Soft Information in Bank Lending: The Use of Trade Credit

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Abstract.- I empirically examine whether banks incorporate information about firms' trade credit repayment patterns into their credit decisions. I provide evidence consistent with transaction banks being unwilling to lend to firms that pay trade credit after the due date. In contrast, relationship banks use "soft" information accumulated throughout their extended interactions with firms, and disregard the trade credit repayment patterns. I use an instrumental variable approach in order to identify the direction of the signal from trade creditors to banks. I also take into account other sources of information accessible to banks to examine the different channels through which banks could have obtained the credit quality of firms other than the commercial relationships with suppliers. Finally, the results still hold after taking into account the endogenous decision of firms to apply for a loan or not.

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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.[1] 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.[2]

One condition for relationship lending to exist is that banks gather "soft" information about the firm's credit quality.[3] 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.[4] Crucial as it is for the relationship lending literature, the use of soft information by relationship banks has been hardly studied in the literature. The paper by Liberti (2003) with data on one particular foreign bank in Argentina is among the few to address this issue directly in the economics literature. 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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[1]For theoretical arguments of the cost advantages of banks over other outsiders in producing and transferring information, see for example Leland and Pyle (1997), Diamond (1984), Fama (1985), or Diamond(1991). For empirical evidence, see James (1987), Lummer and McConnell (1989), or Slovin, Sushka, and Polonchek (1993).

[2]Reviews of the relationship lending literature can be found in Boot (2000) and in Freixas (2005). Hoshi, Kashyap, and Scharfstein (1990), Petersen and Rajan (1994) , Berger and Udell (1995), and Schenone (2004) provide empirical examples about the value of such relationships.

[3]Berger (1999).

[4]See Petersen (2004) for a discussion on soft vs. hard information.

In this paper, 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 a very detailed survey about the financing practices of small firms to analyze whether relationship banks base their credit-granting decisions on information about the trade credit relationships between the firm and its input suppliers. I find that transaction banks –that is, banks that do not have a long relationship with their clients– have a lower probability of granting a credit to firms with negative information about the credit relationship with its input suppliers. However, this negative information does not seem to affect the credit-granting decisions of relationship banks. The results suggest that relationship banks base their decision of granting a loan on their own information, and not on information gathered by others. These findings present evidence that soft information plays an important role in relationship banks. The results also show evidence that when soft information is not available, then the information about the firms' relationship with the suppliers is an important determinant of the banks' credit decisions.

There are at least two ways in which banks gather information about the firm-supplier relationships. Reports of credit information brokers such as Dun & Bradstreet contain information about the promptness with which the firms make their trade credit payments (Kallberg and Udell 2003). If such a credit report is not available, banks can still check with the firms' suppliers to learn about the firms' credit quality.[5,6] The availability of this information makes it plausible for banks to use the trade credit relationships to discriminate among lenders.

Using the trade credit relationships between the firm and its input suppliers to test for the use of soft information in bank lending is especially relevant in the context of small firm financing for two reasons. First, by far the most important sources of

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

[6] Notice that the information of trade credit payment obtained through a credit information broker is hard, whereas checking with the firm's suppliers leads to soft information about the credit quality of the firm.

external finance for small firms are bank loans and trade credit.[7] Therefore, banks can access information about trade credit repayment for a vast majority of small firms. Second, given that small firms are mainly privately owned, hard information about them is likely to be scarce. Banks that are willing to lend to small firms must elicit information about their credit quality from additional sources, other than this scarce hard information. How the firm behaves in the trade credit relationships with its suppliers is one possible source of information. The soft information gathered by the bank in the course of its relationship with the firm is another such source. Only banks that have conducted long relationships with a firm can obtain soft information about the firm's credit quality. Therefore, the relative intensity with which the trade credit repayment patterns of small firms are used in the decisions of relationship banks versus transaction banks illustrates the importance of soft information in relationship banking.

I now explain my findings in a more detailed way. I use a sample of small firms that recently asked for a bank loan and try to obtain answers to four questions. First, do banks incorporate information about the trade credit repayment patterns into their credit-granting decisions? To answer this question, I first run a regression of the bank's binary response to the firm's credit application on the fraction of purchases that the firm paid after the due date. I find that there is a strong correlation between paying large proportions of trade purchases after the due date and being rationed from credit. I further use an instrumental variable approach in order to identify the causality from trade credit repayment patterns to the banks' decisions. As instruments, I use the credit terms offered to the firms by their suppliers. Results show that banks do take into account the trade credit repayment patterns in their credit-granting decisions.

The second question I address is the following: Is the banks' access to other sources of information driving the results? Relationship banks that have conducted

[7] Berger and Udell (1998)

long relationships with their clients are more likely to have collected enough "soft" information about their credit quality than transaction bank. Intuition indicates that relationship banks should not need to rely on a third party to make their credit-granting decision. In order to analyze this situation, I identify the firms that ask for a loan to relationship banks. I find that the signal of trade credit is much stronger when banks have not established relationships with the firms. I perform a similar exercise with other sources of information that the bank could access apart from trade credit, and the results are alike. These results suggest that relationship banks use intensively the soft information about the firms' credit quality.

Next, I pose the following question: Are the previous results driven by the particular choice of measures for the trade credit repayment patterns? To verify whether this is the case, I substitute the "hard" variable containing the fraction of purchases paid after the due date with a variable indicating whether the firms have been denied credit from a supplier. This variable is not contained in the reports of the credit information brokers, and therefore it is soft information about the credit relationship between the firm and its suppliers. I find that relationship banks are more likely to use this soft information about the credit relationship between the firms and their suppliers. Since relationship banks are more likely to have access to this information than transaction banks, this finding provides further evidence that relationship banks use the soft information they have gathered about the firms' credit quality. Furthermore, it presents evidence for the conventional wisdom that suppliers have an information advantage over banks in providing funds to small firms. If a supplier has denied credit to a firm, it must be that he has some soft information about the credit quality of the firm that has led him to do so. If banks react to the supplier's denial by not granting the loan, it must be because this soft information provided by the supplier is valuable to the bank. In other words, suppliers have an information advantage over the banks. This generalized idea has been used as an assumption in some theoretical models of trade credit (Biais and Gollier 1997, Jain 2001), and has been rationalized in a recent model for trade credit (Burkart and Ellingsen 2004).

The previous results hold in a sample of firms that use trade credit. However, it could be possible that the firms that do not use trade credit are of an inferior credit quality than those that do. Therefore, as a next step I ask: Is the use of trade credit *per se* informative to banks about the credit quality of the firms? To analyze this, I classify the firms into those that used trade credit, and those that did not, and use an instrumental variables approach to find the effect of using trade credit on the banks' decisions. I find that the mere use of trade credit is uninformative to banks. Two observations are consistent with this finding. First, the use of trade credit is not a signal *per se* because the motives for offering trade credit to firms are unrelated to the firm's credit quality. For example, suppliers may offer trade credit because they want to boost their sales (Nadiri 1969), because they must relieve their inventories (Ferris 1981), or because they are signaling the quality of their products (Smith 1987, Lee and Stowe 1993). Second, I find that firms that do not use trade credit typically conduct personal relationships with their banks, i.e., they tend to match with relationship banks. These banks usually have enough soft information about the firms that do not use trade credit, and therefore they do not interpret the fact that these firms do not get trade credit as a bad signal.

The sample that I use is restricted to the firms that asked for a loan. Firms that asked for a loan made the decision to go to a bank for a loan, taking into account other factors that could be related to their credit quality, and consequently, to their decision of paying late or not. Thus the sample is not necessarily random. As a robustness check, I explicitly take into account this potential 'sample selection' issue with a two-step estimation method. The results still hold after controlling for the non-randomness of the sample.

This paper contributes both to the relationship lending and to the trade credit literature. First, it presents evidence consistent with relationship banks gathering, processing, and using soft information about the credit quality of their clients. Second, it provides support to the information advantage theories of suppliers over banks in a sample of small US firms.[8] Finally, this paper also adds to the literature on the financing of small firms, by showing how reputation may play an important role in the availability of credit for small firms.[9]

The remainder of the paper is organized as follows. Section 2 presents the sources of data for this study, the variables, and a brief description of the characteristics of the sample. In Section 3 I present the empirical strategy and the main results of the paper. First, I describe the identification hypothesis in Section 3.1. In Section 3.2 I address confounding stories through which the bank's credit decisions could be related to the credit quality of the firms other than through the trade credit repayment patterns. Section 3.3 studies whether the results obtained previously rely on the chosen measures for trade credit repayment patterns of the firms. Finally, in Section 3.4 I check whether the results still hold after controlling for a potential sample selection bias. Concluding remarks are left for Section 4.

2 Description of the 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 this study, because of several reasons. First, the vast majority of these firms are private. The average ownership share of

[8] Cook (1999) provides evidence of trade credit being used by banks as a signal for credit quality in a sample of Russian firms.

[9] Diamond (1989) has a theoretical model for the effect of reputation in the credit markets.

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. Second, 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 as a signaling device to banks, the effect is likely to be present in this environment. Third, 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 trade credit repayment patterns of the firms is one possible source. Gathering information throughout repeated interactions with the firms is another way of obtaining information.

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. In order to directly measure the effect of trade credit on the bank's decision to grant the credit or not, I focus on the most recent application for a bank loan.

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.[10] Out of the remaining sample, only 900 applied for a new loan, and 39 of these

[10] 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

applied for a loan to friends or family, to a government agency, or to other business firms. Since we are interested in exploring whether banks use the information about the trade credit repayment pattern, I drop these 39 firms to get a sample of 861 firms that asked for a loan to a financial institution. For these 861 firms, I estimate whether the *use of trade credit* has any effect on the credit-granting decision of the banks. In other analysis, I estimate whether the information contained in the trade credit *repayment pattern* of firms affects their probability of getting a bank loan. For this analysis, we need to focus on the firms that used trade credit during 1998. 195 did not. Therefore, after eliminating these firms I get a resulting sample of 666 firms that asked recently for a loan and used trade credit.[11]

2.2 Variables

For all of the firms in the selected sample, there is information about whether the bank granted the loan or not. 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. In what follows, this is the variable that will measure how the credit-granting decision of banks changes depending on the relationship between the firm and its suppliers. It is the dependent variable in all of the regression analysis.

There are several variables in the survey that can be thought of as proxies for the nature of the credit relationship between the firm and its suppliers: (1) The fraction of the purchases made during 1998 that the firm paid after the due date; (2) A binary variable for the firms that have been denied credit from any supplier; (3) The fraction of the purchases made during 1998 that the firm paid during the discount period, if such a discount was offered; (4) A binary variable for the firms that paid after the due date at least once; (5) A binary variable for the firms that have a credit relationship

the items as a function of the other two. As a result, a few firms reported negative assets.

[11]The precise description of how I construct the sample is available in the Appendix.

with their suppliers; (6) The number of suppliers offering credit to the firm; (7) The terms of trade credit offered to the firm by its most important supplier (length of payment period, length of discount period, size of the discount). I use the fraction of purchases made during 1998 (variable 1) to explain the variations in the credit-granting decisions of the bank in most of the analysis. I then replace this variable with measures (2) to (5), to find out whether the results are specific to the choice of the dependent variable.

It is possible that the fraction of trade purchases paid after the due date is low because the bank granted the loan to the firm, and that the direction of the causality that we are looking for does not exist. Similarly, it is possible that the measures (2) to (5) are related to the decision of the banks to grant the loan because of an inverse causality. Therefore, it is necessary to identify whether banks indeed use the relationship between the firm and its suppliers as a signal of credit quality, and to rule out that the credit behavior of the firm with its suppliers is caused by the bank's decision of granting the loan or not. I use an instrumental variables approach for this identification of causality. As instruments for variables (1) to (4), I use the terms of trade credit offered by the most important supplier of the firm (variable 7). As an instrument for variable (5), I use a proxy for the within-industry bargaining power of the firm. I construct this proxy as the size of the firm, measured in number of employees, divided by the total number of employees of firms with at most 500 employees in the same two-digit SIC industry classification during 1997. I gather the information about the total size of the industries from the Small Business Administration's website.[12]

There are several other firm characteristics that may explain the variation in the firms' credit quality and consequently, the variability in the credit-granting decision of banks. In what follows, I include measures for what bank analysts traditionally refer to as the "five C's of credit": Capital, capacity, character, collateral, and conditions.[13]

[12]See http://www.sba.gov/advo/research/data.html

[13]Greenbaum and Thakor (1995).

For example, firm's size, age, profitability, and sales growth are measures of its capital and repayment capacity. Some governance characteristics (i.e. limited liability and owner-managed dummies) are measures of the firms' character. A dummy variable for whether the owner of the firm has his own home is a measure for availability of collateral. Finally, the firm's industry, location (region and whether it is in a Metropolitan Statistical Area), and the concentration of the banking credit market 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. 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. Among other information, the survey has questions about: (1) The type of bank (commercial bank, insurance company, venture capitalist, etc.); (2) The number of years that the bank has conducted a business relationship with the firm; and (3) The most frequent method of conducting business with the firm (in person, by phone, electronically, etc.).[14] These characteristics may determine the bank's credit-granting decision, so it is necessary to take them into account in the subsequent analysis.

Finally, 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 is a collateral for the loan. I also take into account these factors in the analysis. A very detailed description of how the variables were constructed is available in the Appendix.

[14]Unfortunately, the public version of the dataset does not contain information about the size of the banks.

2.3 Summary statistics

Table 1 presents summary statistics for some selected characteristics of the firms that recently asked for a loan, according to the usage of trade credit during 1998. The first column contains firms that did not use trade credit at that time. The second column contains firms that used trade credit, and paid more than 25% of the purchases after the due date. The third column contains firms that used trade credit and paid less than 25%, but strictly positive amounts of purchases after the due date. The fourth column contains firms that never paid their trade credit purchases after the due date. Finally, the last column contains all of the firms in the selected sample. The difference between the mean and the median of the returns on assets, accounts payable over assets, bank loans over assets, and cash over assets is quite high because of the presence of outliers. In order to avoid the results from being driven by these outliers, I winsorize these variables at the 1% and 99% levels. The values reported in Table 1 correspond to the winsorized variables.

The first fact that is immediately apparent from Table 1 is that non-users of trade credit are the typical candidates for being "growth" firms. First of all, they are much smaller and younger than the rest of the firms. 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. The owners of the firms that did 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 this category is high. This evidence is consistent with the idea that trade credit is one of the first sources of external finance for small firms (Berger and Udell 1998). Trade credit is accessible to nearly all firms, the exception being the smallest start-ups.

Table 1 also shows that apparently, 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. 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. Consistently with Berger and Udell's (1998) story about the financing of small 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 last five rows of Table 1 show that non-users of trade credit seem to have much closer ties with their banks. Even though non-users of trade credit are much younger than the rest of the firms, they do not have shorter relationships with their banks. Moreover, the length of the relationship with the bank is longer *relative to their age*: The ratio of the length of the relationship with the bank to the age of the firm is highest for the non-users of trade credit. Furthermore, a larger proportion of bankers conduct business personally with non-users of trade credit than with users of trade credit. Given that non-users of trade credit are also smaller, then the banks with which they match are also typically small, and small banks tend to conduct more personal business relationships, and to rely more on soft information than large banks (Berger, Miller, Petersen, Rajan and Stein 2005). This can be further confirmed by observing that among the non-users of trade credit, there is a smaller proportion of firms with hard information - a smaller number of firms in this group used financial records to answer the survey. Put together, all these pieces of evidence point out that non-users of trade credit are more opaque than the rest, and that the bank loans extended to non-users of trade credit are mostly 'character' loans, i.e. loans based in soft information collected by the loan officers. This shall become more evident in Section 3.3, when we find that the use of trade credit is not used by banks to discriminate among borrowers.

The last row of Table 1 shows that the proportion of rejected applications among non-users of trade credit is very high, and only comparable to the proportion of rejected applications among the users of trade credit that paid more than a quarter of their purchases after the due date. Given that, as noted before, there is not much information about these small firms, this is not a surprising result. Moreover, this finding provides some evidence supporting the role of trade credit as conveyor of soft information to banks. Lacking information about the credit repayment patterns of the firms, banks prefer to deny credit to these opaque firms. This result shall be confirmed in Section 3.3.

It is also worth briefly describing the differences in the variables across different categories of users of trade credit. These firms are not significantly different from each other in terms of size, age, or governance; however, the firms that pay more than a quarter of their purchases after the due date seem to be more constrained: they are in average less liquid and more leveraged than firms that pay small fractions of the purchases after the due date. On top of that, they have a loan rejection rate of 37%, which is significantly different from the 16-18% rejection rate among the 'good' payers.

Why is the rejection rate among bad payers so high? The first possibility is that these firms are constrained because they are more risky - being more leveraged and less liquid, their repayment capacity is doubtful, even if they seem to be profitable and growing. The second possibility is that they are constrained because banks do not have enough information about them. Looking at the three last rows of Table 1, we observe that the length of the relationship with the banks is shorter for these firms, both in absolute terms and relative to their age. Moreover, the proportion of impersonal bank-firm relationships is highest among these firms, although the difference is not statistically significant. However, the proportion of firms with hard information among the late payers much higher than among non-users of trade credit. Therefore, a third possibility that cannot be ruled out is that the firms are being rationed from the credit *because* they pay late.

As a first approach to discriminate between these three possibilities, Table 2 presents summary statistics of two variables that measure the relationship between a firm and its supplier, conditioning on whether the firm obtained the bank loan or not. Panel A contains the distribution of the use of trade credit conditioning on the credit-granting decision of banks; 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 section I perform regression analysis in order to find out why the bad payers of trade credit are consistently rationed from bank credit.

3 The effects of trade credit payment history on the probability of being granted a loan

In this section I address the question of whether banks incorporate information about the trade credit repayment patterns into their credit-granting decisions. In Section 3.1, I deal with the identification of the direction of the signal from suppliers to banks, using an instrumental variables approach. In Section 3.2, I take into account other sources of information accessible to banks that could be driving the results. I then analyze whether results found so far are robust to different choices of independent variables in Section 3.3. Finally, in Section 3.4 I verify whether the results are robust to a potential non-random sample selection.

3.1 The basic models: estimation and results

I start by estimating the following linear probability model:

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

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 1 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, as I noted before, 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 shadowed by other factors. This endogeneity problem causes the estimated coefficients of all of the variables to be inconsistent. Therefore, I redo the estimations using an estimation method that yields consistent results: Two-Stage Least Squares (TSLS) estimation.

I assume the following model in the population:

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

$$y_{2i} = \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_i, \tag{3}$$

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 2 is the structural equation of interest, and equation 3 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 3. 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 2. As it is well known, in order for the system of equations 2 and 3 to be well identified, it is necessary to include in equation 3 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 2. 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.[15]

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 2004), 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

[15]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.

is processed using statistical methods, in what is called "Credit Scoring". 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). 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 2.

Table 3 contains the results of the estimations. The coefficients of equation 1 are in Column 1; Columns 2, 3, and 4 contain the results for different specifications of the second stage of the TSLS estimation of equation 2.[16]

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.[17] Moreover, by doing so the

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

[17]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).

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 3. 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, 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 the firms with unlimited liability, but has no effect on firms with 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, a house is a valuable collateral only for the firms whose owners are liable for the firm's debts.

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 3 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.

3.2 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 unobserved heterogeneity. The results of this section provide additional insights on how banks use soft and hard information about the firms' credit quality.

3.2.1 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 3.1 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:

$$y_{1i} \;=\; \beta_0 + \beta_1^1 y_{2i} I_i(x) + \beta_1^2 y_{2i}(1 - I_i(x)) + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i, \qquad (4)$$

$$y_{2i} I_i(x) \;=\; \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{1i}, \qquad (5)$$

$$y_{2i}(1 - I_i(x)) \;=\; \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{2i}. \qquad (6)$$

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 5 and 6, and in the second stage I estimate the coefficients of the structural equation of interest, equation 4.

By estimating both equations 5 and 6 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 4, Section (i) contains the estimated coefficients of equation 4. 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 specification, I use the same controls as in Column 2 of Table 3.

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 3. These results suggest that the direction of the causality has been well identified.

3.2.2 Hard information, soft information, and trade credit availability

In this section I explore how the trade credit repayment patterns affect the firms' probability of getting a loan when banks possess (1) hard information of better quality, or (2) soft information about the credit quality of the firms. Possessing other (or better) sources of information about the firm should decrease the banks' reliance on trade credit payment reputation as a signal for trade credit quality.

In order to get a proxy for whether the banks have access to hard information about the firm, I use a survey question asking whether the respondent used financial statements or accounting reports in order to answer the survey. If the firm used financial statements or accounting reports to answer the survey, then it is likely that the bank had access to similar hard information to do the credit analysis (Berger, Miller, Petersen, Rajan and Stein 2005). Thus, I repeat the regressions of section 3.1 but estimating two different coefficients for the fraction of purchases paid after the due date: one for the firms that used financial reports to answer the survey, and one for the ones that did not. Since hard information is easier to assess, banks' reliance on the soft information contained in the trade credit repayment records should be lower when hard information is accessible. 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 without financial statements.

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. In both cases, we could expect the banker to have more soft information about the firm than if the business is usually conducted by telephone or electronically. With this idea in mind, I estimate two different coefficients for the fraction of purchases paid after the due date: one for the firms that conducted business with their banks in a personal way, and the other one for the firms that did not conduct business with their banks personally. Banks that have their own soft information available about the firm should depend less on soft information gathered by others - in this case, the suppliers. Therefore we should expect the trade credit reputation record to have a stronger effect when banks do not have other sources of information, hard or soft, about the credit quality of the firms.

I estimate the following model with TSLS:

$$y_{1i} = \beta_0 + \beta_1^1 y_{2i} I_i(x) + \beta_1^2 y_{2i}(1 - I_i(x)) + \beta_2 X_i^f + \beta_3 X_i^b + \beta_4 X_i^l + u_i, \quad (7)$$

$$y_{2i} I_i(x) = \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i^f + \gamma_3 X_i^b + \gamma_4 X_i^l + e_{1i}, \quad (8)$$

$$y_{2i}(1 - I_i(x)) = \delta_0 + \delta_1 Z_i + \delta_2 X_i^f + \delta_3 X_i^b + \delta_4 X_i^l + e_{2i}, \quad (9)$$

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 hard (soft) information.

The first rows of part (ii) of Table 4 contain the results of the estimations when $I_i(x)$ is an indicator function for whether firms used financial statements to answer the survey. In the first column, the OLS coefficients are reported; TSLS coefficients are in the second column. Although both coefficients are negative, none of the TSLS coefficients is significant at reasonable confidence levels. There are several reasons why we have not obtained statistical significance for these coefficients. First of all, we should observe that I have already controlled for hard information by including information about the age, the size, and financial measures of the firm. Thus, there could be small residual variation left to be explained with this separation of the sample. Second, as noted by Berger et al (2005), the variable I use might 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. Third, some banks lending to firms without this hard information may have sources of soft information that are more important to their credit decisions than the trade credit repayment patterns, and others do not have such information and must rely on the trade credit repayment patterns. Since we are not controlling for other sources of soft information, the importance of the signal for the banks that do not have soft information about their clients is dampened. As a result, the estimated coefficients are imprecise.

The last rows of part (ii) in Table 4 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.

The results of this section suggest that it is mainly the soft information about the credit quality of the firms what matters to banks that lead personal relationships with the firms. In the next section I examine if banks that have conducted long relationships with the firms also use their soft information for their credit decisions.

3.2.3 Banking relationships and trade credit reputation

Another measure for the availability of other sources of soft information 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 soft information from a third party. In this section I study whether there is any added value about trade credit reputation for banks that have long relationships with firms, or if banks prefer to use their own sources of information about the credit quality of the firms.

Following this idea, I classify the firms into those with shorter relationships with the bank than the median of 3 years, and those with relatively new relationships, and construct an indicator dummy variable with this information. I then estimate equations 7, 8, and 9 where $I_i(x)$ is an indicator function for whether the relationship with the bank is larger than the median.

We should expect the effect of trade credit reputation to be higher for those firms with new relationships with the bank, because they are are relatively unknown to the banks. On the other hand, the effect of trade credit reputation should be small for firms with long relationships, because they have their own information about the firms and do not need to rely on third parties to get this information. In other words, we expect β_1^2 to be negative and larger, in absolute value, than β_1^1.

Part (iii) of Table 4 confirms our basic intuition. 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 3.1. Finally, the fit of the model is good: a generalized R^2 of 21%.

The results of this section, combined with the results of the previous section, highlight the importance of the use of soft information in the banks' decisions. I further reinforce that sources of soft information are more important to banks than sources of hard information by estimating four different coefficients for the fraction of purchases paid after the due date: One for firms that have both hard and soft information, one for firms with hard but no soft information, one for firms with soft but no hard information, and one for firms without hard and soft information sources.[18] Trade credit relationships are only relevant in the latter case. However, the coefficient for firms without hard and soft information cannot be statistically distinguished from the coefficient for firms that have soft, but no hard information available; and is different from the coefficient for the firms with no soft information. This presents evidence that it is the soft information what is important to banks.

[18] These coefficients are not reported in the tables, but are available upon request.

3.3 Other measures for trade credit reputation

Up to this point I have only used one single measure for the reputation of firms with regard to their payment of trade credit: the fraction of purchases paid after the due date. In this section I repeat the estimations of Section 3.1, replacing the fraction of the purchases paid late with several other variables that could as well be proxies for the reputation of the firms according to their trade credit repayment.

3.3.1 Default

As a first alternative measure for the reputation of the firms related to their payment of trade credit, 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 5 contains the results of estimations of equation 1 with OLS (Column 1) and equation 2 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 non-mutually exclusive 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.

3.3.2 Trade credit denial

As a second measure of the reputation of firms regarding the payment of trade credit, 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 2 and 3 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 prefer to 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 5 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 3.1. 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 3.1.

3.3.3 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 3.1 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 3.1 apply for the use of discounts, therefore it is possible to estimate a TSLS model for equation 2 using the trade credit terms as instruments. In Part (iii) of Table 5 I report the fitted coefficients of an OLS model for equation 1 (first column), and in the second column 6 the fitted coefficients of a TSLS model for equation 2.

As can be seen in part (iii) of Table 5, 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 (even "harder") 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. However, a statement telling that the supplier has denied credit to the firm is much more credible because it is a stronger statement.

3.3.4 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.

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.[19] I first estimate equation 2 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 (2004), 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.[20] 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 5 shows the estimated coefficients for the use of trade credit of equation 2, 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.[21] 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

[19] 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)

[20] 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.

[21] 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 3.2.

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 therefore estimate equation 2 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.

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

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 3.1 to 3.3 are based on the subsample of firms that applied for a loan, i.e. possibly a non-random sample: firms in this subsample took a decision to apply for a loan, and the decision could be related to their credit quality. Since the dependent variable in models 1 to 6 can only be observed for this selected sample of firms, the estimations of the previous sections could be biased. I find that selection plays no crucial role.

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 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 banks 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.[22] For this study, I use a two-stage procedure to account for the selection of the sample in the presence of an endogenous independent variable (Wooldridge 2001, p. 567-570). I assume the following limited-dependent variable

[22]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)

equation as a model for the selection of firms into applying for a loan or not:

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

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 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). 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.[23]

First, I estimate η with a probit estimation using all of the firms, both if they applied for a loan or they 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 func-

[23]A number of studies have related the number of bank relationships with firm quality. In this case the selection equation would not be identified, as its error term would be correlated to the decision of banks to grant a loan. However, recent evidence shows that the number of banks is not a measure of firm quality (Machauer and Weber 2000).

tion. Then, I fit equations 2 and 3 with a TSLS procedure, adding $\hat{\lambda}$ as an additional control variable. The added variable, $\hat{\lambda}$ takes care of the sample selection bias.

The results of the TSLS coefficients of equation 2 when the inverse Mills ratio is added as an explanatory variable in equations 2 and 3 are in Table 6.[24] In Column 1, I control for industry only at the one-digit SIC codes, whereas in Column 2, I include two-digit SIC codes for the firms' industry. The coefficient for the sample selection correction is not statistically different from zero at a 90% confidence level, so 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. Moreover, the results of Section 3.1 do not change qualitatively. After controlling for firm self-selection into applying for a loan or not, we still cannot reject the hypothesis that the record of payment of trade credit is an important variable for banks to take into account during their credit-granting decision.

4 Concluding remarks

Lacking own sources of soft information, banks use the commercial relationships of firms to infer the firms' credit quality. Firms that tend to pay their bills after the due date are consistently rationed by banks that do not have soft information about their credit quality. Moreover, banks that find that their clients have been denied credit by their suppliers incorporate this soft 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.

This paper 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 mak-

[24]The estimated coefficients for the selection equation are available upon request.

ing 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 soft information about the credit quality of their clients much more intensively than transaction banks. This is among the first papers to find direct evidence for this.

This paper 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 qualification: it is only negative information about the firms what matters to banks. Positive information about the relationship between a firm and its suppliers is disregarded by banks.

Finally, this paper also adds to the literature on the financing of small firms, by showing how reputation may play an important role in the availability of credit for small firms.

Appendix

A.1. Sample 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. Definition of the Variables

Application.- This binary variable equals one if the respondent of the survey gave a strictly positive number as an answer to the following question: *How many times did [the firm] apply for new loans in the last three years? Do not include renewals for lines of credit, applications for credit cards, requests for loans from owners, or trade credit with suppliers. Do not include applications that were withdrawn or that are still pending.*

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 (**Application = 1**). 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.

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 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?*

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?*

Relationship with Bank.- This variable measures the length, in years, of the relationship that the firm has had with the financial institution to which it asked its most recent loan. With this variable, I separate the firms into those with a relationship longer than the median of 3 years, and those with a shorter relationship than the median.

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.

Used financial records.- This binary variable contains a one if the firm answered the survey by using financial statements or accounting reports, and a zero otherwise.

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.

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

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 56 industry dummies.

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.- 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.

Type of loan.- This variable refers to the type of loan of the firm's most recent application for credit. The type of loan can be any of the following: Line of credit (L/C), capital lease, mortgage, vehicle loan, equipment loan, or other.

Type of institution.- This variable refers to the type of financial institution to which the firm asked its most recent loan. The type of institution can be any 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, Venture Capital Firm or Small Business Investment Company, Credit Card Processing, Check Clearing, Factoring, 401K/Retirement, or Consolidated/Composite Institution.

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Table 1

This table contains the mean (standard deviation) of selected variables, according to their use of trade credit. Firms in Column 1 do not use trade credit. Firms in Column 2-4 use trade credit. Firms in Column 2 paid more than 25% of the purchases after the due date. Firms in Column 2 paid positive amounts of their purchases late, but smaller 25%. Firms in Column 4 never paid their purchases late.

	No Trade Credit	Fraction of Purchases Paid Late (PPL)			All Firms
		PPL>25%	PPL>0% & PPL<25%	PPL=0	
Total Assets ($ Million)	0.691	2.560	3.311	2.095	2.160
	(2.497)	(5.500)	(9.264)	(4.846)	(6.036)
Age of firms (Years)	9.774	14.371	13.917	14.056	13.117
	(8.321)	(11.482)	(9.370)	(11.752)	(10.595)
Profits / Assets (ROA) *	1.605	1.076	0.526	0.945	1.022
	(4.721)	(4.437)	(1.332)	(3.217)	(3.607)
Bank Loans / Assets *	1.189	0.850	0.620	0.556	0.774
	(2.615)	(1.797)	(1.196)	(1.095)	(1.730)
Cash / Assets *	0.227	0.096	0.124	0.171	0.157
	(0.311)	(0.189)	(0.165)	(0.207)	(0.228)
Sales increase **	0.648	0.400	0.418	0.303	0.425
	(1.789)	(1.398)	(1.438)	(1.031)	(1.400)
% Owner managed	0.938	0.863	0.858	0.854	0.876
	(0.241)	(0.345)	(0.350)	(0.354)	(0.330)
% Owner has a home	0.826	0.914	0.951	0.923	0.906
	(0.380)	(0.281)	(0.216)	(0.267)	(0.292)
% Limited liability	0.446	0.749	0.740	0.662	0.649
	(0.498)	(0.435)	(0.440)	(0.474)	(0.477)
% Used financial records	0.113	0.160	0.196	0.129	0.148
	(0.317)	(0.368)	(0.398)	(0.336)	(0.355)
Length of rel. with bank (Years)	5.374	5.150	5.897	6.244	5.742
	(7.202)	(7.323)	(6.902)	(7.906)	(7.401)
Length of bank rel. / firm age	0.622	0.452	0.596	0.550	0.557
	(0.943)	(0.824)	(1.155)	(0.766)	0.923
% Impersonal rel. with bank	0.374	0.457	0.446	0.387	0.412
	(0.485)	(0.500)	(0.498)	(0.488)	(0.493)
% Credit granted	0.626	0.629	0.819	0.836	0.742
	(0.485)	(0.485)	(0.386)	(0.371)	(0.438)
Number of firms	195	175	204	287	861

* Winsorized at 1% and 99% percentiles.

** Winsorized at 1% and 99% percentiles; 23 firms missing in Column 1, 4 firms missing in Column 2, 9 firms missing in Column 3, and 19 firms missing in Column 4.

Table 2: Summary statistics

Panel A: Use of trade credit (0,1)

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.

	Credit not granted	Credit granted	All firms
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%	

*Significantly different at a 1% level

Panel B: Fraction of purchases paid late

This table contains descriptive statistics for the fraction of purchases paid late 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 and used trade credit

	Credit not granted	Credit granted	All firms
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%	

*Significantly different at a 1% level

Table 3

This table presents estimates for the following equation:

LoanGranted $= b_0 + b_1$ *Purchases paid late* $+ b_2$ *Firm Characteristics* $+ b_3$ *Bank Characteristics* $+$
$+ b_4$ *Loan Characteristics* $+u$.

The dependent variable is a binary variable containing a one if the credit for a loan was granted by the bank, and zero otherwise. 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:

Purchases paid late $= g_0 + g_1$ *Trade Credit Terms Offered* $+ g_2$ *Firm Characteristics* $+ g_3$ *Bank Characteristics* $+$
$+ g_4$ *Loan Characteristics* $+e$.

	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]
Eight one-digit SIC industry dummies	yes	yes	no	no
Fifty-one two-digit SIC industry 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]
Eight regional dummies	yes	yes	yes	yes

Table 3

	OLS	TSLS		
	(1)	(2)	(3)	(4)
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]
Savings and Loan 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 Investment	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
Adjusted [Generalized] R-squared	0.19	[0.21]	[0.27]	[0.28]
Gen R-2				

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

(1) Winsorized at 1 and 99% levels

Table 4

This table presents the OLS and TSLS estimators of coefficients $b_1^{\,1}$ and $b_1^{\,2}$ for the following estimation equation:

$$LoanGranted = b_0 + b_1^{\,1}\,Var_1 + b_1^{\,2}\,Var_2 + b_2\,Firm\ Characteristics + b_3\,Bank\ Characteristics + b_4\,Loan\ Characteristics + u.$$

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. *Var1* and *Var2* are interactions of the fraction of purchases paid late with dummy variables for (i) whether the application for the loan occurred after 1998 or not; (ii) whether the bank has hard/soft information about the firm; and (iii) whether the relationship with the bank is smaller than the median. The first stage of the TSLS estimation is:

$$Var_1 = g_0 + g_1\,Trade\ Credit\ Terms\ Offered + g_2\,Firm\ Characteristics + g_3\,Bank\ Characteristics + g_4\,Loan\ Characteristics + e_1.$$

$$Var_2 = g_0 + g_1\,Trade\ Credit\ Terms\ Offered + g_2\,Firm\ Characteristics + g_3\,Bank\ Characteristics + g_4\,Loan\ Characteristics + e_2.$$

Estimated coefficents of all controls are available in the Appendix.
In all specifications I control for industry using the one-digit SIC code.

	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. Hard / soft information		
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]
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]
iii. Firm-bank relationships		
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]

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

Table 5

This table presents the OLS and TSLS estimators of coefficients b1 for the following estimation equation:

LoanGranted = b0+b1Var1+ b2Firm Characteristics+ b3Bank Characteristics+ +b4Loan Characteristics+u.

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. Var1 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.

The first stage of the TSLS estimation is:

Var1 = g0+g1Trade Credit Terms + g2Firm Characteristics+g3Bank Characteristics+ +g4Loan Characteristics+e1.

Var2 = g0+g1Trade Credit Terms + g2Firm Characteristics+g3Bank Characteristics+ +g4Loan Characteristics+e2.

Variable	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

* significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. (1) These regressions were made on 806 firms

Table 6

Controlling for sample selection bias

This table presents Instrumental Variables estimates for the following equation:

LoanGranted = b0+b1Purchases paid late+ b2Firm Characteristics+
+ b3Bank Characteristics+b4Loan Characteristics+
+ b5 Inverse Mills Ratio +u.

The coefficients are corrected for a sample selection bias using a two-stage procedure (see the text). The Inverse Mills Ratio is calculated from the selection equation, estimated with a probit equation:

Asked for loan= g0 + g1 Number of banks + g2 Controls + e

The coefficients of the selection equation and the coefficients for the first stage of the IV estimations are available upon request.

	TSLS	
	(1)	(2)
Trade credit reputation		
Purchases paid late (PPL)	-0.413	-0.481*
	[0.260]	[0.279]
Firm characteristics		
Log of assets	0.041***	0.041**
	[0.011]	[0.016]
Log of 1 + age	0.046*	0.037
	[0.026]	[0.033]
ROA (Profits / assets) (1)	0.011*	0.008
	[0.006]	[0.006]
Sales increase 1997-1998 (1)	0.012	0.012
	[0.012]	[0.013]
Sales / Assets (1)	-0.001	0
	[0.002]	[0.002]
Owner managed dummy	0.029	0.048
	[0.043]	[0.045]
Owner has home	0.177***	0.154**
	[0.063]	[0.066]
Limited liability	0.034	0.035
	[0.039]	[0.041]
Eight one-digit SIC industry codes	yes	no
Fifty-one two-digit SIC industry codes	no	yes
Market characteristics		
Concentration of Banking Mkt dummy	-0.036	-0.053
	[0.035]	[0.036]
MSA dummy	-0.099**	-0.117***
	[0.039]	[0.045]
Five regional dummies	yes	yes
Loan characteristics (Omitted=L/C)		
Capital Lease	0.048	0.004
	[0.078]	[0.081]
Mortgage	0.135**	0.111*
	[0.060]	[0.063]
Vehicle loan	0.233***	0.232***
	[0.052]	[0.054]
Equipment	0.114**	0.090*
	[0.047]	[0.050]
Other	0.06	0.047
	[0.044]	[0.047]

Table 6

	TSLS	
	(1)	(2)
Bank characteristics (Omitted=Commercial Bk)		
Savings Bank	-0.104	-0.111
	[0.098]	[0.102]
Savings and Loan Association	0.1	0.095
	[0.196]	[0.201]
Credit Union	0.098	0.137
	[0.111]	[0.113]
Finance Company	-0.052	-0.041
	[0.055]	[0.057]
Insurance Company	0	-0.098
	[0.289]	[0.310]
Brokerage or Mutual Fund Company	0.042	0.076
	[0.123]	[0.130]
Leasing Company	0.095	0.1
	[0.095]	[0.097]
Mortgage Company	-0.165	-0.224
	[0.146]	[0.157]
Venture Capital/ Small Business Investment	0.298	0.433
	[0.280]	[0.295]
Sample selection correction		
Inverse Mills Ratio	0.093	0.045
	[0.057]	[0.117]
Constant	0.016	-0.038
	[0.244]	[0.518]
Observations	634	634
Generalized R-squared	0.21	0.27

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