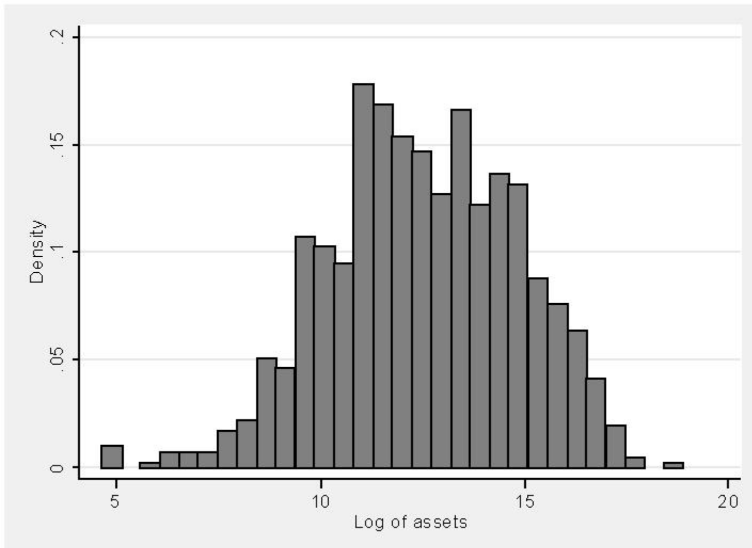

Figure 4: Sample distribution of firms by asset size.

This figure represents the sample distribution of the firms according to their size, as measured by the log of their assets.

SSBF sample, these numbers are 56% and 89%, respectively. This shows that the firms that ask for a loan from a financial institution have a slightly more developed governance structure, and is in line with the financial growth cycle of the firms (Berger and Udell 1998). In terms of their capital structure, the average debt-to-assets ratio is of 77% and their average accounts payable represents a 26.6% of all assets. By themselves, these numbers might look surprisingly high. However, the high averages are due to a few outliers which bias the mean. The median debt- and accounts payable-to-assets ratios (not reported in the table) are 34.4 and 6.6%, respectively. The firms are mostly financed by equity.

These firms typically lead close and lengthy relationships with their lenders (or, in this case, potential lenders). The average relationship length with their potential lender is of 5.7 years, and approximately equal to half their age. The majority of the firms applied for loans to institutions with which they have some kind of relationship link: 59% of the firms asked for a credit to a lender with which it has a personal relationship, and 54% to its primary financial services provider.

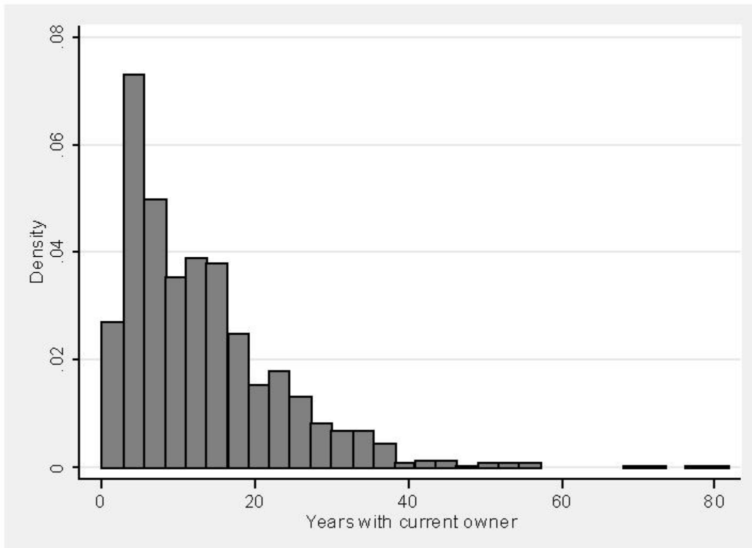

Figure 5: Sample distribution of firms by age.

This figure represents the sample distribution of the firms according to their age, as measured by the number of years under the current ownership.

Finally, the last couple of rows in Table 1 show that 74% of the firms that applied for a loan actually obtained the credit. The high figure could be due to two factors. First of all, the data comes from a survey responded by the firms' owners, who might be tempted to respond the survey in an untruthful way, inflating this figure. Second, there is a possibility that the firms choose to apply for a loan to banks in which they have higher odds of obtaining the credit.

A central question that is posed repeatedly throughout the next chapters of this thesis is: What factors are determinant for the success of a loan application? Apart from the typical firm characteristics such as size, age, industry, etc, there are three dimensions which are highlighted throughout this study that could determine the availability of credit. First of all, the quality and type of information that is available to the lender. Second, the credit history of the firms. Third and last, the availability of other types of external credit, in particular trade credit. In the remainder of this Chapter, I describe the sample according to selected variables correlated with these three dimensions.

2.4.2 Description of sample according to the information availability of their lenders

Let us start by analyzing whether there are systematic differences between the firms that apply for loans to institutions that have more information about them and the ones that apply to institutions with less information about the firm. For this purpose, I subdivide the sample into mutually exclusive groups according to the information availability of their potential lenders. I choose the following definitions of information availability for banks: (i) leading a personal relationship with the firm or not (Columns 2 and 3 of Table 1, respectively), (ii) being the firm's primary financial service provider or not (Columns 4 and 5), and (iii) leading a relationship of more or less than one year with the firm (Columns 6 and 7).

From Columns 2 and 3, we may observe that the firms asking for a loan to an institution with whom they lead a personal relationship are significantly smaller, have a more "primitive" ownership structure (smaller percentage of limited liability firms), and tend to have more cash than those that ask for a loan to an institution with whom they lead an impersonal relationship. The former are also less likely to base the survey responses on written records - arguably, these firms are less likely to even have such records, and thus hard information about these firms is more limited. Banks leading a personal relationship with the firms are more likely to be also the firm's primary financial services providers, and tend to lead (on average) longer relationships with their borrowers. All the dimensions in which these firms differ place the firms asking for a loan to an institution with which they lead a personal relationship as the typical candidate for a 'character' loan - i.e. a loan where the soft information plays a relatively more important role than hard information. Yet, it is important also to notice that among the firms leading a personal relationship with their lenders, there is a significantly higher rejection rate for their credit applications.

In Columns 4 and 5, I analyze whether the firms that asked for the loan to their primary financial services provider differs significantly from the ones that asked for the loan to any other bank. There are two main differences between these groups of firms. First, firms that apply for loans to a financial institution that they do not consider as their 'primary' financial services provider are younger in average. Young firms are establishing their reputation (Diamond 1989) and consequently are less likely to even have a primary financial services provider. Second, firms applying for a loan to their primary services provider are less leveraged in average. One interpretation for this is that the more leveraged firms probably know that their primary financial institution will not be willing to increase their leverage even further, and hence they apply for a new loan to a less informed institution. Probably as a consequence of the fact that the banks that are not the primary financial services providers of their potential lenders face a pool of firms of more uncertain credit quality, these banks are significantly less likely to grant the loans.

Similarly, the last two columns of Table 1 compare the firms that have led a relationship with their lender of less than one year, with those that have led a relationship of one year or higher. Firms leading long relationships with their potential lender are naturally older - the two variables are clearly correlated. Moreover, these firms are also larger on average, and rely more trade credit than the firms applying for a loan to a bank with which they have shorter relationships. Banks lending to firms with which they have led a short relationship are less likely to have soft or hard information about them: the proportion of personal and primary relationships is very low among this class (39% and 23%, respectively), and the average length of the relationship with the potential lender is much shorter relative to their age. The loans granted among these banks are more likely to be 'transaction' loans.

In the preceding paragraphs we have made a rough characterization of firms according to the information available to the bank where they apply for their loan. From the discussion of these paragraphs, we could be tempted to label the firms applying to personal banks as "character" loans, the ones applying to a non primary institution as "risky" loans, and the ones applying to a bank with which they have a short relationship with the bank as "transaction" loans. Nevertheless, the chosen classifications of the information sets available to the financial institutions are not mutually exclusive, so for example a firm could apply for a loan to an impersonal bank which is also its primary financial services provider and with which it has a relationship of more than 1 year. Hence, it is not intended by this analysis to make a deduction of the reasons for a loan rejection by only observing the characteristics of the bank to which the firm applied for a loan. The determinants of the loan approval or rejection rates should be studied with a more detailed analysis, which will be carried out in Chapters 3 and 5.

2.4.3 Characterization of firms according to their credit history

Another determinant of loan rejections which is highlighted in Chapter 3, is the credit history of the firms or their owners (Diamond 1989). Let us now discuss the characteristics of the firms with different credit history. Table 2 presents summary statistics for some selected characteristics of the firms' recent credit history. In Columns 1 - 3, the credit history refers to the percentage of the firms' purchases that are paid after the due date, i.e., their trade credit history. Consequently, the sample is restricted to the users of trade credit (666 firms). Within these three columns, these firms are further subdivided into the firms that never pay their trade credit purchases after the due date (Column 1), those that pay less than a quarter of their trade credit purchases after the due date (Column 2), and those that pay 25% or more of their purchases after the due date (Column 3). On the other hand, Columns 4 and 5 refer to the owner's credit history, i.e., whether the owner was ever delinquent in any personal or business obligation anytime during the 7 years before the survey took place. Column 4 contains the firms with owners with a good credit history, while Column 5 contains the firms with delinquent owners.

Table 2 shows that firms with different credit histories do not differ significantly in their size, age, or governance structure. However, there are very apparent differences in their financial structure. The firms with a good credit history (those that claim to pay all of their purchases on time, or those that have not been delinquent in the recent past) are usually the most liquid (higher cash-to-assets ratio) and the less leveraged (lower bank loan- and accounts payable-to-assets ratios). Analogously, firms with paying more than a quarter of their purchases after the due date, or firms that have been delinquent in at least one personal or business obligation, are highly illiquid and relatively more leveraged. Not surprisingly, there is a significantly lower proportion of firms with a bad credit history applying for loans to their primary financial services provider. Since it is more likely that the primary financial services provider is aware of the firm's delinquencies, firms with a bad credit history tend to apply for new loans to other banks. This finding contributes to our earlier assumption that the firms choosing to apply to an institution other than their primary services provider are signaling a relatively high level of risk.

Finally, the last row of Table 2 confirm the reputation build-up theories (Diamond 1989). Firms with good credit histories are significantly more likely to receive a new loan. This result is not surprising, and as it shall become apparent later on, it shall be of crucial importance in the analyses of Chapter 3.

2.4.4 Description of users and non-users of trade credit

The last chapter in this thesis deals with the importance of the use and extent of use of trade credit for the firms' access to institutional lending. It is hence important to grasp a basic idea of the characteristics of the firms that never use trade credit, and how they compare to the firms that use trade credit more or less extensively. In Table 3, firms are classified into non-users (Column 1) and users (Column 2) of trade credit. The firms in Column 2 are further subdivided according to the intensity with which they use trade credit. Firms making up to half of the purchases through trade credit are in Column 3. In Column 4, the firms make more than half and up to 98% of their total purchases through trade credit. Finally, Column 5 contains the firms that make more than 98% of their purchases through trade credit.

The first fact that is immediately apparent from the first two columns of Table 3 is that non-users of trade credit are the typical candidates for being "growth" firms. They are much smaller and younger than the rest of the firms, and in fact the size and age of firms increases with the use of trade credit (see Columns 3 to 5). They also have higher profitability and sales increase ratios. Among these firms, there is a larger number of firms with unlimited liability, and a larger number of firms that are owner managed, than among the trade credit users. Once again, Columns 3 to 5 show that the firms that use trade credit more intensively have a less primitive ownership and governance structure. The owners of the firms that do not use trade credit are also poorer - a smaller proportion of them owns a home. All these facts indicate that the proportion of start-ups among the non users of trade credit category is high. The findings are also in line with the financial life cycle theories of the firm.

There are two surprising findings in Table 3. First, it seems that firms that do not use trade credit rely more on bank finance than the rest of the firms – the average bank loans to assets ratio is highest for the non-users of trade credit, and in fact it decreases with the use of trade credit. However, a closer look at the distribution of the loans-to-assets ratio suggests that this is not always the case. 25% of the non-users of trade credit have a ratio of bank loans to assets of less than 3.6%; whereas this figure goes up to 12% among users of trade credit. The median ratio of bank loans to assets is 34% for both the subsample of firms that did not use trade credit and the subsample of firms that did (figures not reported in the table). Consistently with the financial life cycle theories about the financing of firms, these findings provide evidence that bank loans are another important external source of finance for small firms. Together with the previous findings, these results show that as firms grow older and larger, they begin to have easier access to both trade credit and bank credit.

The second surprising result is that the average accounts payable is equal among the users and non-users of trade credit. This is due to 81 firms in the sample that claimed to have never used trade credit, but nevertheless have median and mean accounts payable-to-assets ratio of 12.8% and 57.6%, respectively. This fact is plausible due to the fact that accounts payable include not only all accounts with suppliers, but may include tax bills and similar liabilities. Nevertheless, the median accounts payable to assets ratio is 0% for non users of trade credit and 9.6% for users of trade credit.

Table 3 also shows that the proportion of rejected applications among non-users of trade credit is very high, and that the rejection rate decreases with the use of trade credit. To the extent that firms with low trade credit usage are also small and young, and hence opaque, this result is just as expected, as banks are more reluctant to lend to firms for which they have no information. This finding is consistent with the role of trade credit as conveyor of information to banks. Lacking information about the credit repayment patterns of the firms, banks prefer to deny credit to these opaque firms. However, this hypothesis shall be duly tested in Chapter 5

The last rows in Table 3 compare the loan terms given by banks to the different categories of trade credit users for the loans that were approved. While the quantity of credit approved is generally equal to the total amount that the firms applied for, the interest rate seems to decline for the firms that use trade credit more intensively. However, non users of trade credit are also younger, so we must distinguish this effect from the fact that younger firms may pay higher rates on their loans (Dennis, Dunkelberg and Hulle 1988).

2.4.5 Descriptive statistics for selected variables

I end this section by presenting the detailed summary statistics of two variables that measure the relationship between a firm and its suppliers: the use of trade credit and, conditioned on being users of trade credit, the fraction of purchases paid after the due date. I further condition each of the variables on whether the firm obtained the bank loan or not. Panel A of Table 4 contains the distribution of the use of trade credit conditioning on the credit-granting decision of banks, while Panel B contains the conditional distribution of the fraction of purchases paid late. There is a significantly higher proportion of users of trade credit among the firms that were granted a credit from a bank. Furthermore, firms that were granted a credit from a bank tend to pay a significantly smaller amount of the purchases after the due date. There seems to be an important correlation between the banks' decisions and the firms' use of trade credit. However, whether there is a causal relationship between the relationship of firms with their suppliers and the corresponding response of banks towards the firms' applications has to be studied in a formal analysis. In the following chapters I perform regression analysis in order to find out why and under what conditions are the bad payers of trade credit rationed from bank credit.

2.5 Chapter 2 Tables

Table 1: Summary statistics according to lender's information availability.

This table contains the mean (standard deviation) of selected variables, according to the information availability of the lenders of the most recent request for a loan. The sample consists of the firms who recently asked for a loan to a financial institution. Column 1 refers to the complete sample. In columns 2 and 3, I subdivide the sample into two mutually exclusive groups of firms leading a personal or an impersonal relationship with their lender. In Columns 4 and 5, I subdivide the sample into the firms that consider their lender as their primary financial services supplier, and firms that do not. Finally, firms are classified into the ones that have lead a relationship with the lender of one year or more, and firms with relationship length of less than one year, in Columns 6 and 7. Between-group t-tests for differences in means were performed for firms in Column 2 vs firms in Column 3, Columns 4 vs 5, and Columns 6 vs 7, respectively.

	1 All firms	2 Personal	3 Impersonal	4 Primary	5 Not primary	6 Rel $>$ 1 yr	7 Rel $\leq$ 1 yr
Assets ($ Million)	2.160	1.691***	2.827***	2.171	2.146	2.441**	1.679**
	(6.036)	(5.875)	(6.206)	(5.065)	(7.017)	(6.793)	(4.423)
Age (yrs)	13.117	13.243	12.938	14.328***	11.689***	14.470***	10.808***
	(10.595)	(11.336)	(9.451)	(11.334)	(9.466)	(11.134)	(9.168)
Profits / Assets (ROA)[1]	1.022	1.164†	0.819†	1.002	1.045	1.029	1.009
	(3.607)	(4.216)	(2.485)	(3.804)	(3.364)	(3.669)	(3.503)
Bank loans / Assets[3]	0.773	0.770	0.777	0.618***	0.957***	0.732	0.844
	(1.722)	(1.680)	(1.782)	(1.282)	(2.115)	(1.655)	(1.831)
Accts Payable / Assets[3]	0.266	0.286	0.237	0.244	0.292	0.309**	0.192**
	(0.680)	(0.748)	(0.568)	(0.609)	(0.755)	(0.770)	(0.480)
Cash / Assets[2]	0.157	0.168*	0.142*	0.148†	0.168†	0.159	0.155
	(0.228)	(0.241)	(0.208)	(0.214)	(0.243)	(0.235)	(0.217)
Sales increase[1,4]	0.425	0.453	0.385	0.346*	0.519*	0.397	0.475
	(1.399)	(1.504)	(1.238)	(1.314)	(1.491)	(1.441)	(1.320)
% Owner managed	0.876	0.881	0.868	0.863	0.891	0.880	0.868
	(0.330)	(0.324)	(0.339)	(0.345)	(0.312)	(0.325)	(0.339)
% Home ownership	0.906	0.909	0.901	0.912	0.899	0.917	0.887
	(0.292)	(0.288)	(0.299)	(0.284)	(0.302)	(0.276)	(0.317)
% Limited liability	0.668	0.626***	0.727***	0.674	0.661	0.676	0.654
	(0.471)	(0.484)	(0.446)	(0.469)	(0.474)	(0.468)	(0.476)
% Impersonal	0.412	0.000***	1.000***	0.262***	0.590***	0.298***	0.607***
	(0.493)	(0.000)	(0.000)	(0.440)	(0.492)	(0.458)	(0.489)
% Primary fin inst	0.541	0.680***	0.344***	1.000***	0.000***	0.724***	0.230***
	(0.499)	(0.467)	(0.476)	(0.000)	(0.000)	(0.448)	(0.421)

Continued on next page

Table 1 – Continued from previous page

	1 All firms	2 Personal	3 Impersonal	4 Primary	5 Not primary	6 Rel $>$ 1 yr	7 Rel $\leq$ 1 yr
% Records	0.148	0.128**	0.175**	0.139	0.157	0.147	0.148
	(0.355)	(0.335)	(0.380)	(0.347)	(0.364)	(0.355)	(0.355)
Rel. length (months)	68.907	87.040***	43.062***	96.470***	36.390***	107.867***	2.381***
	(88.814)	(97.521)	(66.752)	(92.404)	(71.982)	(91.582)	(4.357)
Rel length / age	0.557	0.714***	0.335***	0.728***	0.356***	0.859***	0.043***
	(0.923)	(1.038)	(0.669)	(0.887)	(0.925)	(1.047)	(0.121)
% Credit granted	0.742	0.706***	0.794***	0.820***	0.651***	$0.761^{\dagger}$	$0.711^{\dagger}$
	(0.438)	(0.456)	(0.405)	(0.385)	(0.477)	(0.427)	(0.454)
Observations	861	506	355	466	395	543	318

* Between-groups difference significant at 10%, ** Between-groups difference significant at 5%,
*** Between-groups difference significant at 1%.

† One-tailed test for the between-groups difference significant at 10%.

[1] Winsorized at the 1 and 99% levels.

[2] Winsorized at 1%.

[3] Winsorized at 99%.

[4] Some observations lost due to missing sales for 1997.

Table 2: Summary statistics according to credit repayment.

This table contains the mean (standard deviation) of selected variables, according to the proportion of purchases on trade credit that are paid after the due date (Columns 1-3) and to the delinquency history of the owner of the firm (Columns 4 and 5). In Columns 1-3, the users of trade credit that recently asked for a bank loan are subdivided according to the proportion of purchases paid after the due date, or purchases paid late (PPL). Column 1 contains the firms that never paid their trade credit purchases after the due date; Column 2 contains the firms that paid less than 25% of their trade credit purchases after the due date; and Column 3 contains those that paid 25% or more of their purchases after the due date. In Columns 4 and 5, the firms that asked recently for a bank loan are subdivided into those that have an owner that has not been delinquent in any personal or business obligation (Column 4) and those that have an owner that has been delinquent in at least one personal or business obligation in the 7 years previous to the survey.

	1 PPL=0%	2 PPL < 25%	3 PPL ≥ 25%	4 Not delinq	5 Delinquent
Assets ($ Million)	2.095†	3.311	2.560	2.383*	1.600*
	(4.846)	(9.264)	(5.500)	(6.706)	(3.842)
Age (yrs)	14.056	13.917	14.371	13.348	12.541
	(11.752)	(9.370)	(11.482)	(10.844)	(9.941)
Profits / Assets (ROA)[1]	0.945†	0.526•	1.076	1.153*	0.693*
	(3.217)	(1.332)	(4.437)	(3.911)	(2.679)
Bank loans / Assets[3]	0.556	0.619	0.848°°	0.708*	0.936*
	(1.090)	(1.190)	(1.788)	(1.581)	(2.027)
Acc payable / Assets[3]	0.161†††	0.304	0.423°°°	0.211***	0.404***
	(0.420)	(0.707)	(0.851)	(0.590)	(0.851)
Cash / Assets[2]	0.171†††	0.124	0.096°°°	0.177***	0.107***
	(0.207)	(0.165)	(0.189)	(0.238)	(0.192)
Sales increase[1,4]	0.303	0.418	0.400	0.421	0.435
	(1.031)	(1.438)	(1.397)	(1.378)	(1.452)
% Owner managed	0.854	0.858	0.863	0.875	0.878
	(0.354)	(0.350)	(0.345)	(0.331)	(0.328)
% Home ownership	0.923	0.951	0.914	0.914	0.886
	(0.267)	(0.216)	(0.281)	(0.281)	(0.318)
% Limited liability	0.683	0.750	0.766°	0.665	0.675
	(0.466)	(0.434)	(0.425)	(0.472)	(0.469)
% Impersonal	0.387	0.446	0.457	0.411	0.415
	(0.488)	(0.498)	(0.500)	(0.492)	(0.494)
% Primary fin inst	0.592	0.559••	0.440°°°	0.571***	0.467***
	(0.492)	(0.498)	(0.498)	(0.495)	(0.500)
% Records	0.129††	0.196	0.160	0.138	0.171
	(0.336)	(0.398)	(0.368)	(0.345)	(0.377)
Rel. length (months)	74.930	70.760	61.794	74.683***	54.467***
	(94.877)	(82.830)	(87.872)	(94.802)	(69.795)
Rel length / age	0.550	0.596	0.452	0.600**	0.450**
	(0.766)	(1.155)	(0.824)	(0.954)	(0.831)
% Credit granted	0.836	0.819•••	0.628°°°	0.816***	0.557***
	(0.371)	(0.386)	(0.485)	(0.388)	(0.498)
Observations	287	204	175	615	246

[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%.
[4] Some observations lost due to missing sales for 1997.
†,(††),[†††] Difference between columns 1 and 2 significant at 10% (5%) [1%].
•,(••),[•••] Difference between columns 2 and 3 significant at 10% (5%) [1%].
°,(°°),[°°°] Difference between columns 1 and 3 significant at 10% (5%) [1%].
*,(**),[***] Difference between columns 4 and 5 significant at 10% (5%) [1%].

Table 3: Summary statistics according to trade credit (TC) use.

This table contains the mean (standard deviation) of selected variables, according to the use of trade credit or not (columns 1-2) and to percentage of purchases that are done in trade credit (columns 3-5). In columns 1-2, the firms that recently asked for a bank loan are subdivided into the firms that did not use trade credit (column 1), and that were offered and used trade credit (column 2). In columns 3-5, the users of trade credit were classified into firms that paid less than 50% of their purchases with trade credit, firms that paid at least half and less than 98% of their purchases through trade credit, and firms that paid more than 98% of their purchases with trade credit.

	1 No TC	2 TC	3 0% < TC ≤ 50%	4 50% < TC ≤ 98%	5 TC > 98%
Assets ($ Million)	0.691***	2.590***	1.139†††	2.528**	3.857***
	(2.497)	(6.669)	(3.135)	(5.531)	(9.562)
Age (yrs)	9.774***	14.096***	11.597††	14.142*	16.041***
	(8.321)	(10.987)	(8.716)	(11.582)	(11.315)
Profits / Assets (ROA)[1]	1.605**	0.851**	1.048	0.833	0.720
	(4.721)	(3.192)	(3.892)	(3.065)	(2.740)
Bank loans / Assets[3]	1.187***	0.652***	0.891†	0.654•	0.456°°°
	(2.603)	(1.339)	(1.903)	(1.172)	(0.956)
Acc payable / Assets[3]	0.239	0.274	0.246	0.266	0.308
	(0.758)	(0.656)	(0.694)	(0.596)	(0.713)
Cash / Assets[2]	0.227***	0.137***	0.182†††	0.128	0.114°°°
	(0.311)	(0.193)	(0.226)	(0.186)	(0.167)
Sales increase[1,4]	0.648**	0.364**	0.433	0.344	0.343
	(1.788)	(1.268)	(1.588)	(1.054)	(1.296)
% Owner managed	0.938***	0.857***	0.881	0.842	0.863
	(0.241)	(0.350)	(0.325)	(0.365)	(0.345)
% Home ownership	0.826***	0.929***	0.868†††	0.952	0.944°°
	(0.380)	(0.256)	(0.340)	(0.215)	(0.230)
% Limited liability	0.472***	0.725***	0.572†††	0.7394••	0.827°°°
	(0.500)	(0.447)	(0.496)	(0.440)	(0.379)
% Impersonal	0.374	0.423	0.358	0.426	0.472°°
	(0.485)	(0.494)	(0.481)	(0.495)	(0.500)
% Primary fin inst	0.538	0.542	0.522	0.545	0.553
	(0.500)	(0.499)	(0.501)	(0.499)	(0.498)
% Records	0.113	0.158	0.138	0.1424•	0.198
	(0.317)	(0.365)	(0.346)	(0.350)	(0.399)
Rel. length (months)	64.487	70.201	57.182	67.9354•	84.274°°°
	(86.425)	(89.524)	(73.643)	(91.321)	(96.581)
Rel length / age	0.622	0.538	0.602	0.479	0.581
	(0.943)	(0.917)	(1.070)	(0.753)	(1.012)
% Credit granted	0.626***	0.776***	0.648†††	0.7874••	0.863°°°
	(0.485)	(0.417)	(0.479)	(0.410)	(0.345)
Observations	195	666	159	310	197
Approved loans					
% Granted	1.002	0.995	1.022	0.993	0.982
	(0.242)	(0.206)	(0.342)	(0.167)	(0.133)
Interest rate (%)	9.548**	8.956**	9.589†††	8.933	8.607°°°
	(3.107)	(2.078)	(2.334)	(2.080)	(1.817)
% Collateralized	0.738***	0.859***	0.835	0.873	0.853
	(0.442)	(0.349)	(0.373)	(0.334)	(0.355)
Observations	122	517	103	244	170

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Table 3 – Continued from previous page

	1	2	3	4	5
	No TC	TC	$0\% < \text{TC} \leq 50\%$	$50\% <$ $\text{TC} \leq 98\%$	$\text{TC} > 98\%$

[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%.
[4] Some observations lost due to missing sales for 1997.
$^{\dagger,(\dagger\dagger),[\dagger\dagger\dagger]}$ Difference between columns 3 and 4 significant at 10% (5%) [1%].
$^{\bullet,(\bullet\bullet),[\bullet\bullet\bullet]}$ Difference between columns 4 and 5 significant at 10% (5%) [1%].
$^{\circ,(\circ\circ),[\circ\circ\circ]}$ Difference between columns 3 and 5 significant at 10% (5%) [1%].
$^{*,(**),[***]}$ Difference between columns 1 and 2 significant at 10% (5%) [1%].

Table 4: Trade credit use and late payment.

This table contains descriptive statistics for a binary variable containing the use of trade credit for the firms that were granted the credit, the firms that were not granted the credit, and all the firms in the sample of firms that asked recently for a new loan.

Panel A: Use of trade credit

	Not granted	Granted	All
Mean*	67.1%	80.9%	77.4%
Standard Deviation	47.1%	39.3%	41.9%
10% Percentile	0.0%	0.0%	0.0%
Median	100.0%	100.0%	100.0%
90% Percentile	100.0%	100.0%	100.0%
Number of firms	222	639	861
% Sample	25.8%	74.2%	

Panel B: Fraction of purchases paid after due date

	Not granted	Granted	All
Mean*	27.4%	13.9%	16.9%
Standard Deviation	31.5%	24.0%	26.5%
10% Percentile	0.0%	0.0%	0.0%
Median	20.0%	1.0%	2.5%
90% Percentile	80.0%	50.0%	50.0%
Number of firms	149	517	666
% Sample	22.4%	77.6%	

3 Soft information in small business lending

3.1 Introduction

Information is a crucial input for the lending activity. In a world in which information were freely available to all lenders, funds would always flow to firms with positive net present value projects. In practice, the firms' managers have private information about the value of their projects. This asymmetric information between borrowers and lenders creates a profit opportunity to banks and other financial intermediaries: by producing information about the firm and using it in their credit decisions, banks are able to overcome the asymmetric information problems and profitably facilitate lending to firms with good investment opportunities.[21] This observation has led economists to create the concept of "relationship lending" reflecting how some banks obtain private information about their clients through a continued relationship.[22]

One condition for relationship lending to exist is that banks gather "soft" information about the firm's credit quality.[23] Soft information refers to any kind of data other than the relatively transparent public information about the firm such as financial statements or the availability of collateral.[24] Crucial as it is for the relationship lending literature, the use of soft information by relationship banks has been hardly studied in the empirical literature.[25] The nature of soft information is partly to blame for this gap. Soft information is essentially qualitative in nature, so it cannot be easily or verifiably recorded in written form. Thus, it is difficult to obtain data sources containing soft information.

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[21] Chapter 1 contains a discussion of the cost advantages of banks over other outsiders in producing and transferring information. See also Leland and Pyle (1977), Diamond (1984), Fama (1985), or Diamond(1991). For empirical evidence, see James (1987), Lummer and McConnell (1989), or Slovin, Sushka, and Polonchek (1993).

[22] Chapter 1 contains a brief review of this literature. More complete reviews can be found, for example, in Boot (2000), Ongena and Smith (2000) and in Freixas (2005).

[23] Berger (1999).

[24] Petersen (2004) contains an excellent discussion on soft versus hard information.

[25] As mentioned in Chapter 1, among the few works to address the topic are Liberti (2003) Cole, Goldberg and White (2004), Berger et al. (2005), and Liberti (2005).

In this chapter, I investigate empirically whether banks use soft information in their credit decisions. Given the difficulty to obtain direct measures for the soft information used by banks, I proceed indirectly. Specifically, I use the very detailed Survey of Small Business Finances (SSBF) described in Chapter 2 to analyze whether banks with access to private soft information sources are equally reliant on the information of public credit registries as the banks that do not have access to soft information about the firms. I find that the reliance on public hard information - as that contained in a credit registry - is very strong whenever banks have no access to sources of private information (soft or hard) about the firm's credit quality. On the other extreme, banks that have access to soft *and* hard private information about the firms tend to ignore the public records. In fact, the reliance on the hard information contained in public registries is significantly diminished whenever banks have access to sources of soft information about the firm's credit quality, but have at very best limited access to sources of private hard information about the firms. These results present evidence of two basic facts. First of all, the findings confirm the well-established relationship lending theories, i.e. that banks accumulate private information about the firm's credit quality in the course of their mutual relationship. The second result qualifies the first finding, by highlighting the important role played by the *soft* component of the private information accumulated by banks: When soft information is not available to banks, reliance on external signals of quality is crucial for the banks' decisions, but the reliance is significantly reduced as soon as there is soft information availability. This second fact is, in fact, the main contribution to the literature of the present chapter.

The line of reasoning employed in the analysis of this chapter is the following. Information about the small firms contained in the sample is likely to be scarce, as most of them are privately owned, and do not have audited financial statements or the like. Hence, banks that are willing to lend to small firms must somehow elicit information about their credit quality. How the firm behaves in other credit relationships is one possible source of information. The private information, soft or hard, gathered by the bank in the course of its relationship with the firm is another such source. Only banks that have established a personal relationship with a firm can obtain soft information about the firm's credit quality. Therefore, a comparison of the relative intensity with which the firms' credit history is used in the decisions of banks with soft information versus privately uninformed banks (i.e. 'transaction banks') illustrates the importance of soft information in relationship banking.

The analysis of this chapter consist of two basic steps. In the first one, I classify the firms in the sample according to the type of private information available to their lenders: only hard, only soft, hard and soft, or no private information. Then, I compare the relative importance that each group of banks assigns to the information contained in public credit registries when making their credit decision. I use two items typically included in public credit registries. First of all, information on the proportion of trade credit obligations that the firm pays on time. Second, information on whether the owner of the firm has defaulted on any previous personal or business obligations.

While both the trade credit history of the firm and the personal credit history of its owner are relevant external sources of information about the firm's credit quality, information regarding the trade credit repayment is especially relevant given the characteristics of the sample under study. First of all, while both pieces of information are likely to be present in the reports of credit information brokers,[26] even banks without such a credit report could, and usually do,[27] check with the firms' suppliers to learn about the firms' credit quality. The availability of this information makes it plausible for banks to use the trade credit relationships to discriminate among lenders.

Second, using the trade credit relationships between the firm and its input suppli-

[26]For example, the reports created by Dun & Bradstreet - which incidentally is the provider of the sampling framework of the dataset used in this study - includes information about the promptness with which the firms make their trade credit payments (Kallberg and Udell 2003).

[27]Greenbaum and Thakor (1995), p. 241.

ers to test for the use of soft information in bank lending is especially relevant in the context of small firm financing, because by far the most important sources of external finance for small firms are bank loans and trade credit.[28] Therefore, banks can access information about trade credit repayment for a vast majority of small firms.

Third, as will become clearer in the following sections, information about the repayment to suppliers allows us to clearly identify the causality from the trade credit repayment patterns to the decision making of banks. I use two approaches to identify this causality. First, I exploit a time dimension present in the sample in order to identify the timing of any potential trade credit default and the consequent decision of banks to grant or reject the credit application. Second, I exploit several characteristics of the trade credit contract to establish an instrumental variable approach that allows us to further identify the causality. As shall be explained in more detail in the text, such an identification is impossible to do for the personal credit history of the owner given the particular characteristics of the sample under study.

Fourth and last, information regarding the proportion of trade purchases duly paid presents a continuous measure of the reputation of firms. In contrast, the existence of a previous default is a binary variable that does not allow us to classify the best and the worst firms among those that have not defaulted, and at the same time assigns a very negative reputation to those that have defaulted.

This chapter contributes to the existent literature by highlighting the importance of *soft* information in the loan decision making process. There are four recent papers that are closely related to this work: those of Cole, Goldberg and White (2004), Berger et al (2005), and Liberti (2003,2005). However, it differs from each one of them in several ways. First of all, as mentioned in Chapter 1, all of them are implicit or explicit tests of the theoretical predictions of Stein's (2002) model, and hence are focused on identifying the differences in the use of soft information across different institutional or organizational setups. In this chapter, the focus is rather on the relative

[28] Berger and Udell (1998)

importance of soft information with regard to hard private information in bank lending, independently of bank size or organizational structure. Research in this subject is important per se for two main reasons. First, because the central assumption in the theoretical relationship lending literature is that relationship lenders have access to soft information.[29] Yet, empirical support to this assumption has been scarce at the very best. Second, the relative importance of soft information with respect to private hard information measures has been the subject of intense recent debate. This debate has been driven primarily by the possibility to adopt Internal Rating Based Systems (IRB) that involve both hard and soft information measures for banks affected by the Basel II regulations.[30] Yet, IRB approaches rely necessarily on the "hardening" of soft information, by transforming the subjective soft information into a quantitative form. As shall become clearer in the following sections, in this chapter I deal with soft information in its purest form - i.e., without any "hardening" - and show that it plays a crucial role in small business lending. The extent to which the hardening of soft information through IRB could lead to a loss of important subjective information remains an open question.

Other differences with the previous literature regard the definition of soft information, and how it is identified. In this chapter I explicitly isolate the soft information from any private hard information source, thus providing with an objective measure of soft information. Cole et al (2004) and Berger et al (2005), on the other hand, do not use explicit measures of soft information. Instead, they find isolated pieces of evidence which, put together, *could* imply more intensive use of soft information by small financial institutions. In this sense, probably the papers that relate the most to this work are Liberti (2003,2005), where soft information is clearly differentiated from hard information.[31] However, these papers differ in approach in two ways. First of all, the

[29]See Berger (1999).

[30]For a recent summary of the state of the art in this literature, refer to the discussion of the literature presented in Grunert, Norden and Weber (2005).

[31]In particular, Liberti (2005) is especially related to this chapter, as it deals directly with the relative importance of soft versus hard information in bank lending.

data in both papers refer to the lending practices of one particular bank, whereas the approach in this chapter is much wider in that it considers a cross-sectional dataset. Secondly, Liberti's papers rely on quantitative evaluations of subjective data - i.e., on soft information that has been "hardened". As explained before, the approach used in the present chapter makes such a hardening of soft information unnecessary.

The remainder of the chapter is organized as follows. I first present the empirical strategy and a few preliminary results on the use of private information in Section 3.2. In Section 3.3, which is the core section of this chapter, I identify the soft and hard components of the private information used by banks, and verify the importance of the use of soft information in bank lending. Section 3.4 takes care of the potential endogeneity bias which could be leading the results of the preceding sections. A further robustness check is performed in Section 3.5, where I verify whether the results still hold after controlling for a potential sample selection bias. Finally, in Section 3.6 I substitute the trade credit variable with the credit history variables, to confirm that the results are not driven by the choice of the external signal observed by the banks. Concluding remarks are left for Section 3.7.

3.2 Preliminary models: Banks as information gatherers

3.2.1 The credit decision

Consider the credit analysis performed by a loan officer facing a loan application by a small firm. Such an analysis should enable him to determine the ability and willingness of the borrower to repay the loan. The analysis usually looks at the borrower's past record (reputation) and its economic prospects. Credit analysts traditionally refer to the crucial inputs for the analysis as the 'five Cs of credit': capacity, capital, conditions, collateral, and character.

To determine the *capital* and the repayment *capacity* of a firm, the loan officer would look at the firm's financial statements and its growth prospects. Industrial considerations, and the general macroeconomic situation at the time and place of the application would be also included in the analysis, as they are determinants of the economic *conditions* that affect the borrower's ability to repay the loan. Should things go wrong for the borrower, the loan officer should make sure that the firm, or its owner, has enough assets - or *collateral* - that could be liquidated by the bank in case of default. Finally, the bank officer will also make an evaluation of the firm's *character*, or the desire to settle its debt obligations.

Of course, banks can have more or less information about a firm's capital, capacity, condition, collateral, and character depending on how much information they gather about the firm. For example, if the bank has led a relationship with the firm, it will necessarily have access to more information than a bank that has no such relationship.

With these considerations in mind, we could start by modelling the credit-granting decision of the bank facing a loan application from a given firm i with the following simple function:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i. \tag{1}$$

In this equation, y_i represents the decision of the bank to grant the credit or not (i.e. a binary variable containing a one if firm i was granted a loan, and zero otherwise). The vector $\left(x_i, X_i^f\right)$ represents the characteristics of firm i included in the credit analysis, and includes all of the variables measuring the previously discussed five Cs of credit. For reasons that shall become apparent shortly, I have separated one firm-specific variable, x_i, from vector X_i^f. Let this variable be a measure of the firm's character, as contained in its reputation regarding previous credit relationships. Vector X_i^b contains measures indicating the amount of information that the lender bank has about firm i, and other bank-specific characteristics, since different institutions will probably have different criteria regarding loan approvals. Finally, let X_i^l be a vector containing the characteristics of the loan that the firm asked to the bank, as the decision of the loan officer will be likely to vary depending on the type of loan applied for.

3.2.2 Relationship vs. transaction lending

Consider now two banks facing the same credit application. Suppose that the banks are equal, except that one of them has led a relationship with the firm ('relationship' lending), while the other one is facing the credit application by that firm for the first time ('transaction' lending). As mentioned before, the relationship lending literature would claim that the relationship bank has access to private information about the firm's credit quality. The transaction bank, on the other hand, only has access to public sources of information about the firm, plus any information that it can gather about the firm's credit quality. Let us now go back to variable x_i. Suppose this variable is an external measure of reputation that both the relationship and the transaction bank could observe. This variable is likely to have a very important weight in the credit decision of the transactions bank. However, the relationship bank has observed closely the firm and gathered information that could substitute this external (public) measure of reputation. Therefore, we should expect the behavior of relationship banks to be different from the behavior of transactions bank regarding the variable x_i.

Let us modify slightly the previous model by introducing $I(x)$, an indicator function that identifies the firms that are asking for the loan to banks with access to a source of private information. In other words,

$$I_i(x) = \begin{cases} 1, & \text{if lender bank of firm } i \text{ has a private source of information} \\ 0, & \text{otherwise} \end{cases}$$

By interacting $I(x)$ with x_i, we might identify whether the relationship lending hypothesis can be observed in the data. Consider, then, the following model:

$$y_i = \beta_0 + \beta_1^P x_i^P + \beta_1^N x_i^N + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i, \tag{2}$$

where y_i, X_i^f, X_i^b, and X_i^l are defined as before; $x_i^P = x_i I_i(x)$ (for privately informed banks), and $x_i^N = x_i(1 - I_i(x))$ (for banks with no private information).

The information gathering hypothesis of the relationship lending literature, restated with this model, would say that if firms have a bad reputation (measured by a high value of variable x_i) then transaction banks would grant them the loan with a lower probability than firms with a good reputation, i.e. $\beta_1^N < 0$. Relationship banks, however, would rely less on this variable as they have gathered private information which is superior. In other words, $\beta_1^N < \beta_1^P$. In the extreme, if the information gathered in the course of the relationship is good enough, these privately informed banks should substitute completely the public reputation with their own information. In this case, $\beta_1^P = 0$. To the extent that banks gather soft information during their relationship, the difference in the magnitude of β_1^P and β_1^N will give us an idea of the importance of soft information.

The relationship lending literature identifies several measures to account for the existence of a relationship and construct our binary variables $I(x)$.[32] For example, the time duration of the relationship has been widely used to proxy for the strength of a bank-firm relationship (Petersen and Rajan 1994, Berger and Udell 1998, Cole 1998). Another common proxy is the scope of the relationship, measured by the number of services provided by the bank (Petersen and Rajan 1994, Berlin and Mester 1999). More recent measures involve the banks' self-assessments of their status as relationship banks (Elsas and Krahnen 1998, Elsas 2005),[33] or whether the firm and the bank lead a personal relationship (Berger, Miller, Petersen, Rajan and Stein 2005). Following this trend, I construct several measures that allow for the classification of the firms according to whether or not their lenders have access to superior (private) information about the firm: (i) a binary variable identifying the firms with a relationship with the lender bank of more than the median of three years, (ii) a binary variable identifying the firms with a relationship with the lender bank of more than one year, (iii) a binary variable identifying the firms that have a checking or a savings account with

[32] See Ongena and Smith (2000) and Elsas(2005).

[33] More precisely, their status as Hausbanks, in Germany.

the lender bank, (iv) a binary variable identifying the firms that classify their lender bank is its primary provider of financial services,[34] and (v) an indicator for whether the firm and the bank usually conduct their business in a personal way.[35] Variables (i) and (ii) are measures of the duration of the relationship; they differ in that the latter recognizes that the benefits of a bank relationship may accrue only in the early part of the relationship (Ongena and Smith 2000), while the former splits the sample equally. Variable (iii) intends to capture the availability of hard information that may be gathered by the bank through other information-intense sources, such as a checking or savings account. Variable (iv) intends to identify the banks that are closest to the firm, and hence those that may be best informed about its credit quality. Finally, variable (v) intends to capture the information that may be gathered by a bank that leads a very close and personal relationship with a firm - in other words, soft information.

At this point we should make a brief reflection on the type of information available through each of the sources identified in the previous paragraph. Consider the duration of a relationship, i.e. variables (i) and (ii). During a long relationship, banks are indeed more likely to gather information about the firm. Yet, this information need not be soft, or hard. It could be both. The same is true for the primary financial services providers of firms, variable (iv), although in this case we are more certain that the bank has hard information gathered through the services it has supplied. On the other hand, the availability of a checking or savings account with the bank (variable iii) is a clear indication that the bank has hard information about the firm; still, having an account does not rule out the availability of soft information. Finally, a bank that leads a personal relationship with a firm certainly has gathered soft information about the firm's character. In fact, variable (v) will become the focus of this study.

[34] To the best of my knowledge, this is the first study to use the firm's, rather than the bank's, self-assessment of the quality of its lender as its primary financial services provider.

[35] Two possible responses in the survey suggest that there is a personal relationship between the firm and the bank: when business is usually conducted in person, and when there is usually a visit from the bank's representative to the firm's premises.

If, as our hypothesis claims, soft information is a crucial input in relationship lending, we should observe that indeed, banks with access to a personal relationship with a firm will ignore the external measure of reputation of the firm. Table 5 contains a summary of the sources of information available by lending banks, and what type of information they mostly convey: whether soft or hard.

3.2.3 Estimation: Variables and methods

In Table 6, I estimate the coefficients of Equations 1 and 2 on the sample of small firms that applied recently for a bank loan. All estimations are performed with a probit model with heteroskedasticity correction, and the reported coefficients correspond to the marginal effects of the coefficients for the average firm.

Variable y_i is the bank's approve/reject decision. I include the firm's size and age, governance structure, industry, year of the application, market structure, and several financial variables from the firm's financial statements to control for the five Cs of credit in vector X_i^f. As measures of size and age, I choose to include the log of assets and the log of the firm's age, respectively, for two reasons. First, the log of the variables allows for a non-linear decreasing marginal effect of the age and size in the decision of banks. Second, the fit of the models and the significance of the variables improve with respect to the model with the linear effects (not reported). As measures for the firm's location, I use nine dummies for the firm's region, an MSA indicator, and an indicator for the concentration of the deposit market in the location of the firm. For the industry I include the two-digit SIC code indicators. As indicators of the firm's and its owner's financial situation, I include the return on assets, its sales increase with respect to last year, its liquidity, the leverage, whether the principal owner has a home, and whether the principal owner belongs to a minority group. For the governance structure, I include indicators for limited liability, and whether it is owner managed. Regarding the bank and loan characteristics in X_i^b and X_i^l, I include indicators for the type of lender bank, whether it is the primary financial services provider, the type of loan applied for, and the year of the application.

Results for the estimation of Equation 1 are contained in the first column of Table 6. Columns 2-6 contain the estimated coefficients of Equation 2 when the measures of information availability $I(x)$ are, respectively, whether the lender institution is the firm's primary financial services provider (Column 2), whether the length of the relationship with the lender is longer than the sample median (Column 3), whether the length of the relationship with the lender is longer than one year (Column 4), whether the firm has a checking or a savings account with the lender institution (Column 5), and whether the relationship with the lender institution is typically personal (Column 6). The focus of these estimations will be on the coefficients β_1^P and β_1^N, which, under the information gathering hypothesis, should be statistically different. Moreover, β_1^N should be negative.

As a robustness check, in Column 7 I report the coefficients of Equation 2 once more, using as $I(x)$ a survey question asking whether the respondent used financial statements or accounting reports in order to answer the survey. The availability of such written records is an indicator that the firm has written records, and as such it is less opaque than the rest of the firms. In general, we should expect banks to be more reliant on the firm's external credit history if they are very opaque (have no written records), so β_1^N should also be negative in this case. However, banks do not necessarily have private information about the firms that have written records. Therefore, even for those firms that are less opaque, we should find a negative relationship between the reputation variable and the probability of obtaining the loan. In other words, given that the division of the sample in this case is not driven by differences in private information, we should not be able to differentiate β_1^P from β_1^N in this case.

My choice for the external measure of reputation of the firms, x_i, is the percentage of trade credits paid after the due date. As mentioned before, this variable is likely to be present in the reports of credit information brokers such as Dun & Bradstreet (Kallberg and Udell 2003). Moreover, even if such a credit report is not available, banks can still check with the firms' suppliers to learn about the firms' credit quality. Therefore it is very likely that all banks in the sample can access this information and use it to discriminate among lenders.

As mentioned before, this variable presents additional advantages over other measures of reputation that could be likewise available to banks, such as the firm's or the principal owner's default history in previous credit relationships. For example, trade credit is a very important source of financing for small firms, and tends to be present long before a firm may access institutional credit (Berger and Udell 1998, Petersen and Rajan 1997). Hence we may observe this variable for a large number of firms in the sample. In contrast, only the firms that have actually defaulted and that have been reported to the credit bureau will be present in the owner's default history. Second, this variable presents us with a continuous measure of reputation, while the default is a binary variable that offers much less variation. Third and related, the presence of a firm or its owner in a default register may be a too strong negative signal. For example, a bank may be facing an application for a bank loan that overall is above average. However, the firm is present in a default record. Hence, even if the hard and soft facts gathered by the bank are not bad, it will be difficult for this bank to extend a credit to this firm. The strong negative impact that this variable has on the lending decision of the firms may swamp the effect of the availability of private information that we want to observe according to the approach of Equation 2. As a consequence of these caveats, we will concentrate most of the analysis on the trade credit reputation variable. Nevertheless, as a robustness check we shall still substitute this variable later in Section 3.6.

Finally, when interacting the trade credit variable with any information source available to the lender bank, I also control for such a source. In this way it is possible to isolate the effect of the trade credit variable from the pure effect of the information availability.

3.2.4 Analysis of results of Table 6

Let us now analyze how the availability of private information affects the extent to which banks react to the external signal of reputation. The first observation that is immediately apparent from Table 6 is that paying a large fraction of purchases after the due date has a negative impact on the probability of the bank granting the loan. This result is just as expected: a negative reputation affects the likelihood of getting a loan in a negative way. In fact, the coefficient of the purchases paid late is always negative, both when it is not interacted with the information dummies (Column 1), and when it is interacted with these variables (Columns 2-6). Moreover, according to the information gathering hypothesis of relationship lending, whenever the lending institution does not have a superior source of information, the coefficients are both larger in absolute value, and always significant at a 99% confidence level. If, however, the bank has some source of information, the coefficients for the purchases paid after the due date, while negative, are never significant at a 99% level of confidence, and even lose the significance when we measure a relationship availability as having a relationship longer than the median of 3 years. These results suggest that the reputation of the firm (as proxied by the fraction of purchases paid after the due date) is less important whenever the banks have additional sources of information, hard or soft, about the credit quality of the firms.

The last two rows of Table 6 contain the Chi-squared statistic for the test that $\beta_1^P = \beta_1^N$, and its corresponding p-value. From these figures, we may observe that the coefficients are statistically different at confidence levels of 95% for three measures of information availability (when the relationship with the lender is longer than the median, when it is longer than one year, and when the relationship is personal in nature). In other words, our hypothesis that $\beta_1^N < \beta_1^P$ is confirmed for all of the measures that we have identified in Table 5 as containing some degree of soft information. In particular, the coefficients are statistically different at its highest level when the variable used is the existence of a personal relationship (see the last two rows of Column 6).

While we do find the difference between β_1^N and β_1^P to be statistically significant for all the measures with soft information, such a differentiation does not appear when the variable measures opacity of the firms, rather than information availability (Column 7). These results highlight the importance of the accumulation of private information in bank lending. Further, from the fact that the coefficients do not turn out to be statistically different for the measures of hard information, we may see that these results already signal the importance of *soft* information in bank lending.

To make sure that the results are not driven by the distribution of the variables among the different information classifications, I study these distributions in Table 7. Panel A of the table shows, for each of the variables, the distribution of the sample firms depending on the degree of information available to the lending bank. As is apparent from the table, most of the classifications divide the sample into classes of roughly the same size. An exception to this is the availability of written records in the firms: 85% of the firms reported having no written records to answer the survey questions. Probably it is the small sample size for the firms that used records to answer the survey what leads to a reduction in the estimation of β_1^P in this case. So, even when, as expected, we find that in this case β_1^N cannot be statistically distinguished from β_1^P, we should be careful in drawing conclusions from this result as it may be driven by distributional considerations and reduced variability.

Panel B of Table 7 shows the correlation among the variables that measure information availability for the lender. The first thing to note is that having written records is not correlated with any of the other measures of information availability, already giving credence to our hypothesis that this variable measures mainly the opaqueness of the firms and not private information availability of the banks. On the other hand, the correlation among the rest of the variables, although positive, is not as high as would be expected: in most cases, these correlation coefficients are between 0.20 and 0.50. One obvious exception to this is the high correlation between firms with relationships of length longer than one year, and firms with relationships of length longer than three years ($\rho = 0.82$). The other notable exception is the high correlation between being the primary service provider and having a savings or checking account ($\rho = 0.74$). These results, overall, show that each of the measures for relationship lending are different.

3.2.5 A timing consideration

At this point, we should remember that we are dealing with a cross-sectional database. The probit regressions done up to now show the estimated coefficients for the fraction of the purchases paid late during 1998 on the decision of the financial institution of granting the loan or not, *independently* of the moment in which this decision was made. However, as can be shown in Figure 6, the fraction of purchases paid after the due date during 1998 is a very imperfect proxy for the signal that banks observed about the firms' quality for those firms applying for credit before 1998. Moreover, the firms that obtained a loan before 1998 were more likely to pay a lower fraction of their purchases after the due date during 1998 than those that did not get one, because they were relatively more liquid. Fortunately, there is information in the survey about the year in which the firm applied for its loan. Therefore, it is possible to repeat the estimations of Table 6, but eliminating the firms that asked for a loan before 1998. This is what I do in Table 8.[36]

When we eliminate the firms that asked for a loan during or after 1998, we find that the fraction of purchases paid after the due date is statistically meaningful at a 99% confidence level for the decision to grant a loan for all the cases when the bank does not have private information availability (Columns 1-5 of Table 8). In particular, Column 5 shows that the effect is especially relevant when the lender has a source

[36]For further robustness, I also repeat the estimations of columns 2-7 of Table 6 on the subsample of firms that asked for a loan after 1998 (i.e., eliminating the firms that asked for a loan during 1998). The results, available upon request, remain qualitatively unchanged, although the reduction in the sample size reduces the precision of some estimates.

of soft information about the firm. The economic significance of the coefficients are quite meaningful, in around 40% for the average firm. In other words, if the average firm with a lender bank that is uninformed increases the fraction of purchases paid after the due date by 10%, the reduction in its probability of obtaining a bank loan would be of around 4 percentage points.

On the other hand, whenever the bank is privately informed about the firm, the information about the fraction of purchases paid after the due date, while negative, is only statistically significant (at a 10% level) for three of the measures (Columns 1, 3, and 4). Yet, the last two rows in Table 8 show that the coefficients β_1^P and β_1^N are statistically different for all of the measures for private information availability. In fact, the lowest p-value is reached for our best measure of soft information availability. The results are also significant, although at a lower level of confidence (95%) when the measure of sources of information is the firm's self-assessment of the lender bank being the primary financial services provider. A plausible explanation for this fall in significance with this variable is that, even when the bank is the firm's primary financial services provider, it does not necessarily have access to much private information about the firm. This is similar to what happens with the availability of written records of the firm, our measure for the degree of opacity of the firm (Column 6). The coefficients cannot be statistically distinguished at a 90% level for this measure, reinforcing our hypothesis that the differential treatment of the trade credit variable stems from informational issues, and not from other confounding effects. In other words, the results we obtained previously are confirmed, and even reinforced, when we do the estimations on the sub-sample of firms that applied for a loan after or during 1998.

From these results, we could be tempted to conclude that it is the accumulation of *soft* information what really matters for banks not to rely on information gathered by others. However, some care must still be taken before jumping into these conclusions. First of all, we must remember that just as the sources of hard information do not exclude gathering soft information in the process, our measures for sources of soft information do not exclude some parallel accumulation of hard information. In other words, hard and soft information accumulation are not mutually exclusive. Therefore, it could be well the case that the results that we see for our measures that contain soft information are in fact driven by hard information availability. What we can say at this point is that the *private* information accumulated by the banks - soft or hard - is crucial in determining whether to grant the loan or not.[37] Whether soft information plays a role or not shall be discussed in Section 3.3.

3.2.6 Effect of other observable variables on credit availability

Before disentangling the role played by soft and hard information in the lending decision of banks, we should briefly analyze the other results of the regressions of Tables 6 and 8, in order to explore whether the estimated coefficients have economical and statistical significance.

First of all, it is worth looking at the coefficients of the dummy variables that contain the firm's access to information sources. Consistent with the results of Cole (1998), the existence of a relationship with the bank - as measured by the firm's self-assessment about whether the bank is its primary financial institution - boosts the availability of credit. This result is significant at a 99% confidence level. Nevertheless, once we control for the bank being the firm's primary provider of financial services, the marginal effect of having either a long or a personal relationship with the bank is negative, and this result is both economically and statistically significant. Since the survey question expressly excludes all loan renewals and only considers requests for new loans, the sign of these variables could be capturing the effect that firms with shorter relationships are more likely to get new loans. Unfortunately, there is no question in the survey referring to loan renewals, and therefore we cannot test this conjecture. Nevertheless, I check whether the coefficients on these relationship

[37] I thank Hans Degryse for this important remark.

variables still hold if we only control for one of the relationship variables at the time. By eliminating the primary financial services provider indicator, I find the following coefficients (not reported in the tables): β=-0.018, z=-0.55 for relationships shorter than one year; β=-0.105,z=-1.8 for relationships shorter than the median, and β=0.074, z=1.97 for the impersonal relationships.[38] While the former two have the expected negative signs that are in line with Cole's (1998) findings, the third preserves the positive sign. One possible interpretation of this finding is that the 'transaction' banks - i.e. those that do not tend to lend based on character considerations - are relatively less risk averse than the 'character' banks that lend based relatively more on soft information, and hence caeteris paribus assign a higher probability to grant the loan.

Regarding the coefficient for the dummy variable indicating whether the firm has a savings or checking account with the lending bank, it is neither economically nor statistically significant once we control for the primary financial services provider. This is not surprising, considering that these variables are highly correlated (recall Table 7). In fact, when we substitute the latter with the former variable in the model, we obtain a coefficient of the order of β=0.155 with a z-statistic of 3.30. On the other hand, and as was to be expected, the availability of financial records does not have an economically nor statistically significant effect on the availability of credit, not even when we do not control for the primary financial institution. It is the quality of the financial situation of the firms, instead of the fact of having records, what determines the availability of credit to the firms.

Let us now consider the signs and economic significance of the control variables. First of all, and consistent with previous findings, we observe that larger firms, as well as older firms, have greater probabilities of being granted a loan. Similarly, more profitable firms - the ones with higher return on assets - have a larger probability of

[38]These coefficients correspond to the same model as in Column 1 of Table 6 for the sample of firms applying for a loan during or after 1998. In each model, the primary financial services provider indicator is eliminated and replaced by the corresponding relationship variable.

being granted a loan than unprofitable firms. This variable is significant at a 10% level.

On the other hand, firms that have a positive sales growth do not have a significantly higher probability of being granted a loan than those that have been stagnant. Nevertheless, the sign of this variable is positive, as expected. The lack of significance is probably due to the fact that size and age of firms are negatively correlated with sales increase: smaller and younger firms have more growth potential. Once the size and age have been netted out, there seems to be no marginal benefit for growing firms.

The behavior of the variables measuring liquidity (i.e., cash over assets in 1998) and leverage (total debt over assets for year 1998) is consistent with the timing of the loan decision relative to 1998. When all the firms are included in the analysis, the 1998 liquidity had a positive sign (although not significantly different from zero). Yet, when we eliminate the firms asking for a loan before 1998, the sign turns out to be negative (although still not significant). This sign reversal could be caused by the firms that were granted a loan before 1998, which of course were relatively more liquid during 1998.

On the other hand, the effect of the 1998 leverage on the dependent variable is undetermined when we mix the firms that asked for a loan before our benchmark year and those that asked during or after this year. When we only include the relevant firms, we find a more intuitive result: The firms that were highly leveraged during 1998, which are more risky, have a lower probability of obtaining a loan during or after 1998. The decrease in probability is statistically significant at confidence levels of 90 to 95%.

The governance structure (namely, if the firm is limited liability or owner managed) does not affect the probability of obtaining a bank loan once we control for other firm characteristics such as size and age. However, an important determinant for obtaining a bank loan is that the owner has a house. Given that the significance of this variable survives the exclusion of the firms that asked for a loan before 1998, we may conclude that the owner's home could serve as a collateral for the loans, especially when there is unlimited liability. This is exactly what I find when I interact the limited liability binary variable with the home ownership dummy (not reported in the tables): The coefficient on the home variable is positive and significant at a high confidence level when there is unlimited liability. Finally, I find strong evidence suggesting discrimination in bank lending, consistent with Coleman (2002). The coefficient on a minority owner is negative and statistically significant at confidence levels of 95%.

The negative coefficient on the dummy variable for Metropolitan Statistical Area suggests that all else equal, firms located in an urban area have a smaller probability of getting a loan than those outside an MSA. Firms are more likely to be concentrated inside MSAs, so this result suggests that competition for funding is likely to be fierce in these environments. Although this result is statistically significant at confidence levels above 95%, the significance does not survive the exclusion of the firms asking for a loan before 1998, therefore this is not conclusive evidence. Similarly, firms do not seem to be significantly less likely to get a loan when the *banking* market is concentrated, as we may see from the coefficient of this variable.[39]

The results in Tables 6 and 8 also illustrate that the criteria for selecting the firms that will be granted a loan are different depending on the type of loan asked for. *Caeteris paribus*, banks tend to grant loans more easily for specific purposes, such as buying a vehicle, equipment, or land, than to grant an open line of credit (the reference category for type of loan asked for is a dummy for a line of credit). It is easier to grant a loan for a specific purpose because the object that the loan is financing is itself the collateral for the loan, should the payer default. A line of credit, on the contrary, should be secured with other assets of the firm. An unsecured line of credit involves a greater default risk or more costly information collection about

[39]There is also no effect of the interaction of these two variables on the probability of granting a bank loan.

the credit quality of the firm.

The coefficients for the type of lender are not significantly different from zero, the only exception to this being the depositary institutions (savings banks, savings and loan associations, and credit unions), which *caeteris paribus* tend to grant loans relatively more easily than commercial banks, the omitted variable. Nevertheless, there are very few observations for this variable, and this result is not robust to the addition of the firms that asked for loans before 1998. Hence this result may only be coincidental. This suggests that, once taking into account the risk class of the firms, the practice of granting loans is quite homogeneous across different types of financial intermediaries. This is consistent with the findings of Carey, Post, and Sharpe (1998).

Let us now look at the measures of goodness of fit of the models. When we include all of the firms in the regressions, the Pseudo R^2 of the probit models is between 32 and 33%. Roughly, a third of the variance of the dependent variable is explained by the model. Moreover, the Pseudo R^2 increases roughly 3 percentage points when we eliminate the firms that asked for a loan before 1998, while the signs of the variables remain the same. We should notice, however, that the significance of some of the control variables is slightly affected by the reduction of the sample size from 634 in Table 6 to 505 firms in Table 8. Nevertheless, the level of statistical significance is improved for one of the control variables, namely, the leverage ratio, due to the better identification of the timing of events.

3.3 Soft information, hard information

3.3.1 Disentangling information types

Once we have found that the availability of private information is relevant for the lending decision of banks, it would be advisable to uncover the role of soft information in this process. For this matter, let us go back to Table 5 for a moment. Recall that the best proxy for soft information availability in the bank is the variable that measures whether the bank and the firm typically interact in a personal fashion. Hence, I have labelled this variable with an "S", for soft. What would happen if we interact it with one variable that contains mainly hard information, labelled with an "H" in Table 5? The results of such an interaction can be seen in Panel A of Table 9. To set an example, let us interact the personal relationship variable with the "H" variable that indicates whether the firm has a checking or savings account with the bank. If the bank does not lead a personal relationship with the firm, and neither does it manage one account, then we could say that such a bank has no information, soft or hard, about the firm's credit quality. If the bank does not manage an account, but leads a personal relationship with the firm, we may say that that bank has mostly soft information, and that the hard information about the firm's credit quality is basically limited to the publicly available hard information. Similarly, if the bank does not lead a personal relationship with the bank, but manages an account of the firm, then we may say that the bank has mostly private hard information, but no soft information. Finally, a bank that manages one of the firm's accounts and has a personal relationship with the firm has both hard and soft private information about the firm's quality.

We can also interact our "S" variable with a variable that measures both hard and soft information, labelled as "B" in Table 5. The results of such an interaction may be observed in Panel B of Table 9.[40]

Our best proxy for soft information availability is the existence of a personal relationship between the borrower and the lender. A personal interaction necessarily (either willingly or not) provides the lender with a subjective evaluation of the borrower. The same cannot be said for the rest of the variables identified in Table 5 as containing soft information - the variables measuring the relationship length: even the lengthiest of relationships could be absolutely impersonal. Consequently, I shall use the indicator of a personal relationship as the soft information proxy (variable

[40]The interaction between a "B" and an "H" variable would break down the firms into groups having no information, only hard information, or hard and soft information. Since we are not able to isolate the soft component of information through this interaction, I have not included it in Table 9.

"S") in the subsequent analysis. To isolate soft information from hard information availability, I shall interact this variable with each of the other variables identified in Table 5, thus obtaining four different classifications of the firms according to the type of information available to the lender. Additionally, I interact this soft information proxy with the use of written records to answer the survey, arguably a proxy of the opaqueness of the firms.

As noted already from Table 7, our soft information proxy is not too highly correlated with the rest of the variables. In fact, Table 10 contains the distributions of firms according to the cross-tabulations of our proxy of soft information and each of the other variables. The table shows that firms that lead a personal relationship with the bank tend to lead lengthy or information-intensive relationships as well. The reciprocal is also true: impersonal relationships are associated with short or 'transactional' relationships. These associations jointly account for 60 to 70% of the firms. The other 40 to 30% of the firms are roughly equally distributed into firms for which their lenders have personal relationships and no other source of information, and firms that have impersonal relationships, but lead a lengthy or information-intensive relation. Yet, there is a considerable number of firms in each of the categories. The one notable exception is the cross-tabulation of a personal relationship with the existence of written records. This is due to a small amount of firms reporting the use of written records to answer the survey (14%). Yet, even considering this case the number of firms in each category is always above 50, and it is above 100 in most other cases. Hence, I will use these classifications for the analysis described in the following section.

3.3.2 The central model: Soft information lending

With the above proposed identification of soft and hard information, it is possible to estimate the relative importance of soft information in bank lending. To do it, it is necessary to compare the difference between the lending practices of banks that have no private information about the firm's credit quality with the lending practices of the banks that have only (or mostly) soft information available to make their lending decision. I propose the following model in order to carry out the comparison:

$$\begin{aligned} y_i &= \beta_0 + \beta_1^U x_i * U_i + \beta_1^S x_i * S_i + \beta_1^H x_i * H_i + \beta_1^B x_i * B_i + \\ &\quad + \beta_2^B B_i + \beta_2^S S_i + \beta_2^H H_i + \beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + u_i, \end{aligned} \tag{3}$$

where y_i, x_i, X_i^f, X_i^b, and X_i^l are defined as before; and $B_i = I_i^H(x) I_i^S(x)$, $S_i = (1 - I_i^H(x)) I_i^S(x)$, $H_i = I_i^H(x)(1 - I_i^S(x))$, and $U_i = (1 - I_i^H(x))(1 - I_i^S(x))$, where:

$$I_i^H(x) = \begin{cases} 1, & \text{if lender bank of firm } i \text{ has a source of hard information} \\ 0, & \text{otherwise} \end{cases},$$

and

$$I_i^S(x) = \begin{cases} 1, & \text{if lender bank of firm } i \text{ has a source of soft information} \\ 0, & \text{otherwise} \end{cases}.$$

The extent of importance of the public reputation of the firms in the credit decision of banks should be summarized in the coefficients β_1^K. In general, banks that have no access to private sources of information should place a strong weight on the outside reputation of the firms, so we should observe $\beta_1^U < 0$. Moreover, these institutions should rely much more on the reputation variable than the banks that have both private soft and private hard information who substitute this public reputation with private information: $\beta_1^U < \beta_1^B$.

How about the relative importance of soft and hard information in bank lending? Under the hypothesis that soft information plays a role, we should find that the banks that have mostly soft information available would tend to ignore the information contained in the trade credit repayment patterns, i.e. $\beta_S = 0$, or at least they should rely on this signal to a much less extent than uninformed ones, i.e. $\beta_1^S < \beta_1^U$. Similarly, if private hard information plays a role as well, we should find $\beta_H = 0$, or at least $\beta_H < \beta_U$. In the following section we analyze whether these hypothesis hold in the data.

3.3.3 Estimation method and results

The results of the estimations of Equation 3 are contained in Table 11. In all of the estimations of this table, I use the existence of a personal relationship with the lender as the source of private soft information for the bank, i.e., the "S" variable identified in Table 5. I interact this variable with the following sources of hard information ("H" or "B" variables) to disentangle the information types available to the lenders: (i) whether the bank is the firm's primary financial services provider (Columns 1 and 6), (ii), whether the relationship with the bank is longer than 1 year (Columns 2 and 7), (iii) whether the relationship with the bank is longer than the median (Columns 3 and 8), (iv) whether the bank manages an account (Columns 4 and 9), and (v) whether the bank keeps written records (Columns 5 and 10). The estimations of Columns 1-5 correspond to all of the firms asking for a loan, while Columns 6-10 correspond to firms asking for a loan during or after 1998, to control for the timing dimension mentioned in Section 3.2.5. I use the same variables for X^f, X^b and X^l as in the previous sections. Since we are only changing the breakdown of the interactions between the purchases paid after the due date and the sources of information dummies, the coefficients for the control variables are qualitatively equal to those in Tables 6 and 8, and are not reported in the table. Similarly, as in the previous sections, the method of estimation is a probit model with heteroskedasticity correction. The results are reported in marginal form and evaluated at the sample mean.

We can see in the first row of Table 11 that β_1^B, the coefficient for the purchases paid after the due date when the bank has a source of private soft *and* hard information about the credit quality of the firms is never significantly different from zero. Confirming our results of the previous section, privately informed banks substitute the publicly available information with their own private information sources. However, as soon as the bank lacks some type of information, soft or hard, about the firm's credit quality, then the fraction of purchases paid after the due date gains significance in the determination of who gets a loan or not. In particular, when the bank lacks both sources of information, it relies strongly and significantly on the purchases paid after the due date. In fact, β_1^U (in marginal form) ranges from -0.31 to -0.52 depending on the "H" variable, and is significant at highest level for all the specifications.

What happens when the bank's only source of private information is a source of *soft* information? Let us examine β_1^S. Notice that this coefficient is negative, is always smaller (in absolute value) than β_1^U. The fourth row of Table 11 from bottom to top contains the Chi squared statistic for the test that $\beta_1^S = \beta_1^U$, and below it is its p-value. These coefficients are not statistically differentiated when we consider the whole sample of firms. Yet, the significance improves greatly when we focus on the more representative group of firms that asked for a loan during or after 1998 (Columns 6-10). In this case, β_1^U is significantly smaller than β_1^S at a 10% level when the measures considered are the primary financial services provider (Column 6) and a relationship longer than the median (Column 8). A one-tailed test yields also statistical difference when the measure is a relationship longer than the median (Column 7). In other words, soft information seems to matter in small business lending.[41]

How about hard information? First of all, notice that this coefficient is not always smaller in absolute value than β_1^U. Nevertheless, in the last two rows of Table 11 I perform the test $\beta_1^H - \beta_1^U = 0$ to see whether there is any differential effect of having only hard information available. I find that these two coefficients cannot be

[41] These results are further reinforced when we only consider the firms that asked for a loan after 1998 (estimates not reported): In this case the difference is statistically meaningful at confidence levels of 95% or higher for all of our measures.

distinguished from each other at significance levels of 10% or lower, not even when we eliminate all the firms of the sample except those that asked for a loan after 1998. The highest p-value (0.13) occurs when the source of “hard” information is a relationship greater than the median length, which we had identified as a variable that does not exclude the existence of soft information. Together with our previous findings, this suggests that gathering private hard information about the firm’s credit quality is not as important as gathering private soft information about the firm’s credit quality. This does not mean that hard information is not relevant for banks. Recall that we have already controlled for all the sources of public hard information available to us (size, age, governance structure, balance sheet items, etc.). However, the results seem to indicate that the marginal effect of an additional source of *private* hard information accumulated by banks what is not as important as the marginal effect of an additional source of soft information.

The results in this section highlight the relative importance of soft information in bank lending. While the accumulation of both hard and soft information is crucial in the decision of banks of whether to lend to the firms or not, gathering private soft information about the firm’s credit quality seems to be also decisive.

In order to obtain a better intuition of how the availability of soft and hard information affects the probability of obtaining a bank loan, I present a simplified graph of the results in Figure 7. The graph plots the estimated probability of obtaining a bank loan for an average firm, as a function of the fraction of trade credit purchases paid after the due date (represented by the horizontal axis). Each of the four lines represent such probabilities when the lender has access to each of the four different private information sets identified before: only hard information, only soft information, both soft and hard information, and no private information. The estimated probabilities correspond to the model in Column 7 of Table 11, where the lenders that have access to private hard information are identified as those with a relationship length with their borrower of more than one year.

Figure 7 shows how privately informed banks that have both soft and hard information about their lenders - let's call them 'relationship' banks, represented by the solid line in the figure - tend to be rather indifferent about the public records of the firms' defaults. The estimated probability of granting the loans in this case is quite constant, independently of the fraction of purchases paid after the due date. In the other extreme, we have the 'transaction' banks, i.e. those that have no sources of private information (soft or hard) about the firms, represented by the dotted line in the figure. These banks present a very strong reaction to the public information contained in the trade credit records. Figure 7 also shows how the availability of soft or hard private information tends to smoothen this strong reaction to the hard public information contained in the trade credit records. The dashed line represents the probability of granting a bank loan to an average firm when the lender has only access to hard information - let's call these 'cookie-cutter' banks. For a greater visual clarity, the graph does not contain confidence intervals. However, from the coefficients of Column 7 in Table 11, we may observe that the probability of granting a loan when only private hard information is available is not statistically distinguishable from the respective probability when no information is available. In contrast, the availability of soft information significantly changes the credit granting decision of banks. These banks - let's call them 'character' banks - have a significantly smoother reaction to the availability of hard public information than the 'transaction' banks. In fact, these results are reinforced for other measures of hard information available in the rest of the columns of Table 11.

3.4 Controlling for endogeneity: IV estimations

So far, we have assumed that the fraction of purchases paid after the due date affects the probability of obtaining a bank loan, but that obtaining a bank loan, or the prospect of obtaining one, does not affect the fraction of trade credits paid late. However, let us now consider a firm that is liquidity constrained in 1998. If this firm anticipates that she will be granted a loan next year when she applies for one, they she may behave well and pay her suppliers in a timely fashion in order to avoid problems in the future. Conversely, if she suspects that she will not be granted a loan, she might as well act according to her constrained status and pay a fraction of her purchases after the due date. If we ignore this possible two-way relationship between both variables, the estimated effect of the fraction of purchases paid late on the granting decision of banks will be inconsistent, and the conclusions of our previous sections may be biased.

In order to estimate the coefficients of the last sections consistently, we should use a Two-Stage Least Squares (TSLS) estimator. In order to use this estimator we need valid instruments for the fraction of purchases paid late. In other words, we need a set of variables Z_i that are (i) partially correlated with the fraction of purchases paid late once the other exogenous variables have been netted out, and (ii) uncorrelated with the error term in Equation 1. As instruments for the fraction of purchases paid after the due date, I propose the trade credit terms offered to firms - i.e., the length of the credit period, the length of the discount period, and the magnitude of the discount offered-,[42] and the bargaining power of the firm vis-a-vis its suppliers.

There are several reasons why the terms of trade credit offered to firms are correlated with the fraction of purchases paid late, once the effect of the rest of the variables has been netted out. First of all, given that the implicit interest rate charged by suppliers is higher the shorter the credit period, then all else equal the fraction of purchases paid late by a firm should be smaller the shorter the net period. On the other hand, the incentives for paying on time are high if the discount is large. Hence, the fraction of purchases paid late should be smaller for longer discount periods and for larger discounts, *caeteris paribus*.

On the other hand, the terms of trade credit offered should not affect the decisions

[42]The most common credit terms offered by suppliers in the US are net terms and two-term trade credit (Ng, Smith and Smith 1999). When net terms are offered, the firm receives the goods in day zero, and must pay the full amount of credit in a period preestablished by the supplier. When two-term trade credit is offered, the supplier grants a discount for early payment.

of banks to lend to the firms. Regardless of the firm's size, there is evidence suggesting that trade credit terms offered to the firms are typically stable within industries, and do not vary depending on the firm's credit quality (Smith 1987, Petersen and Rajan 1994, Ng et al. 1999). In contrast, banks usually do a careful examination of all of the factors that may lead to default on the repayment of the loan. Usually, data about the firm and its owner is processed using statistical methods, in what is called "Credit Scoring".[43] Each application is examined independently, and only in rare cases do banks systematically deny or grant loans to all the firms within a same industry. Therefore, the instruments chosen should not be correlated with the error term of Equation 1.

Finally, the higher the firm's bargaining power in relation to its suppliers, the lower is their threat to stop the firm's future supplies (Cuñat 2006). Thus, all else equal, a firm with a large bargaining power could pay a larger fraction of its purchases after the due date than a firm with no bargaining power. However, the bargaining power of the firms with respect to their suppliers should not affect the bank's probability of granting the loan.

I therefore assume the following model in the population:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i \tag{4}$$

$$x_i = \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_i, \tag{5}$$

where y_i, x_i, X_i^f, X_i^b, and X_i^l are defined as before, and Z_i is a vector containing the terms of trade credit offered to the firm by its most important supplier and the bargaining power of the firm. Here, Equation 4 is the structural equation of interest, and Equation 5 is the reduced-form equation for the fraction of purchases paid late. In this TSLS estimation method, the fraction of purchases paid late is first estimated

[43] Credit Scoring techniques have been used for a long time for processing hard information about the firm (Greenbaum and Thakor 1995).Recently, Credit Scoring has also been introduced for small businesses, processing soft information about their credit quality (Berger, Frame and Miller 2005, Mester 1997)

using Equation 5 and using as instruments ten dummies for the length of the net period, five dummies for the length of the discount period, another five dummies for the size of the discount, and the natural logarithm of the number of suppliers of the firm, as a proxy of the bargaining power. In the second stage, the predicted values for the fraction of purchases paid after the due date are substituted for the real values of this variable in Equation 4.

For simplicity, both the first and the second stage regressions of the above system are estimated by ordinary least squares. It could be argued that the endogenous variable should be estimated with a tobit model, as it is censored at 0 and 100%. However, the consistency of the second stage estimates is not affected by the functional form of the first stage estimation (Angrist and Krueger 2001). Similarly, the linear estimation leads to an easier interpretation of the coefficients, and it typically captures the average effect of economic interest even when the correct specification is nonlinear. We confirm this when estimating a linear probability model for Equations 1, 2, and 3 (not reported), which yields estimates that are very similar to their probit counterparts which were estimated in the previous section.

Table 12 contains the coefficients of the first stage estimations of equation 5. The last rows of the table contain tests for the validity of the instruments (the test that the coefficients of the instruments are jointly zero and the test for overidentification). These tests show that the chosen instruments are valid with high significance levels. Moreover, the signs of the coefficients of the instruments are as were expected: the shorter the net period, the smaller the percentage of purchases paid after the due date (the omitted dummy is financing from 60 to 120 days); the longer the discount period, the larger the percentage of purchases paid after the due date; the more bargaining power of the firm, the larger the fraction of purchases paid after the due date.[44]

I also repeat the estimation of Equations 2 and 3 with instrumental variables,

[44]Although the latter variable is not statistically significant, the tobit functional form for this first stage regression (not reported) yields an estimate of 0.039 at a 5% significance level.

assuming the following models in the population:

$$
\begin{aligned}
y_i &= \beta_0 + \beta_1^P x_i^P + \beta_1^N x_i^N + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i \\
x_i^P &= \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{1i}, \\
x_i^N &= \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{2i};
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
y_i &= \beta_0 + \beta_1^U x_i^U + \beta_1^S x_i^S + \beta_1^H x_i^H + \beta_1^B x_i^B + \beta_2^B B_i + \\
&\quad + \beta_2^S S_i + \beta_2^H H_i + \beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + u_i, \\
x_i^U &= \alpha_0 + \alpha_1 Z_i + \alpha_2 X_i^f + \alpha_3 X_i^b + \alpha_4 X_i^l + e_{1i}, \\
x_i^S &= \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{2i}, \\
x_i^H &= \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{3i}, \\
x_i^B &= \eta_0 + \eta_1 Z_i + \eta_2 X_i^f + \eta_3 X_i^b + \eta_4 X_i^l + e_{4i},
\end{aligned}
\tag{7}
$$

where all of the variables are defined as before.

The IV regressions for the second-stage estimation of the system of Equations 6 are reported in Table 13, while the second stage estimations of the IV regressions of system 7 are in Table 14. For comparison purposes, the first column of Table 13 contains the estimator of Equation 4. Columns 2-7 of the same table contain the estimators of the second stage equation of model 6 for different definitions of the information ($I_i(x)$) which is indicated on the first row. Analogously, columns 1-5 of Table 14 are done for the interaction of having a personal relationship with the lender bank and different definitions of the hard information contained in $I_i^H(x)$, which are indicated in the first row. All of the reported estimations were made on the subsample of firms that asked for a loan during or after 1998.

In terms of the observable variables, the results of Tables 13 and 14 are qualitatively very similar to the findings of Sections 3.2 and 3.3. For all of the specifications tested, I find that size, age, profitability, collateral availability, and relationship with the bank are positively correlated to the probability of getting a loan, while being highly leveraged or being a minority owner are negatively correlated with obtaining a bank loan. However, the loss of efficiency of the IV estimator implies a loss in the statistical significance of some of the coefficients with respect to their OLS or probit counterparts.

How the trade credit repayment records of the firms affect the probability of getting a new loan also remains unchanged in the new specifications that take into account the potential endogenous relationship among these variables. The first column of Table 13 shows that the coefficient on the purchases paid after the due date is still negative and significant, although the significance level descends to a 10%. As in the OLS or probit cases, the negative effect of trade credit on the purchases paid after the due date is mainly due to the banks that do not have private sources of information: When we control for other sources of private information available to banks in columns 2-7 of Table 13, we find that $\beta_1^N < 0$. Moreover, a Chi-squared test about the equality of β_1^N and β_1^P shows that the coefficients are different at a 1% level (last rows of the estimation).

When we separate soft and hard information in Table 14, we find that while β_1^U is still significantly lower than zero, we cannot distinguish β_1^S, β_1^H, or β_1^B from zero. These findings highlight the importance of having any private source of information - soft or hard - about the firm's credit quality. When there is no source of private information available to banks, trade credit becomes a very valuable piece of information. Yet, the loss of efficiency of the TSLS estimations does not let us distinguish β_1^S or β_1^H from β_1^U for all measures for hard information except being the firm's primary financial services provider, in which the β_1^S is different from β_1^U at a 5% level, and β_1^H is different from β_1^U at a 10% level.

At this point, we desire to choose between the potentially inconsistent OLS or probit models and the inefficient IV estimators. I perform several tests of endogeneity of the purchases paid after the due date, to find out whether using the less efficient IV estimator is justified. First of all, I perform a two-stage test in which the residuals of Equation 5 are added to an OLS estimation of Equation 1 (Wooldridge 2001, p.119-120). The coefficient of the residuals is 0.235 with a standard error of 0.294. Therefore we accept the null hypothesis that the residuals are not consistently correlated with the error term. I confirm the results by performing the Wu-Hausman F-test and a Durbin-Wu-Watson Chi-squared test for endogeneity in Equation 4.[45] The respective p-values for these tests are 0.413 and 0.393, so the null hypothesis that the regressor is exogenous cannot be rejected. Finally, I perform Hausman tests about the difference between the probit and the respective IV estimators. In all cases, I cannot reject the null hypothesis that the difference in the coefficients is systematic. Therefore, there is no evidence that the probit estimates of the previous sections are inconsistent.

3.5 Non-random sample: Correcting for firm self-selection

Let us now consider the firm's decision of applying for a loan or not. This is not a random choice - it is the result of an internal, probably complex, decision-making process. The estimations based on Sections 3.2 to 3.4 are based on the subsample of firms that applied for a loan, i.e. possibly a non-random sample: firms in this subsample made a decision to apply for a loan, and the decision could be related to their credit quality or the availability of a relationship with a bank. Since the dependent variable in Equations 1, 2, and 3 can only be observed for this selected sample of firms, the estimations of the previous sections could be biased.

Intuitively, this is what happens when the sample is selected as the result of firms deciding whether to apply for credit or not. Some of the characteristics leading firms to apply for a credit can be observed by the banks (for example, firm size or sales), but others are unobservable (for example, the value of the firms' projects). Since the decision of applying for a loan is not random, some of the unobserved characteristics behind the decision of firms to apply or not for a loan may be correlated

[45] These tests were performed under the assumption of homoskedasticity of the error term.

with the unobserved characteristics that affect whether the bank grants the credit or not. For example, the value of the future projects of the firms is an unobservable characteristic that may affect both whether the firm applies for a credit and the subsequent decision of banks to grant the credit or not. The correlation between the unobservable characteristics influencing both the decision of firms to apply for credit and the bank's subsequent granting decision can lead to biased results when regressing the decision of banks on the variables capturing this choice of applying for a loan or not. The decision of applying for a loan is observed by banks - at least partially - so they may update their beliefs about the unobserved characteristics related to the credit quality of the firms with this information. We therefore need to explicitly take this updating of beliefs of banks into account, controlling for the selection of firms.

The procedure to deal with sample selection bias has been widely studied in the econometric literature.[46] For this study, I assume the following model for the selection of the sample:

$$\begin{aligned} w_i^* &= \eta X_i + u_i \qquad (8) \\ w_i^o &= \begin{cases} 1, \text{ if } w_i^* \geq 0 \\ 0, \text{ otherwise} \end{cases}, \end{aligned}$$

where X_i is a vector of observable characteristics of the firms that determine their choice of applying for a loan or not, w^* represents the utility of applying for a loan, and w^o is the observable counterpart of the utility of applying for a loan, i.e. a binary variable containing a one if the firm applied, and a zero otherwise.

I use a maximum likelihood estimation to account for the selection of the sample with a binary response model (Wooldridge 2001, p. 570-571). That is, I assume that the error term of the selection equation and the error term of Equation 1 (or Equations 2 or 3, respectively) are distributed as bivariate normal.

[46]For a discussion of the bias of the estimators when there is sample selection, see, for example, Maddala (1983, Chapter 9) or Wooldridge (2001, Chapter 17)

I include size, age, profitability, sales increase, sales over assets, market and governance characteristics of the firms in the vector X_i. Additionally, I include the number of banks with which the firm has a relation, as an identification variable for the selection equation. The idea behind identification is the following: The higher the number of banks, the more choices the firm has to apply when applying for a loan, so this variable is likely to be correlated with the firms' decision of asking for a loan or not. On the other hand, the firms in the sample are mostly small and private firms, so the loans are typically small, and the banks with which they have relations are likely to be also small (Berger, Miller, Petersen, Rajan and Stein 2005, Cole et al. 2004). These banks typically do not extend syndicated loans - and it is definitively not the case for any of the firms in the sample-, so the number of banks with which a firm has a relationship should not affect the credit-granting decision of banks.[47]

The results of the joint maximum likelihood estimation of Equations 2 (3) and 8 are summarized in Table 15 (16). For comparison purposes, Table 16 also contains the joint maximum likelihood estimation of Equations 1 and 8.[48] While the identification variable is highly significant in the selection equation, the results for the other variables, including the interaction between the percentage of purchases paid after the due date and the private sources of information of banks, does not change qualitatively with respect to the results of the previous sections. Furthermore, the Wald χ^2 test for the zero correlation between the selection error term and the error term of the structural equation cannot be rejected at relevant confidence levels for any of the specifications. Therefore, there is no evidence that the unobservable firm characteristics leading to the decision of firms to apply for a loan or not are systematically related to the credit-granting decisions of the banks. After controlling for firm self-selection into applying for a loan or not, we still find that the access of banks to

[47]Evidence regarding the correlation between the number of bank relationships and firm's firm quality is mixed. While some evidence suggests that the number of bank relationships is related to firm quality (Harhoff and Koerting 1998, Farinha and Santos 2002), more recent evidence shows that this is not necessarily the case (Machauer and Weber 2000, Guiso and Minetti 2004).

[48]Note that the estimated coefficients are not reported in marginal form in these tables.

sources of soft information are crucial for the bank's decision making process.

3.6 Further evidence on the use of soft information

A natural question that arises when observing the results of the previous sections is whether the results are casually driven by the choice of trade credit as the source of hard public information of banks. It is worthwhile to try to find whether the same effect survives when we replace the fraction of purchases paid after the due date with other variables containing hard information about the firm that could be accessible to all banks. One obvious choice in this regard is the owner's credit history. Along with the trade credit repayment history, rating agencies typically include a description of the owners' credit history in their reports. The SSBF dataset also contains information about whether the principal owner has been delinquent on a personal or a business obligation during 60 days or more, in the three years previous to the survey, which is a good proxy to the information contained in the credit reports. In this section, I repeat the previous analysis but interacting the access of banks to sources of private information with this binary variable.[49]

An important consideration that we should take into account when using this variable is that, contrary to what we had with the trade credit variable, the timing of the delinquency with respect to the loan application cannot be determined from the survey. Figure 8 contains a diagram of the timing of events. The survey recollects the average fraction of purchases paid after the due date (PPL) during 1998, and with that information we may identify that event with respect to the timing of the loan application. However, this clear timing identification does not occur for the delinquency variable. We only know that the delinquency occurred during the previous seven years

[49] As a matter of fact, the survey contains also binary variables for whether (i) the firm has declared bankruptcy or (ii) there have been judgments against the firm's principal owner in the seven years previous to the survey. However, of the firms that recently asked for a loan, only 39 firms have had a judgment, and 22 have declared bankruptcy in the past seven years. Therefore, I choose to base the analysis of this section to the delinquency variable, which contains much more variability (246 firms answer positively to this question).

before the survey took place, but we cannot know whether the delinquency occurred before, during, or after the loan application. Therefore, it could well be the case that a firm is delinquent as a result of not obtaining a bank loan in the past three years, i.e. we could have a marked endogeneity in our estimations. Moreover, this variable presents several caveats with respect to the trade credit variable that we have already pointed out in Section 3.2: Less variability (only 246 firms out of 861 reported to be delinquent); binary variable, in contrast to the continual measure for late payment of trade credit; too powerful signal of repayment inability.

Ignoring for a moment the caveats pointed out in the previous paragraph, Tables 17 and 19 contain the results for the effect of being delinquent in at least one obligation on the probability of obtaining a bank loan. The former contains estimations for Equation 2, while the latter contains the estimations for Equation 3.

As was the case with the fraction of purchases paid after the due date, and as was expected, we observe a highly significant negative correlation between this variable and the bank's decision to grant a loan (Column 1 of Table 17). Moreover, as we expected, the impact of this variable is smaller when the bank has some source of private information (i.e., in this case the coefficient for delinquency is always smaller in absolute value, see Columns 2 to 6). Note, however, that these differences are only significant (at a 5% level) when the bank has sources of hard private information, as accumulated through the savings or checking accounts. For the rest of the variables we cannot say that the differences are significant. In particular, the coefficients are practically indistinguishable when the source of information for the bank is a personal relationship. These results show evidence that, in the presence of very strong negative signals of credit quality, the availability of soft information is not enough to make banks less dependent on this strong external signal. However, if there is enough hard private information of the bank, then the reliance on the negative external signal of credit quality may be significantly reduced.

When we further subdivide the sample according to full private information availability (soft and hard), only soft, only hard, or none, we continue to find a decreasing reliance on the external delinquency variable as soon as the bank has an internal source of private information. In other words, $\beta_1^U > \beta_1^B$ and $\beta_1^U > \beta_1^S$. We do not find the coefficient β_1^H to be significantly different from zero, however. The coefficients are not estimated very precisely in this case. The cause for this could be the reduced sample size for the category of firms with hard private information availability but no soft information availability: the number of sample firms in this category is in general smaller in this case (see the distribution of the firms in Table 18). This reduces the variability in the delinquency variable for firms whose lender has a private hard information source, but that doesn't lead a personal relationship with the bank.

The importance of soft information that we found in the previous sections is confirmed again in Table 19: The coefficients β_1^S do seem to be much smaller than the coefficients for β_1^U for all of our measures. However, the last rows of show that these coefficients are not statistically distinguishable at reasonable confidence levels. In fact, we cannot even distinguish the coefficients β_1^B and β_1^U at reasonable levels (the χ^2 statistics for this test are and its corresponding p-value are not reported in the table). I believe these somewhat disappointing results are due to the caveats of the delinquency variable, which I have identified previously. In particular, the strong endogenous relationship between being delinquent and not obtaining a loan are probably biasing the results and increasing the significance of the negative correlation between the variables for all information sets.

From the results in this section we may conclude that a very strong external reputation of a firm may preclude its access to bank credits even when the bank has private sources of information. Only if a bank has a source of hard private information could it ignore the bad reputation of the firm and substitute this external reputation with its own valuable information. In other words, it seems that soft information loses its protagonism when there are very strong negative signals about the firms.

3.7 Concluding remarks

Consistent with the relationship lending literature, I find direct and clear-cut evidence that, through relationships, banks gather private information and use it in their credit decisions. A bank that lacks any source of private information, will tend to rely on the firm's reputation in the credit markets to infer the firm's credit quality. However, whenever there is a source of private information the reliance on the firms' reputation is much weaker, or it may even disappear in some cases.

The second and central contribution of this chapter regards an analysis of the use of soft information in bank lending. I find that whenever the lenders' only source of private information is a personal relationship with their borrowers that precludes the gathering of private hard information, the loan granting decision is quite independent of the outside reputation of the borrowers. In other words, the availability of soft information seems to matter quite a lot in the decision-making process of 'relationship' banks. The results are robust to several classifications of banks according to their availability of soft and hard private information. Moreover, the results tend to be confirmed for different measures of outside reputation, although they are much more clear-cut whenever the borrowers' reputation is not too negative. In extreme cases - for example, whenever the lender has previously defaulted in another credit relationship - the existence of soft information per se does not seem to be enough to counteract the effect of a negative credit reputation, so even banks with soft information tend to systematically deny all credit applications coming from such firms. In this extreme case, the evidence points out that only when soft information is complemented with hard private information can the lenders substitute the outside gathered reputation with their own privately gathered information.

A final and related contribution of this chapter is to provide evidence that, even when a relationship bank has a private source of information about the firm, if the external signal of credit quality is too negative, the bank shall be likewise denied from credit. This result highlights the value of information exchanges, and shows how reputation may play a central role in the availability of credit for small firms, as suggested by Diamond (1989).

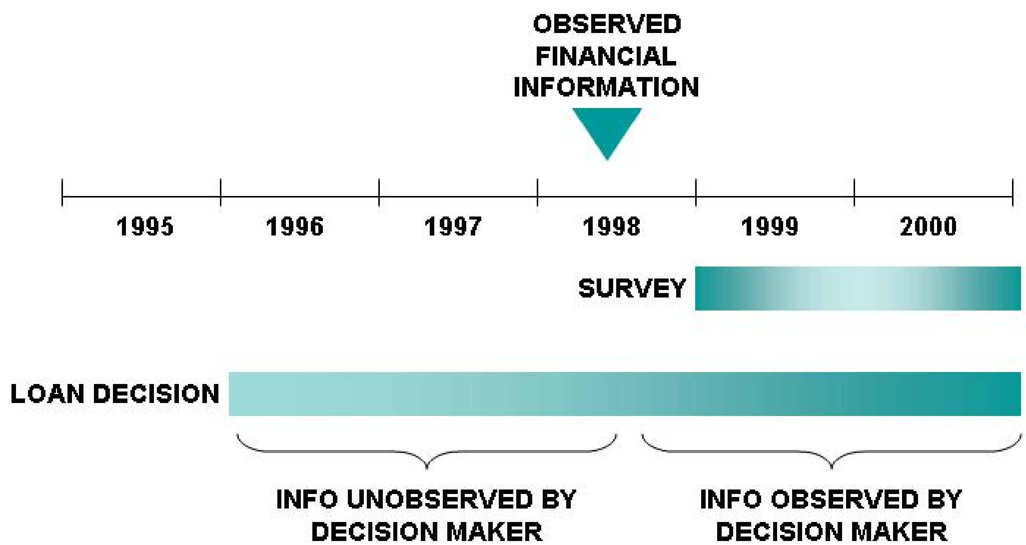

Figure 6: Information available to lender at decision-making time

This timeline represents the information available to the lender at the time of making the credit decision. The short horizontal bar that appears just below the timeline represents the distribution of the sample firms according to the moment in which they were surveyed. The dark shading represents a higher frequency of sample firms, and shows that most of the firms were surveyed at the beginning of 1999 or at the end of 2000. On the other hand, as indicated by the arrow that appears at the top of the figure, the survey collected most of the financial information about the firms for year 1998. For example, when referring to the trade purchases paid after the due date, the survey question is the following: *"During 1998, did the firm ever make payments on account after the bill was due in full?...* [If yes], ... *What percentage of the balances on account were made after the bill was due in full?"*. Finally, the survey recollects information about the most recent loan approved for the firms in the previous three years before the survey took place. Indeed, the survey question is: *''How many times did the firm apply for new loans in the last three years?"* ...[if greater than zero]... *"When did the firm make this most recent request for a loan that was approved?"* The lower horizontal bar contains the distribution of firms according to the dates where the applications for the most recent loan occurred (i.e., anytime within the 3 year-period before the survey took place). A high proportion of firms reported their most recent loan as occurring after 1998. Clearly, the financial information in the survey - such as the purchases paid after the due date - could have been observed by the lenders only for the firms that applied for the loan after 1998, or (at the limit) also for those that applied for the loan during 1998.

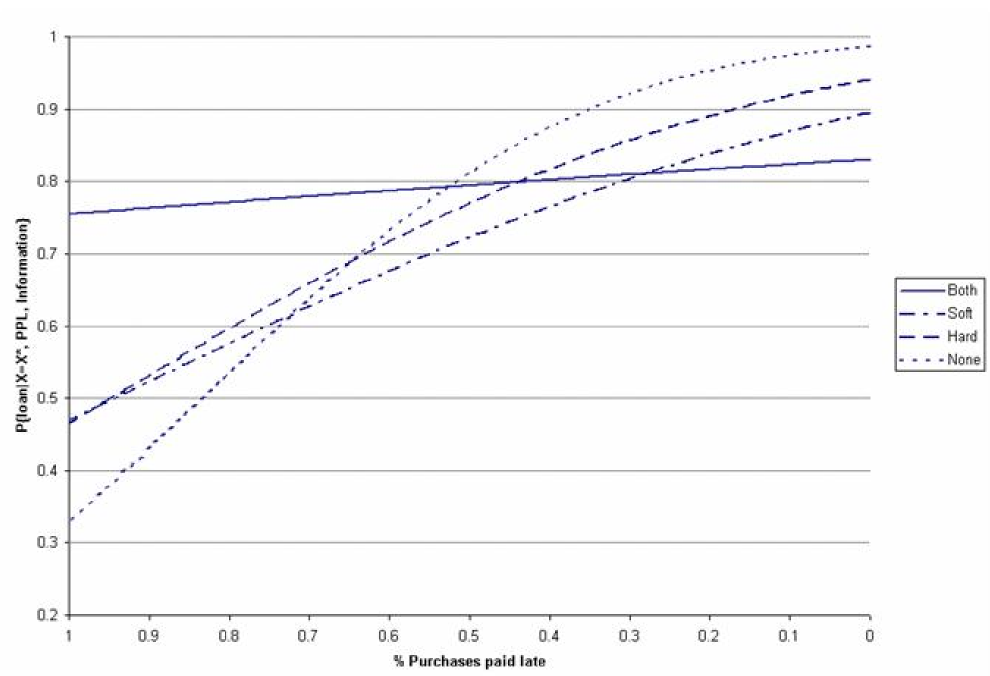

Figure 7: Effect of public information on loan decisions when private information is available

This figure represents the estimated probability of obtaining a bank loan for an average firm under different information availabilities of the lender, and as a function of the public measure of reputation, as proxied by the proportion of trade purchases paid after the due date. The estimated probabilities are calculated from the model of Column 7 in Table 11. In this graph, a bank is considered to have only soft information about the firm if it leads a short (shorter than 1 year) but personal relationship with the firm's owner or manager; and a bank is considered to have only private hard information about the firm if they both have lead a relationship of more than one year but the relationship is impersonal.

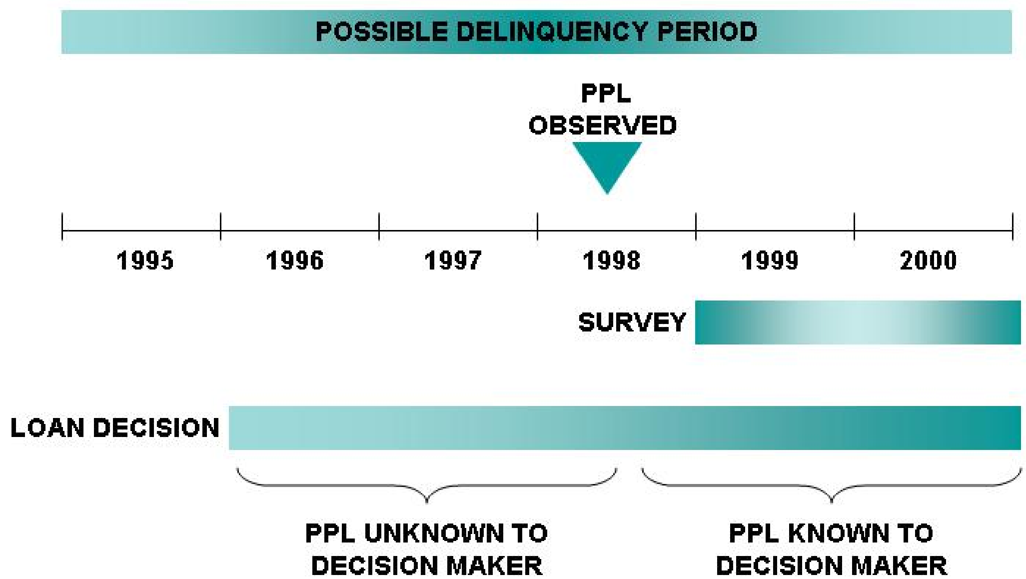

Figure 8: Who knows what when

This timeline represents the information available to the lender at the time of making the credit decision. The short horizontal bar that appears just below the timeline represents the distribution of the sample firms according to the moment in which they were surveyed. The dark shading represents a higher frequency of sample firms. Most of the financial information recollected by the survey - and in particular the proportion of trade purchases paid late, or PPL - refer to year 1998, as indicated by the arrow that appears at the top of the figure. The survey also recollects information about past delinquencies of the firm, but without the possibility of identifying the precise moment when such delinquency occurred. In fact, the relevant question in the survey is: *"Within the past three years, has the firm or its principal owner been 60 or more days delinquent in personal or business obligations?"* The upmost bar in the figure represents the possible period where a potential delinquency could have happened, namely from 1996 to 2000. Finally, the survey also recollects information about the most recent loan approved for the firms in the previous three years before the survey took place, with the possibility of identifying when this application occurred. In fact, the lower horizontal bar contains the distribution of firms according to the dates where the applications for the most recent loan occurred. A high proportion of firms reported their most recent loan as occurring after 1998. Clearly, as indicated by the lower bar, the financial information in the survey - such as the purchases paid after the due date - could have been observed by the lenders only for the firms that applied for the loan after 1998, or (at the limit) also for those that applied for the loan during 1998. However, the timing of the delinquency cannot be clearly determined.

3.8 Chapter 3 Tables

Table 5: Information sources.

This table shows the different private information sources that may be available for the lending institution, and type of information that can be gathered through each source. The precise definition of each of the variables included in the first column is available in the Appendix.

Variable	Hard info.	Soft info.	Label
i. Relationship length > Median	yes	yes	B
ii. Relationship length > 1 year	yes	yes	B
iii. Checking or savings account	yes	maybe	H
iv. Primary financial services provider	yes	maybe	H
v. Conducts personal relationship	maybe	yes	S

Table 6: Probit estimations for the use of private information.

This table shows the estimated coefficients for the following equation:

$$y_i \quad = \quad \beta_0 + \beta_1^P x_i^P + \beta_1^N x_i^N + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i,$$

where y_i measures whether the loan was granted or not; x_i^P is the fraction of purchases paid after the due date by firm i if the bank has private information and zero otherwise, x_i^N is the fraction of purchases paid after the due date by firm i if the bank has no private information (zero otherwise), and X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, and up to 4 year dummies. Column 1 contains the estimations of the model when $I_i(x)$ is a vector of ones, while columns 2 to 7 contain the estimated coefficients when $I_i(x)$ are indicator functions for different sources of information availability for the lender institutions, indicated at the top of each column. The sample for these regressions contains all of the firms that recently applied for a loan and used trade credit. The reported coefficients correspond to the marginal effects for the average firm.

	1	2	3	4	5	6	7
		Primary	Rel > Med	Rel > 1yr	Account	Personal	Records
Purchases paid late (PPL)	-0.226***						
	[0.051]						
PPL if information		-0.155**	-0.109	-0.127**	-0.161**	-0.133**	-0.063
		[0.070]	[0.070]	[0.063]	[0.069]	[0.061]	[0.134]
PPL if no information		-0.301***	-0.350***	-0.377***	-0.313***	-0.366***	-0.258***
		[0.078]	[0.078]	[0.085]	[0.075]	[0.075]	[0.054]
Primary inst	0.176***	0.146***	0.215***	0.224***	0.205***	0.199***	0.179***
	[0.031]	[0.037]	[0.038]	[0.037]	[0.046]	[0.033]	[0.031]
No information			0.110***	0.121***		0.154***	
			[0.036]	[0.031]		[0.034]	
Information					-0.065		-0.036
					[0.044]		[0.052]
Log of assets	0.031***	0.032***	0.032***	0.032***	0.032***	0.027***	0.030***
	[0.009]	[0.010]	[0.009]	[0.009]	[0.010]	[0.009]	[0.009]
Log of 1 + age	0.046**	0.045*	0.058**	0.054**	0.047**	0.040*	0.047**
	[0.024]	[0.024]	[0.024]	[0.023]	[0.024]	[0.022]	[0.023]
Profits over assets[1]	0.007	0.007*	0.007*	0.007*	0.007	0.007*	0.007
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Sales increase[1]	0.017	0.017	0.017	0.019	0.017	0.017	0.018
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.011]	[0.012]
Cash over assets[2]	0.062	0.056	0.064	0.058	0.061	0.049	0.062
	[0.075]	[0.076]	[0.074]	[0.073]	[0.075]	[0.069]	[0.074]

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Table 6 – Continued from previous page

	1	2	3	4	5	6	7
		Primary	Rel > Med	Rel > 1yr	Account	Personal	Records
Leverage[3]	-0.004	-0.004	-0.003	-0.004	-0.003	-0.003	-0.005
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Owner managed dummy	0.031	0.033	0.035	0.043	0.033	0.035	0.024
	[0.044]	[0.044]	[0.044]	[0.045]	[0.044]	[0.043]	[0.043]
Limited liability	0.014	0.012	0.012	0.012	0.013	-0.002	0.023
	[0.037]	[0.037]	[0.037]	[0.037]	[0.037]	[0.033]	[0.037]
Owner has home	0.184**	0.193**	0.187**	0.188**	0.190**	0.191**	0.174**
	[0.078]	[0.081]	[0.083]	[0.082]	[0.080]	[0.082]	[0.076]
Concentrated deposit mkt	-0.054*	-0.054*	-0.058*	-0.057*	-0.057*	-0.048*	-0.053*
	[0.030]	[0.030]	[0.030]	[0.030]	[0.030]	[0.029]	[0.030]
MSA dummy	-0.059*	-0.063**	-0.067**	-0.066**	-0.064**	-0.063**	-0.058*
	[0.031]	[0.030]	[0.030]	[0.030]	[0.030]	[0.028]	[0.031]
Minority owner	-0.103**	-0.100**	-0.100**	-0.099**	-0.102**	-0.101**	-0.106**
	[0.044]	[0.044]	[0.044]	[0.044]	[0.044]	[0.043]	[0.043]
Type of loan (Omitted=Line of Credit)							
Capital lease	0.074**	0.070*	0.076**	0.075**	0.070*	0.058	0.073**
	[0.035]	[0.038]	[0.036]	[0.036]	[0.038]	[0.037]	[0.035]
Mortgage	0.087***	0.087**	0.082**	0.079**	0.085**	0.090***	0.090***
	[0.033]	[0.034]	[0.034]	[0.034]	[0.034]	[0.028]	[0.031]
Vehicle loan	0.167***	0.166***	0.165***	0.164***	0.166***	0.160***	0.166***
	[0.021]	[0.021]	[0.020]	[0.020]	[0.021]	[0.021]	[0.021]
Equipment loan	0.088***	0.090***	0.093***	0.090***	0.091***	0.079***	0.088***
	[0.027]	[0.027]	[0.026]	[0.027]	[0.027]	[0.027]	[0.027]
Other loan	0.038	0.036	0.043	0.042	0.035	0.041	0.038
	[0.032]	[0.032]	[0.031]	[0.031]	[0.032]	[0.030]	[0.032]
Type of institution (omitted = Commercial Bank)							
Depositary inst	0.035	0.04	0.031	0.036	0.028	0.035	0.025
	[0.052]	[0.053]	[0.053]	[0.051]	[0.054]	[0.051]	[0.051]
Finance company	-0.007	0.002	0	-0.003	-0.011	-0.048	-0.007
	[0.056]	[0.056]	[0.056]	[0.057]	[0.062]	[0.066]	[0.057]
Other lender	0.057	0.063*	0.058	0.054	0.057	0.027	0.053
	[0.038]	[0.038]	[0.040]	[0.041]	[0.042]	[0.047]	[0.039]
Observations	634	634	634	634	634	634	634
Pseudo R^2	0.31	0.314	0.325	0.328	0.315	0.337	0.314

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Table 6 – Continued from previous page

	1	2	3	4	5	6	7
		Primary	Rel > Med	Rel > 1yr	Account	Personal	Records
χ^2 for $H_0 : \beta_1^P I = \beta_1^N$		2.131	5.677	6.202	2.376	6.008	1.838
P-value		0.144	0.017	0.013	0.123	0.014	0.175

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 7: Distributions and correlations of information sources.
Panel A illustrates how the firms in the sample are distributed according to the information available to their potential lenders, and Panel B contains the sample correlations for the different information measures.

Panel A

	Primary provider	Length > Median	Length > 1 year	Checking or savings	Personal rel.	Written records
Information	54.1%	53.3%	63.1%	56.6%	58.8%	14.8%
No Information	45.9%	46.7%	36.9%	43.4%	41.2%	85.2%

Panel B

	Primary provider	Length > Median	Length > 1year	Checking or savings	Personal rel.	Written records
Primary financial services provider	1					
Rel. length > Median	0.4278	1				
Rel. length > 1 year	0.4787	0.8177	1			
Checking or savings account	0.7402	0.4621	0.5334	1		
Personal relationship	0.3321	0.2377	0.3025	0.4274	1	
Written records	-0.0246	0.0216	-0.0006	-0.0319	-0.0641	1

Table 8: Probit estimations on firms asking for loan after or during 1998.

This table shows the estimated coefficients for same equation as in Table 6, but on the sample of firms asking for a loan during or after 1998. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, and up to 2 year dummies. The reported coefficients correspond to the marginal effects for the average firm.

	1	2	3	4	5	6
	Primary	Rel > Med	Rel > 1yr	Account	Personal	Records
PPL if information	-0.132*	-0.071	-0.114*	-0.122*	-0.099	-0.039
	[0.076]	[0.071]	[0.065]	[0.073]	[0.062]	[0.131]
PPL if no information	-0.341***	-0.406***	-0.425***	-0.381***	-0.422***	-0.273***
	[0.086]	[0.094]	[0.100]	[0.086]	[0.083]	[0.060]
Primary inst	0.126***	0.193***	0.216***	0.203***	0.183***	0.176***
	[0.041]	[0.042]	[0.042]	[0.052]	[0.036]	[0.035]
No information		0.106***	0.137***		0.158***	
		[0.040]	[0.035]		[0.039]	
Information				-0.097*		-0.05
				[0.052]		[0.060]
Log of assets	0.019*	0.021**	0.020**	0.020*	0.017*	0.016
	[0.011]	[0.010]	[0.010]	[0.011]	[0.010]	[0.010]
Log of 1 + age	0.063**	0.072***	0.073***	0.064**	0.058**	0.066**
	[0.027]	[0.028]	[0.027]	[0.027]	[0.026]	[0.027]
Profits over assets[1]	0.008*	0.008*	0.007	0.007	0.007*	0.007
	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]	[0.005]
Sales increase[1]	0.017	0.016	0.02	0.017	0.017	0.019
	[0.013]	[0.012]	[0.013]	[0.013]	[0.012]	[0.013]
Cash over assets[2]	-0.029	-0.017	-0.014	-0.019	-0.016	-0.017
	[0.085]	[0.082]	[0.080]	[0.082]	[0.074]	[0.082]
Leverage[3]	-0.018**	-0.017*	-0.018**	-0.018**	-0.015*	-0.019**
	[0.009]	[0.009]	[0.009]	[0.009]	[0.008]	[0.009]
Owner managed dummy	0.033	0.025	0.037	0.029	0.03	0.016
	[0.052]	[0.050]	[0.051]	[0.051]	[0.049]	[0.049]
Limited liability	-0.001	-0.004	-0.003	0	-0.012	0.014
	[0.041]	[0.042]	[0.041]	[0.041]	[0.037]	[0.042]
Owner has home	0.169*	0.156*	0.166*	0.163*	0.151*	0.148*
	[0.090]	[0.091]	[0.091]	[0.090]	[0.087]	[0.083]
Concentrated mkt	-0.036	-0.04	-0.04	-0.039	-0.029	-0.035
	[0.034]	[0.035]	[0.034]	[0.034]	[0.032]	[0.034]

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Table 8 – Continued from previous page

	1	2	3	4	5	6
	Primary	Rel > Med	Rel > 1yr	Account	Personal	Records
MSA dummy	-0.049	-0.051	-0.053	-0.052	-0.05	-0.044
	[0.036]	[0.036]	[0.036]	[0.036]	[0.033]	[0.037]
Minority owner	-0.118**	-0.116**	-0.119**	-0.128**	-0.116**	-0.127**
	[0.053]	[0.051]	[0.052]	[0.053]	[0.051]	[0.051]
Type of loan (Omitted=L/C)						
Capital lease	0.088**	0.088**	0.089***	0.086**	0.071**	0.088***
	[0.035]	[0.035]	[0.034]	[0.036]	[0.035]	[0.034]
Mortgage	0.083**	0.078**	0.075*	0.080**	0.087***	0.087**
	[0.038]	[0.039]	[0.039]	[0.038]	[0.030]	[0.034]
Vehicle loan	0.167***	0.166***	0.164***	0.166***	0.160***	0.167***
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.024]
Equipment loan	0.101***	0.102***	0.100***	0.100***	0.086***	0.095***
	[0.029]	[0.028]	[0.028]	[0.029]	[0.028]	[0.029]
Other loan	0.041	0.049	0.044	0.04	0.047	0.044
	[0.036]	[0.035]	[0.035]	[0.036]	[0.032]	[0.035]
Type of institution (Omitted = Commercial Bank)						
Depositary inst	0.107***	0.098***	0.103***	0.097***	0.088***	0.091**
	[0.033]	[0.033]	[0.030]	[0.036]	[0.034]	[0.036]
Finance company	-0.04	-0.047	-0.048	-0.057	-0.085	-0.05
	[0.070]	[0.072]	[0.073]	[0.079]	[0.079]	[0.072]
Other lender	0.04	0.037	0.032	0.033	0.01	0.029
	[0.050]	[0.052]	[0.054]	[0.054]	[0.056]	[0.052]
Observations	505	505	505	505	505	505
Pseudo R^2	0.338	0.351	0.355	0.343	0.361	0.337
χ^2 for $H_0 : \beta_1^P = \beta_1^N$	3.724	8.664	7.418	5.976	10.55	2.569
P-value	0.054	0.003	0.006	0.015	0.001	0.109

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 9: Interaction of information sources.
This table illustrates the types of information that may be available to the lending institutions when it has up to two different sources of information.

Panel A: Interaction between S and H variables

	Does not satisfy S	Satisfies S variable
Does not satisfy H variable	No information	Mostly soft information
Satisfies H variable	Mostly hard information	Soft and hard information

Panel B: Interaction between S and B variables

	Does not satisfy S	Satisfies S variable
Does not satisfy B variable	No information	Mostly soft information
Satisfies B variable	Soft and hard information	Soft and hard information

Table 10: Cross tabulations of personal relationships with other information sources.
This table contains the cross-tabulation of the sample firms regarding the availability of a personal relationship and the other measures of information availability for the potential lenders.

Hard information		Soft information	
		No	Yes
Availability	Proxy	Impersonal rel	Personal rel
No	Not Primary	27.1%	18.8%
Yes	Primary	14.2%	40.0%
No	Rel $\leq$ Median	25.1%	21.6%
Yes	Rel $>$ Median	16.1%	37.2%
No	Rel $\leq$ 1 year	22.4%	14.5%
Yes	Rel $>$ 1year	18.8%	44.3%
No	No account	28.3%	15.1%
Yes	Checking / Savings	12.9%	43.7%
No	No records	34.0%	51.2%
Yes	Records	7.2%	7.5%

Table 11: Probit estimations for use of soft information.

This table shows the estimated coefficients for the following equation:

$$y_i \quad = \quad \beta_0 + \beta_1^U x_i^U + \beta_1^S x_i^S + \beta_1^H x_i^H + \beta_1^B x_i^B + \beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + u_i,$$

where y_i is a dichotomic variable for whether the lender institution granted the loan or not, x_i^X is the percentage of trade credit purchases paid after the due date when the bank has no information ($X = U$), has only soft information ($X = S$), has only hard information ($X = H$), or has both types of information ($X = B$), and $I_i^X(x)$ is and indicator function for the type(s) of information available to the bank. X_i^f, X_i^b, and X_i^l are matrices of firm, bank, and loan characteristics whose coefficients are not reported but are available upon request. For all estimations, the source of soft information is a personal relationship with the firm, and the source of hard information is indicated at the top of each column. The estimations of columns 1-5 correspond to all of the firms asking for a loan, while columns 6-10 correspond to firms asking for a loan during or after 1998. The reported coefficients correspond to the marginal effects for the average firm.

	All firms					Firms asking for loan during or after 1998				
	1	2	3	4	5	6	7	8	9	10
Hard info source	Primary	Rel>1yr	Rel>Med	Account	Records	Primary	Rel>1yr	Rel>Med	Account	Records
PPL, soft & hard	-0.073	-0.081	-0.038	-0.085	0.174	-0.053	-0.05	0.002	-0.045	0.177
	[0.071]	[0.071]	[0.081]	[0.070]	[0.156]	[0.079]	[0.071]	[0.079]	[0.074]	[0.152]
PPL, soft, no hard	-0.236*	-0.285**	-0.280***	-0.304**	-0.203***	-0.185	-0.252*	-0.247**	-0.277**	-0.172**
	[0.126]	[0.121]	[0.105]	[0.134]	[0.064]	[0.117]	[0.133]	[0.119]	[0.127]	[0.069]
PPL, no soft, hard	-0.442***	-0.289**	-0.314**	-0.489***	-0.398**	-0.385***	-0.311***	-0.269**	-0.419***	-0.361*
	[0.139]	[0.118]	[0.122]	[0.141]	[0.189]	[0.145]	[0.121]	[0.127]	[0.148]	[0.192]
PPL, no soft & no hard	-0.335***	-0.412***	-0.393***	-0.315***	-0.360***	-0.436***	-0.502***	-0.520***	-0.419***	-0.440***
	[0.085]	[0.100]	[0.095]	[0.083]	[0.081]	[0.104]	[0.117]	[0.110]	[0.101]	[0.093]
Primary institution	0.015	0.235***	0.223***	0.203***	0.210***	-0.007	0.214***	0.191***	0.195***	0.197***
	[0.046]	[0.039]	[0.039]	[0.045]	[0.033]	[0.052]	[0.042]	[0.041]	[0.051]	[0.036]
Both		-0.257***	-0.268***	-0.188***	-0.324**	-0.254***	-0.268***	-0.260***	-0.228***	-0.334**
		[0.058]	[0.065]	[0.064]	[0.131]	[0.087]	[0.066]	[0.073]	[0.080]	[0.144]
Soft	-0.211***	-0.160*	-0.203**	-0.203**	-0.166***	0.081**	-0.181*	-0.250***	-0.235**	-0.185***
	[0.076]	[0.088]	[0.080]	[0.085]	[0.043]	[0.041]	[0.104]	[0.096]	[0.096]	[0.052]
Hard	0.108***	-0.091	-0.117	-0.013	-0.036		-0.134	-0.156	-0.103	-0.092
	[0.031]	[0.077]	[0.087]	[0.081]	[0.076]		[0.095]	[0.101]	[0.116]	[0.102]
Observations	634	634	634	634	634	505	505	505	505	505
Pseudo R^2	0.342	0.346	0.347	0.344	0.347	0.366	0.371	0.373	0.369	0.372
χ^2 for $H_0 : \beta_1^S = \beta_1^U$	0.463	0.732	0.712	0.005	2.494	3.025	2.317	3.35	0.899	6.073
P-value	0.496	0.392	0.399	0.942	0.114	0.082	0.128	0.067	0.343	0.014
χ^2 for $H_0 : \beta_1^H = \beta_1^U$	0.420	0.663	0.27	1.062	0.035	0.080	1.337	2.291	0	0.139
P-value	0.519	0.416	0.603	0.303	0.851	0.777	0.248	0.130	0.998	0.709

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12: First stage IV regressions.

This table shows the estimated coefficients for the first stage in the system of equations 4 and 5. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, up to 4 year dummies, the institution type of the lender, the type of credit asked to a bank, and a constant term.

	1	2
Primary institution	-0.036	-0.03
	[0.023]	[0.027]
Days of credit		
No credit	-0.199*	-0.206
	[0.116]	[0.137]
Up to 7 days	-0.303***	-0.316***
	[0.095]	[0.118]
8 to 10 days	-0.152	-0.165
	[0.097]	[0.123]
11 to 14 days	-0.039	-0.107
	[0.133]	[0.158]
15 days	-0.14	-0.122
	[0.111]	[0.140]
16 to 20 days	-0.251***	-0.302**
	[0.095]	[0.118]
21 to 30 days	-0.146	-0.16
	[0.089]	[0.113]
31 to 45 days	-0.072	-0.081
	[0.112]	[0.142]
46 to 60 days	-0.13	-0.15
	[0.103]	[0.130]
120 or more	-0.295**	-0.361**
	[0.140]	[0.153]
Discount period		
No discount period	0.154*	0.104
	[0.086]	[0.107]
10 days	0.126*	0.124*
	[0.064]	[0.074]
11 to 14 days	0.215***	0.232**
	[0.082]	[0.097]
15 to 29 days	0.087	0.102
	[0.072]	[0.081]
30 days or more	0.261**	0.201
	[0.114]	[0.128]
Discount size		
No discount	0.005	0.06
	[0.058]	[0.084]
Up to 1.5%	0.056	0.084*
	[0.042]	[0.051]
2.01% to 4.99%	-0.018	-0.003
	[0.065]	[0.070]
More than 5%	0.078	0.083
	[0.060]	[0.068]
Log number suppliers	0.01	0.011
	[0.009]	[0.011]
Log of assets	-0.009	-0.008
	[0.007]	[0.009]
Log of 1 + age	0.01	0.018
	[0.017]	[0.021]

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	1	2
Profits over assets[1]	0.002	0.002
	[0.003]	[0.003]
Sales increase[1]	-0.002	0.004
	[0.011]	[0.014]
Cash over assets[2]	-0.284***	-0.289***
	[0.067]	[0.076]
Leverage[3]	0.013*	0.014*
	[0.007]	[0.008]
Owner managed dummy	0.011	0.009
	[0.030]	[0.037]
Limited liability	0.023	0.009
	[0.028]	[0.035]
Owner has home	-0.052	-0.032
	[0.049]	[0.057]
Banking mkt concentrated	0.025	0.036
	[0.025]	[0.030]
MSA dummy	-0.005	0.012
	[0.030]	[0.035]
Minority owner	-0.013	-0.005
	[0.032]	[0.036]
Observations	634	505
R^2	0.13	0.13
F-test for instrument validity	2.442	2.207
P-value	0	0.002
Sargan test (Overidentification)	19.173	25.716
P-value	0.446	0.138

Notes: Standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels.
[2] Winsorized at the 1% level.
[3] Winsorized at the 99% level.

Table 13: Second stage IV regressions for system 6.

This table shows the estimated coefficients for the second stage in the system of equations 6 on the sample of firms that asked for a loan during or after 1998. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, and 2 year dummies. Columns 2-7 contain coefficients estimated for different measures of information availability for the lender, where the measure used is indicated in the first row. For comparison purposes, column 1 contains the coefficients of the second stage equation 4.

	1	2	3	4	5	6	7
		Primary	Rel>Med	Rel>1 yr	Account	Personal	Records
Purchases paid late (PPL)	-0.509*						
	[0.277]						
PPL if information		0.249	0.239	0.146	0.234	-0.002	0.062
		[0.406]	[0.339]	[0.367]	[0.391]	[0.356]	[0.738]
PPL if no information		-1.090***	-1.397***	-1.425***	-1.124***	-1.471***	-0.526*
		[0.376]	[0.417]	[0.479]	[0.359]	[0.506]	[0.282]
Primary inst	0.167***	-0.067	0.179***	0.180***	0.175***	0.181***	0.176***
	[0.037]	[0.102]	[0.045]	[0.047]	[0.056]	[0.041]	[0.038]
Rel. $\leq$ median			0.334***				
			[0.099]				
Rel $\leq$ 1 year				0.365***			
				[0.113]			
Has account					-0.278***		
					[0.100]		
Impersonal rel.						0.339***	
						[0.100]	
Used records							-0.109
							[0.137]
Log of assets	0.020*	0.026**	0.029**	0.031**	0.029**	0.024*	0.018
	[0.011]	[0.012]	[0.012]	[0.012]	[0.012]	[0.013]	[0.012]
Log of 1 + age	0.065**	0.055*	0.066**	0.070**	0.063**	0.067**	0.066**
	[0.027]	[0.029]	[0.029]	[0.029]	[0.028]	[0.030]	[0.027]
Profits over assets[1]	0.01	0.013**	0.015**	0.011*	0.011*	0.009	0.009
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.007]	[0.006]
Sales increase[1]	0.018	0.013	0.011	0.022	0.014	0.017	0.019
	[0.014]	[0.013]	[0.014]	[0.013]	[0.013]	[0.015]	[0.014]

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	1	2	3	4	5	6	7
		Primary	Rel>Med	Rel>1 yr	Account	Personal	Records
Cash over assets[2]	-0.109	-0.157	-0.165	-0.103	-0.094	-0.146	-0.09
	[0.119]	[0.127]	[0.134]	[0.128]	[0.129]	[0.129]	[0.118]
Leverage[3]	-0.016	-0.016	-0.015	-0.016	-0.017	-0.012	-0.019*
	[0.011]	[0.011]	[0.012]	[0.011]	[0.011]	[0.010]	[0.011]
Owner managed dummy	0.034	0.055	-0.015	0.019	0.043	0.059	0.018
	[0.047]	[0.049]	[0.050]	[0.048]	[0.049]	[0.053]	[0.051]
Limited liability	0.009	-0.025	-0.029	-0.042	-0.029	-0.032	0.02
	[0.046]	[0.049]	[0.051]	[0.051]	[0.048]	[0.048]	[0.046]
Owner has home	0.177**	0.219**	0.131	0.157*	0.175**	0.150*	0.164**
	[0.073]	[0.088]	[0.090]	[0.088]	[0.087]	[0.088]	[0.074]
Banking mkt concentration	-0.04	-0.04	-0.052	-0.044	-0.045	-0.037	-0.035
	[0.039]	[0.041]	[0.043]	[0.042]	[0.041]	[0.043]	[0.039]
MSA dummy	-0.05	-0.065	-0.062	-0.079*	-0.063	-0.041	-0.038
	[0.041]	[0.041]	[0.044]	[0.044]	[0.041]	[0.046]	[0.045]
Minority owner	-0.118**	-0.111**	-0.113**	-0.092*	-0.123**	-0.083	-0.124**
	[0.049]	[0.052]	[0.050]	[0.051]	[0.050]	[0.054]	[0.049]
Type of loan (Omitted = Line of Credit)							
Capital lease	0.085	0.074	0.066	0.096	0.069	0.003	0.084
	[0.087]	[0.094]	[0.102]	[0.099]	[0.095]	[0.093]	[0.091]
Mortgage	0.084	0.084	0.059	0.065	0.078	0.071	0.109
	[0.064]	[0.068]	[0.067]	[0.068]	[0.068]	[0.071]	[0.074]
Vehicle loan	0.210***	0.170***	0.174***	0.188***	0.191***	0.202***	0.215***
	[0.052]	[0.054]	[0.053]	[0.053]	[0.053]	[0.061]	[0.052]
Equipment loan	0.108**	0.156***	0.146***	0.128***	0.163***	0.097*	0.115**
	[0.046]	[0.049]	[0.051]	[0.049]	[0.050]	[0.052]	[0.047]
Other loan	0.039	0.032	0.031	0.025	0.021	0.021	0.038
	[0.051]	[0.051]	[0.054]	[0.054]	[0.052]	[0.057]	[0.050]
Type of institution (Omitted=Commercial Bank)							
Depositary institution	0.102	0.148*	0.098	0.134*	0.08	0.115	0.092
	[0.072]	[0.086]	[0.067]	[0.072]	[0.065]	[0.078]	[0.065]
Finance company	-0.018	0.013	-0.036	-0.056	-0.042	-0.028	-0.02
	[0.061]	[0.066]	[0.068]	[0.072]	[0.071]	[0.074]	[0.064]

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	1	2	3	4	5	6	7
		Primary	Rel>Med	Rel>1 yr	Account	Personal	Records
Other lender	0.08	0.123	0.082	0.059	0.11	0.127	0.064
	[0.079]	[0.088]	[0.097]	[0.094]	[0.094]	[0.098]	[0.077]
Constant	0.19	0.299	0.195	0.089	0.355	-0.028	0.235
	[0.220]	[0.245]	[0.241]	[0.235]	[0.235]	[0.262]	[0.233]
Observations	505	505	505	505	505	505	505
χ^2 test for H_0 : $\beta_1^N = \beta_1^P$		6.504	11.581	6.787	9.084	6.804	0.615
P-value		0.011	0.001	0.009	0.003	0.009	0.433

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 14: Second stage IV regressions for system 7.

This table shows the second stage IV estimated coefficients for system of equations 7 on the sample of firms asking for a loan during or after 1998 (505 observations). Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, 2 year dummies, and a constant term. The measure used for soft information availability is having a personal relation with the lender, while the hard information measure is indicated in the first row.

	1 Primary	2 Rel>Med	3 Rel>1 yr	4 Account	5 Records
PPL, soft & hard	0.152	0.182	0.285	0.08	1.511
	[0.509]	[0.428]	[0.351]	[0.457]	[1.198]
PPL, soft, no hard	-0.181	-0.486	-1.66	-0.039	-0.445
	[0.566]	[1.023]	[1.068]	[0.886]	[0.442]
PPL, no soft, hard	-0.15	-0.51	-0.357	-0.104	-4.219
	[0.884]	[0.837]	[0.918]	[0.925]	[2.573]
PPL, no soft & no hard	-1.714***	-1.782**	-1.279**	-1.664***	-1.304**
	[0.569]	[0.698]	[0.550]	[0.622]	[0.521]
Primary inst	-0.263*	0.192***	0.174***	0.180***	0.208***
	[0.139]	[0.053]	[0.046]	[0.057]	[0.048]
Personal rel, non primary inst	-0.468***				
	[0.152]				
Impersonal rel, primary inst	0.057				
	[0.158]				
Personal rel, length > 1 year		-0.470***			
		[0.145]			
Personal rel, length ≤ 1 year		-0.32			
		[0.281]			
Impersonal rel, length > 1 year		-0.305			
		[0.227]			
Personal rel, length>median			-0.358***		
			[0.111]		
Personal rel, length ≤ median			-0.039		
			[0.271]		
Impersonal rel, length > median			-0.249		
			[0.206]		
Personal rel, has account				-0.436***	
				[0.126]	
Personal rel, no account				-0.482*	
				[0.248]	
Impersonal rel, has account				-0.391**	
				[0.183]	
Personal rel, records					-0.639**
					[0.264]
Personal rel, no records					-0.245*
					[0.127]
Impersonal rel, records					0.278
					[0.359]
Log of assets	0.026*	0.028*	0.031**	0.028**	0.018
	[0.013]	[0.014]	[0.013]	[0.013]	[0.015]
Log of 1 + age	0.060**	0.068**	0.058**	0.059*	0.06
	[0.030]	[0.029]	[0.029]	[0.030]	[0.040]
Profits over assets[1]	0.01	0.009	0.017**	0.01	0.011
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Sales increase[1]	0.016	0.021	0.009	0.015	0.013
	[0.015]	[0.015]	[0.013]	[0.015]	[0.018]

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Table 14 – Continued from previous page

	1 Primary	2 Rel>Med	3 Rel>1 yr	4 Account	5 Records
Cash over assets[2]	-0.165	-0.107	-0.219	-0.131	-0.192
	[0.132]	[0.131]	[0.140]	[0.137]	[0.139]
Leverage[3]	-0.012	-0.014	-0.01	-0.014	-0.013
	[0.010]	[0.010]	[0.012]	[0.010]	[0.011]
Owner managed dummy	0.05	0.033	-0.001	0.049	0.051
	[0.051]	[0.055]	[0.057]	[0.051]	[0.061]
Limited liability	-0.058	-0.057	-0.024	-0.063	0.028
	[0.048]	[0.054]	[0.055]	[0.048]	[0.063]
Owner has home	0.174*	0.146	0.138	0.142	0.185**
	[0.093]	[0.094]	[0.090]	[0.095]	[0.092]
Banking mkt concentration	-0.026	-0.044	-0.043	-0.033	-0.04
	[0.045]	[0.044]	[0.043]	[0.045]	[0.061]
MSA dummy	-0.054	-0.062	-0.053	-0.039	-0.062
	[0.046]	[0.048]	[0.046]	[0.048]	[0.076]
Minority owner	-0.112*	-0.08	-0.118**	-0.122**	-0.111*
	[0.059]	[0.052]	[0.056]	[0.058]	[0.061]
Type of loan (Omitted = Line of Credit)					
Capital lease	-0.025	0.037	0.06	-0.044	-0.142
	[0.110]	[0.101]	[0.104]	[0.133]	[0.171]
Mortgage	0.106	0.087	0.031	0.112	0.076
	[0.075]	[0.088]	[0.093]	[0.075]	[0.091]
Vehicle loan	0.186***	0.199***	0.163***	0.201***	0.168**
	[0.059]	[0.056]	[0.057]	[0.058]	[0.072]
Equipment loan	0.126**	0.118**	0.122**	0.130**	0.033
	[0.055]	[0.051]	[0.057]	[0.060]	[0.080]
Other loan	0.031	0.025	0.023	0.018	-0.034
	[0.056]	[0.057]	[0.055]	[0.056]	[0.075]
Type of institution (Omitted=Commercial Bank)					
Depositary institution	0.158*	0.144*	0.074	0.128	0.045
	[0.082]	[0.085]	[0.081]	[0.082]	[0.098]
Finance company	-0.025	-0.054	-0.061	-0.068	0.038
	[0.081]	[0.078]	[0.072]	[0.088]	[0.104]
Other lender	0.12	0.093	0.06	0.132	0.324
	[0.105]	[0.103]	[0.104]	[0.121]	[0.213]
χ^2 test for $H_0 : \beta_1^S = \beta_1^U$	4.464	0.874	0.076	1.637	1.628
P-value	0.035	0.35	0.783	0.201	0.202
χ^2 test for $H_0 : \beta_1^H = \beta_1^U$	2.808	1.262	0.872	2.567	1.198
P-value	0.094	0.261	0.35	0.109	0.274

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 15: Joint ML estimation for equations 2 and 8.

This table shows the joint maximum likelihood estimations of equations 8 and 2 on the sample of firms asking for a loan during or after 1998. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, 2 year dummies, MSA dummy, and a constant term. The measure used for information availability is indicated in the first row.

	1		2		3		4		5		6	
	Primary		Rel > Med		Rel > 1yr		Account		Personal		Records	
	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply
No. of bk rels		0.275***		0.275***		0.275***		0.275***		0.275***		0.275***
		[0.014]		[0.014]		[0.014]		[0.014]		[0.014]		[0.014]
PPL if information	-0.585		-0.288		-0.509		-0.539		-0.504		-0.176	
	[0.361]		[0.348]		[0.316]		[0.351]		[0.325]		[0.641]	
PPL if no information	-1.610***		-1.925***		-2.042***		-1.818***		-2.191***		-1.296***	
	[0.391]		[0.437]		[0.482]		[0.394]		[0.433]		[0.291]	
Primary inst	0.510**		0.814***		0.928***		0.858***		0.874***		0.770***	
	[0.232]		[0.223]		[0.227]		[0.275]		[0.212]		[0.197]	
No information			0.529***		0.760***				0.866***			
			[0.199]		[0.207]				[0.230]			
Information							-0.478*				-0.191	
							[0.263]				[0.241]	
Log of assets	0.122**	0.062***	0.135**	0.062***	0.133**	0.062***	0.127**	0.062***	0.111*	0.062***	0.104*	0.062***
	[0.060]	[0.016]	[0.057]	[0.016]	[0.057]	[0.016]	[0.059]	[0.016]	[0.063]	[0.016]	[0.059]	[0.016]
Log of 1 + age	0.269*	-0.192***	0.310**	-0.192***	0.317**	-0.192***	0.274**	-0.192***	0.284**	-0.192***	0.293**	-0.192***
	[0.138]	[0.037]	[0.139]	[0.037]	[0.138]	[0.037]	[0.138]	[0.037]	[0.139]	[0.037]	[0.139]	[0.037]
Profits over assets[1]	0.040*	0.006	0.040*	0.006	0.037*	0.006	0.036*	0.006	0.038*	0.006	0.035	0.006
	[0.021]	[0.008]	[0.021]	[0.008]	[0.022]	[0.008]	[0.021]	[0.008]	[0.022]	[0.008]	[0.022]	[0.008]
Sales increase[1]	0.087	0.019	0.084	0.019	0.105*	0.019	0.089	0.019	0.092	0.019	0.097	0.019
	[0.061]	[0.019]	[0.059]	[0.019]	[0.063]	[0.019]	[0.062]	[0.019]	[0.060]	[0.019]	[0.061]	[0.019]
Cash over assets[2]	-0.184	-0.492***	-0.138	-0.491***	-0.122	-0.491***	-0.143	-0.492***	-0.121	-0.491***	-0.113	-0.491***
	[0.405]	[0.124]	[0.392]	[0.124]	[0.387]	[0.124]	[0.399]	[0.124]	[0.388]	[0.124]	[0.402]	[0.124]
Leverage[2]	-0.080*	0.028**	-0.071	0.028**	-0.078*	0.028**	-0.078*	0.028**	-0.071*	0.028**	-0.087**	0.028**
	[0.045]	[0.012]	[0.043]	[0.012]	[0.044]	[0.012]	[0.044]	[0.012]	[0.042]	[0.012]	[0.043]	[0.012]
Owner managed dummy	0.144	-0.025	0.106	-0.026	0.165	-0.025	0.127	-0.026	0.148	-0.026	0.074	-0.026
	[0.222]	[0.079]	[0.221]	[0.079]	[0.219]	[0.079]	[0.224]	[0.079]	[0.228]	[0.079]	[0.225]	[0.079]
Limited liability	0.035	0.123*	0.028	0.122*	0.033	0.122*	0.046	0.123*	-0.034	0.123*	0.101	0.123*
	[0.205]	[0.067]	[0.205]	[0.067]	[0.204]	[0.067]	[0.202]	[0.067]	[0.207]	[0.067]	[0.198]	[0.067]
Owner has home	0.645**	0.068	0.607**	0.068	0.647**	0.068	0.631**	0.068	0.623**	0.069	0.590**	0.069
	[0.267]	[0.100]	[0.275]	[0.100]	[0.269]	[0.100]	[0.267]	[0.100]	[0.276]	[0.100]	[0.258]	[0.100]
Bk mkt concentrated	-0.159	0.028	-0.18	0.028	-0.181	0.028	-0.172	0.028	-0.145	0.028	-0.162	0.028
	[0.168]	[0.060]	[0.170]	[0.060]	[0.170]	[0.060]	[0.168]	[0.060]	[0.170]	[0.060]	[0.168]	[0.060]
Minority owner	-0.449**	0.098	-0.439**	0.098	-0.454**	0.098	-0.487***	0.098	-0.487**	0.098	-0.495***	0.098
	[0.190]	[0.070]	[0.187]	[0.070]	[0.192]	[0.070]	[0.189]	[0.070]	[0.197]	[0.070]	[0.184]	[0.070]
Capital lease	0.564*		0.568*		0.598*		0.548		0.492		0.585*	
	[0.331]		[0.343]		[0.340]		[0.337]		[0.328]		[0.328]	
Mortgage	0.507		0.464		0.449		0.485		0.644*		0.564*	
	[0.324]		[0.319]		[0.321]		[0.323]		[0.342]		[0.318]	
Vehicle loan	1.405***		1.399***		1.419***		1.412***		1.581***		1.459***	
	[0.321]		[0.314]		[0.323]		[0.324]		[0.324]		[0.320]	
Equipment loan	0.617***		0.630***		0.630***		0.622***		0.584**		0.585***	
	[0.223]		[0.226]		[0.222]		[0.223]		[0.227]		[0.226]	
Other loan	0.216		0.264		0.243		0.213		0.28		0.237	
	[0.200]		[0.207]		[0.206]		[0.203]		[0.211]		[0.206]	
Depositary institution	0.821*		0.708*		0.792*		0.696		0.712		0.639	
	[0.481]		[0.397]		[0.421]		[0.431]		[0.474]		[0.394]	
Finance company	-0.171		-0.2		-0.208		-0.238		-0.374		-0.216	
	[0.285]		[0.286]		[0.291]		[0.305]		[0.300]		[0.288]	
Other lender	0.239		0.231		0.2		0.206		0.074		0.176	
	[0.305]		[0.315]		[0.320]		[0.318]		[0.318]		[0.301]	
Constant	2.418	-1.074**	1.826	-1.075**	1.652	-1.074**	2.467	-1.075**	2.096	-1.076**	2.854	-1.076**
	[0.000]	[0.440]	[0.000]	[0.440]	[0.000]	[0.440]	[0.000]	[0.440]	[0.000]	[0.440]	[0.000]	[0.440]
Wald χ^2	0.587		0.912		0.897		0.687		0.291		0.545	
P-value	0.444		0.34		0.344		0.407		0.589		0.461	
χ^2 for $H_0 : \beta_I = \beta_N$	3.95		8.921		7.515		6.309		10.136		2.449	
P-value	0.047		0.003		0.006		0.012		0.001		0.118	

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Table 15 – Continued from previous page

	1		2		3		4		5		6	
	Primary		Rel > Med		Rel > 1yr		Account		Personal		Records	
	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 16: Joint ML estimation for equations 3 and 8.

This table shows the joint maximum likelihood estimations of equations 8 and 3 on the sample of firms asking for a loan during or after 1998 (2711 original observations and 505 uncensored observations). Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, 2 year dummies, and a constant term. The structural equation of interest contains, additionally, a vector of lender and loan characteristics. The measure used for information availability is indicated in the first row. The first column contains the ML coefficients for equations 8 and 1

	1		2		3		4		5		6	
			Primary		Rel>Med		Rel>1yr		Account		Records	
	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply
No. of bk rels		0.275***		0.275***		0.275***		0.275***		0.275***		0.275***
		[0.014]		[0.014]		[0.014]		[0.014]		[0.014]		[0.014]
Purchases paid late (PPL)	-1.089***											
	[0.261]											
Primary inst	0.744***		-0.099		0.981***		0.840***		0.915***		0.943***	
	[0.199]		[0.280]		[0.235]		[0.229]		[0.278]		[0.208]	
PPL, soft & hard			-0.271		-0.238		0.047		-0.229		0.942	
			[0.405]		[0.369]		[0.411]		[0.386]		[0.799]	
PPL, soft, no hard			-0.919		-1.296*		-1.250**		-1.417**		-0.899**	
			[0.594]		[0.674]		[0.580]		[0.640]		[0.361]	
PPL, no soft, hard			-1.847**		-1.521**		-1.250*		-2.049**		-1.931*	
			[0.793]		[0.624]		[0.650]		[0.824]		[1.012]	
PPL, no soft & no hard			-2.251***		-2.579***		-2.622***		-2.186***		-2.295***	
			[0.501]		[0.600]		[0.567]		[0.490]		[0.490]	
Personal rel, non primary inst			-0.975***									
			[0.276]									
Impersonal rel, primary inst			0.479									
			[0.342]									
Personal rel, length > 1 year					-1.240***							
					[0.287]							
Personal rel, length ≤ 1 year					-0.720**							
					[0.329]							
Impersonal rel, length > 1 year					-0.624*							
					[0.332]							
Personal rel, length>median							-1.115***					
							[0.284]					
Personal rel, length ≤median							-0.945***					
							[0.300]					
Impersonal rel, length>median							-0.687**					
							[0.333]					
Personal rel, info inst									-1.047***			
									[0.340]			
Personal rel, non info inst									-0.895***			
									[0.296]			
Impersonal rel, info inst									-0.487			
									[0.422]			
Personal rel, records											-1.095***	
											[0.392]	
Personal rel, no records											-0.927***	
											[0.258]	
Impersonal rel, records											-0.376	
											[0.372]	
Log of assets	0.111*	0.062***	0.128**	0.062***	0.130**	0.062***	0.137**	0.062***	0.129**	0.062***	0.091	0.062***
	[0.060]	[0.016]	[0.064]	[0.016]	[0.059]	[0.016]	[0.058]	[0.016]	[0.064]	[0.016]	[0.061]	[0.016]
Log of 1 + age	0.288**	-0.192***	0.282**	-0.192***	0.305**	-0.192***	0.266*	-0.192***	0.284**	-0.192***	0.289**	-0.192***
	[0.136]	[0.037]	[0.140]	[0.037]	[0.141]	[0.037]	[0.143]	[0.037]	[0.141]	[0.037]	[0.140]	[0.037]
Profits over assets[1]	0.035	0.006	0.041*	0.006	0.039*	0.006	0.043**	0.006	0.042**	0.006	0.041*	0.006
	[0.022]	[0.008]	[0.021]	[0.008]	[0.021]	[0.008]	[0.020]	[0.008]	[0.021]	[0.008]	[0.022]	[0.008]
Sales increase[1]	0.089	0.019	0.094	0.019	0.104*	0.019	0.083	0.019	0.097	0.02	0.100*	0.019

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Table 16 – Continued from previous page

	1		2		3		4		5		6	
			Primary		Rel>Med		Rel>1yr		Account		Records	
	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply	Grant	Apply
	[0.060]	[0.019]	[0.059]	[0.019]	[0.062]	[0.019]	[0.059]	[0.019]	[0.059]	[0.019]	[0.059]	[0.019]
Cash over assets[2]	-0.116	-0.492***	-0.087	-0.491***	-0.131	-0.491***	-0.186	-0.491***	-0.059	-0.491***	-0.188	-0.491***
	[0.399]	[0.124]	[0.391]	[0.124]	[0.383]	[0.124]	[0.385]	[0.124]	[0.390]	[0.124]	[0.388]	[0.124]
Leverage[3]	-0.080*	0.028**	-0.069*	0.028**	-0.071*	0.028**	-0.061	0.028**	-0.069*	0.028**	-0.086**	0.028**
	[0.043]	[0.012]	[0.042]	[0.012]	[0.042]	[0.012]	[0.041]	[0.012]	[0.041]	[0.012]	[0.042]	[0.012]
Owner managed dummy	0.113	-0.026	0.104	-0.026	0.173	-0.026	0.102	-0.026	0.094	-0.026	0.101	-0.026
	[0.222]	[0.079]	[0.217]	[0.079]	[0.219]	[0.079]	[0.218]	[0.079]	[0.218]	[0.079]	[0.233]	[0.079]
Limited liability	0.043	0.123*	-0.08	0.123*	-0.028	0.123*	-0.04	0.123*	-0.073	0.123*	0.094	0.123*
	[0.203]	[0.067]	[0.211]	[0.067]	[0.209]	[0.067]	[0.207]	[0.067]	[0.208]	[0.067]	[0.205]	[0.067]
Owner has home	0.619**	0.069	0.630**	0.069	0.654**	0.069	0.608**	0.068	0.646**	0.069	0.603**	0.069
	[0.260]	[0.100]	[0.275]	[0.100]	[0.279]	[0.100]	[0.283]	[0.100]	[0.280]	[0.100]	[0.269]	[0.100]
Bk mkt concentrated	-0.175	0.028	-0.153	0.028	-0.156	0.028	-0.153	0.028	-0.159	0.029	-0.141	0.029
	[0.168]	[0.060]	[0.174]	[0.060]	[0.170]	[0.060]	[0.169]	[0.060]	[0.173]	[0.060]	[0.169]	[0.060]
MSA dummy	-0.267	-0.239***	-0.327	-0.239***	-0.335	-0.240***	-0.305	-0.240***	-0.334	-0.239***	-0.305	-0.239***
	[0.203]	[0.067]	[0.210]	[0.067]	[0.208]	[0.067]	[0.205]	[0.067]	[0.211]	[0.067]	[0.213]	[0.067]
Minority owner	-0.469**	0.098	-0.478**	0.098	-0.478**	0.098	-0.475**	0.098	-0.505***	0.098	-0.547***	0.098
	[0.187]	[0.070]	[0.196]	[0.070]	[0.199]	[0.070]	[0.195]	[0.070]	[0.194]	[0.070]	[0.194]	[0.070]
Capital lease	0.596*		0.513		0.534		0.544		0.543		0.422	
	[0.327]		[0.327]		[0.334]		[0.336]		[0.333]		[0.337]	
Mortgage	0.528		0.602*		0.551		0.567*		0.585*		0.707**	
	[0.322]		[0.341]		[0.337]		[0.336]		[0.341]		[0.333]	
Vehicle loan	1.464***		1.570***		1.518***		1.506***		1.576***		1.581***	
	[0.314]		[0.338]		[0.325]		[0.324]		[0.334]		[0.331]	
Equipment loan	0.576***		0.613***		0.621***		0.617***		0.615***		0.576**	
	[0.223]		[0.230]		[0.224]		[0.227]		[0.229]		[0.230]	
Other loan	0.251		0.286		0.269		0.29		0.278		0.262	
	[0.205]		[0.212]		[0.210]		[0.209]		[0.211]		[0.211]	
Depositary institution	0.72		0.811*		0.775*		0.723*		0.679		0.566	
	[0.439]		[0.480]		[0.446]		[0.403]		[0.435]		[0.429]	
Finance company	-0.208		-0.437		-0.338		-0.377		-0.498		-0.367	
	[0.281]		[0.308]		[0.304]		[0.298]		[0.330]		[0.302]	
Other lender	0.195		0.005		0.089		0.051		-0.047		0.117	
	[0.299]		[0.328]		[0.333]		[0.319]		[0.339]		[0.332]	
Constant	2.547	-1.075**	2.938	-1.076**	3.439***	-1.074**	2.914	-1.074**	3.101	-1.077**	3.356	-1.079**
	[0.000]	[0.440]	[0.000]	[0.440]	[1.224]	[0.440]	[0.000]	[0.440]	[0.000]	[0.440]	[0.000]	[0.440]
Observations	2711	2711	2711	2711	2711	2711	2711	2711	2711	2711	2711	2711
Wald χ^2			0.339		0.638		0.929		0.288		0.398	
P-value			0.56		0.424		0.335		0.591		0.528	
χ^2 for $H_0 : \beta_1^S = \beta_1^U$			3.171		2.319		3.307		0.994		5.741	
P-value			0.075		0.128		0.069		0.319		0.017	
χ^2 for $H_0 : \beta_1^H = \beta_1^U$			0.197		1.575		2.68		0.021		0.105	
P-value			0.657		0.21		0.102		0.884		0.746	

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 17: Probit estimation with delinquency variable, information use.

This table shows the probit estimations for the use of information on the owner's delinquency when the lenders are informed or uninformed about the firm's credit quelity. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, 2 year dummies, and a constant term. The measure used for information availability is indicated in the first row of columns 2-7. For comparison purposes, column 1 contains the marginal effect of being delinquent on the bank's decision of granting the loan or not.

	1	2	3	4	5	6	7
	Delinq	Primary	Rel>1yr	Rel>Med	Account	Personal	Records
Owner delinquent	-0.240***						
	[0.037]						
Delinquent, info.		-0.197***	-0.217***	-0.218***	-0.190***	-0.262***	-0.248**
		[0.058]	[0.050]	[0.057]	[0.054]	[0.053]	[0.115]
Delinquent, no inf		-0.319***	-0.356***	-0.325***	-0.353***	-0.266***	-0.261***
		[0.061]	[0.071]	[0.062]	[0.063]	[0.067]	[0.042]
Information	0.169***	0.139***			0.039		0.016
	[0.033]	[0.040]			[0.042]		[0.052]
No information			0.05	0.038		0.086**	
			[0.038]	[0.038]		[0.039]	
Log of assets	0.032***	0.033***	0.032***	0.031***	0.030***	0.028***	0.030***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Log of 1 + age	0.034	0.032	0.047**	0.047*	0.041*	0.044*	0.045*
	[0.023]	[0.023]	[0.024]	[0.025]	[0.023]	[0.023]	[0.023]
Profits over assets[1]	0.004	0.004	0.004	0.004	0.005	0.005	0.004
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Sales increase[1]	0.005	0.005	0.001	0.001	0.003	0.002	0.002
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Cash over assets[2]	0.095	0.098	0.11	0.106	0.097	0.117	0.105
	[0.070]	[0.070]	[0.072]	[0.072]	[0.071]	[0.071]	[0.072]
Leverage[3]	0.006	0.006	0.005	0.005	0.004	0.004	0.004
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Owner managed dummy	0.023	0.021	0.027	0.024	0.019	0.031	0.025
	[0.049]	[0.049]	[0.050]	[0.050]	[0.049]	[0.050]	[0.050]
Limited liability	0.052	0.051	0.056	0.057	0.055	0.057*	0.059*
	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]
Owner has home	0.187***	0.185***	0.140**	0.144**	0.155**	0.155**	0.151**
	[0.064]	[0.064]	[0.059]	[0.060]	[0.062]	[0.061]	[0.061]

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Table 17 – Continued from previous page

	1 Delinq	2 Primary	3 Rel>1yr	4 Rel>Med	5 Account	6 Personal	7 Records
Bk mkt concentration	-0.079**	-0.081**	-0.077**	-0.077**	-0.077**	-0.066**	-0.074**
	[0.031]	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]
MSA dummy	-0.076**	-0.082**	-0.078**	-0.078**	-0.078**	-0.080**	-0.075**
	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]	[0.031]	[0.032]
Minority owner	-0.179***	-0.178***	-0.177***	-0.176***	-0.181***	-0.180***	-0.174***
	[0.042]	[0.042]	[0.042]	[0.042]	[0.042]	[0.042]	[0.042]
Capital lease	0.061	0.063	0.057	0.058	0.061	0.055	0.058
	[0.050]	[0.050]	[0.053]	[0.052]	[0.052]	[0.052]	[0.052]
Mortgage	0.087**	0.085**	0.083**	0.085**	0.091**	0.092***	0.087**
	[0.035]	[0.036]	[0.038]	[0.038]	[0.036]	[0.035]	[0.037]
Vehicle loan	0.199***	0.198***	0.207***	0.207***	0.204***	0.206***	0.208***
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
Equipment loan	0.116***	0.116***	0.120***	0.122***	0.119***	0.118***	0.121***
	[0.027]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Other loan	0.041	0.04	0.051	0.05	0.044	0.056*	0.049
	[0.034]	[0.034]	[0.034]	[0.034]	[0.034]	[0.033]	[0.034]
Depositary inst.	0.017	0.017	-0.026	-0.035	-0.002	-0.032	-0.025
	[0.052]	[0.052]	[0.062]	[0.063]	[0.057]	[0.063]	[0.061]
Finance company	0.072*	0.078**	-0.005	-0.003	0.057	-0.054	-0.003
	[0.041]	[0.040]	[0.056]	[0.055]	[0.047]	[0.065]	[0.054]
Other lender	0.048	0.049	-0.038	-0.036	0.023	-0.085	-0.027
	[0.047]	[0.047]	[0.064]	[0.064]	[0.057]	[0.073]	[0.061]
Observations	806	806	806	806	806	806	806
χ^2 for $H_0 : \beta_1^P = \beta_1^N$		2.24	2.179	1.599	3.827	0.001	0.097
P-value		0.134	0.14	0.206	0.05	0.979	0.755

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 18: Cross tabulations of personal relationships with other information sources. This table contains the cross-tabulation of the 861 sample firms regarding the availability of a personal relationship and the other measures of information availability for the potential lenders.

Sample distribution

	Not prim.	Prim	Rel ≤ med	Rel > med	Rel ≤ 1 yr	Rel > 1 yr	No acc.	Chck Svgs	No rec	Rec.
Personal	18.8%	40.0%	21.6%	37.2%	14.5%	44.3%	15.1%	43.7%	51.2%	7.5%
Impersonal	27.1%	14.2%	25.1%	16.1%	22.4%	18.8%	28.3%	12.9%	34.0%	7.2%

Percentage of firms that have defaulted

	Not prim.	Prim	Rel ≤ med	Rel > med	Rel ≤ 1 yr	Rel > 1 yr	No acc	Chck Svgs	No rec	Rec
Personal	34.4%	25.0%	35.2%	26.2%	40.0%	24.4%	27.2%	36.9%	37.0%	24.4%
Impersonal	29.2%	28.0%	26.9%	30.9%	29.5%	27.0%	28.7%	29.0%	30.5%	25.4%

Table 19: Probit estimation with delinquency variable, soft information use.

This table shows the probit estimations for the use of information on the owner's delinquency when the lenders have soft or hard information about the firm's credit quality. Apart from the variables that appear on the table, the regressions include 2-digit SIC industry codes, 9 regional dummies, and 2 year dummies. The measure used for information availability is indicated in the first row of columns 2-7.

	1 Primary	2 Rel>1yr	3 Rel>Med	4 Account	5 Records
Delinquent, soft & hard	-0.239***	-0.266***	-0.275***	-0.231***	-0.17
	[0.070]	[0.065]	[0.073]	[0.066]	[0.141]
Delinquent, soft	-0.282***	-0.273**	-0.260***	-0.296***	-0.284***
	[0.094]	[0.108]	[0.090]	[0.103]	[0.059]
Delinquent, hard	-0.022	-0.121	-0.084	-0.05	-0.420**
	[0.098]	[0.089]	[0.091]	[0.098]	[0.192]
Delinquent, uninformed	-0.355***	-0.419***	-0.410***	-0.375***	-0.249***
	[0.087]	[0.101]	[0.094]	[0.087]	[0.074]
Soft & hard	0.028	-0.150***	-0.152**	-0.061	-0.116
	[0.052]	[0.058]	[0.061]	[0.056]	[0.094]
Soft	-0.202***	-0.219**	-0.223***	-0.235***	-0.069
	[0.076]	[0.095]	[0.084]	[0.088]	[0.043]
Hard	0.067	-0.151*	-0.184**	-0.056	0.098
	[0.052]	[0.085]	[0.089]	[0.082]	[0.060]
Log of assets	0.028***	0.028***	0.028***	0.027***	0.027***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Log of 1 + age	0.029	0.043*	0.04	0.039*	0.043*
	[0.022]	[0.024]	[0.025]	[0.023]	[0.023]
Profits over assets[1]	0.004	0.005	0.005	0.006	0.005
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Sales increase[1]	0.006	0.004	0.002	0.003	0.002
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Cash over assets[2]	0.106	0.112	0.111	0.108	0.112
	[0.068]	[0.071]	[0.071]	[0.069]	[0.071]
Leverage[3]	0.006	0.005	0.005	0.003	0.003

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	1 Primary	2 Rel>1yr	3 Rel>Med	4 Account	5 Records
	[0.006]	[0.005]	[0.006]	[0.005]	[0.006]
Owner managed dummy	0.02	0.026	0.023	0.014	0.028
	[0.048]	[0.049]	[0.049]	[0.046]	[0.050]
Limited liability	0.042	0.048	0.05	0.044	0.056
	[0.033]	[0.034]	[0.034]	[0.034]	[0.035]
Owner has home	0.196***	0.150**	0.148**	0.165***	0.171***
	[0.066]	[0.060]	[0.060]	[0.064]	[0.064]
Banking mkt concentration	-0.072**	-0.072**	-0.074**	-0.069**	-0.065**
	[0.031]	[0.032]	[0.032]	[0.031]	[0.032]
MSA dummy	-0.086***	-0.080**	-0.078**	-0.079**	-0.078**
	[0.031]	[0.031]	[0.031]	[0.032]	[0.031]
Minority owner	-0.188***	-0.188***	-0.189***	-0.193***	-0.179***
	[0.043]	[0.042]	[0.042]	[0.042]	[0.042]
Capital lease	0.065	0.053	0.059	0.058	0.054
	[0.047]	[0.052]	[0.049]	[0.050]	[0.052]
Mortgage	0.093***	0.094***	0.092***	0.102***	0.092***
	[0.033]	[0.034]	[0.035]	[0.032]	[0.035]
Vehicle loan	0.196***	0.206***	0.206***	0.204***	0.205***
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
Equipment loan	0.111***	0.119***	0.121***	0.113***	0.115***
	[0.027]	[0.028]	[0.028]	[0.028]	[0.028]
Other loan	0.053	0.058*	0.058*	0.055*	0.056*
	[0.032]	[0.033]	[0.033]	[0.033]	[0.033]
Depositary institution	0.009	-0.034	-0.042	-0.01	-0.028
	[0.056]	[0.064]	[0.066]	[0.060]	[0.063]
Finance company	0.025	-0.064	-0.072	-0.004	-0.058
	[0.053]	[0.066]	[0.067]	[0.060]	[0.065]
Other lender	-0.016	-0.111	-0.127	-0.048	-0.084
	[0.062]	[0.076]	[0.078]	[0.072]	[0.073]
Observations	806	806	806	806	806
χ^2 for $H_0 : \beta_1^S = \beta_1^U$	0.347	0.955	1.279	0.371	0.183
P-value	0.556	0.328	0.258	0.542	0.669
χ^2 for $H_0 : \beta_1^H = \beta_1^U$	4.942	4.234	5.21	5.149	0.577
P-value	0.026	0.04	0.022	0.023	0.448

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

4 Risk management in SME lending: Are character loans different?

4.1 Introduction

In the previous chapter, we found evidence that soft information plays an important role in the first stage of the lending decisions of banks, namely the decision to grant the loan or not. In this chapter, I extend the scope of the research of the previous section to study whether soft information is also used by banks in subsequent stages of the lending process. In particular, I investigate whether soft information is important for determining the interest rate and the collateral requirements specified in the loan contract, once we control for the selection of firms into those that obtain the credit and those that do not.

Numerous studies have investigated the effects of having an existing relationship between the firm and the financial institution on the interest rate and the collateral requirements.[50] At least for the US case, there is an overall consensus that the existence of a relationship tends to lower both the interest rate charged for the loans, and the probability of being asked to post a collateral. However, it is not clear what role (if any) is played by *soft* information in the setting of the interest rate and on the collateral requirements. Through the existence of a relationship with the firm, a bank gathers private information, both soft and hard, about the firm's true credit quality. In this chapter, I provide an answer to whether banks use soft or hard information more intensively in this stage of the lending decision, or whether it is the joint accumulation of private soft and hard information what matters for setting the loan terms.

Using the SSBF sample of small US firms, I find that loan terms of character loans

[50]For example, the US case has been studied in Petersen and Rajan (1994), Berger and Udell (1995), and Chakraborty and Hu (2006), among others. Evidence for other countries includes Angelini, Di Salvo and Ferri (1998), Elsas and Krahnen (1998), Harhoff and Körting (1998), and Degryse and Van Cayseele (2000), among others.

are set in a way to limit the risk of lending based on pure soft information criteria. Collateral is required with a high likelihood to firms that were granted the loan based strongly on 'character' considerations. The result is even stronger if those firms or their owners have been delinquent in some other credit relationship. However, I find no compelling evidence to conclude that banks set more favorable rates to firms for which they have only soft information, relative to those for which they have only hard information: it is rather the joint accumulation of soft and hard information what really makes the difference regarding the interest rate. Together with the results of the previous chapter, these results suggest that banks that lend based on soft information - i.e., that lend using the 'character' approach - use collateral as a credit risk management tool. On the other hand, banks that lend based on more standard criteria use credit rationing to deal with credit risk.

The results obtained in this chapter are robust to several considerations. First, a potential sample selection bias stemming from the fact that the sample on which I base all the estimations corresponds only to the firms that have been granted the credit. However, under the premise of asymmetric information, prices do not adjust to clear the markets in the credit markets. Instead, lenders restrict access to credit to the most risky borrowers (Stiglitz and Weiss 1981). Hence, if the estimations are purely based on the observed sample the results could be biased. I control for this potential selection bias by correcting the estimations with the standard Heckman selection correction estimators. In fact, in contrast to previous studies that use these estimators, the resulting Heckman estimations obtained in this chapter are quite stable under different model specifications.

On the other hand, several authors have pointed out that the real benefits of relationship lending are observed for lines of credit rather than on collateralized loans or leases (Berger and Udell 1995, Chakraborty and Hu 2006). Therefore, as a robustness check, I also verify whether the results continue to hold when we consider only lines of credit, and eliminate all of the other loans.

The remainder of this chapter is organized as follows: In Section 4.2 I analyze the role of soft information in the setting of the interest rate. In Section 4.3 I perform a similar analysis for the collateral requirements. In Section 4.4 I repeat all analysis for the subsample of firms that were granted a line of credit - as the benefits of relationship lending have been suggested to be strongest in this subsample -, and finally in Section 4.5 I present the conclusions.

4.2 Interest rates

4.2.1 Determinants of interest rate

I start by examining what variables are the most important determinants of the interest rate charged by banks by estimating regressions for this variable. Financial theory would tell us that the price of a bank loan is determined by the underlying cost of funds plus a premium that depends on the riskiness or credit quality of the customer. Following this theory, I consider this model as a starting point for the setting of interest rates for a bank loan:

$$\text{Rate} \;=\; \beta_0 + \beta_1 X_i^r + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i. \tag{9}$$

Here, X_i^r represents the underlying costs of funds, while X_i^f is a vector of firm-specific characteristics, X_i^b is a vector of characteristics of the bank to which the firm went for a loan, and X_i^l is a vector containing the type of loan that the firm asked to the bank, and the year of the application.[51]

I report the estimated coefficients for Equation 9 on the first columns of Table 20 (labelled as Part A). I include the prime rate, the default spread for Baa rated bonds, and a term structure spread in order to control for changes in the macroeconomic

[51] Other possible loan-related determinants of the interest rate charged would be other terms of the loan, such as collateral requirements or loan maturity. I do not include these variables in the model and interpret this equation as the reduced form of the complete system, which may be estimated without bias with ordinary least squares (Dennis, Nandy and Sharpe 2000).

conditions that affect the cost of funds, X_i^r.[52] On the other hand, in order to control for the firm's credit quality, I include the size and age of the firm, a number of financial ratios (leverage, cash availability, profitability), growth opportunities (sales increase), and several governance characteristics of the firm. I also control for bank-specific characteristics and for the type of loan.

The focus of these estimations is once again the importance of soft information in the pricing of the bank loans. To estimate the importance of soft information, I shall follow a similar indirect approach to the one used in the previous chapter; namely, I interact a variable that measures the degrees of information available to the lender bank with a variable that should be widely available for all banks at this stage of the credit decision, and that at the same time is an important determinant for the interest rate charged by the banks. Therefore, before we estimate the importance of soft information for the setting of the interest rates, we need to identify a variable that satisfies these conditions. Hence, I shall start by exploring the estimated coefficients of Equation 9 and find among the most important determinants of the interest rates charged to the firms, those that satisfy the above requirements.

An obvious candidate to be used as variables widely available to all banks and of significant importance to set the interest rate is the reputation of the firm. I therefore include the same two variables measuring the credit history of the firms as in the previous chapter: whether firms typically pay their trade credit after the due date, or whether the firm has been delinquent in the past. As argued before, these variables should be accessible to all lender banks. Moreover, we could expect that these variables play an important role in the pricing of the loans. However, the first three columns of Part A in Table 20 show that, in contrast to the important role played by the credit history in the credit granting decisions of banks, these variables do not seem to be important determinants of the interest rate charged by banks.

[52] All definitions for these variables are in the appendix. I obtained the data for the interest rate variables from the Federal Reserve Statistical Release (http://www.federalreserve.gov/releases/h15/update/).

Another obvious candidate to interact with the information availability dummies could be the rating classification due to Dun & Bradstreet. However, Column 4 of Table 20 (Part A) shows that this variable is still not significant. We must therefore select a different variable that is an important determinant of the interest rate charged by the banks.

One possibility is to choose a variable in the financial statement of the firm. However, Table 20 shows that, although some of the variables seem to be important determinants of the interest rate, they are not always significant across the different specifications. In contrast, one variable that is significantly negative across all the different specifications is the indicator variable for the business owner possessing a home. This relationship indicates that, all else equal, firms whose owners do not possess a home are charged a higher interest rate. The relationship makes perfect economic sense, as the lack of an asset to secure the loan increases the bank's cost of lending in the case of default. The case is obvious when the firms are organized as unlimited liability partnerships or sole proprietorships. Still, even when the firms are organized as a corporation with limited liability, it is common in SME lending to ask for a personal guarantee or a personal asset to secure the loans, obviating the effect of the limited liability restriction.[53] Moreover, at this point in the lending process it is very plausible that banks have gathered this information about the firm's owner, and more importantly, that it is incorporated in the pricing of the loan. Hence I choose this variable to interact it with the different information availability sets.

4.2.2 Sample selection

Before continuing to disentangle the effects of soft and hard information in the setting of the interest rates, we must take into account a potential sample selection bias. The seminal paper by Stiglitz and Weiss (1981) pointed out that in the presence of adverse selection or moral hazard, credit markets are different to the markets for any other

[53]Indeed, in our sample, a total of 80% of the firms were required a personal guarantee or a personal asset to guarantee the loan repayment.

standard good: in credit markets, prices do not always adjust to clear the markets. Higher interest rates give incentives to the riskier credits to line up for the loan, or influences the borrowers to take up riskier projects. Hence, lenders may choose to ration the credits they give instead of raising the interest rate to clear the market.

The firms considered in the first five columns of Table 20 are necessarily the firms that were not credit rationed, as we observe the interest rates set by the banks only for the firms that actually got a loan. However, under the Stiglitz and Weiss paradigm, the unobserved factors affecting the interest rate set by the bank may be systematically correlated with the fact of obtaining the loan. Ignoring this sample selection problem could be biasing the results of the previous section. Therefore, in Part B of Table 20 I correct for this potential sample selection problem. The procedure to deal with sample selection bias has been widely studied in the econometric literature.[54] I consider the following model for the selection of the sample:

$$\begin{aligned} w_i^* &= \eta X_i + u_i \qquad (10)\\ w_i^o &= \begin{cases} 1, & \text{if } w_i^* \geq 0 \\ 0, & \text{otherwise} \end{cases}, \end{aligned}$$

where $X_i = [X_i^f, X_i^b, X_i^l, Z_i]$ is a vector of observable characteristics of the firms that determine whether the firms obtain a loan or not, w^* represents the score obtained by each firm in their credit evaluation by the lender bank, and w^o is the observable counterpart of the credit score of the firm, i.e. a binary variable containing a one if the firm obtained the loan, and a zero otherwise. X_i contains the size, age, profitability, sales increase, sales over assets, market and governance characteristics of the firms, the type of financial institution lending to the firm and certain characteristics of the relationship between the lender and borrower, and the type of loan. Additionally,

[54] For a discussion of the bias of the estimators when there is sample selection, see, for example, Maddala (1983, Chapter 9) or Wooldridge (2001, Chapter 17)

X_i contains Z_i, a vector with identification variables that are significant for the loan granting process but insignificant for the interest rate setting. These variables include a dummy variable indicating if the majority of the owners belong to any racial minority and a dummy variable indicating whether the majority of the owners are female. All of these variables have been shown to be significant for the loan granting process, but not necessarily so for the setting of the interest rate.[55]

I use the Heckman two-stage coefficient estimation to account for the selection of the sample with a binary response model. That is, I first estimate η of the selection equation with a probit estimation using all of the firms, both those that got a loan and those that did not. I then use the estimated coefficients, $\hat{\eta}$ to calculate the Inverse Mills Ratio for each observation, $\hat{\lambda}_i = \phi(\hat{\eta}X_i)/\Phi(\hat{\eta}X_i)$, where $\phi()$ is the standard normal density function, and $\Phi()$ is the standard normal distribution function. Then, I fit Equation 9 with an OLS regression, adding $\hat{\lambda}$ as an additional control variable. The added variable, $\hat{\lambda}$ takes care of the sample selection bias (Wooldridge 2001, p. 570-571).

Part B of Table 20 contains the estimated coefficients considering the sample selection bias. In the first column, I consider the delinquency variable in both the selection and the interest rate equation, while in the second column I only consider the delinquency variable in the selection equation. While the coefficient estimations do not change qualitatively with regard to the coefficients in Part A, the significant positive sign of the Mills ratio shows evidence of sample selection due to credit rationing.[56] Our variable of interest, the home ownership dummy, is still significantly negative, thus confirming our suspicion that this variable is important in the determination of the interest rate even after accounting for sample selection.[57] On the other hand, the

[55]Evidence on discrimination in the small business credit market has been found in Blanchflower, Levine, and Zimmerman (2003) and in the previous chapter of this thesis.

[56]In Table 20 I only show the results of a selected number of specifications for the Heckman model. However, it is important to point out that these estimations are quite stable throughout different specifications.

[57]As a robustness check, I reestimate the coefficients with sample selection with a maximum likelihood estimation, assuming that the error term of the selection equation and the error term of

delinquency variable loses all statistical significance once we take into account the selection bias. It seems, in fact, that having been delinquent is only important in the setting of the interest rate to the extent that it matters in the decision of granting the loan. These results confirm that the home ownership variable is the adequate one for our final purpose, as its significance survives the sample selection.

4.2.3 The role of private information and soft information

As in the previous chapter, I partition the observations into groups for which the lender bank has different information sets. Then I interact these variables with the home ownership variable to find out whether banks treat the firms for which they have private information differently from those for which they do not. Given that there is both theoretical and empirical support for sample selection, I estimate all coefficients with the Heckman two step approach, considering Equation 10 for the loan granting process and the following model for the setting of the interest rate:

$$\begin{aligned} \text{Rate}_i &= \beta_0 + \sum_{k \in K} \beta_1^k Home_i * I_i^k + \sum_{j \in K, j \neq k^*} \beta_2^j I_i^j + \\ &\quad + \beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + \beta_6 X_i^r + \beta_7 \hat{\lambda}_i + u_i. \end{aligned} \tag{11}$$

Here, K represents a partition of the observations according to the information availability of the lender bank, and I^k takes a value of 1 for all the observations within the same information availability set k, and zero otherwise.

The coefficients for the interest rate equation (Equation 11) when we consider the interaction between the home ownership variable and two dummies measuring presence or absence of private information in the lender bank (i.e., $K = \{$P (privately informed),N (not informed)$\}$) are reported in Table 21.[58] As in the previous chapter,

Equation 9 are distributed as a bivariate normal. The results do not change qualitatively.

[58] The estimated coefficients for the first-stage Heckman regressions for granting the loan, and the estimates for the rest of the control variables are not reported since they are qualitatively equal to the ones in Table 20.

I use different criteria widely used in the literature to divide the sample into firms according to whether the lender has private information availability, namely: whether the bank is the primary financial services provider of the firm (Column 1 of Table 21), whether the bank leads a personal relationship with the firm (Column 2), whether the firm has a checking or savings account with the bank (Column 3), whether the bank and the firm have done business for more than one year (Column 4) or for more the median relationship length (Column 6), or whether the firm used written records to answer the survey (Column 6). Recall that while the first 5 are direct measures of information availability of the lender bank, the last one is more related to the opaqueness of the firm.

Table 21 shows evidence that the accumulation of private information matters when determining the interest rate charged by the banks. This can be seen by observing the coefficients for the home availability dummy interacted, respectively, with information availability (first row of Table 21) and no information availability for the lender bank (second row). The coefficient is always negative, suggesting that the cost of lending is effectively lower for the bank when the firm's owner has a home. However, it is only significantly negative for the firms where the bank has a more restricted access to private information about the firm. On the other hand, when the relevant measure refers to the opacity of the firm (Column 6), the situation is surprisingly reversed: the home ownership variable is only significant when the firm has records available, i.e. for the less opaque firms.

In order to explore whether the coefficients found in Table 21 are driven by distributional issues of the sample, Table 22 contains the distribution of the sample according to the information availability of the firms. The first row of Panel A contains the percentage of the successful firms (i.e. the ones that got a credit, 639 in our sample) for which the bank had access to each of the information sources stated in each column. The sample is roughly equally split among relationship banks and transaction banks: A little more than a half of the banks (roughly 60%) had some kind of information relationship about their borrowers; the rest of the banks seemed to lend in a more 'transactions' oriented fashion. Moreover, the second rows of Panel A and Panel B show the percentage of firms owning a home in each of the sub-samples. The numbers are neither quantitatively nor statistically different. The same is true for the number of delinquent firms in each group (third row of each panel). However, when the measure for information is the availability of written records (last column of Table 22), the distribution of firms across groups is quite asymmetric: 85% of the firms that were granted credit had no written records, and only 15% had. Moreover, the sample is quite heterogeneous regarding both the availability of a home and the delinquency variable. This could be driving the differences that we observe in Column 6 of Table 21.

The last rows of Table 21 show the F-statistic for the test of equality of coefficients β_1^P and β_1^N. The coefficients are only statistically different (at a 5% level) when the bank is the firm's primary financial services provider. A one-sided test would also yield statistical significance (at a 10% level) when the measure is the existence of an account. We discussed in the previous chapter that both these measures have an important component of hard information. In contrast, the coefficients β_1^P and β_1^N are not statistically different for the other three measures, which may involve large amounts of soft information. This could be evidence that the availability of private hard information is more important than soft information when setting the interest rate. However we still need to isolate the soft and the hard components of private information in order to conclude.

Before we analyze what happens when we isolate the soft information component from the hard information component, let's analyze the coefficients for the information availability. Consistent with previous studies (Petersen and Rajan 1994, Berger and Udell 1995), the results in Table 21 show that firms that lead some kind of relationship with the bank are benefitted by obtaining a lower interest rate. This can be seen through the statistically significant negative coefficient for the dummy indicating the availability of a savings or checking account with the lender bank (Column 3), and through the significantly positive coefficient for the dummy of a relationship smaller than one year (Column 4). Similar results continue to hold, though with lower significance, when the bank is the primary financial services provider (lower interest rate, see Column 1), when the bank and the firm lead an impersonal relationship (larger interest rate, see Column 2), and when the relationship between the bank and the firm is shorter than the median (larger interest rate, see Column 5). However, the results are inverted when we measure information availability through the existence of written records. Nevertheless, as it has been argued before, this measure is the less adequate for measuring information availability of the lender bank, and it might be driven by the distribution of the sample.

We now know that private information is important in determining the interest rate charged by banks to small firms, and that (probably) hard information is more important in this stage of the credit application. However we would also like to disentangle whether there is a special role played by soft information. Following the same procedure as in the previous chapter, I divide the sample into four groups of firms, depending on whether the bank has access only to hard information, only to soft information, to both types of information, or if it has no (or limited) private sources of information about the firm (recall Table 9 in Chapter 3). Table 23 presents the analogous estimated coefficients for the interactions of home availability with four dummies measuring respectively the presence of hard information, soft information, both types, or none.

The first four rows of Table 23 show that, while banks do tend to charge lower interest rates to owners having a real estate property (i.e. $\beta_1^U < 0, \beta_1^S < 0, \beta_1^H < 0, \beta_1^B < 0$), the reliance on this signal is only significative whenever the bank has no source of information, soft nor hard, about the firm. These results suggest that once the bank has access to any source of private information about the firm, then it does not necessarily charge a higher interest rate to the firms whose owner does not possess a home. However, the tests of difference of β_1^S, β_1^H, and β_1^B versus β_1^U in the last rows of Table 23 show that these differences are not statistically significant. However, a one-sided test would yield the coefficients β_1^H and β_1^B statistically different from β_1^U (at a 10% level) when the source of hard information availability comes from being the bank's primary financial services provider. Near significance is also reached when the measure is the availability of a savings or checking account. Recall that these two measures are our best proxies for hard private information availability. From these results, we cannot conclude from coefficient β_1^S that soft information per se matters in the setting of the interest rate. However, it seems that hard private information is much more relevant than soft information to determine the interest charged for a bank loan.

The distribution of the firms among the categories of their lender banks (no private information, only soft, only hard, both) is displayed in Table 24. Note that the relative majority of the lenders (around 40%) extend loans to firms with which they have both sources of soft and hard private information. Around 26% are arms-length loans, i.e. the loans are given by banks that do not have any source of private information. The rest of the lenders either have a personal relationship but no source of hard information, or viceversa. The number of firms in each of these latter categories is somewhat reduced, at 18% or less. This reduced sample size could be driving the lack of precision of the estimations pointed out in the preceding paragraph. In other words, the fact that β_1^H and β_1^S are statistically equal to zero could be due either to the fact that availability of soft or hard information is enough for banks not to look at external signals of quality to set the interest rate - i.e. both soft and hard information matter - , or due to the fact that the sample is reduced in this case. In the same fashion, the sample size of the firms whose lender is privately informed (with soft and hard information sources) is sufficiently large in all cases; this suggests that indeed $\beta_1^B = 0$ is due to the availability of information, and not to the reduced sample size.

Table 23 also contains the estimated coefficients for the bank information availability dummies, β_2^K. Notice first of all that the availability of private information reduces the interest rate charged by the lender, i.e. $\beta_2^K < 0$ when $K \in \{H, S, B\}$ (the omitted variable is the dummy for no private information availability, i.e. $I_i^U(x)$). These variables are significantly negative in Columns 3 and 4, i.e. when we consider the length of the relationship (a measure that contains both soft and hard information) as the measure for the private information availability. β_2^B is also significant when the measure of hard information availability is the existence of a savings or checking account (Column 2). These results are consistent with Berger and Udell's (1995) findings: firms that lead a relationship with the bank seem to benefit from a lower interest rate. In particular, firms for which banks have soft information are charged lower interest rates, all else equal, than firms for which the banks have no private information ($\beta_2^S < 0$). These results are significant for the models in Columns 3 and 4, at significance levels of 5 and 10%, respectively. They are also significant for one-tailed tests in the rest of the models. This suggests that a bank that leads a personal relationship with the firm will be charged, all else equal, a lower interest rate than a firm for which the bank has no information at all. Analogously, since $\beta_2^H < 0$ we may say that the existence of hard private information is also important for the setting of the interest rate. These findings in fact qualify the findings of Berger and Udell (1995), noting that the reduction of interest rate happens independently of the source of the relationship, i.e. whether it is a source of soft of hard information.

In order to obtain a better intuition of how the availability of soft and hard information affects the interest rate on the loan, I present a simplified graph of the results in Figure 9. The horizontal axis contains the home availability variable, which represents the cost of lending to a borrower. Clearly, lending to a borrower that does not have a home is costlier than lending to one that has a home, as this asset can be seized in case of default. The vertical axis, on the other hand, contains the annualized interest rate charged. Each of the lines represent the estimated interest rates whenever the financial institution granting the loan has soft / hard / both /

no information about its customer, as estimated in the third column of Table 23. As can be seen in the upper dotted line, the banks that do not have any private information about the firms charge in average 250 bps less to firms whose owners possess a home, with respect to those that do not have one. However, the three lower lines show that when there is some private information availability, the difference in the cost charged to the firms whose owners have a home with respect to those that do not is significantly smaller, at only minus 50 to 100 bps on average. Moreover, having any source of private information at hand (soft or hard) reduces the interest rate charged to the borrower by an average 200 bps when the borrower does not have a home and by an average of 100 bps when she does. Although I do not graph confidence intervals in order to maximize the clearness of the graph, the three lower lines cannot be statistically distinguished among each other, but are different from the upper one. Thus, we may conclude that soft information is important in the setting of the interest rate; however, it is relatively not more important than hard private information availability.

From the results in this section, we may conclude that there is evidence that soft information is important for the setting of the interest rates by banks. On the one hand, the existence of a personal relationship but no source of hard information tends to reduce the interest rate charged to banks. On the other hand, the reliance of the external signal (home ownership by the principal owner of the firm) is reduced in the presence of a source of soft information. However, it seems that the availability of hard information is relatively more important in the setting of the loan terms, as the reliance on the external signal is only significantly different for informed vs. uninformed banks when there is a source of hard information. In the next section we investigate the roles of soft and hard information on the probability to ask the firm to post collateral.

4.3 Collateral

4.3.1 Determinants of collateral requirements

To determine the role of soft information in the requirement to post collateral for a given loan, I follow a similar approach as in the case of interest rate. I hence start by proposing a model to explain the determinants of whether a loan is collateralized or not. Economic theory suggests that different factors regarding the type of lender, the type of loan, and the type of borrower should be taken into account to determine a loan collateralization status. I therefore start by proposing the following model:

$$\text{Collateral}_i \quad = \quad \gamma_0 + \gamma_1 X_i^f + \gamma_2 X_i^b + \gamma_3 X_i^l + u_i, \tag{12}$$

As usual, X^f, X^b, and X^l refer to vectors of firm-, bank-, and loan-specific characteristics, respectively. I include the age, the size, several financial statement items (profitability, cash availability, sales increase, leverage, etc.), governance characteristics, credit quality, location, and industry as the firm characteristics affecting the secured status of the loan. I also include the type of the institution granting the loan, and whether the firm and the bank have some kind of lending relationship. As for the loan-specific characteristics, I control for the type of loan and the year of the application.[59] Results of fitting a probit model to Equation 12 are shown in Panel A of Table 25.

As we did with the interest rates, we must now identify a variable that is both economically and statistically significant in explaining the secured status of the loan. The obvious candidates are, once more, the credit history or credit quality of the firms or their owners. Hence, in Columns 1-5 of Panel A, Table 25, I include several

[59] A notable element that is absent in this specification is the interest rate, which may clearly play a role in the posting of collateral. Analogously, collateral is absent from the interest rate equations of the previous sections. The omission of these variables is not relevant, as we may identify each of the models 12 and 9 as the reduced-form equation of a more complete model containing the interactions among both variables (Dennis et al. 2000). Moreover, inclusion of endogenous variables in a model with sample selection is not a simple issue (Wooldridge 1998, p.571), and well beyond the scope of this investigation.

proxies for the credit history or credit quality of the firm within the vector X_i^f. These proxies include the proportion of trade credit that the firm has paid after the due date, whether it has been delinquent in personal or business obligations, and the credit rating given by the Dun & Bradstreet corporation. Included in the regression are also several financial variables that could be adequate candidates to be economically and statistically significant to explain the secured status of the loan.

Economic theories are ambiguous regarding the effect of the credit quality on the secured status of a loan. In a context of adverse selection, some models pose that collateral can be used by firms as a signaling instrument of credit quality (Bester 1985, Besanko and Thakor 1987*a*, Besanko and Thakor 1987*b*, Chan and Thakor 1987). In consequence, among a pool of ex-ante undistinguishable borrowers, the best credit risks will be more willing to post collateral, so we should observe a positive relationship between the proxies of credit quality and collateral. Other models claim that collateral can help resolve a variety of moral hazard problems such as asset substitution, underinvestment, or underprovision of effort (Myers 1977, Smith and Warner 1979, Stultz and Johnson 1985, Boot, Thakor and Udell 1991). As a consequence, the firms that have the highest observable credit risk should be associated with greater probability of collateral. The latter theories are more consistent with the general perception among bankers, and most of the empirical evidence supports them (Berger and Udell 1990, Boot et al. 1991, Harhoff and Koerting 1998, Chakraborty and Hu 2006). However, recent empirical studies that have been able to distinguish between firms with observed and unobserved credit quality have also found evidence for the adverse selection theories of collateral (Jimenez, Salas and Saurina 2006).

In the results of Panel A of Table 25 we find evidence for both theories of collateral. On the one hand, the positive and significant coefficient for the delinquency variable shows evidence of collateral used to mitigate moral hazard (Columns 2 and 3). On the other hand, in Column 4 we find that firms with the best credit ratings (low risk, the omitted dummy for the Dun & Bradstreet classification of risk level) have a very high probability of posting collateral, pointing rather towards the theories of collateral as an instrument used to signal credit quality. But, at the same time, the firms with the worst credit rating do have an increased probability of being required to use collateral with respect of the firms of average risk. The latter result evidences once more the need to require collateral to mitigate moral hazard.

Given the results described in the previous paragraphs, we must be very cautious regarding the choice of variable for disentangling the effects of soft and hard information availability on the collateral requirements. I choose to interact the delinquency variable with the information availability dummies for several reasons. First of all, it is highly plausible that the moral hazard effect dominates for the firms that have a bad credit history story. Indeed, Table 25 shows that firms with lowest ratings do seem to post collateral with a higher probability with respect to the other firms. However, tests of hypothesis of equality of coefficients among the other ratings (not reported) reveal that the signalling effect is not present among the rest of the firms. Among the lowest risk firms the percentage of firms that default is at its lowest level (12.9%, compared to 19.9% for the firms with moderate risk, 27.7% among the average risk firms, 31.6% for the significant risk firms, and 55.1% on the firms with high risk). In other words, the non-linear relationship observed for the credit rating variable implies that banks are not unanimous in requiring firms to post collateral with a probability that decreases with an improved credit rating. Hence, interacting this variable with the information availability dummies could add confounding effects that are not due to pure information issues, but to the role of collateral as signaling device or as moral hazard mitigator. In contrast, banks do seem to be unanimous in imposing collateral with a higher probability to firms that have been delinquent in their personal or business obligations. Therefore, this delinquency variable tends to be the best candidate in order to test our hypothesis of differentiated uses of information among banks. Moreover, our third candidate variable (trade credit paid on time), we do not find any significant effect on the probability of securing the loan.

The same holds for the rest of the financial variables.

4.3.2 Sample selection

As was the case for the interest rate, in the collateral estimations we cannot ignore a potential estimation bias due to the fact that firms have been non-randomly selected by the banks to be granted the credit. Therefore, in Panel B of Table 25 I estimate the equations for collateral taking into account Equation 10 for the selection process. As identification variables in Z_i, I once again include dummies for the sex and the race of the principal owners of the firms, which turn out to be significant, consistent with the previous literature mentioned in the previous section. Additionally, I find evidence consistent with a systematic non-random selection of the firms due to the credit granting process (significant coefficient for the Mills ratio). I estimate Equation 12 through two procedures, maximum likelihood and the Heckman two-stage procedure, and the results do not change qualitatively.[60]

The results in Panel B of Table 25 continue providing evidence (at higher confidence levels than in the model without selection) that the delinquency indicator is an important determinant for the collateral requirement of a loan. All else equal, a firm having a delinquency in the past is more likely to be asked to post collateral by the bank. On the other hand, the risk rating provided by the Dun & Bradstreet corporation continues presenting the non-linear specification observed in Column 4 in Panel A: firms with the best credit rating are equally likely to be asked to post collateral than those of medium to high risk. Finally, the trade credit variable continues to be statistically equal to zero even after controlling for the sample selection bias (estimations not reported in the table). These results still support our choice of variable for disentangling the effects of private information, and its essential components (soft and hard information) on the availability of collateral. I shall use this variable in the next section.

[60] In Table 25 I report the Heckman coefficients since these are by definition already in marginal form and hence easier to interpret and compare with the other specifications.

4.3.3 The role of private and soft information

Following a similar approach as in the case of the interest rate estimations, I construct several different partitions for the observations in the sample, according to two criteria: (i) whether the lender bank has private information about the firm or not (to discern whether there is a role played by private information in the decision of requiring collateral), and (ii) whether the lender bank has soft information, hard information, both kinds or none (to determine whether there is a differential role of soft information in the posting of collateral). I then create dummy variables for the sets in each of the partitions, interact them with the delinquency variable that I chose in the previous section, and estimate the following model:

$$\begin{aligned} \text{Collateral}_i &= \gamma_0 + \sum_{k \in K} \gamma_1^k Delinquent_i * I_i^k + \sum_{j \in K, j \neq k^*} \gamma_2^j I_i^j + \\ & +\gamma_3 X_i^f + \gamma_4 X_i^b + \gamma_5 X_i^l + u_i. \end{aligned} \tag{13}$$

I start by determining whether private information plays an important role in the collateral requirements, by interacting the delinquency variable with the indicator variables created by each of the six different partitions for private information availability or unavailability used in the previous section. The estimated coefficients, corrected for sample selection, for γ_1^k and γ_2^k, $k \in \{P, N\}$ of Equation 13 are displayed in Table 26. Each of the columns in the table corresponds to one of the six partitions for information availability: The bank is the firm's primary financial services provider (Column 1); the bank and the firm lead a personal relationship (Column 2); the firm has an account with the bank (Column 3); the firm has lead a relationship of at least one year with the bank (Column 4); the firm has lead a relationship of at least the sample median length (Column 5); the firm has written records (Column 6).

A number of conclusions may be drawn from Table 26. First of all, we still find that banks do take into account the owner's credit history. For all the partitions for private information availability or lack of it, banks assign a higher likelihood of posting collateral to the firms that have defaulted in the past: $\gamma_1^P < 0$ and $\gamma_1^N < 0$ are always significantly different from zero at 10% or lower levels - at least with a one-sided test (as in the case for leading an impersonal relationship with the bank, in which the corresponding p-value is 0.168). However, banks do not seem to treat differently the delinquent firms for which they have some information source from those for which they do not have private information, i.e. the test for $\gamma_1^P = \gamma_1^N$ cannot be rejected (see the last two rows in Table 26). Albeit, consistent with previous results in the literature (Chakraborty and Hu 2006, Berger and Udell 1995), we from the coefficient for the dummy for the bank being the firm's primary financial services provider that relationships do matter in the determination of collateral requirements. One-sided tests for these coefficients to be equal to zero can be rejected in all the columns except Column 3, i.e. where the relationship variable refers to the existence of an account with the lender bank.

One interesting feature present in Table 26 is that the coefficients γ_1^N tend to be larger and to have higher statistical significance than γ_1^P. In fact, the significance of γ_1^N disappears when the information available to the lender is gathered through a personal relationship with the firm. Apparently, banks leading a personal relationship require delinquent firms to post collateral with a higher probability than those with a 'clean' credit history. However, banks without a personal relationship do not seem to care about the credit history of the firms when deciding whether to give them collateral or not. The result is a bit puzzling, as it is expected that the banks without information should rely on hard information more intensively than those with private information about the firm. In particular, this should happen when the source of information is a personal relationship. Still, some of those firms that do not lead a personal relationship could have other sources of information. It may well be that the soft information collected through a personal relationship is not important for the determination of the collateral, but the lender bank has other sources of information that do matter, which are guiding the observed results. Consequently we should, as in the previous section, separate the firms according to the different sources of information available to the lenders in order to understand exactly what is driving these results.

In Table 27, I disentangle the different information types. I.e. I estimate four coefficients for the delinquency variable, γ_1^k for $k \in \{U, S, H, B\}$. As usual, I use different classifications of the firms into U (bank is privately uninformed about the firm), S (bank has soft information), H (bank has hard information), and B (bank has both soft and hard information about the firm).

In Table 27 we find, once again, evidence that banks tend to require collateral when there is a notable bad credit history. When the bank has no private information, the reliance on the delinquency variable is positive ($\gamma_1^U > 0$), a one-tailed test yields statistical significance for this coefficient (as expected). Interestingly, the statistical significance increases when banks *have* soft information about the firm, i.e. γ_1^S and γ_1^B are statistically different from zero with two-sided tests in most cases. However, these coefficients are not statistically different from γ_1^U. In other words, there does not seem to be a strong differential treatment regarding collateral depending on the availability of information of the lenders.

On the other hand, in Table 27 we also find that character loans, i.e. those loans granted only on the basis of soft information, have all else equal a higher probability of posting collateral than transaction loans, i.e. $\gamma_2^S > 0$. This result is, in fact, statistically different from zero at 5 or 10% level when we identify hard information as having an account at the lender bank or being the firm's primary financial services provider, i.e. our best proxies for hard information sources. This surprising result reinforces the findings of the previous paragraph, and point out that indeed banks giving out character loans seem to protect themselves against any subjective decisions by requiring to secure the loan.

Regarding the collateral requirements, the main findings may be summarized in

Figure 10. This figure represents the estimated probabilities of each firm to be required to post collateral, depending on the information available to their lenders, as a function of whether they have defaulted in the past or not. The model I use to predict the probabilities is that in the third column of Table 27. From the figure we can observe that the availability of soft information seems to *increase*, rather than decrease, the probability of requiring the firm to post collateral, and that this is especially true whenever the firm has a negative reputation. In fact, although the confidence intervals are not shown for the sake of clearness, the probability of asking the posting of collateral is statistically higher when the lender bank has soft information than in all the other cases. One interpretation of these findings is that banks lending on a 'character' base (i.e. based on soft information) use collateral relatively more in order to manage the potentially higher risks due to soft information-based lending.

Overall, the results in Tables 26 and 27 are not very conclusive regarding the role of information availability on the collateral requirements. However these results do seem to point out that external signals of quality are less important on the presence of hard private information, but play a more predominant role on the presence of soft information. This evidence points out that all else equal, character loans are more likely to be asked to post a collateral. Even further, character loans with a bad credit reputation are very likely to be required to post collateral. This could be very plausible in the light of the results obtained in the previous chapter, where we found that private information availability is very important for granting loans. In other words, firms with a bad credit history may be still granted the credit provided the bank has positive private information about the firm. Yet, such firms cannot be unconditionally granted the credit, as they are indeed riskier than those that have not defaulted. They are hence granted the credit conditional on having it secured.

But before drawing such a conclusion, let us discuss the caveats of the approach carried out in this section. On the one hand, we have relied on a variable that may be a too strong signal of credit quality. Just as we discussed in Chapter 3, having a negative delinquency record could be a too strong indicator of repayment impossibility, that opaques the importance of any other information that could be gathered by banks.

On the other hand, both in the regressions of this section and the previous one, we have studied the interest rate and collateral requirements of a pool of general loans. However, many studies have highlighted that the true benefits of information gathering may be observed only in lines of credit (Berger and Udell 1995, Chakraborty and Hu 2006). In the following section, I repeat the regressions considering the smaller subsample of lines of credit, and eventually revising our assumption for the delinquency variable as a signal of external credit quality.

4.4 Robustness checks: Lines of Credit

To verify whether the previous results are confirmed in a sample where the relationships are arguably more important, I repeat the previous estimations on the subsample of firms that asked for a line of credit. Part A of Table 28 contains four different specifications of Equation 9 on this sample, correcting for the sample selection bias due to the credit rationing paradigm of Stiglitz and Weiss, just as in the previous sections.

Note that the results in Table 28 do not change qualitatively with respect to those of Table 20, even when we restrict the sample only to lines of credit. This reassuring result shows evidence that the specification models chosen for the determinants of the interest rate in Equation 9 are quite realistic. In particular, our chosen variable for the interactions, i.e. the home ownership dummy, continues being negative and significant for lines of credit, even at higher levels.[61]

There is only one change in the significance of one variable that I consider worth noting. Notice that the inverse Mills ratio loses all its significance. This result is rather

[61] Indeed, in this subsample the quantity of loans that are asked a guaranteed loan is significantly increased, especially among the limited liability firms, covering a wide 95% of all firms.

puzzling, as it does not adjust to the Stigliz-Weiss paradigm of credit rationing under asymmetric information. In particular on the framework of lines of credit, we should tend to observe credit rationing, rather than adjustments in the interest rate, for the worst credits.

Notice, however, that so far we have considered a binary selection equation to grant or not to grant the credit. In the context of lines of credit, it is probably more relevant to take into account the quantity of the line of credit in the credit decision. In other words, depending on each firm's credit quality (and therefore, on each firm's risk), the bank may grant a large line of credit, a smaller line of credit, or none at all.[62] If this is the case, a more general selection equation should consider the quantity of credit obtained through the line of credit, which is a variable that is censored at zero. In other words, it is probably more sensible to consider the following tobit selection equation for our regressions:

$$
\begin{aligned}
w_i^* &= \eta X_i + u_i \qquad (14)\\
w_i^o &= \begin{cases} w_i^*, \text{ if } w_i^* \geq 0 \\ 0, \text{ otherwise} \end{cases}
\end{aligned}
$$

As usual, $X_i = [X_i^f, X_i^b, X_i^l, Z_i]$ is a vector of observable characteristics of the firms that determine whether the firms obtain a loan or not. Now, w^* represents the quantity obtained by each firm in their credit evaluation by the lender bank, divided by the assets of the borrower. w^o is simply the observable counterpart of w^*, i.e. it equals w^* in case the bank grants a line of credit to the firm, and zero otherwise.

Part B of Table 28 contains the coefficients estimated by considering Selection Equation 14 and the interest rate Equation 9.[63] Notice how in this correct specifica-

[62] As an analogy, consider the granting of a credit card line of credit. Finance company usually grant different sizes of lines of credit to different customers, but the same interest rate for a range of customers.

[63] I use a two-step methodology for estimations with a tobit selection equation suggested by

tion the selection coefficient for the selection bias is is now significant, consistent with Stiglitz and Weiss's paradigm. On the other hand, we also find that the coefficient for the availability of a relationship (the bank being the primary financial services provider of the firm) is now significantly negative. This is consistent with both the intuition and the results of Berger and Udell (1995), that the real benefits of a relationship are accrued for the relationship loans per excellence, i.e. lines of credit. The rest of the results remain qualitatively unchanged.

Now that we have found the relevant selection model for our interest rate equation, we may proceed to estimate Equation 11 with the two usual variants: two interactions for the home availability variable (for lenders with information availability/unavailability), and four interactions for the home availability variable (for soft and hard/ only soft/ only hard/ no information availability). Tables 29 and 30 contain, respectively, the estimations with two and four interactions for the home availability dummy.

It is immediately apparent from Table 29 that having a source of private information is very important for the setting of the interest rates. The coefficients β_1^N are always smaller (i.e., more negative) than β_1^P for all of our measures of private information availability. Moreover, they are almost always statistically significant among them (at least one-tailed tests). In contrast, β_1^P is not different from β_1^N when the measure refers to the availability of written records, a measure (as we discussed before) more of opacity than of private information for the lender banks. The same happens when the relevant measure is the dummy for being the firm's most informed lender (primary provider of financial services). It is not important whether the lender is the most informed relative to others, what really matters is having enough information about the firm.

Notice, however, that there is no evidence that private information availability

Wooldridge (1998). In the first stage, the tobit selection equation is estimated. The residuals of the first stage estimation are then included in the second stage for the selected sample. The statistic to test for sample selection bias is simply the t-test of the first-stage residuals on the second-stage regression (Vella 1992).

completely substitutes for external information in the setting of the interest rates. The tests for $\beta_1^P = 0$ are rejected in all of the cases, for confidence levels of least 5% or 10%. This contrasts strongly with what we found in the first stage of the credit granting decision, where the availability of a private information source was enough for banks not to notice the hard external facts about the firm. It also contrasts strongly with the results found on the complete sample of firms, considering all the different types of loans.

Nevertheless, I would like to place emphasis on the fact that for our best proxy of soft information availability (the existence of a personal relationship between the firm and its lender), β_1^P is statistically different from β_1^N at a 6% confidence level. This result seems to indicate that, for the setting of an interest rate, banks are likely to guide themselves by their knowledge of the firms based on soft information. Yet, soft information is not enough: $\beta_1^S < 0$ indicates that those soft facts are complemented with other hard facts, for example the availability of a house for the principal owner of the firm. On the other hand, evidence that hard information is crucial for the setting of the interest rate is weaker. For example, the p-value for the test $\beta_1^N = \beta_1^P$ is 0.20 when the relevant measure is our best proxy for hard information availability (having an account with the lender bank), i.e. only a one-sided test would yield the coefficients significantly different from each other. Still further, we find that when the bank has had a relationship of at most one year with the bank, the p-value for the test $\beta_1^P = \beta_1^N$ is 0.14. The statistical difference for these two coefficients is greater when the length of the relationship is higher, i.e. in this case the p-value is 0.09, suggesting that as the relationship grows the bank learns more about the firm and the decision on the interest rate is based more and more on hard information. All these results are begging us disentangle the soft and the hard components of soft information in order to understand whether soft information per se is important in the setting of the interest rate (Table 30).

As a final remark on the results of Table 29, notice that the coefficients for our indicator variables I_i^k are always negative for all measures of private information availability. Banks with some source of private information tend to reward firms by charging them, all else equal, a lower interest rate. Once again, these results are consistent with the findings of Berger and Udell (1995).

The latter result still holds when we disentangle the soft and the hard components of information (Table 30). Relative to the firms for which banks have no private information, banks with any private information source tend to reward their borrowers by charging them a lower interest rate. This result holds regardless of the form of the information, soft or hard: β_2^S and β_2^H are both significantly negative, and so is β_2^B.

Table 30 also shows that both soft and hard information play an important role in the setting of the interest rate: we find that β_1^S and β_1^H are both smaller in absolute value, and statistically different from β_1^U. The reliance on the external signal of credit quality diminishes once a source of soft or hard information is available. Notice that we cannot distinguish β_1^S nor β_1^H from zero. We could be tempted to conclude that this is because of the relative importance of soft or hard information in the setting of the interest rates. However, another reason for the lack of precision in these estimations could be the reduced number of firms that either (i) have a personal relationship with their lender, but the lender has no source of hard information availability, or (ii) have an impersonal relationship with their lender, but the lender has a source of hard information. Probably this is the most likely reason, since when both sources of hard and soft information are available, there is still some reliance on the external signal of repayment capacity (β_1^B is still significantly negative).

Overall, the results in this section confirm the results found when we performed the estimations on all kinds of loans, with a somewhat stronger statistical significance. Hence, this presents evidence, once again, that soft information is important in the setting of the interest rates. However, as before, we find that soft information is not relatively more important than hard information. Both types of information tend to complement themselves.

Let us now analyze what is the role of soft information in the posting of collateral requirements. As in the case for interest rate, I start by estimating Equation 12 but taking into account the Sample Selection Equation 10. Part A of Table 31 contains these coefficients.

In contrast to what happened for the interest rate, the coefficients for Equation 12 do change slightly when we use the subsample of firms that asked for a line of credit. In particular, the delinquency variable loses all significance, as does the inverse mills ratio. Making a similar reasoning as we did in the interest rate case, I decide to consider a quantity rationing, rather than a binary decision, as the selection equation, i.e. Selection Equation 14. The estimated coefficients with this selection equation are reported in Part B of Table 31. Still, even after considering this quantity rationing, we do not find evidence of sample selection,[64] and the delinquency variable is not significant.

The latter results suggest that, when deciding on the collateral requirements for lines of credit, banks do not really consider the delinquency history of the firms. This variable plays a lead role in the credit granting decision, but then loses all significance at this stage of the decision process. Hence, interacting this delinquency variable with different information sets to disentangle the roles of soft and hard information would be meaningless in the subsample of lines of credit, simply because this variable does not seem to play a role. One possibility that we cannot discard, though, is that the variable appears to be not significant because the sample of firms includes loans given by lenders that are privately informed, as well as those uninformed. There is a slight probability that the private information gathered by privately informed banks substitutes entirely for this delinquency variable, hence reducing the significance of the coefficient on the entire sample of lines of credit. However, the estimation of Equation

[64] The only case in which we do find evidence of sample selection is in Column 5, when we include the percentage of trade purchases paid after the due date as an explanatory variable. In this case the sample changes slightly with respect to the estimations of Columns 6-8, as we can only observe this variable for firms that are users of trade credit. Yet, the rest of the coefficients do not change qualitatively.

13 with the Sample Selection Equation 14 (not reported) yields insignificant results for coefficients β_1^P and β_1^N for all the measures of private information availability, I_i. Therefore, if we want to follow a similar approach as in Section 4.3, we should replace the delinquency variable with one variable that is a significant determinant of the collateral requirements on lines of credit.

Table 31 suggests other candidate variables to interact with the information availability dummies. For example, we find that having a Dun & Bradstreet credit rating of moderate risk or higher leads to a significant lower collateral requirement than the low risk rating (the omitted dummy). Yet, as discussed before, this result is consistent with the signalling hypothesis of collateral and as such is probably not the best variable to consider: the signalling is done by the firm, and not by the lender. With our approach we are interested in comparing the use of private information as a substitute for other hard information available to the lender, and used by him to base his credit decisions. In this sense the credit rating is probably not the correct variable to use. The best strategy would be to resort to another variable, for example, a variable in the financial statements of the firm, or a variable containing the governance characteristics of the firms.

I discard the use of a financial variables, as all of them yield non-significant coefficients at confidence levels of 10% or lower. The only variable that is consistently significantly different from zero refers to the limited liability status of the firm. It seems from the results of Table 31 that firms with limited liability are related to a lower collateral requirement. We should probably expect the opposite relationship to hold between the limited liability and the secured status of the firm, i.e. when the owner has limited liability, the bank can recuperate at the most the value of the firm's assets. However, with unlimited liability the bank is able to liquidate also the owner's assets in case of non-payment of a business obligation. All else equal, a firm with unlimited liability represents a lower credit risk for the bank, and should be associated with a lower collateral requirement. I believe, therefore, that in our case this variable is capturing the fact that, in our sample of small firms, those with limited liability are relatively more advanced than those with unlimited liability, and in a certain way have survived to a selection process. In other words, I believe that this variable is not the same one that is observed by banks and on which banks rely in order to decide on the collateral requirements. As such, we should not base our analysis of the use of soft information on this variable.

Given that our approach for disentangling soft and hard components of information cannot be implemented in this subsample of lines of credit without making further assumptions, I choose not to carry on with this robustness check for the collateral requirements, and leave this open to further research.

4.5 Concluding remarks

We could summarize the most important results of this chapter as follows: First of all, we find evidence that private information availability lowers the interest rate charged to banks, independently of whether the information is soft or hard. We therefore qualify the result that had been found in the literature regarding the benefits of relationship lending: The benefits of obtaining a lower interest rate through relationship lending accrue both for cookie cutter and for character loans, with no apparent difference between them.

Second, the reliance on public signals of credit quality that determine the interest rate that should be charged by banks is significantly reduced when the lender has soft and hard information availability. Yet, it seems that the availability of hard facts about the lender is much more important than the availability of soft information in order to substitute these public measures for determining the interest rate.

Third, it seems that, all else equal, character loans are more likely to be required to post collateral than cookie-cutter loans; in particular when there is evidence of a bad reputation of the lender. This last result suggests that the loan terms for 'character' loans tend to compensate for the potential higher risks incurred by lending to such firms due to subjective criteria.

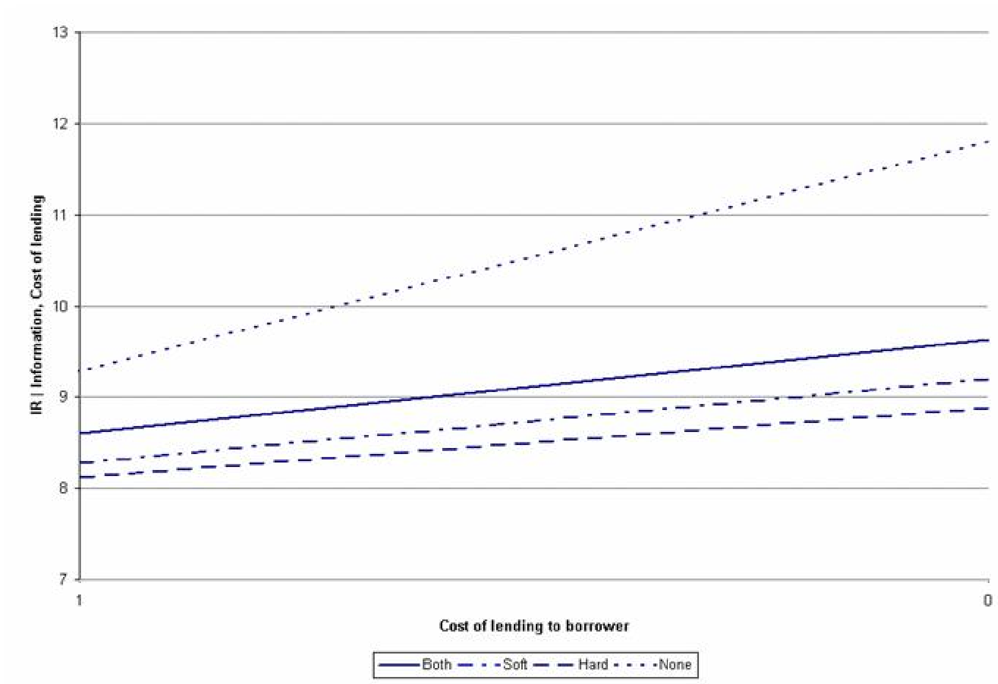

Figure 9: Private information availability and interest rates

This figure represents the estimated interest rate when the lender has access to different information sources about the borrower, and as a function of the cost of lending to the borrower. The graphs correspond to the sample estimated interest rate with the model obtained in the third column of Table 23; hence, we say a bank has soft information whenever it leads a personal relationship with the firm, and it has hard private information whenever its relationship with the firm has been longer than 1 year. The horizontal axis represents the home ownership of the principal owner of the firm. Clearly, the latter variable can only take the extreme values of 0 (high cost of lending) or 1 (lower cost of lending), and the continuous lines show only the general tendency of banks to charge a lower interest rate whenever the owner of the business has a home, which reduces the cost of lending to all unlimited liability firms and to firms guaranteeing the loans with personal property.

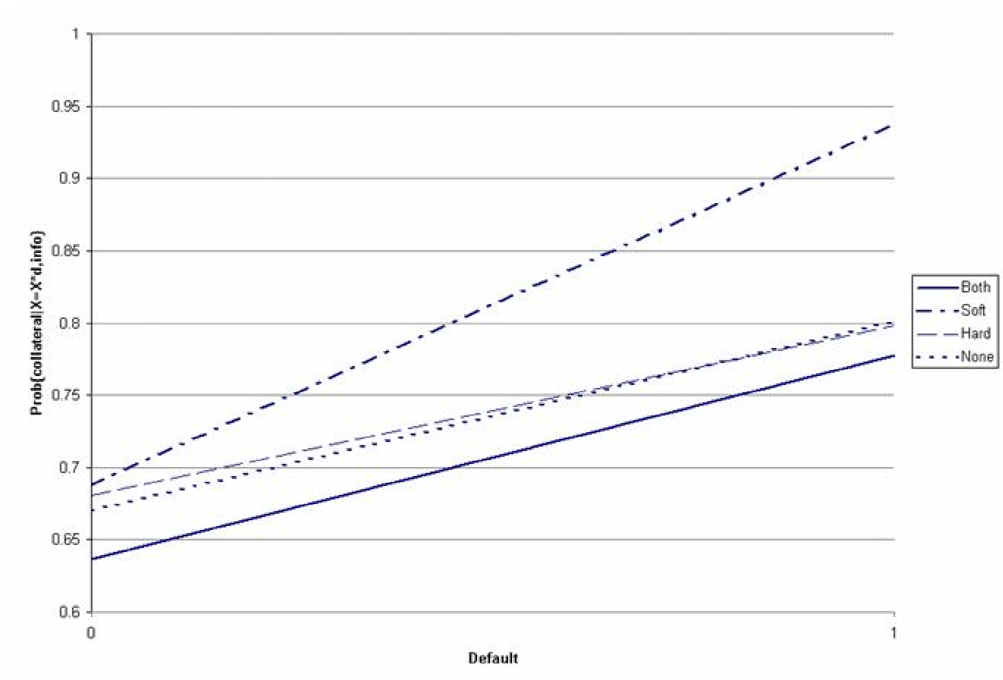

Figure 10: Information availability and collateral requirements

This figure represents the estimated probability of requiring the posting of collateral for an average firm under different information availabilities of the lender, and as a function of whether the firm or its owner have defaulted in other credit relationships. The model used to predict the probabilities is that in the third column of Table 27; hence soft information is due to a personal bank-firm relationship and hard information is obtained from a relationship with the customer of at least one year. To construct this figure, first the probabilities of default are estimated, respectively, for firms that have not defaulted and for firms that have defaulted (under each of the four different information sets), and then extrapolated for the rest of the values - which we may interpret as probabilities of default - by connecting the two extremes. The resulting lines with positive slopes represent the general tendency of banks to require collateral with a higher probability to those firms that have experienced a default in their past, or that have a higher probability of experiencing a default.

4.6 Chapter 4 Tables

Table 20: Determinants of interest rates.

This table contains regressions where the dependent variable is the interest rate set for the most recent granted loan. Apart from the independent variables, the regressions include industry, year, geographical region and MSA dummies, and variables controlling the type of the lender bank, the type of loan, and the concentration of the commercial bank deposits in the region where the firm is established.

	A: OLS Regressions					B: Regressions with Sample Selection			
						1		2	
	1	2	3	4	5	Grant	IR	Grant	IR
Purchases paid late	-0.42		-0.161						
	[0.465]		[0.417]						
Delinquency	0.365	0.432*				-0.851***	0.07	-0.851***	
	[0.249]	[0.221]				[0.127]	[0.279]	[0.127]	
Prime rate	1.226**	0.665	1.173**	0.59	0.623		0.636		0.63
	[0.517]	[0.502]	[0.515]	[0.503]	[0.503]		[0.451]		[0.451]
Term premium	0.105	0.132	0.114	0.155	0.141		0.128		0.129
	[0.244]	[0.225]	[0.246]	[0.222]	[0.226]		[0.227]		[0.227]
Default spread	0.930*	1.016**	0.878*	0.975**	0.972**		1.026**		1.022**
	[0.504]	[0.477]	[0.506]	[0.475]	[0.475]		[0.443]		[0.443]
Log of assets	-0.242***	-0.246***	-0.249***	-0.253***	-0.251***	0.125***	-0.194***	0.125***	-0.190***
	[0.059]	[0.057]	[0.059]	[0.059]	[0.058]	[0.037]	[0.062]	[0.037]	[0.061]
Log of 1 + age	-0.367**	-0.355**	-0.371**	-0.317**	-0.349**	0.131	-0.278*	0.131	-0.272*
	[0.146]	[0.140]	[0.146]	[0.140]	[0.141]	[0.098]	[0.148]	[0.098]	[0.147]
Profitability[1]	-0.034	-0.026	-0.039	-0.03	-0.031	0.015	-0.017	0.015	-0.017
	[0.033]	[0.032]	[0.033]	[0.032]	[0.032]	[0.016]	[0.027]	[0.016]	[0.027]
Sales increase[1]	0.101*	0.145**	0.110*	0.142**	0.153**	0.021	0.137**	0.021	0.137**
	[0.061]	[0.065]	[0.059]	[0.062]	[0.063]	[0.041]	[0.067]	[0.041]	[0.067]
Cash to assets[2]	-0.864*	-0.173	-0.971*	-0.174	-0.342	0.411	-0.063	0.411	-0.071
	[0.523]	[0.622]	[0.528]	[0.626]	[0.612]	[0.296]	[0.493]	[0.296]	[0.494]
Leverage[3]	0.159*	0.024	0.166*	0.019	0.038	0.025	0.036	0.025	0.038
	[0.090]	[0.075]	[0.086]	[0.075]	[0.074]	[0.027]	[0.050]	[0.027]	[0.049]
Owner managed	0.017	0.012	0.003	-0.014	0.003	0.11	0.036	0.11	0.037
	[0.224]	[0.212]	[0.225]	[0.219]	[0.214]	[0.186]	[0.264]	[0.186]	[0.265]
Limited liability	0.209	-0.099	0.241	-0.063	-0.065	0.249*	-0.007	0.249*	0.003
	[0.258]	[0.249]	[0.262]	[0.251]	[0.251]	[0.144]	[0.227]	[0.144]	[0.225]
Owner has home	-1.035**	-1.310**	-1.020**	-1.295**	-1.337**	0.631***	-0.974**	0.631***	-0.950**
	[0.475]	[0.539]	[0.486]	[0.552]	[0.544]	[0.201]	[0.424]	[0.201]	[0.414]
Concentration	-0.04	-0.235	-0.045	-0.192	-0.245	-0.325**	-0.357*	-0.325**	-0.368*
	[0.211]	[0.200]	[0.212]	[0.205]	[0.201]	[0.133]	[0.207]	[0.133]	[0.204]

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Table 20 – Continued from previous page

	A: OLS Regressions					B: Regressions with Sample Selection			
						1		2	
	1	2	3	4	5	Grant	IR	Grant	IR
MSA dummy	-0.402*	-0.426*	-0.385	-0.423*	-0.421*	-0.353**	-0.576**	-0.353**	-0.588**
	[0.232]	[0.221]	[0.235]	[0.222]	[0.223]	[0.161]	[0.237]	[0.161]	[0.234]
Primary inst	0.136	-0.009	0.131	-0.031	-0.012	0.685***	0.277	0.685***	0.299
	[0.216]	[0.204]	[0.216]	[0.203]	[0.205]	[0.131]	[0.247]	[0.131]	[0.232]
Bank type (Omitted=Commercial bk)									
Other depositary	-0.29	-0.639**	-0.343	-0.647**	-0.701**	0.044	-0.585	0.044	-0.587
	[0.323]	[0.305]	[0.312]	[0.293]	[0.299]	[0.264]	[0.380]	[0.264]	[0.382]
Finance company	-0.119	0.5	-0.118	0.531	0.512	0.368*	0.633*	0.368*	0.645**
	[0.432]	[0.448]	[0.437]	[0.445]	[0.453]	[0.222]	[0.329]	[0.222]	[0.327]
Other institution	-0.027	0.139	-0.065	0.126	0.132	0.207	0.238	0.207	0.246
	[0.391]	[0.401]	[0.391]	[0.397]	[0.396]	[0.248]	[0.425]	[0.248]	[0.426]
Loan type (omitted=L/C)									
Capital lease	0.318	0.23	0.339	0.242	0.218	0.277	0.368	0.277	0.378
	[0.427]	[0.472]	[0.425]	[0.464]	[0.470]	[0.258]	[0.464]	[0.258]	[0.464]
Mortgage	-0.652**	-0.559*	-0.664**	-0.528*	-0.583**	0.441**	-0.306	0.441**	-0.288
	[0.326]	[0.289]	[0.331]	[0.296]	[0.289]	[0.222]	[0.360]	[0.222]	[0.355]
Vehicle loan	-1.163***	-0.964***	-1.165***	-0.992***	-0.946***	1.362***	-0.462	1.362***	-0.421
	[0.285]	[0.292]	[0.286]	[0.295]	[0.294]	[0.245]	[0.379]	[0.245]	[0.344]
Equipment loan	-0.242	-0.185	-0.22	-0.198	-0.184	0.577***	0.093	0.577***	0.115
	[0.261]	[0.263]	[0.259]	[0.263]	[0.263]	[0.187]	[0.301]	[0.187]	[0.290]
Other loan	-0.197	-0.03	-0.195	-0.061	-0.018	0.172	0.096	0.172	0.107
	[0.307]	[0.304]	[0.308]	[0.308]	[0.305]	[0.163]	[0.286]	[0.163]	[0.284]
Moderate risk				-0.158					
				[0.299]					
Average risk				0.136					
				[0.287]					
Significant risk				0.273					
				[0.326]					
High risk				0.617*					
				[0.371]					
Minority owner						-0.626***		-0.626***	
						[0.138]		[0.138]	
Majority woman						-0.194		-0.194	
						[0.138]		[0.138]	
Mills ratio						1.308**		1.412***	

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Table 20 – Continued from previous page

	A: OLS Regressions					B: Regressions with Sample Selection			
						1		2	
	1	2	3	4	5	Grant	IR	Grant	IR
						[0.631]		[0.486]	
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.332	8.173	4.102	8.829*	8.804*	3.495	7.012	3.495	6.981
	[5.189]	[4.962]	[5.169]	[4.988]	[4.967]	[0.000]	[4.576]	[0.000]	[4.578]
Observations	498	607	498	607	607		806		806
Adj. R^2	0.14	0.16	0.14	0.16	0.15				

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 21: Interest rate and private information.

This table shows the estimated coefficients β_1^k and β_2^k, $k \in \{P, N\}$ for the following model:

$$\begin{aligned} \text{Rate}_i &= \beta_0 + \sum_{k \in \{P,N\}} \beta_1^k Home_i * I_i^k + \beta_2^P I_i^P + \\ & +\beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + \beta_6 X_i^r + \beta_7 \hat{\lambda}_i + u_i, \end{aligned} \tag{15}$$

where the dependent variable is the interest rate on the most recently granted loan, $Home$ is a dummy for home availability of the firm's principal owner; I_k, $k \in \{P, N\}$ are dummies for private information availability of the firm by the lender bank ($k = P$) and no private information availability ($k = N$); X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics; and $\hat{\lambda}$ is the inverse Mills ratio of the sample selection Equation 10. Criteria for information availability are the following: The bank is the firm's primary financial services provider (Column 1), the bank leads a personal relationship with the firm (Column 2), the firm has a savings or checking account with the bank (Column 3), bank-firm relationship is longer than one year (Column 4), the bank-firm relationship is longer than the median (Column 5), the firm has written records (Column 6).

	1 Primary	2 Personal	3 Account	4 Rel > 1yr	5 Rel > Med	6 Records
Home, info	-0.368	-0.6	-0.434	-0.594	-0.709	-2.445***
	[0.511]	[0.585]	[0.563]	[0.518]	[0.574]	[0.771]
Home, no inf	-1.954***	-1.318**	-1.537***	-1.539**	-1.156**	-0.363
	[0.639]	[0.552]	[0.560]	[0.618]	[0.554]	[0.489]
Primary inst	-1.233	0.319	0.590*	0.558**	0.517**	0.297
	[0.791]	[0.242]	[0.318]	[0.264]	[0.255]	[0.230]
Impersonal rel.		0.959				
		[0.783]				
Has account			-1.555*			
			[0.800]			
Rel $\leq$ 1 yr				1.505*		
				[0.775]		
Rel $\leq$ median					0.988	
					[0.763]	
Used records						2.519***
						[0.881]
Mills ratio	1.343***	1.245***	1.288***	1.319***	1.331***	1.292***
	[0.485]	[0.479]	[0.479]	[0.471]	[0.473]	[0.490]
Observations	806	806	806	806	806	806
F-stat for H_0 : $\beta_1^N = \beta_1^P$	4.038	0.852	2.071	1.469	0.337	5.088
P-value	0.044	0.356	0.15	0.226	0.561	0.024
Chi-squared	1218.101	1051.096	1358.731	788.237	764.301	1052.704
P-value	0	0	0	0	0	0

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 22: Distributions of information sources among granted credits.
This table illustrates how the firms in the sample are distributed according to the information available to their actual lenders. The first row in Panel A contains the percentage of firms (out of 639) for which their lenders are informed. The second (third) row of Panel A contains the percentage of those firms whose owner has a home (have been delinquent). Analogously, Panel B contains the percentage of firms (out of 639) for which the lenders are informed. The second (third) row of Panel B contains the percentage of those firms whose owner has a home (have been delinquent).

	Primary provider	Length > Median	Length > 1 year	Checking or savings	Personal rel.	Written records
Panel A: Information available to lender banks						
% firms	59.8%	56.2%	64.6%	59.0%	55.9%	15.3%
% with home	94.2%	95.5%	95.2%	95.5%	95.2%	89.8%*
% delinquent	20.7%	21.2%	21.8%	20.4%	20.4%	29.6%*
Panel B: Information not available to lender banks						
% firms	40.2%	43.8%	35.4%	41.0%	44.1%	84.7%
% with home	94.6%	92.9%	92.9%	92.7%	93.3%	95.2%*
% delinquent	22.6%	21.8%	20.8%	22.9%	22.7%	20.0%*

* Statistically different at a 5% level

Table 23: Interest rate and soft information.

This table shows the estimated coefficients β_1^k and β_2^k, $k \in \{U,S,H,B\}$ for the following model:

$$\begin{aligned}\text{Rate}_i &= \beta_0 + \sum_{k\in\{B,S,H,U\}} \beta_1^k Home_i * I_i^k + \sum_{k\in\{B,S,H\}} \beta_2^k I_i^k + \\ &\quad + \beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + \beta_6 X_i^r + \beta_7 \hat{\lambda}_i + u_i.\end{aligned} \tag{16}$$

where the dependent variable is the interest rate on the most recently granted loan, $Home$ is a dummy for home availability of the firm's principal owner; I_k, $k \in \{U,S,H,B\}$ are dummies for no information availability of the firm by the lender bank ($k = U$), only soft information availability ($k = S$), only hard information availability ($k = H$) and hard and soft information availability ($k = B$); X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics; and $\hat{\lambda}$ is the inverse Mills ratio of the sample selection Equation 10. The bank has soft information availability when it leads a personal relationship with the firm. Criteria for hard information availability are the following: The bank is the firm's primary financial services provider (Column 1), the firm has a savings or checking account with the bank (Column 2), bank-firm relationship is longer than one year (Column 3), the bank-firm relationship is longer than the median (Column 4), the firm has written records (Column 5). The combination of the soft information variable with each of the five hard information variables partitions the observations into the four groups $\{U,H,S,B\}$.

	1 Primary	2 Account	3 Rel > 1yr	4 Rel > Med	5 Records
Home, soft & hard	-0.562	-0.414	-0.706	-0.774	0.222
	[0.603]	[0.655]	[0.641]	[0.731]	[2.087]
Home, soft	-1.41	-1.448	-0.235	-0.402	-0.766
	[1.432]	[1.255]	[1.219]	[0.881]	[0.602]
Home, hard	-0.336	-0.608	-0.486	-0.793	-2.932***

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	1	2	3	4	5
	Primary	Account	Rel > 1yr	Rel > Med	Records
	[0.829]	[1.091]	[0.832]	[0.897]	[0.836]
Home, no info	-1.876***	-1.516**	-1.758**	-1.501**	0.099
	[0.698]	[0.634]	[0.704]	[0.675]	[0.751]
Primary institution		0.608*	0.570**	0.617**	0.289
		[0.321]	[0.267]	[0.261]	[0.240]
Soft & hard	-1.12	-1.857**	-1.968**	-1.671*	0.255
	[0.887]	[0.914]	[0.932]	[0.973]	[2.199]
Soft	-0.901	-0.787	-2.702*	-2.294**	0.542
	[1.563]	[1.395]	[1.379]	[1.073]	[0.918]
Hard	-1.502	-1.853	-2.530**	-2.196**	3.170***
	[1.056]	[1.269]	[1.054]	[1.087]	[1.067]
Mills ratio	1.350***	1.207**	1.402***	1.416***	1.105**
	[0.488]	[0.481]	[0.463]	[0.464]	[0.485]
Observations	806	806	806	806	806
F-test for $H_0 : \beta_1^S = \beta_1^U$	0.088	0.002	1.185	1.024	0.874
P-value	0.767	0.962	0.276	0.312	0.35
F-test for $H_0 : \beta_1^H = \beta_1^U$	2.114	0.523	1.406	0.405	7.158
P-value	0.146	0.47	0.236	0.524	0.007
F-test for $H_0 : \beta_1^B = \beta_1^U$	2.289	1.606	1.3	0.57	0.003
P-value	0.13	0.205	0.254	0.45	0.956
Chi-Squared	486.989	1795.781	1748.62	1629.795	1570.309
P-value	0	0	0	0	0

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 24: Cross tabulations of personal relationships with other information sources among approved applications.
Panel A contains the cross-tabulation of 639 sample firms that were granted the credit regarding the availability of a personal relationship and the other measures of information availability for the lenders. Panel B contains, for each of the four subgroups of firms, the percentage of firms whose principal owner has a house. Panel C contains, for each of the four subgroups, the percentage of delinquent firms

	Not prim.	Prim	Rel $\leq$ med	Rel > med	Rel $\leq$ 1 yr	Rel > 1 yr	No account	Chck Svgs	No recs	Recs
A: Distribution of firms										
Personal	13.3%	42.6%	17.7%	38.2%	12.1%	43.8%	11.7%	44.1%	48.7%	7.2%
Impersonal	26.9%	17.2%	26.1%	18.0%	23.3%	20.8%	29.3%	14.9%	36.0%	8.1%
B: Home ownership among each category										
Personal	97.6%	94.5%	92.9%	96.3%	93.5%	95.7%	94.7%	95.4%	94.9%	97.8%
Impersonal	93.0%	93.6%	92.8%	93.9%	92.6%	94.0%	92.0%	95.8%	95.7%	82.7%
C: Delinquency among each category										
Personal	25.9%	18.8%	23.0%	19.3%	24.7%	19.3%	28.0%	18.4%	18.3%	34.8%
Impersonal	20.9%	25.5%	21.0%	25.2%	18.8%	27.1%	20.9%	26.3%	22.2%	25.0%

Table 25: Determinants of collateral.

This table contains regressions where the dependent variable is a binary for a collateral requirement for the most recent granted loan. Apart from the independent variables shown below, the regressions include industry, year, geographical region and MSA dummies, and variables controlling the type of the lender bank, the type of loan, and the concentration of the commercial bank deposits in the region where the firm is established.

	A: Probit Regressions (marginal effects)					B: Regressions with Sample Selection			
						1		2	
	1	2	3	4	5	Grant	Collateral	Grant	Collateral
Purchases paid late	0.027	-0.044							
	[0.100]	[0.109]							
Delinquent		0.098*	0.083*			-0.851***	0.150**		
		[0.055]	[0.049]			[0.127]	[0.058]		
Moderate risk				-0.262***				-0.421	-0.163**
				[0.085]				[0.310]	[0.068]
Average risk				-0.166*				-0.633**	-0.066
				[0.086]				[0.306]	[0.069]
Significant risk				-0.209**				-0.713**	-0.085
				[0.091]				[0.313]	[0.074]
High risk				-0.119				-0.944***	0.01
				[0.103]				[0.326]	[0.087]
Log of assets	0.046***	0.047***	0.047***	0.045***	0.046***	0.125***	0.028**	0.137***	0.025*
	[0.015]	[0.015]	[0.013]	[0.013]	[0.013]	[0.037]	[0.013]	[0.037]	[0.014]
Log of 1 + age	-0.003	-0.002	0.002	-0.008	0.003	0.131	-0.015	0.066	-0.018
	[0.036]	[0.036]	[0.033]	[0.033]	[0.033]	[0.098]	[0.031]	[0.096]	[0.031]
Profitability	0.007	0.008	0.007	0.007	0.006	0.015	0.004	0.024	0.003
	[0.007]	[0.007]	[0.006]	[0.005]	[0.006]	[0.016]	[0.006]	[0.016]	[0.006]
Sales growth	-0.01	-0.012	-0.011	-0.015	-0.01	0.021	-0.005	0.009	-0.008
	[0.016]	[0.015]	[0.014]	[0.014]	[0.014]	[0.041]	[0.014]	[0.040]	[0.014]
Cash to assets	-0.206	-0.18	-0.136	-0.139	-0.167	0.411	-0.154	0.675**	-0.181*
	[0.149]	[0.149]	[0.117]	[0.116]	[0.116]	[0.296]	[0.104]	[0.290]	[0.105]
Leverage	0.008	0.006	0.002	0.002	0.005	0.025	0	0.008	0.002
	[0.016]	[0.015]	[0.011]	[0.011]	[0.011]	[0.027]	[0.010]	[0.027]	[0.010]
Owner managed	-0.038	-0.036	-0.068	-0.07	-0.07	0.11	-0.052	0.129	-0.053
	[0.060]	[0.060]	[0.059]	[0.059]	[0.058]	[0.186]	[0.055]	[0.184]	[0.055]
Limited liability	0.062	0.054	0.034	0.042	0.04	0.249*	0.02	0.211	0.03
	[0.061]	[0.060]	[0.052]	[0.053]	[0.052]	[0.144]	[0.048]	[0.140]	[0.047]
Owner has home	0.041	0.038	-0.021	-0.016	-0.025	0.631***	-0.076	0.644***	-0.073
	[0.106]	[0.105]	[0.092]	[0.094]	[0.092]	[0.201]	[0.089]	[0.197]	[0.089]

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	A: Probit Regressions (marginal effects)					B: Regressions with Sample Selection			
						1		2	
	1	2	3	4	5	Grant	Collateral	Grant	Collateral
Primary inst	-0.012	-0.011	-0.016	-0.019	-0.017	0.685***	-0.076	0.727***	-0.081
	[0.052]	[0.052]	[0.048]	[0.047]	[0.047]	[0.131]	[0.052]	[0.129]	[0.053]
Minority owner						-0.626***		-0.573***	
						[0.138]		[0.135]	
Woman owner						-0.194		-0.168	
						[0.138]		[0.135]	
Mills ratio							-0.284**		-0.257*
							[0.132]		[0.132]
Constant						3.495	-0.055	3.798	0.132
						[0.000]	[0.338]	[0.000]	[0.353]
Observations	498	498	607	607	607		806		806

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 26: Collateral and private information.

This table shows the estimated coefficients γ_1^k and γ_2^k, $k \in \{P, N\}$ for the following model:

$$\begin{aligned} \text{Collateral}_i &= \beta_0 + \sum_{k\in\{N,P\}} \gamma_1^k Delinq_i * I_i^k + \gamma_2^P I_i^P + \\ &\quad + \gamma_3 X_i^f + \gamma_4 X_i^b + \gamma_5 X_i^l + \gamma_6 \hat{\lambda}_i + u_i, \end{aligned} \tag{17}$$

where the dependent variable is the interest rate on the most recently granted loan, *Delinq* is a dummy for delinquency of the owner in personal or business obligations; I_k, $k \in \{P, N\}$ are dummies for personal information availability of the firm by the lender bank ($k = P$) and no personal information availability ($k = N$); X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics; and $\hat{\lambda}$ is the inverse Mills ratio of the sample selection Equation 10. Criteria for information availability are the following: The bank is the firm's primary financial services provider (Column 1), the bank leads a personal relationship with the firm (Column 2), the firm has a savings or checking account with the bank (Column 3), bank-firm relationship is longer than one year (Column 4), the bank-firm relationship is longer than the median (Column 5), the firm has written records (Column 6).

	1 Primary	2 Personal	3 Account	4 Rel > 1yr	5 Rel > Med	6 Records
Delinquent, info	0.143**	0.173**	0.130*	0.137**	0.117*	0.183*
	[0.067]	[0.071]	[0.069]	[0.066]	[0.069]	[0.104]
Delinquent, no inf	0.160**	0.103	0.188**	0.195**	0.214***	0.137**
	[0.078]	[0.071]	[0.076]	[0.080]	[0.075]	[0.063]
Primary institution	-0.073	-0.084	-0.065	-0.079	-0.079	-0.074
	[0.055]	[0.054]	[0.071]	[0.060]	[0.058]	[0.052]
Impersonal rel.		-0.053				
		[0.050]				
Has account			-0.007			
			[0.070]			
Relationship $\leq$ 1 year				-0.017		
				[0.053]		
Rel. $\leq$ median					-0.02	
					[0.050]	
Used records						0.008
						[0.060]
Mills ratio	-0.286**	-0.264**	-0.303**	-0.311**	-0.315**	-0.274**
	[0.133]	[0.126]	[0.130]	[0.127]	[0.128]	[0.132]
Observations	806	806	806	806	806	806
Chi^2 for $H_0 : \gamma_1^P = \gamma_1^N$	0.039	0.681	0.464	0.428	1.309	0.176
P-value	0.843	0.409	0.496	0.513	0.253	0.675

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 27: Collateral and soft information.

This table shows the estimated coefficients γ_1^k and γ_2^k, $k \in \{U, S, H, B\}$ for the following model:

$$\begin{aligned} \text{Collateral}_i &= \gamma_0 + \sum_{k \in \{B,S,H,U\}} \gamma_1^k Delinq_i * I_i^k + \sum_{k \in \{B,S,H\}} \gamma_2^k I_i^k + \\ &\quad + \gamma_3 X_i^f + \gamma_4 X_i^b + \gamma_5 X_i^l + \gamma_6 \hat{\lambda}_i + u_i. \end{aligned} \tag{18}$$

where the dependent variable is the binary for collateral requirement on the most recently granted loan, *Delinq* is a dummy for delinquency of the firm's principal owner in the recent past; I_k, $k \in \{U, S, H, B\}$ are dummies for no information availability of the firm by the lender bank ($k = U$), only soft information availability ($k = S$), only hard information availability ($k = H$) and both hard and soft information availability ($k = B$); X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics; and $\hat{\lambda}$ is the inverse Mills ratio of the sample selection Equation 10. The bank has soft information availability when it leads a personal relationship with the firm. Criteria for hard information availability are the following: The bank is the firm's primary financial services provider (Column 1), the firm has a savings or checking account with the bank (Column 2), bank-firm relationship is longer than one year (Column 3), the bank-firm relationship is longer than the median (Column 4), the firm has written records (Column 5). The combination of the soft information variable with each of the five hard information variables partitions the observations into the four groups $\{U, H, S, B\}$.

	1 Primary	2 Account	3 Rel > 1yr	4 Rel > Med	5 Records
Delinquent, soft & hard	0.204***	0.136*	0.148*	0.12	0.297**
	[0.078]	[0.076]	[0.077]	[0.080]	[0.142]
Delinquent, only soft	0.105	0.237*	0.248**	0.273**	0.139*
	[0.116]	[0.122]	[0.121]	[0.106]	[0.076]
Delinquent, only hard	0.008	0.066	0.093	0.078	0.03
	[0.103]	[0.108]	[0.092]	[0.100]	[0.145]
Delinquent, uninformed	0.181**	0.125	0.133	0.137	0.122
	[0.089]	[0.086]	[0.097]	[0.089]	[0.079]
Soft & hard	-0.021	0.06	0.062	0.059	0.067
	[0.063]	[0.081]	[0.069]	[0.069]	[0.093]
Only soft	0.166**	0.146*	0.065	0.039	0.048
	[0.078]	[0.082]	[0.081]	[0.075]	[0.053]
Only hard		0.073	0.015	0.001	0.003
		[0.094]	[0.069]	[0.072]	[0.084]
Primary inst	0.015	-0.065	-0.08	-0.076	-0.079
	[0.073]	[0.071]	[0.060]	[0.059]	[0.054]
Mills ratio	-0.297**	-0.273**	-0.282**	-0.268**	-0.265**
	[0.129]	[0.124]	[0.122]	[0.122]	[0.127]
Observations	806	806	806	806	806
Chi-sq. for $H_0 : \gamma_1^S = \gamma_1^U$	0.324	0.639	0.614	1.108	0.032
P-value	0.569	0.424	0.433	0.293	0.857
Chi-sq. for $H_0 : \gamma_1^H = \gamma_1^U$	1.814	0.203	0.099	0.213	0.33
P-value	0.178	0.652	0.753	0.644	0.566
Chi-sq. for $H_0 : \gamma_1^B = \gamma_1^U$	0.045	0.011	0.017	0.023	1.301
P-value	0.831	0.917	0.897	0.88	0.254

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 28: Determinants of interest rates in Lines of Credit.

This table contains regressions where the dependent variable is the interest rate set for the most recent granted loan. Apart from the independent variables, the regressions include industry, year, geographical region and MSA dummies, and variables controlling the type of the lender bank, the type of loan, and the concentration of the commercial bank deposits in the region where the firm is established. The sample consists of the firms that were approved a line of credit. Part A of the Table contains the coefficients estimated taking into account a Probit selection model on the base of obtaining the credit or not. Part B contains the coefficients estimated taking into account a Tobit model on the base of the quantity of the loan, adjusted by the assets.

	A: Regressions with Probit Selection				**B: Regressions with Tobit Selection**			
	1	2	3	4	5	6	7	8
Owner delinquent	-0.104				0.492			
	[0.681]				[0.474]			
Purchases paid late (PPL)		-1.294				-0.301		
		[1.035]				[0.873]		
Moderate risk			-0.466				-0.498	
			[0.775]				[0.861]	
Average risk			-0.086				-0.049	
			[0.801]				[0.891]	
Significant risk			0.153				0.238	
			[0.829]				[0.912]	
High risk			0.671				0.747	
			[0.905]				[1.004]	
Prime rate	1.123	1.626*	1.221	1.125	1.155	1.639	1.201	1.143
	[0.835]	[0.879]	[0.840]	[0.835]	[0.925]	[1.000]	[0.944]	[0.925]
Term premium	1.278***	0.919	1.290***	1.277***	1.225**	0.822	1.233**	1.239**
	[0.492]	[0.562]	[0.492]	[0.492]	[0.545]	[0.639]	[0.553]	[0.545]
Default spread	0.874	0.205	1.022	0.877	0.812	0.399	0.862	0.745
	[0.873]	[0.925]	[0.878]	[0.874]	[0.969]	[1.061]	[0.986]	[0.967]
Log of assets	-0.262*	-0.339**	-0.299***	-0.273**	-0.357***	-0.476***	-0.359***	-0.345***
	[0.136]	[0.153]	[0.114]	[0.114]	[0.115]	[0.132]	[0.116]	[0.114]
Log of 1 + age	-0.033	0.159	0.01	-0.039	-0.088	-0.01	-0.046	-0.104
	[0.298]	[0.328]	[0.299]	[0.292]	[0.314]	[0.337]	[0.327]	[0.314]
Profitability[1]	0.016	0.043	0.023	0.015	0.014	0.039	0.019	0.011
	[0.046]	[0.050]	[0.045]	[0.045]	[0.049]	[0.055]	[0.049]	[0.049]
Sales increase[1]	0.229	0.237	0.223	0.237	0.342**	0.277	0.305*	0.328*
	[0.164]	[0.194]	[0.154]	[0.155]	[0.170]	[0.212]	[0.171]	[0.169]
Cash to assets[2]	-0.737	-1.183	-0.816	-0.786	-1.384	-1.106	-1.339	-1.417
	[0.965]	[1.140]	[0.905]	[0.904]	[0.932]	[1.240]	[0.947]	[0.932]

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Table 28 – Continued from previous page

	A: Regressions with Probit Selection				B: Regressions with Tobit Selection			
	1	2	3	4	5	6	7	8
Leverage[3]	-0.101	0.239	-0.135	-0.104	-0.048	0.269	-0.08	-0.044
	[0.100]	[0.178]	[0.097]	[0.097]	[0.111]	[0.203]	[0.113]	[0.111]
Owner managed	-0.579	-0.087	-0.65	-0.583	-0.667	-0.42	-0.768	-0.696
	[0.542]	[0.629]	[0.541]	[0.537]	[0.583]	[0.628]	[0.595]	[0.583]
Limited liability	1.251***	1.458***	1.369***	1.237***	1.264***	1.633***	1.416***	1.298***
	[0.448]	[0.507]	[0.436]	[0.436]	[0.479]	[0.556]	[0.486]	[0.478]
Owner has home	-2.448**	-1.724	-2.797***	-2.532***	-3.345***	-2.652**	-3.437***	-3.259***
	[1.079]	[1.098]	[0.937]	[0.923]	[0.943]	[1.038]	[0.952]	[0.940]
Concentration	-0.401	0.071	-0.346	-0.391	-0.307	0.286	-0.269	-0.307
	[0.398]	[0.429]	[0.387]	[0.390]	[0.421]	[0.440]	[0.425]	[0.421]
MSA dummy	-0.199	-0.285	-0.172	-0.187	-0.051	0.046	-0.037	-0.03
	[0.482]	[0.537]	[0.468]	[0.472]	[0.506]	[0.518]	[0.511]	[0.506]
Other depositary	-0.871	0.167	-0.904	-0.888	-1.016	-0.087	-1.065	-1.083
	[0.860]	[1.043]	[0.833]	[0.844]	[0.902]	[1.116]	[0.906]	[0.900]
Finance company	2.725***	2.953***	2.870***	2.666***	2.051**	2.604**	2.376**	2.129**
	[1.013]	[1.030]	[0.932]	[0.932]	[0.993]	[1.067]	[1.012]	[0.990]
Other institution	-0.928	-0.457	-1.072	-0.965	-1.151	-1.199	-1.192	-1.117
	[0.983]	[1.102]	[0.936]	[0.946]	[1.018]	[1.032]	[1.027]	[1.018]
MRL inst is primary inst	-0.431	-0.279	-0.469	-0.463	-0.801*	-0.756*	-0.782*	-0.812*
	[0.483]	[0.570]	[0.431]	[0.431]	[0.425]	[0.452]	[0.428]	[0.425]
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.024	1.893	5.842	6.361	9.107	5.629	8.409	8.932
	[8.812]	[8.962]	[8.565]	[8.522]	[9.252]	[9.843]	[9.403]	[9.253]
Inverse Mills	0.891	1.312	0.596	0.73				
	[1.347]	[1.427]	[0.861]	[0.836]				
Selection corr.					-0.033**	-0.530*	-0.028**	-0.030**
					[0.014]	[0.272]	[0.014]	[0.014]
Observations	289	224	289	289	183	150	183	183
Adjusted R-squared					0.2	0.18	0.19	0.2

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

Table 29: Interest rate and private information in lines of credit.

This table shows the estimated coefficients β_1^k and β_2^k, $k \in \{P, N\}$ for the following model:

$$\begin{aligned} \text{Rate}_i &= \beta_0 + \sum_{k \in \{P,N\}} \beta_1^k Home_i * I_i^k + \beta_2^P I_i^P + \\ &+ \beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + \beta_6 X_i^r + \beta_7 v_i + u_i, \end{aligned} \tag{19}$$

where the dependent variable is the interest rate on the most recently granted loan, $Home$ is a dummy for home availability of the firm's principal owner; I_k, $k \in \{P, N\}$ are dummies for private information availability of the firm by the lender bank ($k = P$) and no private information availability ($k = N$); X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics; and v_i is corresponding residual of the Sample Selection Equation 14. Criteria for information availability are the following: The bank is the firm's primary financial services provider (Column 1), the bank leads a personal relationship with the firm (Column 2), the firm has a savings or checking account with the bank (Column 3), bank-firm relationship is longer than one year (Column 4), the bank-firm relationship is longer than the median (Column 5), the firm has written records (Column 6).

	1 Primary	2 Personal	3 Account	4 Rel > 1yr	5 Rel > Med	6 Records
Home, info	-2.743**	-2.268**	-2.369**	-2.600**	-2.636**	-3.086*
	[1.089]	[1.041]	[1.159]	[1.049]	[1.033]	[1.642]
Home, no inf	-4.872**	-6.221***	-4.783***	-5.641***	-6.065***	-2.992**
	[1.902]	[1.828]	[1.507]	[1.813]	[1.798]	[1.184]
No information	2.134			3.738*	4.435**	
	[2.194]			[2.033]	[2.012]	
Information			-3.292*			0.642
			[1.927]			[1.933]
Primary inst	-0.795*	-4.647**	-0.065	-0.225	-0.159	-0.807*
	[0.457]	[2.038]	[0.709]	[0.549]	[0.494]	[0.429]
Selection corr.	-0.029**	-0.029**	-0.028**	-0.029**	-0.033**	-0.030**
	[0.014]	[0.014]	[0.014]	[0.013]	[0.013]	[0.014]
Observations	183	183	183	183	183	183
Adjusted R-squared	0.19	0.2	0.21	0.22	0.24	0.19
F-test for Ho: $\beta_1^P = \beta_1^N$	0.942	3.748	1.665	2.202	2.864	0.002
P-value	0.333	0.055	0.199	0.14	0.093	0.963

Notes: Standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 30: Interest rate and soft information in lines of credit.

This table shows the estimated coefficients β_1^k and β_2^k, $k \in \{U,S,H,B\}$ for the following model:

$$\begin{aligned} \text{Rate}_i &= \beta_0 + \sum_{k\in\{B,S,H,U\}} \beta_1^k Home_i * I_i^k + \sum_{k\in\{B,S,H\}} \beta_2^k I_i^k + \\ & +\beta_3 X_i^f + \beta_4 X_i^b + \beta_5 X_i^l + \beta_6 X_i^r + \beta_7 v_i + u_i. \end{aligned} \tag{20}$$

where the dependent variable is the interest rate on the most recently granted loan, $Home$ is a dummy for home availability of the firm's principal owner; I_k, $k \in \{U,S,H,B\}$ are dummies for no information availability of the firm by the lender bank ($k = U$), only soft information availability ($k = S$), only hard information availability ($k = H$) and hard and soft information availability ($k = B$); X_i^f, X_i^b, and X_i^l are vectors of firm-, bank-, and loan-specific characteristics; and v_i is the residual of the Sample Selection Equation 14. The bank has soft information availability when it leads a personal relationship with the firm. Criteria for hard information availability are the following: The bank is the firm's primary financial services provider (Column 1), the firm has a savings or checking account with the bank (Column 2), bank-firm relationship is longer than one year (Column 3), the bank-firm relationship is longer than the median (Column 4). The combination of the soft information variable with each of the five hard information variables partitions the observations into the four groups $\{U,H,S,B\}$.

	1	2	3	4
	Primary	Account	Rel > 1yr	Rel > Med
Home, soft & hard	-2.470**	-2.904**	-2.614**	-2.747**
	[1.142]	[1.286]	[1.154]	[1.153]
Home, only soft	-2.89	-2.13	-2.428	-2.529
	[2.503]	[1.860]	[2.473]	[2.489]
Home, only hard	-0.174	0.046	-0.677	-0.587
	[2.523]	[2.527]	[2.520]	[2.507]
Home, no info	-10.216***	-10.382***	-9.465***	-9.939***
	[2.626]	[2.639]	[2.628]	[2.598]
MRL inst is primary inst	0	0.088	-0.333	-0.128
	[0.000]	[0.705]	[0.550]	[0.506]
Soft & hard	-8.903***	-8.828***	-7.739***	-8.380***
	[2.888]	[3.000]	[2.868]	[2.861]
Only soft	-8.584**	-9.177***	-8.164**	-8.053**
	[3.681]	[3.341]	[3.623]	[3.629]
Only hard	-11.673***	-12.111***	-10.448***	-11.163***
	[3.590]	[3.667]	[3.551]	[3.541]
Sample sel.	-0.023*	-0.022	-0.021	-0.025*
	[0.014]	[0.014]	[0.014]	[0.014]
Observations	183	183	183	183
Adjusted R-squared	0.24	0.23	0.25	0.25
F-test for $H_0 : \beta_1^S = \beta_1^U$	4.026	6.314	3.752	4.188
P-value	0.047	0.013	0.055	0.043
F-test for $H_0 : \beta_1^H = \beta_1^U$	7.859	8.461	5.94	6.893
P-value	0.006	0.004	0.016	0.01
F-test for $H_0 : \beta_1^B = \beta_1^U$	7.371	6.629	5.733	6.457
P-value	0.007	0.011	0.018	0.012

Notes: Standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
The estimated coefficients for $I_i(x) = Records$ not reported due to non-convergence of the tobit selection equation.

Table 31: Determinants of collateral in lines of credit.

This table contains regressions where the dependent variable is the dummy variable for a collateral requirement in the most recent granted loan. Apart from the independent variables, the regressions include industry, year, geographical region and MSA dummies, and variables controlling the type of the lender bank, the type of loan, and the concentration of the commercial bank deposits in the region where the firm is established. The sample consists of the firms that were approved a line of credit. Part A of the Table contains the coefficients estimated taking into account a Probit selection model on the base of obtaining the credit or not. Part B contains the coefficients estimated taking into account a Tobit model on the base of the quantity of the loan, adjusted by the assets of the firm.

	A: Regressions with Probit Selection				**B: Regressions with Tobit Selection**			
	1	2	3	4	5	6	7	8
Purchases paid late	0.026				-0.138			
	[0.219]				[0.179]			
Owner delinquent		0.075				0.038		
		[0.136]				[0.096]		
Moderate risk			-0.479***				-0.481***	
			[0.151]				[0.170]	
Average risk			-0.461***				-0.460***	
			[0.157]				[0.176]	
Significant risk			-0.491***				-0.482***	
			[0.162]				[0.179]	
High risk			-0.441**				-0.437**	
			[0.178]				[0.199]	
Log of assets	0.075**	0.080***	0.081***	0.088***	0.099***	0.086***	0.078***	0.087***
	[0.032]	[0.027]	[0.022]	[0.023]	[0.028]	[0.023]	[0.023]	[0.023]
Log of 1 + age	-0.024	-0.026	-0.042	-0.022	0.006	-0.022	-0.046	-0.024
	[0.069]	[0.058]	[0.058]	[0.058]	[0.071]	[0.063]	[0.064]	[0.063]
Profitability[1]	-0.003	-0.005	-0.005	-0.004	-0.002	-0.004	-0.006	-0.005
	[0.011]	[0.009]	[0.009]	[0.009]	[0.011]	[0.010]	[0.010]	[0.010]
Sales increase[1]	-0.057	-0.022	-0.025	-0.028	-0.066	-0.027	-0.025	-0.028
	[0.040]	[0.032]	[0.029]	[0.030]	[0.043]	[0.033]	[0.033]	[0.033]
Cash over assets[2]	0.033	0.056	0.113	0.092	-0.025	0.091	0.098	0.089
	[0.240]	[0.191]	[0.178]	[0.179]	[0.259]	[0.188]	[0.187]	[0.188]
Leverage[3]	-0.001	0.027	0.024	0.03	-0.013	0.027	0.021	0.027
	[0.038]	[0.020]	[0.019]	[0.019]	[0.042]	[0.022]	[0.022]	[0.022]
Owner managed	-0.025	-0.034	-0.048	-0.031	0.03	-0.029	-0.053	-0.031
	[0.133]	[0.107]	[0.106]	[0.106]	[0.132]	[0.118]	[0.118]	[0.118]
Limited liability	-0.204*	-0.218**	-0.198**	-0.208**	-0.245**	-0.214**	-0.203**	-0.212**
	[0.108]	[0.089]	[0.086]	[0.087]	[0.118]	[0.097]	[0.097]	[0.097]

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Table 31 – Continued from previous page

	A: Regressions with Probit Selection				B: Regressions with Tobit Selection			
	1	2	3	4	5	6	7	8
Owner has home	0.273	0.119	0.196	0.18	0.441**	0.169	0.175	0.176
	[0.236]	[0.215]	[0.185]	[0.185]	[0.220]	[0.191]	[0.189]	[0.190]
Concentrated market	-0.021	0.015	-0.011	0.008	-0.063	0.009	-0.007	0.009
	[0.090]	[0.078]	[0.076]	[0.077]	[0.093]	[0.085]	[0.084]	[0.085]
MSA dummy	-0.093	-0.173*	-0.191**	-0.181*	-0.154	-0.181*	-0.186*	-0.180*
	[0.113]	[0.096]	[0.092]	[0.094]	[0.110]	[0.103]	[0.102]	[0.103]
Other depositary inst	0.289	0.073	0.086	0.085	0.327	0.085	0.074	0.079
	[0.214]	[0.168]	[0.162]	[0.166]	[0.229]	[0.181]	[0.178]	[0.180]
Finance company	-0.215	-0.243	-0.202	-0.2	-0.169	-0.208	-0.21	-0.201
	[0.219]	[0.198]	[0.180]	[0.182]	[0.226]	[0.198]	[0.196]	[0.197]
Other institution	-0.133	-0.12	-0.04	-0.093	-0.008	-0.103	-0.053	-0.1
	[0.234]	[0.195]	[0.184]	[0.188]	[0.220]	[0.206]	[0.204]	[0.206]
Primary institution	0.009	0.022	0.057	0.046	0.087	0.044	0.047	0.043
	[0.121]	[0.096]	[0.084]	[0.085]	[0.096]	[0.086]	[0.085]	[0.086]
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mills ratio	-0.136	-0.078	0.071	0.038				
	[0.308]	[0.269]	[0.170]	[0.167]				
Selection coeff.					0.167***	0.001	0.001	0.001
					[0.057]	[0.003]	[0.003]	[0.003]
Observations	224	289	289	289	150	183	183	183
R-squared					0.36	0.3	0.34	0.3

Notes: Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
[1] Winsorized at the 1 and 99% levels. [2] Winsorized at 1%. [3] Winsorized at 99%

5 Trade credit and information spillovers

Trade credit plays a fundamental role in the financing of firms. In large firms, accounts payable amount to roughly twice as much as other short-term liabilities (Rajan and Zingales 1995).[65] In small business lending, the role of trade credit is still more significant. For example, Robb (2002) finds that trade credit amounts to around one third of *all* SME debt, while Berger and Udell (1998) find that accounts payable of SMEs are roughly 15% of all assets.

In this chapter, I explore whether trade credit may provide a special service to financial institutions by alleviating the information asymmetries between borrowers and lenders, and how. This research question stems from several theoretical and empirical observations. On the theoretical side, in their search for an answer for the coexistence of trade credit and a specialized financial sector, researchers have proposed that suppliers may be more able than banks to infer the credit quality of opaque firms. Several theories provide different reasons for this 'information advantage'. For example, suppliers' customers are more homogeneous than the banks' - they usually belong to the same industry as the supplier itself - so it is easier to discern among the best credits (Emery 1984, Mian and Smith 1992, Jain 2001). Moreover, suppliers must constantly visit their clients' premises, which allows them to have timely information about their clients' situation (Ferris 1981). On the other hand, suppliers deliver in kind, instead of cash which may be easily diverted for non-productive activities. This delivery in species allows them to learn about the firm's intentions to produce (Burkart and Ellingsen 2004). In contrast, cash lenders cannot learn about the intention to produce, because cash can be easily diverted to other activities. Using the basic intuition of these explanations, Biais and Gollier (1997) explicitly model how banks may observe the decision of suppliers to grant credit or not, and base their own decision on this observation.

Empirically, there are a number of results that point towards a role of trade

[65] Similar figures were found by Petersen and Rajan (1997) and Giannetti (2003)(Giannetti 2003).

creditors as alleviators of information asymmetries. I have already pointed out that trade credit is relatively more important in the financing of small firms, which in general are more opaque than large ones. On the other hand, Petersen and Rajan (1997) find that firms use trade credit relatively more when credit from financial institutions is not available. In fact, in an earlier paper, the same authors find that this occurs when the firm does not have a long relationship with the bank, i.e. the bank has no private information about the firm. This suggests that once the banks may discern the credit quality of the firms through their relationship with suppliers, firms are less rationed and consequently trade credit is no longer the predominant source of financing for firms.[66] More strikingly, Burkart, Ellingsen, and Giannetti (2006) find that firms that use trade credit tend to borrow from a larger number of banks, utilize more distant banks, and have shorter relationships with their banks, possibly indicating that trade credit users have relatively easier access to less informed sources of finance. Finally, a direct link between trade credit and access to bank loans is given by Cook (1999), who finds that users of trade credit are more likely to obtain bank loans than non-users of trade credit in an emerging economy. In this paper I search such a link in the US economy.

If it is true that there is an informational link between trade credit and bank credit, then it is desired to find out how is it that banks learn about the credit quality of their lenders through trade credit. I provide answers for this question by studying the relationships between several variables linked to trade credit and the decision of banks to grant loans or not in a sample of small firms, the SSBF. I start the analysis by analyzing thoroughly whether the reputation obtained through the buyer-seller credit relationship serves as a signal of quality for banks. A crucial

[66]The explanation provided by Petersen and Rajan (1994) for this finding is that once they gain access to bank credit, firms substitute the costly trade credit with the more convenient credit obtained by banks. However, recent evidence by Burkart, Ellingsen, and Giannetti (2006) for the same firms as Petersen and Rajan suggests that trade credit is a cheap form of financing in most cases. In the light of these recent findings, the hypothesis of trade credit as a source of funding of last resort cannot be sustained.

variable included in the reports of credit rating agencies is the credit history of the firm regarding its relationships with suppliers (Kallberg and Udell 2003), so this first approach makes empirical sense. In fact, I obtain a positive answer: trade credit reputation matters for the availability of bank finance, and this result is robust to any possible endogeneity and sample selection issues. While this result provides a positive answer to the 'information spillover' hypothesis of trade credit, it does not highlight any special role of suppliers. Through any previous credit relationship, firms could also create themselves a reputation.

I therefore analyze more direct links between trade credit and bank loan availability. I analyze, for example, whether the use of discounts offered by suppliers, or a denial to offer trade credit by any supplier, could be used by banks as a signal of credit quality. Finally, I perform a direct test of Biais and Gollier's (1997) model of trade creditors as providing certification of credit quality. If the authors are right, we should observe - like Cook (1999) - that users of trade credit are more likely to obtain bank loans relative to non-users of trade credit (or that more intensive users of trade credit should get more easy access to bank loans). I avoid any possible inverse causality story by providing instrumental variable estimations to identify the direction of the signal from trade credit to bank loan availability. I find that the denial of trade credit by a supplier lowers the probability of obtaining a bank loan, and that users of trade credit are more likely to obtain a bank loan than non-users. However, only the denial of trade credit remains significant in explaining the credit decision of banks once we account for a potential endogenous relationship between the trade credit variable and the bank decision. In fact, both the use of trade credit and the quantity of trade credit obtained may not be the signal sought for by banks. After all, as Biais and Gollier recognized, this could lead to a collusion between the buyer and the seller firm, in which the seller gives credit to the buyer only for the purposes of obtaining a bank loan. Moreover, banks as information collectors could - and indeed, do - investigate firms much more thoroughly than simply observing whether they use trade credit and how much. So a trade credit denial from one of the suppliers could be more significative for banks. Through a denial of trade credit, banks could infer a poor credit quality, and there is no possibility of collusion in this case, as the information conveyed to the markets is negative.

The rest of this chapter is organized as follows: In Section 5.1 I analyze whether the reputation of the firm accrued through its trade credit repayment history affects the likelihood of firms of obtaining a bank loan. I control for any potential inverse causality by estimating the model with an instrumental variable approach. In Section 5.2 I check for the robustness of the results by exploiting a time dimension in the otherwise cross-sectional database. In this section I also control for any potential unobserved heterogeneity about the credit quality of the firms. In Section 5.3 I verify whether the relationship between trade credit and the availability of bank loans could be explained, other than reputation, from the informational advantage theories of trade credit. Finally, Section 5.4 concludes.

5.1 Trade credit as a means to construct a reputation

I start this analysis by identifying whether the reputation gained by firms in their trade credit relationships with suppliers may provide the private loan markets with a positive information spillover. As a starting point, I propose the following linear probability model:

$$y_{1i} = \beta_0 + \beta_1 y_{2i} + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i, \tag{21}$$

where y_{1i} is a binary variable containing a one if firm i was granted a loan, and zero otherwise; y_{2i} is the fraction of purchases paid after the due date by firm i, X_i^f is a vector of firm-specific characteristics, X_i^b is a vector of characteristics of the bank to which the firm went for a loan, and X_i^l refers to the type of loan that the firm asked to the bank.

Equation 21 implicitly assumes that the fraction of purchases paid after the due date affects the probability of getting a loan, but not the other way round. However, it is also possible that the firms that get the loan pay a smaller fraction of their purchases late than those that do not get a loan *because* they had access to a loan. If we ignore this two-way relationship between both variables, the estimated effect of the fraction of purchases paid late on the granting decision of banks will be biased. In fact, this endogeneity problem causes the estimated coefficients of all of the variables to be inconsistent. Therefore, a more correct estimation method yielding consistent results would be the Two-Stage Least Squares (TSLS) estimation.

For the TSLS estimation, I assume the following model in the population:

$$y_{1i} = \beta_0 + \beta_1 y_{2i} + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i \qquad (22)$$

$$y_{2i} = \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_i, \qquad (23)$$

where y_{1i}, y_{2i}, X_i^f, X_i^b, and X_i^l are defined as before, and Z_i is a vector containing the terms of trade credit offered to the firm by its most important supplier. Here, Equation 22 is the structural equation of interest, and Equation 23 is the reduced-form equation for the fraction of purchases paid late. In this TSLS estimation method, the fraction of purchases paid late is first estimated with equation 23. In the second stage, the predicted values for the fraction of purchases paid after the due date are substituted for the real values of this variable in Equation 22. As it is well known, in order for the system of Equations 22 and 23 to be well identified, it is necessary to include in Equation 23 a set of instrumental variables Z_i that (i) are partially correlated with the fraction of purchases paid late once the other exogenous variables have been netted out, and (ii) are uncorrelated with the error term in Equation 22. As instruments for the fraction of purchases paid after the due date, I choose the trade credit terms offered to firms, i.e., ten dummies for the length of the net period, five dummies for the length of the discount period, and five additional dummies for the magnitude of the discount offered.[67]

There are several reasons why the terms of trade credit offered to firms are correlated with the fraction of purchases paid late, once the effect of the rest of the variables has been netted out. First of all, given that some firms are charged with a penalty for late payment, and that there is a threat of stopping future supplies if the firm pays after the due date (Cuñat 2007), then all else equal the fraction of purchases paid late by a firm should be larger the shorter the net period. On the other hand, the incentives for paying on time are high if the discount period is long or if the discount is large. Hence, the fraction of purchases paid late should be smaller for longer discount periods and for larger discounts, *caeteris paribus*.

On the other hand, the terms of trade credit offered should not affect the decisions of banks to lend to the firms. Trade credit terms offered to the firms are stable within industries, and do not vary depending on the firm's credit quality (Ng et al. 1999). In contrast, banks usually do a careful examination of all of the factors that may lead to default on the repayment of the loan. Usually, data about the firm and its owner is processed using statistical methods, in what is called "credit scoring". Credit scoring techniques have been used for a long time for processing information about the firm (Greenbaum and Thakor 1995).[68] Banks examine each application independently, and only in rare cases do banks systematically deny or grant loans to all the firms within a same industry. Therefore, the instruments chosen should not be correlated with the error term of the structural equation.

Table 32 contains the results of the estimations. The coefficients of Equation 21 are in Column 1; Columns 2, 3, and 4 contain the results for different specifications

[67]The most common credit terms offered by suppliers in the US are net terms and two-term trade credit (Ng et al. 1999). When net terms are offered, the firm receives the goods in day zero, and must pay the full amount of credit in a period preestablished by the supplier. When two-term trade credit is offered, the supplier grants a discount for early payment.

[68]Traditionally, credit scoring techniques process hard information about the firms. Recently, however, credit scoring has also been introduced for small businesses, processing soft information about their credit quality (Berger, Frame and Miller 2005, Mester 1997).

of the second stage of the TSLS estimation of equation 22.[69]

The coefficient for the fraction of purchases paid late is negative, and statistically different from zero at a 99% confidence level, when a linear probability model is fitted into the data (Column 1). However, as discussed before, this coefficient is likely to be biased due to the endogenous relationship between this and the dependent variable. In Column 2 I take into account this potentially endogenous relationship, and the estimated coefficient is still negative. However, the standard errors for the TSLS estimation are higher, and therefore the hypothesis that the coefficient is equal to zero cannot be rejected at a 90% confidence level. Nevertheless, the p-value for the null hypothesis that the coefficient is zero is relatively low, at 0.159.

As noted by Ng et al (1999), often the variations in the trade credit terms offered across industries are apparent at a two-digit SIC code, and sometimes only at a four-digit SIC code. In other words, the chosen instruments are more relevant for finer classifications of the firm's industry. In Column 3, I replace the eight industry dummies with 51 two-digit SIC codes. Not surprisingly, both the R^2 of the first stage and the generalized R^2 of the second stage are improved.[70] Moreover, by doing so the coefficient on the fraction of purchases paid late decreases and becomes even more negative than before. As a result, the coefficient for the fraction of purchases paid late becomes significantly different from zero at a 90% confidence level. This provides evidence that banks indeed take into account the way that firms pay their trade credit in order to make their credit-granting decision.

It is also worth briefly discussing the other controls in the regressions in Table 32. Larger firms, as well as older firms, have greater probabilities of being granted a loan. One reason for this is that the pool of small and young firms contains firms of all qualities. Only the best firms of this pool survive, and grow larger and older. Larger and older firms have proved to be better, as they have survived. Therefore,

[69] The estimated coefficients for the first stage are available upon request.

[70] The generalized R^2 is the relevant measure of goodness of fit of the TSLS models. It is defined as the R^2 of an OLS estimation of the dependent variable on the fitted endogenous variables and the rest of the controls (Pesaran and Smith 1994).

they have higher probabilities of being granted a loan by banks.

Similarly, more profitable firms have a larger probability of being granted a loan than unprofitable firms. On the other hand, firms that have a positive sales growth do not have a high probability of being granted a loan. This is probably due to the fact that size and age of firms are negatively correlated with sales increase: smaller and younger firms have more growth potential. Once the size and age have been netted out, there seems to be no marginal benefit for growing firms.

A first examination suggests that none of the governance characteristics of the firms have a significant effect on the probability of being granted a loan by the bank, whereas the fact of owning a house does affect this probability. However, if I add an interaction of the limited liability and the home ownership dummies (Column 4), I find that (i) having limited liability has a positive effect on the probability of getting a loan, and (ii) owning a house positively affects the probability of getting a loan for both the firms with unlimited and limited liability. Both results are statistically significant at a 99% confidence level, and moreover the inclusion of this interaction does not change qualitatively the coefficients of the rest of the variables. The positive effect of limited liability on the probability of being granted a loan reflects the fact that firms with limited liability are in general better than firms with unlimited liability - even after controlling for size and age, the effect of limited liability is significant. This suggests that having limited liability gives the firms a legal structure that enables banks to better control for the firms' capacity of repaying the loan. On the other hand, as discussed in Chapter 4, most of the limited liability small firms are asked for personal guarantees to secure the credit, so in practice limited liability firms are treated as unlimited liability.

The negative coefficient on the dummy variable for Metropolitan Statistical Area suggests that all else equal, firms located in an urban area have a smaller probability of getting a loan than those outside an MSA. This result is statistically significant at confidence levels above 95%. Firms are more likely to be concentrated inside

MSAs, so this result suggests that competition for funding is likely to be fierce in these environments. Similarly, when the *banking* market is concentrated, firms are less likely to get a loan than when it is competitive. However, this result is not statistically significant. Nevertheless, when I repeat the regressions replacing the MSA dummy with all interactions between the banking market competition index and the MSA dummy (Column 4), I conclude that all else equal, the firms in MSAs and with a concentrated banking market are less likely to get a loan than those outside MSAs and with more competitive banking markets, as we expected. This result is statistically significant at a 5% level.

The results in Table 32 also illustrate that the criteria for selecting the firms that will be granted a loan are different depending on the type of loan asked for. *Caeteris paribus*, banks tend to grant loans more easily for specific purposes, such as buying a vehicle, equipment, or land, than to grant an open line of credit (the reference category for type of loan asked for is a dummy for a line of credit). It is easier to grant a loan for a specific purpose because the object that the loan is financing is itself the collateral for the loan, should the payer default. A line of credit, on the contrary, should be secured with other assets of the firm. An unsecured line of credit involves a greater default risk or more costly information collection about the credit quality of the firm.

Finally, the coefficients for the type of lender are not significantly different from zero. This suggests that, once taking into account the risk class of the firms, the practice of granting loans is quite homogeneous across different types of financial intermediaries (commercial banks, savings banks, insurance companies, finance companies, mortgage companies, etc.). This is consistent with the findings of Carey, Post and Sharpe (1998).

The goodness of fit of the models is quite satisfactory. The adjusted R^2 of the OLS model in Column 1 is 19%. For the TSLS models in Columns 2, 3, and 4, the the generalized R^2 is above 20% in all cases, and near to 30% in Columns 3 and 4.

5.2 Further identification of causality

What would happen if there were some measure for the credit quality of the firms unobserved by us, but observable by the banks? In this case, banks would extend credit to good firms, who incidentally would also pay their trade credit purchases on time. The results of the previous section could only be capturing the effect of these unobservable characteristics on the decisions made by banks.

In this section I classify the firms into groups depending on how much information the banks had about the firms in the moment when they made their credit decisions. Then, I compare if the trade credit repayment patterns of firms are equally informative when banks have additional information about the firms than when they have no additional information. The objective is to rule out the hypothesis that the results of the previous section are caused by any unobserved heterogeneity.

5.2.1 A time dimension

In this section I use information about when the applications for the loans occurred to proxy for the degree of information available to banks. There are two reasons why the timing of these events is important to estimate the strength of the signal acquired by banks through trade credit. First, the fraction of purchases paid after the due date during 1998 is a better proxy for the signal that banks observed about the firms' quality for those firms applying for credit *after* 1998 than for the firms applying before that date. Second, the firms that obtained a loan before 1998 were more likely to pay a lower fraction of their purchases after the due date during 1998 than those that did not get one, because they were relatively more liquid. In other words, the reverse causality between the fraction of the purchases paid late and the decision made by banks is more likely to be present for the firms applying before 1998.

Following this idea, I repeat the regressions of Section 5.1 but estimating two different coefficients for the fraction of purchases paid after the due date: One for the firms that applied for a loan after 1998 (313 firms, roughly half of the sample), and the other one for those that applied for the loan before or during 1998 (321 firms). The first coefficient should be a better measure for the importance of the information contained in the payment of trade credit than the coefficient estimated in the previous section.

Even after separating the firms into the ones applying before 1998 and those applying after 1998, we cannot rule out an inverse causality between the fraction of purchases paid late and the bank's credit granting decision. Firms applying for a credit after 1998 could anticipate the bank's credit-granting decision and base their trade credit repayment strategy according to their expectations. Therefore, if we do not account for this potentially endogenous relationship, the coefficient on the fraction of purchases paid late for the firms applying for loans after 1998 could be biased. On the other hand, the fraction of the purchases paid late during 1998 could be a good approximation of the fraction of purchases paid late in earlier dates. In this case, if we don't control for the endogeneity, the coefficient on the purchases paid late for the firms applying before 1998 would also capture both effects. Consequently, I estimate the following model with a TSLS approach:

$$y_{1i} = \beta_0 + \beta_1^1 y_{2i} I_i(x) + \beta_1^2 y_{2i}(1 - I_i(x)) + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i, \quad (24)$$

$$\begin{aligned} y_{2i} I_i(x) &= \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{1i}, &(25)\\ y_{2i}(1 - I_i(x)) &= \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{2i}. &(26)\end{aligned}$$

Here, y_{1i}, y_{2i}, X_i^f, X_i^b, and X_i^l are defined as before, and $I_i(x)$ is an indicator function taking the value of one if the application for the loan occurred after 1998, and zero otherwise. In the first stage of the estimation I calculate the coefficients for the reduced-form equations (Equations 25 and 26), and in the second stage I estimate the coefficients of the structural equation of interest (Equation 24).

By estimating both Equation 25 and 26 in the first stage of the TSLS regression, I am concentrating on the causal effect that paying a larger fraction of the purchases after the due date has on the probability of being granted a loan. If trade credit provides a useful signal for banks, then *both* coefficients β_1^1 and β_1^2 should be negative. However, the importance of the signal should be greater for the firms that applied after 1998, as for these firms we have a better proxy for the signal observed by banks. Therefore, β_1^1 should larger, in absolute value, than β_1^2.

Table 33, Section (i) contains the estimated coefficients of equation 24. For comparison purposes, I present the results of the coefficients estimated with an ordinary least squares regression in Column 1. Column 2 contains the consistent coefficients estimated with TSLS. For both specifications, I use the same controls as in Column 2 of Table 32.

As we expected, I obtain a negative coefficient for the fraction of purchases paid late, both for firms applying after 1998 and for firms applying before or during this year. Only the former is statistically significant at a 90% confidence interval. As predicted, the precision for the estimation of the effect of paying trade purchases late is better for the firms applying for a loan after 1998, given that in this case the dependent variable is a better proxy for the firms' trade credit reputation. In this specification, I only use the one-digit industry SIC code to control for industry variations and nevertheless the result is significative. When more dummy variables for the two-digit SIC codes are included, the results (not reported) do not change qualitatively, but the fit of the estimations are improved.

The coefficients for the rest of the variables do not change qualitatively due to this change of specification. Moreover, the fits of the first stage equations are satisfactory. The generalized R^2 for the TSLS estimation improves with respect to the comparable estimation in the second column of Table 32. These results suggest that the direction of the causality has been well identified.

5.2.2 Information availability

In this section I explore how the trade credit repayment patterns affect the firms' probability of getting a loan when banks possess any source of private information about the firm's credit quality. Possessing sources of information about the firm could decrease the banks' reliance on trade credit payment reputation as a signal for trade credit quality.

I use several measures regarding the access of information about the firm. The first measure is the length of the relationship between the firm and the bank. Banks that have had long relationships with the firms should have accumulated enough information about their credit quality, so there should be no need to extract other information from a third party.[71] On the contrary, banks that have not led a lengthy relationship with the their borrower should be more inclined to rely on such external information.

The survey also contains information about the most frequent method of conducting business between the firm and the bank to which the firm asked for a loan. Among the possible response options, there are two suggesting that there is a personal relationship between the firm and the bank: when business is usually conducted in person and when there is usually a visit from the bank's representative to the firm's premises. A banker that conducts a personal relationship with their client should be able to gather more information than a banker that has not met her client personally.[72]. Hence, we would expect the credit quality signal observed through the trade credit to be stronger for those banks that conduct an impersonal relationship with their clients.

Finally, I also use a survey question asking whether the respondent used financial statements or accounting reports in order to answer the survey. If the firm used

[71]The underlying assumption between the concept of relationship lending is that, through repeated interaction with the firms through time, banks gather information about the firm.

[72]The kind of collected through a personal interaction may be subjective, and is difficult to quantify and verify by others. For a discussion on soft information and its objective and quantifiable counterpart - hard information - refer to Petersen (2004)

financial statements or accounting reports to answer the survey, then it is likely that the bank had access to similar information to do the credit analysis (Berger, Miller, Petersen, Rajan and Stein 2005).[73] Under the assumption that a bank that has access to such a report can better assess the credit quality of a firm, then we should expect the trade credit signal to be less important.

To account for these complementary sources of information that each bank could have, I repeat the regressions of section 5.1 but estimating two different coefficients for the fraction of purchases paid after the due date: one for the firms for which the bank had access to any information source, and one for the ones that did not. The absence of other information sources should make the lender bank more likely to rely on the trade credit repayment patterns. Thus, we should expect the coefficient for the fraction of payments made after the due date to be higher, in absolute value, for the firms whose lenders do not have alternative sources of information.

I estimate the following model with TSLS:

$$y_{1i} = \beta_0 + \beta_1^1 y_{2i} I_i(x) + \beta_1^2 y_{2i}(1 - I_i(x)) + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i, \quad (27)$$

$$\begin{aligned} y_{2i} I_i(x) &= \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{1i}, && (28) \\ y_{2i}(1 - I_i(x)) &= \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{2i}, && (29) \end{aligned}$$

where, y_{1i}, y_{2i}, X_i^f, X_i^b, and X_i^l are defined as before, and $I_i(x)$ is and indicator function for whether the bank had access other information: financial records, a personal interaction, or a long relationship.

The first rows of part (ii) of Table 33 contain the results of the estimations when $I_i(x)$ is an indicator function measuring whether the lender had a lengthier relationship than the median of 3 years. In the first column, the OLS coefficients are reported;

[73] This variable could be interpreted as a the quantity or quality of the hard information available about the firm.

TSLS coefficients are in the second column.

When the measure of information availability regards the length of the relationship with the firm, our basic intuition is confirmed. The coefficient for the fraction of purchases paid late is negative and statistically significant different from zero at a 95% confidence level for the firms with a short relationship with the bank, even after taking into account the endogenous relationship between the purchases paid late and the credit granting decision of the bank. The effect is even stronger when using the two-digit SIC codes to control for the industry: the p-value for the null hypothesis that the coefficient is zero is 0.014. However, for firms with longer relationships than the median, the effect of trade credit reputation on the decisions of banks to approve or reject the loan is negligible after controlling for the endogenous relationship between these variables. Moreover, the coefficients are statistically different at a 10% level.

I repeat the analysis, but separating the firms into those with relationships of one year or less, and those with longer relationships, and the results (not reported) do not change qualitatively. Moreover, the coefficients of the control variables do not change qualitatively with respect to the results in explained in Section 5.1. Finally, the fit of the model is good: a generalized R^2 of 21%.

The next rows of part (ii) in Table 33 contain the results of the coefficients of the purchases paid after the due date when $I_i(x)$ is an indicator variable for whether the bank usually conducts a personal business relationship with the firm. Roughly half of the firms in the sample conducted a personal relationship with their banker (364 firms). There is a null effect of trade credit repayment record on the decision of banks to grant a loan for these firms. However, banks that did not conduct a personal relationship with the firm do have a very strong reliance on this variable, as can be seen by the negative coefficient for firms without a personal relation with their banker, statistically different at a 95% confidence level. In fact, the coefficients are even statistically different at a 90% confidence level. These results were exactly what we expected to find: the trade credit repayment record of firms is of any use to banks only if they do not have their own sources of soft information.

Finally, the last block of rows in Table 33 contain the estimations when $I_i(x)$ measures the existence of financial records. In this case, we find no significance for the trade credit variable. Although coefficients are negative for both the group of firms with access to the financial records and those without, none of the TSLS coefficients is significant at reasonable confidence levels. One reason for this lack of significance could be that we have already included a number of variables that are likely to be contained in the financial records: age, size, profitability, etc. Hence, the residual variation that could be left for this variable to explain is very little. Second, as pointed out by Berger et al (2005), the variable may be an imperfect proxy for hard information availability. There might be many firms in the sample that have financial statements but did not use them to answer the survey.

The results of this section confirm the basic intuition contained in models such as Biais and Gollier's (1997) and Burkart and Ellingsen's (2004), but with an important qualification: Trade credit can be used as a signal for trade credit only whenever banks do not have access to an alternative source of information. Moreover, the results of this section shed some light on the importance of having alternative sources of information about the firm's credit quality in the credit decisions.

5.3 Information advantage theories of trade credit

Up to this point I have only used one single measure to find a link between trade credit and bank credit availability: the fraction of purchases paid after the due date. We have found that the reputation of the firms, as proxied by its credit repayment history, is helpful for uninformed banks in their decision to grant credit to firms. However, a similar measure of reputation could be acquired by firms through any other credit relationship, apart from their relationship with their suppliers. Hence, while the results of the previous section support the idea that there are positive information spillovers of trade credit into the private loan market, these results do not necessarily imply that banks use this information because suppliers have an information advantage to discern the credit quality of the firms. In this section, I test whether the link between trade credit and bank loan availability is more direct, by repeating the estimations of Section 5.1, but replacing the fraction of the purchases paid late with several other variables that could be signals of credit quality according to the information advantage theories of trade credit.

5.3.1 Default

As a first approach, I use a binary variable for defaulting on trade credit. That is, the variable takes the value of one if the firm paid the trade credit after the due date *at least once* during 1998 - regardless of the fraction of the payment that was made past the due date - and a zero otherwise. The goal is to find out whether default itself is a bad signal for which firms are punished by banks, or if it is the size of the default what matters to banks. Part (i) of Table 34 contains the results of estimations of Equation 21 with OLS (Column 1) and Equation 22 with TSLS (Column 2), substituting the fraction of purchases paid late with a dummy variable for defaulting ever during 1998. Because this new endogenous variable is simply a derivation of the fraction of purchases paid late, it is therefore subject to the same relationships to the dependent variable, and the instruments I use are the same.

Without accounting for the endogenous relationship between paying the trade purchases late and the credit-granting decision of banks, the coefficient for the dummy variable for late payment of trade credit is negative and statistically significant at a 99% confidence level (Column 1). However, we cannot tell whether this negative coefficient is caused because firms that are granted the credit tend to pay their trade purchases on time, or because trade credit payment is used as a signal by banks. In Column 2, when I explicitly search for the effect of trade credit payment on the credit-granting decision of banks, the coefficient - although negative - cannot be statistically distinguished from zero (the p-value is 0.39). This result, combined with the results of the previous sections, suggests two related findings. First, banks do not systematically punish all the firms that pay late, whatever the frequency or the quantity of the late payment. They actually care about how much (or how often) firms pay late. Second, because the fraction of the purchases paid late contains more information than the dummy variable, it is a better proxy for the signal about the credit quality of firms that banks could receive from the relationship between firms and their suppliers.

5.3.2 Trade credit denial

As a second measure, I use a dummy variable taking the value of one if at least one supplier of trade credit denied the request of the firm for trade credit during 1998, and a zero otherwise. Clearly, a denial of trade credit from a supplier is also a bad signal for the credit quality of the firms, so we could examine whether it has any effect on the credit-granting decision of banks. Again, we cannot rule out that there is an endogenous relationship between this variable and the credit-granting decision of banks. Suppliers could be denying a trade credit *because* banks rejected an application for a loan, or viceversa. Thus, a TSLS approach is necessary once again. I estimate Equations 22 and 23 with y_{2i} being now a dummy variable containing a one if the firm was denied trade credit from any supplier, and a zero otherwise. I use as instruments the terms of trade credit offered to a firm, plus the bargaining power of the firm. All else equal, suppliers will deny credit to a bad payer if the credit period that is usually offered to the firm is short than if it is long, or if the discount period is shorter. To see how, imagine a supplier that has two customers of equal credit quality, both equally likely to pay after 20 days, but one facing a net period of 10 days and the other facing a net period of 30 days. Then the supplier will prefer to offer the credit to the customer facing a 30-day net period, and will be more likely to deny the credit to the customer with the 10-day net period. Similarly, if both customers have the same net period of say 30 days, but the discount period is shorter for one of the customers, the supplier will prefer to give the credit to him. On the other hand, the lower the bargaining power of the firm, the less important is this customer to the supplier, and thus the more likely the supplier will deny the credit to a bad firm, all else equal.

Part (ii) of Table 34 show that substituting the fraction of purchases paid late with the dummy variable for trade credit denial does not change the basic results of section 5.1. Both variables are measuring a bad trade credit reputation of firms, and thus the probability of being granted a loan is reduced when these variables take strictly positive values. The second column shows that the coefficient on the dummy variable for denial of trade credit is negative and statistically different from zero at a 90% confidence interval, even after controlling for the endogeneity between the denial of trade credit and the credit-granting decision of the bank. Moreover, the results of the rest of the control variables (not reported) do not change with respect to the results reported in Section 5.1.

5.3.3 Use of discounts

As a third variable for the reputation of firms regarding trade credit, I use a positive signal for credit quality: the fraction of purchases paid during the discount period. Only 190 firms in the sample were offered discounts; therefore, we should distinguish the firms that never paid in the discount period because they were not offered a discount from those that were offered discounts but did not pay during the discount in order not to bias the results. Therefore, I rerun the regressions of Section 5.1 but substituting the fraction of purchases paid late with two variables: one containing the fraction of purchases paid during the discount period if a discount was offered, and a zero if a discount was not offered, and the other one a dummy variable for whether a discount was offered.

Once again, the potential endogeneity between the decision of banks to grant the loan or not and these new measures for trade credit reputation cannot be ruled out. The same arguments for identification that I used in Section 5.1 apply for the use of discounts, therefore it is possible to estimate a TSLS model for Equation 22 using the trade credit terms as instruments. In Part (iii) of Table 34 I report the fitted coefficients of an OLS model for equation 21 (first column), and in the second column the fitted coefficients of a TSLS model for equation 22.

As can be seen in part (iii) of Table 34, the coefficient for this positive proxy of trade credit reputation does not seem to have a significant effect on the probability of banks to grant a loan - not even without taking into account the endogenous relationship among the two variables. In fact, that the OLS coefficients for the amount of purchases paid during the discount period cannot be statistically distinguished from zero, points out that firms do not systematically take advantage of the discounts offered - even when they have liquidity as a result of having a new loan. This fact deserves further study. Furthermore, these results, together with the previous, indicate that banks care more about *negative* information than about positive information about firms. This makes sense, as negative information is more credible than positive information: if a suppliers holds that a given firm is good and pays its purchases on time, banks may or may not believe them.[74] However, a statement telling that the supplier has denied credit to the firm is much more credible because it is a stronger statement.

5.3.4 Mere use of trade credit

In this section I analyze whether the mere fact of using trade credit may be a signal of credit quality. It is unclear whether this variable could be a measure of credit quality. If suppliers have an informational advantage over banks in financing small firms (Biais and Gollier 1997, Jain 2001), then the mere fact of lending to the firm, or the quantity of trade credit offered, could give information about the firm's quality. However, if the reasons for extending trade credit are to minimize transaction costs (Ferris 1981), or to avoid losing a client (Nadiri 1969, Wilner 2000), then the mere fact of having trade credit should not tell much about the credit quality of firms.

[74] The reason for disbelief could be collusion, as observed by Biais and Gollier (1997)

I use two measures for the use of trade credit: (i) a dummy variable for whether the firm used trade credit or not, and (ii) the percentage of total purchases that was made on account during 1998.[75] I first estimate Equation 22 with a TSLS approach, where now y_{2i} is a binary variable for the use of trade credit, and Z_i is a dummy variable for whether the firm has a larger bargaining power than the sample industry median. Following Burkart, Ellingsen and Giannetti (2006), firms with more bargaining power tend to receive more trade credit. Therefore we should expect, *caeteris paribus*, that the instrument be related to the quantity of trade credit observed and to the fact of receiving trade credit or not. However, as argued before, given that banks use a more detailed analysis for extending their credit, the bargaining power of firms should not have an effect on the bank's credit-granting decision.[76] Since y_{2i} now is available for all of the firms that recently asked for a loan, I estimate the model on the whole sample of the firms that asked for a loan (861 firms).

The first row of Part (iv) in Table 34 shows the estimated coefficients for the use of trade credit of Equation 22, estimated using the whole sample of firms that asked recently for a loan. Although the OLS coefficient is positive and significant, the consistent TSLS coefficient in Column 2 shows that there is no causal relation between the use of trade credit and the credit granting-decision of banks.[77] Therefore, there is no evidence in the data that the mere use of trade credit is a signal of the firms' credit quality.

As a second measure for the use of trade credit I use a variable containing the fraction of the total purchases that was made on account during 1998. This variable contains more information than the simple use of trade credit; if this information is useful to banks then we should expect a negative coefficient for this variable. I

[75]The fraction of total purchases made on account should be a proxy of the quantity of trade credit offered to the firms (Petersen and Rajan 1997)

[76]Moreover, the bargaining power of firms within their industry is a proxy of the product market power of the firms, and not a proxy of the power that these firms might have in the credit market for credit.

[77]The results do not change even after taking into account the moment of the application for the loan, or other sources of information available to banks, discussed in Section 5.2.

therefore estimate equation 4 with a TSLS approach, with y_{2i} being the fraction of total purchases made on account and Z_i being a dummy for whether the firm has bargaining power dummy as an instrument. I run the regressions (i) for the whole sample, imputing a zero for the fraction of purchases made on account for the firms that did not use trade credit, and (ii) only on the subsample of firms that used trade credit, for which this variable is strictly positive always.

Part (iv.b) of Table 5 shows that, even if we take into account the quantity of trade credit offered to firms, there is no causal relation between the quantity of trade credit offered and the credit-granting decision of banks - not even when we take into account other sources of information available to banks (not reported). The reported coefficients were estimated with the whole sample; however, the results do not change when I repeat these regressions for the subsample of firms that used trade credit (not reported).

There are two basic lessons that can be obtained from this section. First, banks do not seem to systematically deny credit to any firm that has paid the purchases after the due date. They actually care about how often firms pay their purchases after the due date, and the quantity. Second, it is the negative information what matters to banks. They do not seem to reward the firms that pay their trade credits on time, or the firms that are offered large quantities of trade credit. However, there is evidence suggesting that they do punish the bad payers. In a way, negative information is harder than positive information about the credit quality.

5.4 Concluding remarks

In this chapter I find that trade credit may provide positive information spillovers to the market for private debt. On the one hand, I find that firms that tend to pay their bills after the due date are consistently rationed by banks that do not have private information about the firm's credit quality. Moreover, banks that find that their clients have been denied credit by their suppliers incorporate this information into their credit decisions. It is only *negative* information about the supplier's or the firm's actions regarding their relationship what matters to banks when making credit decisions; positive information about the firm, being less credible, is not incorporated to the bank's lending decision.

Above all, this paper provides evidence about the value of sharing information among lenders. I find that banks that are not able to acquire private information about the firms' credit quality rely on measures of reputation obtained through their relationships with suppliers. This fact supports the theories that propose reputation as a solution to the 'lemons' problem in general buyer-seller setups (Klein and Leffler 1981, Shapiro 1982, Shapiro 1983), and in financial markets (Diamond 1989). Similarly, this chapter also relates to the growing literature of the value of information exchange by lenders (Jappelli and Pagano 1993, Jappelli and Pagano 2002), by providing evidence that the trade credit reports are of utmost importance for small and opaque firms to access institutional credit.

This chapter also provides support to the information advantage theories claiming that banks may use the suppliers' information as a signal of credit quality (Biais and Gollier 1997, Jain 2001), with the following qualifications: First, trade credit may be useful to signal credit quality only when the lenders do not have access to an alternative source of private information about the firm's credit quality. Second, it is only negative information about the firms what matters to banks, such as a denial of trade credit. Positive information about the relationship between a firm and its suppliers is disregarded by banks, as it could be subject to collusion between the firms and its suppliers.

Finally, this chapter also contributes to the information based theories of banking (Leland and Pyle 1977, Diamond 1984, Fama 1985, Diamond 1991) by providing evidence that banks gather and process information about small firms' credit quality before making their lending decision. It also contributes to the relationship lending literature (Diamond 1984, Ramakrishnan and Thakor 1984, Allen 1990, Winton 1995) by showing evidence that relationship banks use their private information about the credit quality of their clients much more intensively than transaction banks.

5.5 Chapter 5 Tables

Table 32: Trade credit and bank lending.

This table contains regressions for the following equation:

$$y_{1i} = \beta_0 + \beta_1 y_{2i} + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i,$$

where y_{1i} is a binary variable containing a one if firm i was granted a loan, and zero otherwise; y_{2i} is the fraction of purchases paid after the due date by firm i, X_i^f is a vector of firm-specific characteristics, X_i^b is a vector of characteristics of the bank to which the firm went for a loan, and X_i^l refers to the type of loan that the firm asked to the bank. Column 1 contains OLS estimates; Columns 2 to 4 contain different specifications for the second stage estimates of a TSLS estimation, where the first stage of the estimation is the following reduced-form equation:

$$y_{2i} = \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_i.$$

In the latter equation, vector Z_i contains characteristics of the trade credit contract (see the text).

	OLS	**TSLS**		
	1	2	3	4
Trade credit reputation				
Purchases paid late	-0.310***	-0.377	-0.536*	-0.487*
	[0.057]	[0.267]	[0.284]	[0.278]
Firm characteristics				
Log of assets	0.033***	0.033***	0.036***	0.037***
	[0.010]	[0.010]	[0.011]	[0.011]
Log of 1 + age	0.061**	0.061**	0.045*	0.046*
	[0.025]	[0.025]	[0.027]	[0.026]
ROA (Profits / assets) (1)	0.011*	0.011*	0.009	0.007
	[0.006]	[0.006]	[0.006]	[0.006]
Sales increase 1997-1998 (1)	0.011	0.01	0.011	0.011
	[0.012]	[0.012]	[0.013]	[0.013]
Sales / Assets (1)	-0.001	-0.001	0	0
	[0.002]	[0.002]	[0.002]	[0.002]
Owner managed dummy	0.032	0.031	0.048	0.052
	[0.043]	[0.043]	[0.045]	[0.045]
Limited liability	0.025	0.028	0.035	0.332***
	[0.038]	[0.040]	[0.041]	[0.122]
Owner has home	0.172***	0.169***	0.149**	
	[0.062]	[0.063]	[0.066]	
Unlimited liability * Home				0.325***
				[0.092]
Limited liability * Home				-0.004
				[0.089]
8 one-digit SIC industry dummies	yes	yes	no	no
51 2-digit SIC dummies	no	no	yes	yes
Market characteristics				
Concentration of Banking Mkt dummy	-0.042	-0.041	-0.054	-0.042
	[0.034]	[0.035]	[0.036]	[0.086]
MSA dummy	-0.084**	-0.086**	-0.111***	
	[0.038]	[0.039]	[0.042]	
MSA * Banking mkt concentrated				-0.109**
				[0.046]
MSA * Banking mkt not concentrated				-0.094
				[0.085]

Continued on next page

Table 32 – Continued from previous page

	OLS	TSLS		
	1	2	3	4
Eight regional dummies	yes	yes	yes	yes
Loan characteristics				
Capital Lease	0.055	0.052	0.002	0.01
	[0.077]	[0.078]	[0.081]	[0.080]
Mortgage	0.143**	0.140**	0.108*	0.109*
	[0.058]	[0.060]	[0.064]	[0.063]
Vehicle loan	0.242***	0.238***	0.228***	0.229***
	[0.050]	[0.052]	[0.055]	[0.054]
Equipment	0.124***	0.121**	0.088*	0.085*
	[0.046]	[0.047]	[0.050]	[0.050]
Other	0.057	0.058	0.047	0.042
	[0.044]	[0.044]	[0.047]	[0.046]
Bank characteristics				
Savings Bank	-0.102	-0.106	-0.113	-0.097
	[0.097]	[0.098]	[0.102]	[0.101]
S&L Association	0.093	0.089	0.097	0.102
	[0.195]	[0.196]	[0.201]	[0.199]
Credit Union	0.096	0.092	0.135	0.124
	[0.110]	[0.111]	[0.114]	[0.113]
Finance Company	-0.071	-0.067	-0.038	-0.047
	[0.053]	[0.055]	[0.057]	[0.057]
Insurance Company	0.03	0.011	-0.11	-0.096
	[0.280]	[0.290]	[0.311]	[0.308]
Brokerage or Mutual Fund Company	0.013	0.024	0.088	0.083
	[0.117]	[0.124]	[0.130]	[0.129]
Leasing Company	0.068	0.069	0.099	0.081
	[0.094]	[0.094]	[0.097]	[0.096]
Mortgage Company	-0.188	-0.189	-0.224	-0.208
	[0.145]	[0.145]	[0.158]	[0.157]
Venture Capital/ Small Business	0.254	0.274	0.453	0.443
	[0.269]	[0.281]	[0.296]	[0.295]
Constant	0.15	0.154	0.274	0.103
	[0.227]	[0.227]	[0.414]	[0.423]
Observations	634	634	634	634
Adj. [Generalized] R-squared	0.19	[0.21]	[0.27]	[0.28]

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 33: Further identification of causality.

This table presents the OLS and TSLS estimators of coefficients β_1^1 and β_2^1 for the following estimation equation:

$$y_{1i} \;\; = \;\; \beta_0 + \beta_1^1 y_{2i} I_i(x) + \beta_1^2 y_{2i}(1 - I_i(x)) + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i,$$

The dependent variable for the regressions is a binary variable containing a one if the credit for a loan was granted by the bank, and zero otherwise. y_{2i} is the fraction of purchases paid after the due date, and $I_i x$ is a binary variable for, respectively, (i) whether the application for the loan occurred after 1998; and (ii) whether the bank has private information about the firm. The first stage of the TSLS estimation is:

$$\begin{aligned} y_{2i} I_i(x) &= \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{1i}, \\ y_{2i}(1 - I_i(x)) &= \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{2i}. \end{aligned}$$

	OLS	**TSLS**
i. Time dimension		
Fraction of purchases paid after the due date	-0.338***	-0.623*
if application for loan after 1998	[0.074]	[0.363]
Fraction of purchases paid after the due date	-0.279***	-0.095
if application for loan was before or during 1998	[0.077]	[0.387]
R- squared (Generalized R- squared for TSLS)	0.19	0.21
ii. Information of the lender bank		
Fraction of purchases paid after the due date	-0.159**	0.119
if bank-firm relationship is longer than 3 yrs	[0.074]	[0.376]
Fraction of purchases paid after the due date	-0.465***	-0.792**
if bank-firm relationship is shorter than 3 yrs	[0.075]	[0.348]
Difference		0.911*
		[0.474]
Adjusted [Generalized] R- squared	0.20	[0.21]
Fraction of purchases paid after the due date	-0.292***	-0.029
if bank conducts personal business with firm	[0.071]	[0.336]
Fraction of purchases paid after the due date	-0.334***	-0.869**
if bank conducts impersonal business with firm	[0.082]	[0.383]
Adjusted [Generalized] R- squared	0.19	[0.21]
Fraction of purchases paid after the due date	-0.205	-0.341
if firm used financial records for survey	[0.130]	[0.730]
Fraction of purchases paid after the due date	-0.328***	-0.382
if firm did not use financial records for survey	[0.060]	[0.283]
Adjusted [Generalized] R- squared	0.19	[0.21]

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 34: Other trade credit measures.

This table presents the OLS and TSLS estimators of coefficients β_1^1 and β_2^1 for the following estimation equation:

$$y_{1i} \quad = \quad \beta_0 + \beta_1 y_{2i} + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i,$$

The dependent variable for the regressions is a binary variable containing a one if the credit for a loan was granted by the bank, and zero otherwise. y_{2i} represents different measures for the use of trade credit: (i) dummy for whether the firm has defaulted on trade credit; (ii) dummy for whether a supplier denied credit; (iii) fraction of purchases made in discount period; (iv) use of trade credit.

	OLS	**TSLS**
i. Default		
Dummy if firm paid late at least	-0.112***	-0.11
once during 1998	[0.031]	[0.127]
Adjusted [Generalized] R-squared	0.17	[0.2]
ii. Denial of trade credit		
Dummy if any supplier has denied credit to the firm	-0.230***	-0.504*
	[0.051]	[0.277]
Adjusted [Generalized] R-squared	0.18	[0.21]
iii. Use of discounts		
Fraction of purchases made during the discount period	0.013	-0.044
	[0.073]	[0.279]
Dummy if discount was offered	0.005	0.153
	[0.039]	[0.137]
Adjusted [Generalized] R-squared	0.15	[0.21]
iv. Use of trade credit		
a. Dummy for use of trade credit (1)	0.080**	-0.262
	[0.037]	[0.516]
Adjusted [Generalized] R-squared	0.15	0.19
b. Fraction of purchases on account, zero if did not	0.001***	-0.003
use trade credit (1)	[0.000]	[0.006]
Adjusted [Generalized] R-squared	0.16	0.19
c. Fraction of purchases on account if used trade credit	0.001**	-0.017
	[0.001]	[0.039]
Adjusted [Generalized] R-squared	0.16	0.19

Notes: Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Sample size is 806 firms.

Appendix

A.1 Data selection

I used the following criteria to select the sample for the estimations:

Total sample	**3,561**
Only firms with strictly positive assets	-76
Only nonfinancial firms	-205
Only nongovernment firms	-6
Only firms requesting a loan	-2,374
Only firms requesting loan to financial institution	-39
Applied recently for a loan	**861**
Only firms with information about trade credit use	-195
Applied for a loan and used trade credit	**666**
Lost observations due to missing sales increase	-32
Sample for regression estimates	**634**

A.2 Variable definitions

1. **Independent variables:**

   Credit Granted.- This binary variable is defined only for the firms that applied at least once in the last three years for a new loan. It takes the value of one if the respondent answered "always approved" to the following question: *Was this (Were these) recent loan application(s) always approved, always denied, or sometimes approved and sometimes denied?* Otherwise, it equals zero.

   Interest rate.- This variable is defined only for the firms that were granted at least one new credit in the last three years. Its value equals the total interest rate for the most recently approved loan, including any extra basis points to close the loan.

   Collateral.- This variable is defined only for the firms that were granted at least one credit in the last three years for a new loan. Its value equals one if the firm had to post any kind of collateral, guarantee, or compensating balance for the most recently granted loan. It equals zero otherwise.

2. **Trade credit variables:**

   Trade Credit Use.- This dichotomic variable equals one if the respondent answered "yes" to the following question: *During 1998, did [the firm] make any purchases of goods or services from suppliers on account rather than pay before or at the time of the delivery?* It equals zero otherwise.

   % Purchases on Account.- This variable contains the recorded answer to the following survey question: *Think of the total dollar amount of all purchases made by the firm during 1998. What percentage of these purchases were made using trade credit?* If the firm did not use trade credit, this variable takes the value of zero.

Denial of Trade Credit.- This dichotomic variable contains a one if the respondent answered "yes" to the following question: *Has any supplier that offers trade credit to business customers denied a request by your firm for trade credit?*

% Purchases Paid Late.- This variable is only defined for those firms that used trade credit during 1998 (**Trade Credit Use = 1**). It takes values in the interval $[0, 1]$. It contains the value of zero if the firm answered "no" to the following question: *During 1998, did the firm ever make payments on account after the bill was due in full?* Otherwise, it takes the value of the response to the following question: *[During 1998], what percentage of the balances on account were made after the bill was due in full?*

3. **Information variables:**

Primary bank.- This dichotomic variable contains a one if the respondent identified the financial institution to which it asked its most recent loan as *"the firm's primary (or most important) source of financial services".*

Relationship greater than 1 year.- This binary variable identifies the firms that had a relationship with their potential lender of one year or more, the moment the firm applied for the loan

Relationship greater than median.- This dummy variable identifies those firms that had a relationship of length larger or equal to the median relationship length of three years the moment they applied for the loan.

Account with bank.- This binary variable identifies the firms that have asked recently for a loan from an institution in which they have either a checking account or a savings account.

Personal relationship with bank.- This binary variable contains a one if the bank to which the firm asked its most recent loan conducts a personal relationship with the firm (i.e., if the business is usually personal or a bank representative visits the firm), and zero otherwise.

4. **Firm-specific variables:**

Assets.- This variable equals the sum, in dollar amounts, of each firm's holdings of cash, accounts receivable, inventory, other current assets, investments, book value of land, depreciable assets, and all other assets.

Age.- This variable equals the year of the interview minus the year that the firm was established, purchased, or acquired by the current owner.

Return on Assets (ROA).- This variable equals the ratio of profits to assets, where profits equal total sales plus other income less the total cost of conducting the business.

Liquidity (Cash to Assets).- This variable equals the ratio of cash to assets, where the cash is equal to the sum of all the cash on hand, in any checking or savings account, in the money market, or in CDs.

Sales Increase.- This variable measures the increase in the level of sales from fiscal year 1997 to 1998.

Leverage.- This variable equals the ratio of total loans and accounts payable to assets.

Limited Liability.- This dichotomic variable equals one if the organization type of the firm is a S-corporation, a C-corporation, a limited liability partnership, or a limited liability company. It equals zero if the company is a sole proprietorship or a partnership.

SIC Industry variables.- The SSBF reports the two-digit Standard Industrial Classification (SIC) code for each firm. With this information, I construct up to 56 two-digit industry dummies. For some models, I control for industry at the one-digit level. In these cases, there are 7 different industries in the sample (Mining, Construction, Manufacturing, Transportation, Wholesale trade, Retail trade, and Services).

Regional variables.- The SSBF reports the census region of each firm. With this information, I construct 9 regional dummies.

MSA.- This dichotomic variable contains a one if the firm belongs to a Metropolitan Statistical Area, and a zero otherwise.

Concentrated Banking Market.- This dichotomic variable contains a one if the 1999 commercial bank deposit Herfindahl index of the MSA or county where the firm's headquarters office is located is greater than 1800.

Risk.- The survey contains the Dun & Bradstreet Credit-Score Rank, which evaluates quantitatively the risk of the firm, in levels going from 1 (Low risk) to 5 (High risk). From this variable, I construct 5 dummies for the risk level of the firm.

5. **Owner-specific variables:**

Owner managed.- This variable contains a one if the firm is managed by a partner, owner, or a stockholder. It contains a zero if the manager is a hired employee or a paid manager.

Home ownership.- This variable contains a one if the principal owner owns his/her home or primary residence, and a zero otherwise.

Minority owner.- This variable contains a one if the 50% or more of the business is owned by people of Hispanic, Latino, Spanish, African-American, Asian, Native Hawaiian or other Pacific Islander, American Indian, or Alaska Native origin. It contains a zero otherwise.

Delinquent.- This variable contains a one if the respondent answered "once or more times" to any of the following questions: *Within the past three years, on how many different personal obligations has the principal owner been 60 or more days delinquent?* or *Within the past three years, on how many different business obligations has the firm been 60 or more days delinquent? Please include trade credit, or credit from suppliers.* It contains a zero otherwise.

6. **Lender-specific variables:**

Type of lender.- This variable contains the type of lender to whom the firm applied for the most recent loan. It could be one of the following: Commercial Bank, Savings Bank, Savings and Loan Association, Credit Union, Finance Company, Insurance Company, Brokerage or Mutual Fund Company, Leasing Company, Mortgage Company, or Venture Capitalist / Small Business Investment Company

7. **Loan-specific variables:**

   Type of loan.- This variable represents the type of loan that the firm recently applied for. It can be one of the following: Line of Credit (L/C), Capital Lease, Mortgage, Vehicle Loan, Equipment Loan, or Other. From this variable, I construct 6 dummies.

   Application year.- This variable contains the year of the most recent application for a loan. 38 applications occurred during 1996, 125 during 1997, 269 during 1998, 384 during 1999, and 4 during year 2000. From this variable, I create up to 5 year dummies to control for the market factors.

   Amount Granted.- This variable is defined only for the firms that applied at least once in the last three years for a new loan. Its value equals the dollar amount of the credit granted, or the authorized credit limit if the loan was a line of credit. If the loan was not granted, its value equals zero. If the firm applied more than once for credit in the last year, the variable contains the dollar amount of the most recent loan that was granted, or zero if the firm was sometimes denied credit.

8. **Interest rate variables:**

   Prime rate.- This is the prevailing prime rate (i.e. the interest rate charged to the most credit-worthy corporations) at the time the bank loan was approved.

   Default spread.- This is the difference between the BAA corporate yields and the ten-year government bonds at the time the bank loan was approved.

   Term structure spread.- This is the difference between the yield on a government bond with the same maturity as the approved loan and the T-bill yield. I use simple linear interpolations to calculate the government yields for maturities other than the reported.

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