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Abstract

Despite its importance to the funding of small enterprises (SMEs), the question of how trade credit is used has not been fully answered. Recently, Uchida *et al.* (2013) showed that trade creditors can act as relationship lenders. To advance this result, we study the use of trade credit as a substitute for relationship lending credit when firms cannot otherwise obtain such credit. Using a sample of SMEs from the Survey of Italian Manufacturing Firms, we show that when opaque firms seeking relationship credit encounter transactional banks, they retain a greater portion of trade credit in their loans. These firms thus substitute trade credit for their missing relationship credit, because trade creditors are better evaluators of firms than are transactional lenders. The results depend on the size and age of the firm, the nature of the bank, and the size of the firm's banking pool.

JEL: G21, L14, L22

Keywords: Banks, Lending Technologies, Small Business, Trade Credit

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1. Introduction

Trade credit is one of the most important sources of financing for small- and medium-sized enterprises (SMEs). However, while prior literature recognizes that trade credit's importance depends on the country—the part of trade credit in total asset varies across Europe, from 13.28% (Netherlands) to 42% (Italy) (Giannetti, 2003)—and on the banking system and legal infrastructure (Demirgüç-Kunt and Maksimovic, 2002), it has not yet solved the puzzle of how trade credit gets used.

There are two possible explanations for the use of trade credit. The first is the real operation explanation, composed of theories of cost minimization (Ferris, 1981), quality supervision (Smith, 1987), and price discrimination (Brennan *et al*., 1988). The second is the financial explanation, composed of all theories about the link between trade credit and financial institutions (e.g., Cook, 1999; Alphonse *et al.*, 2004; Casey and O'Toole, 2014). According to these theories, trade creditors are potential debt suppliers who have the advantage of acquiring private information from the firm through strong relationships (e.g., Biais and Gollier, 1997; Ng *et al.*, 1999; Burkart and Ellingsen; 2004). This advantage enables trade creditors to provide credit to bank-constrained firms, as happened during the financial crisis (Casey and O'Toole, 2014; Minetti et al., 2018).

Uchida *et al.* (2013) link this notion of private information to the classifications of soft and hard information developed by Stein (2002). Private information can be regarded as qualitative information that is transmitted via multiple contacts between suppliers and clients over time, which Stein (2002) calls soft information. According to Uchida *et al.* (2013), trade creditors accumulate soft information about firms through their relationships with them, acquiring information that is not necessarily the same as that known to banks. The authors point out that long relationships between trade creditors and firms allow firms to have access to the same benefits that relationship lenders provide, that is, credit availability when firms are in a downturn (Cuñat, 2007) and easier access to credit renegotiation (Wilner, 2000). The authors in turn develop a "relationship lending" hypothesis: trade creditors can be regarded as relationship lenders because they accumulate soft information. Berger and Udell (2006) define two main types of lending technologies:

- Transaction-based lending based on borrowers' hard information
- Relationship lending, primarily based on borrowers' soft information

Uchida *et al.* (2013) show that trade creditors can become relationship lenders, depending on their relative bargaining power. When buyers are non-dependent on their trade creditors in terms of purchase amounts, trade creditors exhibit the same behavior as relationship lenders. The strength of the relationship between the firm and it supplier is captured by the current measure of relationship lending (Petersen and Rajan, 1994), that is, the relationship length. These findings in turn raise a question: can trade credit be a funding substitute for opaque firms that cannot obtain bank relationship credit?

According to Berger *et al.* (2005) and Stein (2002), the optimal match is as follows: more opaque (transparent) firms, which emit mostly soft (hard) information, should borrow from smaller (larger) relationship (transactional) banks because such banks can optimally evaluate the information emitted. But in some cases, changes in the bank organization can cause the banks to switch from being relationship organizations to being transactional organizations, resulting in firm–bank mismatches. We note two explanations for this change. First, Bonaccorsi Di Patti and Gobbi (2007) find that bank mergers affect the structural organizations of banks and change the availability of credit. Second, Hale (2011) proves that during periods of financial crisis, banks drastically reduce their relationships with clients and favor transactional lending technology over relationship lending technology. Another potential explanation for mismatching comes directly from firms and their ability to accurately observe bank organizations: even if firms have the advantage of using relationships to evaluate bank type, their evaluations are not always reliable. Firms can misperceive their financial partners, judging them, for example, to be relationship banks, when they are actually transactional (Ferri and Murro, 2015). The consequence of these potential changes is that firms can find themselves in a situation where they cannot find another relationship bank, and have no choice than to deal with a transactional bank. In these cases, banks are not able to analyze correctly the information emitted by firms, resulting in a higher probability of misevaluation of the quality of the firm. This misevaluation has impacts: Ferri and Murro (2015) demonstrate that when opaque firms match with transactional banks, their probability of being credit-rationed increases. De Bodt *et al.* (2015) show that these firms must pay higher interest rates and also have to attract more creditors before banks will evaluate them correctly. To our knowledge, though authors have studied the consequences of mismatching when firms stays with their banks, researchers have not yet identified a credit alternative for firms. We consider the potential for firms to use trade credit as an alternative source of funding.

To test our idea, we exploit the tenth wave of the Survey of Italian Manufacturing Firms, run by UniCredit Bank in 2007. This data set presents three main advantages for our analysis: first, it contains accounting information that measures the importance of trade credit to firms' funding. Second, for the first time, it includes a set of questions about bank–firm relationships and perceptions of firms about their banks, allowing us to construct two continuous indicators for lending technology. The first indictor captures the degree of relationship lending, and the second captures the degree of transactional lending. These indicators correspond more closely to reality than previous studies that use discrete measures (i.e., that a bank is relationship or transactional; e.g., Berger and Black, 2011). Finally, the data set is based on Italian firms. Italy provides an ideal testing ground for isolating the link between trade credit and bank credit. In Italy, bank credit is the most important source of financing in the country for SMEs (Minetti, 2011), trade credit represents an important alternative source of financing—on average 42% of total assets, the highest percentage in Europe (Giannetti, 2003).

Our results show that opaque firms that perceive their banks as transactional have higher levels of trade credit, which empirically confirms our idea that these firms use trade credit as a substitute for relationship lending credit in cases of mismatching. However, this effect holds only for older, larger firms, which have greater capacity for negotiation in comparison with smaller, younger firms. Older and larger firms increase their proportion of trade credit in cases of mismatching but decrease it when relationship banks evaluate them, because trade credit is more expensive than bank credit when it is correctly evaluated. Finally, we show that firms change their behavior depending on the nature of their banks (national or local) and on the structures of the firms' banking pools.

In Section 2, we provide a survey of trade credit and present our theoretical predictions. In Section 3, we present our data and methodology, and then in Section 4, we report our results. Section 5 concludes.

2. Related literature and theoretical predictions

2.1. Trade Credit explanations

Most theories that explain the use of trade credit can be classified in two groups. The first group is composed of theories based on real operations. Ferris (1981) offers the transaction cost minimization theory: trade credit permits reductions in the cost of delivering multiple goods by assigning unique monthly or quarterly payments. Trade credit also gives firms time to check the quality of products (Smith, 1987). Brennan *et al.* (1988) show that creditworthy customers pay promptly to receive any available discounts, while risky customers find the price of trade credit to be attractive relative to other options. Trade credit allows firms to manage their inventories and cash flow more easily and according to their need.

The second group includes theories based on financial advantages. These theories propose that trade creditors have some advantages for granting credit that banks do not. For example, Biais and Gollier (1997) develop a model in which trade creditors sometimes acquire private information more easily than banks. This acquisition allows trade creditors to reduce asymmetric information and offer credit to opaque firms when the banks cannot. In this way, trade credit acts as a substitute for bank-credit–constrained firms. Ng *et al.* (1999), McMillan and Woodruff (1999), Cook (1999) among others find similar results, and researchers such as Cuñat (2007) and Lin and Chou (2015) empirically validate this theory. Other researchers show that substitution also becomes more important as firms increase in age and size (Casey and O'Toole, 2014) because older firms are more dependent on trade credit and have better access to it (Klapper *et al.*, 2012).

Burkart and Elligsen (2004), using the model developed by Biais and Gollier (1997), show that the use of trade credit is not a substitute but a complement to bank credit. In fact, with the knowledge that trade creditors acquire and manage more private information than they do, banks regard the granting of trade credit as a signal of firm quality and therefore lend to firms that have trade credit. Agostino and Trivieri (2014) empirically validate this hypothesis. Aktas *et al.* (2012) show that the use of trade credit is positively correlated with the quality of the firm.

Compared with banks, trade creditors also have an advantage in managing collateral (Longhofer and Santos, 2003; Frank and Maksimovic, 2005). The collateral taken by trade creditors—goods sold on credit—has a higher value than the collateral taken by banks, because it is not in the nature of banks to manage these kinds of goods. Moreover, a trade creditor can liquidate the goods more easily than a bank.

Long-term relationships with suppliers also present some advantages. Minetti et al. (2018) find that firms more exposed to bank credit rationing are more likely to participate in supply chains to overcome liquidity shortages. This benefit of supply chains is especially strong when firms establish long-term trading relationships with trading partners. Cuñat (2007) shows that long-term buyer–supplier relationships allow the development of shared informal technology that acts as insurance against liquidity shocks; this technology benefits both parties and cannot be provided by other lenders. This production technology depends on the fraction of trade credit in the total credit of the firm. Long-term relationships also allow firms to renegotiate debt more easily with their sellers (Wilner, 2000). Moreover, industrial organization research (e.g., Johnson *et al.*, 2002) shows that trade credit duration affects buyers' payment decisions, such that longer durations lead to credit payments, whereas short durations favor cash payments.

2.2. Lending Technologies and Soft Information

The banking literature underline the role of lending technologies for firms' credit availability. Berger and Udell (2006, p. 2946) define a lending technology as "a unique combination of primary information source, screening and underwriting policies/procedures, loan contract structure and monitoring strategies/mechanisms". The literature essentially focused on two lending technologies: relationship lending and transactional lending (Berger and Udell, 2006; Bartoli et al., 2013). The main difference between these two technologies is the source of information used in granting and monitoring the loan. Relationship lending is based on soft information, qualitative information obtained via personal interaction, that is difficult to codify and transfer (Rajan, 1992). Instead, transactional lending is primarily based on hard quantitative information, such as information derived from the balance sheets or the collateral guarantees they offer (Berger and Udell, 2006; Bartoli et al., 2013). Thus, the literature proposes that a transaction lending technology is more appropriate for more transparent firms, while the relationship lending technology is more suitable for opaque firms (i.e., the firms that are more affected by problem of asymmetries of information) (Berger et al., 2005; Stein, 2002). Ferri and Murro (2015) suggest that changes in the bank organization or "reverese-asymmetry of information" between the firm and the bank could result in firm–bank mismatches (i.e. an imperfect firm-type/bank-type match). This mismatch has impacts: when opaque firms match with transactional banks, their probability of being credit-rationed increases.

2.3. Hypotheses

Uchida *et al.* (2013) link trade credit and relationship lending literature to develop their relationship lending hypothesis. They first compare the private information that trade creditors acquire (e.g., Biais and Gollier, 1997; Burkart and Ellingsen; 2004) with the information defined by Stein (2002) as soft. They show that trade creditors can play exactly the same roles as banks that use relationship lending technology, that is, accumulating and using information. For firms, information production and management generates the same advantages as those generated by relationship lending technology: better access to credit and better credit conditions, even when firms are in a downturn.

Therefore, trade creditors can be relationship lenders in cases of mismatching, and opaque firms may be able to use trade credit as a funding alternative. To avoid being misevaluated and having to increase their numbers of bank creditors, these firms can decide to borrow from their trade creditors, because their trade creditors can evaluate their soft information. If it's the case, we should observe a higher level of trade credit for opaque firms in case of mismatching:

H1: Opaque firms that encounter banks that use transactional lending technology have a higher portion of trade credit than others.

However, trade credit is more expensive than bank credit,[1] and when firms are liquidity-unrestricted and have an access to relationship lending technology, they may favor cheaper bank credit over more expensive trade credit (Biais and Gollier, 1997; Burkart and Ellingsen, 2004). That is, opaque firms have no interest in substituting their bank credit with trade credit when they are correctly evaluated; when they encounter face banks that manage soft information, they should have lower trade credit. Indeed, we should observe a lower level of trade credit in this case.

H2: Opaque firms that encounter banks that use relationship lending technology have a lower portion of trade credit than others.

3. Methodology and data

3.1. Data sources

The database comes from the 10th wave of the Survey of Italian Manufacturing Firms (SIMF), conducted in 2007 by the UniCredit banking covering the years 2004-2006. It contains information about approximately 4,500 Italian manufacturing firms with more than 10 employees. The strength of this database is its extensive information on firms: balance sheets, income statements, ownership structures, numbers and skill degrees of employees, R&D, internationalization and export, and—of greatest interest—information about firm relationships with the banking system and financial management from the point of view of those firms. By having information about a firm's main bank and its relationship with that bank, from the point of view of the firm, we can analyze a firm's choices according to what it perceives, rather than

[1] A "2/10 net 30'' agreement (take 2% discount if the firm pays in 10 days, otherwise pay in 30 days) means an implicit interest rate of 43.9% for firms that do not take the discount (Ng *et al.*, 1999)

according to reality.[2] We also use information from the Italian National Statistics Office (ISTAT) and from Aiello and Bonanno (2015) to complete our database with macroeconomic variables. All variables are described in Table A1.

Particularly relevant for our analysis, the 2007 wave of the SIMF featured a new set of questions expressly tailored to investigate the relationship between the firm and its main bank (Ferri and Murro, 2015). Unfortunately, only one third of the total number of surveyed firms answered this section of the survey. Thus, our final sample is composed of 962 firms. Table A2 in the Appendix presents the descriptive statistics for the full and the selected sample.[3] On average, firms have 30 years of existence and 138 employees in our sample (columns 3 to 4). The large majority of firms are corporations (96.7%), and more than one-quarter belong to a group or consortium. On average, firms have relationships with 5–6 banks and a relationship length of about 17 years with their main bank, which in about 35% of cases is national. We can note that globally, firms from our sample have the same characteristics in term of size, age or status than firms in the full sample.

3.2. Methodology

To test our hypotheses, we use the following model:

$$y_i = \alpha + \beta * soft_i + \gamma * LT_i + \delta * (soft_i * LT_i) + \theta * control + \varepsilon_i \qquad (1)$$

where y_i is the importance of trade credit in firm funding; $soft_i$ is a measure of the opaqueness of the firm through the use of soft information during the credit application; LT_i is the lending technology used to finance the firm, such that it captures the quantity of soft and hard information managed; $soft_i * LT_i$ is the interaction term between those variables; $control$ is a vector of control variables; ε_i a vector of heteroskedastic-robust standard errors.

3.3. Variables

3.3.1. Trade credit, lending technology, and soft information

We seek to explain the use of trade credit by the type of information used by the firm and the lending technology used by the bank. The use of trade credit can be divided into two terms: quantity and duration. As a measure of the quantity of trade credit, we use one proxy: TC/TL,

[2] For a complete description of the data set, see Bartoli *et al.* (2013).
[3] We cannot rule out self-selection: the firms that answered these questions are slightly larger than the sample mean, while they are similar to the other firms regarding further characteristics, such as main bank type, industry or age.

which is the ratio of the amount of trade credit to the total loan for the firm at the end of December 2006. As a robustness check, we will also use three alternative measures of trade credit: TC/TA, which is the ratio of the amount of trade credit to the total assets for the firm at the end of December 2006. TC/STL, which is the ratio of the amount of trade credit to total outstanding short-term loans at the end of December 2006. DPO (days payable outstanding), which is a measure of the duration of trade credit. This ratio measures how long it takes for the firm to pay its invoices from its suppliers, equal to:

$$DPO = \frac{average\ trade\ payable_{2006}}{cost\ of\ goods\ sold_{2006}} * 360.$$

The higher the ratio, the more important it is that the firm is liquid. Because all our dependent variables are continuous variables, we use ordinary least square models in all cases.

With regard to lending technology, we use the methodology of Bartoli *et al.* (2013) to develop two indicators: one for transactional lending technology (LT_TRANS) and one for relationship lending technology (LT_REL). To capture what kind of lending technology firm respondents believe their banks use, we ask, "In your view, what criteria does your bank follow in granting loans to you?" Firm respondents must provide a weight of 1 (very much) to 4 (nil) for 15 items. Table 1 displays the items, the distribution of the answers for each item, and the manner in which each item is classified in the construction of the indicators.

The respondents believe the most important criteria are accounting criteria: approximately 20% of the sample chose 1 (very important) for criteria 1–4, whereas other items were chosen by about 10% of the sample. Thus, firm respondents believe that banks use more accounting information than other information.

Table 1: Items used to construct our lending technology indicators

This table displays the 15 items used to answer to the question "*In your view, what criteria does your bank follow in granting loans to you?*" the distribution of the answers for each item from 1 (very important) to 4 (nil), and how each item is classified to construct the lending technology indicators, i.e., relationship (R) or transactional (T).

Items	1	2	3	4	T/R
1. Ability of the firm to repay its debt (e.g., years needed to repay its debt)	20.39%	44.73%	8.55%	25.33%	T
2. Financial solidity of the firm (capital/asset ratio)	20.29%	47.37%	7.11%	25.23%	T
3. Firm's profitability (current profits/sales ratio)	18.23%	44.80%	10.09%	26.88%	T
4. Firm's growth (growth of sales)	18.74%	41.92%	13.59%	25.75%	T
5. Ability of the firm to post real estate (not personal) collateral	9.89%	41.40%	18.64%	30.07%	T
6. Ability of the firm to post tangible non-real estate collateral	8.24%	42.43%	18.54%	30.79%	T
7. Support by a guarantee association (e.g., loan, export, R&D)	13.18%	31.31%	15.14%	40.37%	
8. Personal guarantees by the firm's manager or owner	11.33%	46.14%	9.27%	33.26%	T

9. Managerial ability on the part of those running the firm's business	12.46%	49.02%	11.12%	27.39%	R
10. Strength of the firm in its market (number of customers, commercial network)	10.71%	44.49%	15.65%	29.15%	R
11. Intrinsic strength of the firm (e.g., ability to innovate)	14.93%	44.59%	13.18%	27.29%	R
12. Firm's external evaluation or its evaluation by third parties	10.61%	44.39%	16.27%	28.73%	
13. Length of the lending relationship with the firm	11.33%	48.20%	13.29%	27.19%	R
14. Loans granted when the bank is the firm's main bank	11.33%	50.98%	9.17%	28.53%	R
15. Fiduciary bond between the firm and the credit officer at your bank	11.49%	49.54M	11.12%	25.85%	R

With regard to transactional lending technology, Berger and Udell (2006) consider six possible transaction-based lending technologies: financial statements, small business credit scoring, asset-based lending, factoring, fixed-asset lending, and leasing. Unfortunately, the survey provides information for only three of these technologies: financial statements (items 1–4), real estate (item 5), and other fixed assets (items 6–8). We construct an aggregate variable (LT_TRANS), equal to the average of seven dummy variables, which takes a value of 1 if the firm assigned a value of 1 to the previous lending items. The higher the variable, the more the firm regards its bank as transactional.

With regard to relationship lending technology, Berger and Udell (2006) explain that it is primarily based on soft information and developed through contact over time. It represents qualitative information about the firm, such as manager reliability or the intrinsic strength of the firm (Stein, 2002). We focus on all items that can correspond to one of these characteristics: items 9, 10, 11, 13, 14, and 15. The aggregate variable (LT_REL) is equal to the average of six dummy variables and takes a value of 1 if the firm respondent answers 1 in response to the lending items.

We construct our indicator of opaqueness by capturing the emission of soft information by the firm during the credit application, using a methodology similar to that adopted by Uchida *et al.* (2012), Bartoli *et al.* (2013) and Cucculelli et al. (2018). We assume that the firm, knowing whether it emits soft information, chooses its bank accordingly. Therefore, we ask, "Which characteristics are key in selecting your main bank?" Firm respondents must provide a weight ranging from 1 (very important) to 4 (nil) for 14 items, as detailed in Table 2.

Table 2: Items used to construct our soft indicator

This table displays the 14 items used to answer to the question "*Which characteristics are key in selecting your main bank?*" and the distribution of the answer for each item, from 1 (very important) to 4 (nil).

Items	1	2	3	4
1. The bank knows you and your business.	25.64%	45.21%	4.12%	25.03%
2. The bank knows a member of your Board of Directors or the owners of the firm.	13.49%	52.63%	7.83%	26.06%

3.	The bank knows your sector.	14.83%	51.80%	8.65%	24.72%
4.	The bank knows your local economy.	11.74%	55.61%	7.93%	24.72%
5.	The bank knows your relevant market.	9.37%	54.58%	9.99%	26.06%
6.	You have frequent contacts with the credit officer at the bank.	14.93%	50.26%	9.99%	24.82%
7.	The bank takes quick decisions.	18.33%	44.70%	12.77%	24.20%
8.	The bank offers a large variety of services.	18.23%	49.33%	8.14%	24.30%
9.	The bank offers an extensive international network.	14.62%	44.90%	14.11%	26.36%
10.	The bank offers efficient internet-based services.	12.67%	46.24%	14.32%	26.78%
11.	The bank offers stable funding.	11.74%	47.27%	13.08%	27.91%
12.	The bank offers funding and services at low cost.	13.80%	43.36%	14.52%	28.32%
13.	The bank's criteria to grant credit are clear.	13.70%	46.04%	14.62%	25.64%
14.	The bank is conveniently located.	16.48%	46.76%	11.23%	25.54%

The most important characteristics for the firm is the first item: "The bank knows you and your business" (25.64% of the sample). This finding reveals the importance, to the firm, of its relationship with its bank. The two next most important characteristics are the seventh and the eighth items (respectively, 18.33% and 18.23%); both show that one of the first preoccupations of customers is to not lose time with banks. They want a quick-acting bank that can provide all the services they want.

To construct our indicator, we choose two items: 1) the bank knows you and your business; 6) you have frequent contacts with the credit officer at the bank. The variable *SOFT* is a dummy that takes the value of one if the firm respondent answers 1 for both these items. In our sample, 8.65% of firms use mostly soft information when they conduct business with their banks.

Table A3 in the Appendix displays the correlation matrix between our dependent variables and our lending technology and information indicators. Except for the DPO, our lending technology and soft indicators never correlate with our dependent variables. In the case of DPO, correlations are positive and significant with our *SOFT* and *LT_REL* indicators. With regard to the lending technology and information indicators, the indicators *LT_TRANS* and *LT_REL* are correlated significantly and positively. This result supports Bartoli *et al.*'s (2013) finding that relationship and transactional lending technologies are complementary. Finally, the emission of soft information is correlated with the perception of type of bank (transactional or relationship).

3.4. Control variables

We include three additional types of control variables: bank controls, firm controls, and macroeconomic controls. For the bank variables, we define a dummy, NATIONAL, a dummy variable equal to one if the main bank is a national bank or a foreign bank, and zero if the main bank is a smaller mutual bank, larger-sized cooperative bank, savings bank, or other type of bank.

For the firm variables, we control for several characteristics: firm quality, using the leverage and the profitability of the firm (Bartoli et al., 2011). To control for the (lack of) opaqueness of the firm, we control for the portion of firm's total assets that are fixed assets (FA/TA) and AUDIT, equal to one if the firm has a certified accounting statement (potential hard information emitted), zero otherwise (Mc Namara et al., 2017). We control for firm size, using the logarithm of the firm age and the logarithm of the number of employees. To control for firm's relationship with financial institutions, we add the logarithm of the number of institutions the firm deals with (Log Bank); the distance between the firm and its main bank (Distance); the length of relationship between them (Rel. Length); and whether the firm has already been rationed by its bank (Credit Rationed). In addition, we include dummy variables indicating whether a firm is a corporation, it belongs to a business group or a consortium. Finally, we control for firm's geographic location, using a dummy variable for each of the 103 provinces in Italy and firm's sector, including a dummy variable for each of the six sectors represented in the database: agriculture, wholesale, construction, industrial production, service, and transport[4].

The last group of control variables is composed of macroeconomic variables. First, we control for the economic environment and investment opportunities using the gross domestic product (GDP) of the province in which the firm is located (Niskanen and Niskanen, 2006) and the loans/deposit ratio, which is a proxy for the traditional function of banks, that is, the transformation of deposits into loans (Aiello and Bonanno, 2015). The higher the ratios, the better the economy, and the higher the opportunities for investment. Second, we include provincial Herfindahl-Hirschman of bank branches, to control for bank competition that can affect the use of trade credit (Demirgüç-Kunt and Maksimovic, 2002; Murro, 2013). Third, to control for judicial efficiency, we add the number of civil suits pending in each judicial district in Italy (Herrera and Minetti, 2007) considering that more of civil suits pending implies a more inefficient legal system (Bianco *et al.*, 2005).

4. Results

4.1. Trade credit and lending technologies

[4] As a robustness check, we use two-digit ATECO dummies for firms' sectors. Results, available upon request, are qualitatively similar.

Table A4 provides results about the determinants of trade credit. The interaction term *SOFT * LT_TRANS* is positive and highly significant (Column 1); neither *LT_REL* nor *LT_TRANS* are significant. When faced with transactional banks, opaque firms, emitting mostly soft information, have more trade credit in their loans than others. However, for firms that use hard information, it does not change whether they encounter relationship or transactional banks. This finding confirms our first hypothesis: in cases of mismatch, in which opaque firms encounter transactional banks, they substitute trade credit for bank credit. The finding also supports the hypothesis of Uchida *et al.* (2013) that trade creditors can exhibit the same behavior as relationship lenders.

As explained previously, our transactional indicator (*LT_TRANS*) is composed of three technologies: financial statements, real estate, and other fixed assets. We decomposed our transactional indicator into three sub-indicators, *LT_FS*, *LT_RE*, and *LT_OF*; respectively, they capture each previous technology. In Columns 2–5, we test Equation 1, replacing our transactional indicator by each sub-indicator, first separately and then together, to determine whether the substitution is the same for all technologies. Firms substitute their bank loans only when they think their bank manages their financial statement technology (Columns 2 and 5) and real-estate technology (Columns 3 and 5) but not their fixed-asset technology (Columns 4 and 5).

About our second hypothesis: do opaque firms reduce their quantity of trade credit when they are in a good firm-bank matching? We find only weak evidence. In fact, the interaction term *LT_REL * SOFT* is negative and significant, suggesting that opaque firms in good matches have less trade credit in their total loans. However, the coefficient of the interaction term is significant only in some specifications (Columns 1 and 5).

The results for the firm-specific controls are in line with those in the literature. We find that the older the firm, the greater the importance of trade credit to firm funding. This result confirms the finding of Casey and O'Toole (2014) that older firms are more reliant on trade credit than younger firms are. In line with the expectations, trade credit is decreasing with the number of banking relationships, while the coefficient of relationship length with the main bank is not significant.

Consistent with results found by Demirgüç-Kunt and Maksimovic (2002), the higher the branch concentration in the province (HHI), the higher the use of trade credit. With regard to our measure of economic investment opportunities, both the variables *Loans/Deposit* and *GDP* are positive and significant. The greater the investment opportunities, the greater the use of trade credit. This result may seem unexpected. In fact, the literature suggest that higher investment opportunities are often associated with better availability of bank credit, leading to less use of other funding (Huyghebaert, 2006). However, Niskanen and Niskanen (2006) show that high investment opportunities lead to more need for credit than banks can provide; in such conditions, firms also use trade credit.

Finally, with regard to legal system efficiency, the use of trade credit is increasing with the number of civil suits pending in the judicial district. This result is consistent with theory that indicates when the legal system is inefficient and does not protect the banks, the use of bank credit decreases and the use of alternative funding increases (Demirgüç-Kunt and Maksimovic, 2002).

4.2. Robustness tests

Table A5 shows the results of some robustness checks.[5] First, in columns 1-3, we use alternative measure of trade credit (*TC/TA*, *TC/STL* and *DPO*) as dependent variables. Second, in columns 4-7, we create two new lending technology indicators: *MAINTRANS* and *MAINREL* to capture the main lending technology used by the bank. *MAINTRANS* is a dummy variable equal to one if LT_TRANS is larger than the 75% percentile of the distribution and LT_REL is lower than 75%, zero otherwise. *MAINREL* is a dummy variable equal to one if LT_REL is larger than the 75% percentile of the distribution and LT_TRANS is lower than 75%, zero otherwise.

The findings show that when the technology used is transactional, the firms emitting soft information present a higher portion of trade credit than others do. This is true whatever we use LT_REL as indicator of transactional lending (columns 1 to 3) or that we use MAINTRANS (4 to 7).[6] This strongly comfort our main results on the first hypothesis. Interestingly, results about relationship technology are consistent but less robust. When we use *MAINREL* indicator, the findings suggest that opaque firms have less trade credit than others (columns 4 to 7). However, when we consider LT_REL indicator the results disappear (columns 1 to 3).

5. Disentangling the mechanisms

[5] To conserve space, we do not include all control variables in the table, but results are available to any request.
[6] We also test the impact of each sub-indicator of *LT_TRANS* on the part of trade credit and results remain the same as previously. Results are available to any request.

In this section, we use the richness of the database to try to understand the mechanism that links firm-bank relationship and trade collapse.

5.1. Firm characteristics

Klapper *et al.* (2012) and Casey and O'Toole (2014) show that larger and older firms use more trade credit than smaller firms when they are constrained by the bank. One explanation suggests that because of their size and longer relationships with suppliers, they can negotiate better trade credit conditions than smaller firms. If it is true, we should observe a higher level of trade credit in particular for larger and older opaque firms. Moreover, larger and older firms have more often audited financial statements, which allow firms to switch more easily to another creditor. However, Berger and Udell (1995) explain that age can be a proxy for firms' publicly available information. As a firm's age increases, the quantity of information available also increases; the firm can more easily use this information and switch to a transactional banking system when relationship lending is not available. Therefore, the use of trade credit should be more important for smaller and younger firms.

Table A6 displays our results splitting our sample depending on three firms' characteristics: size (columns 1 and 2), age (columns 3 and 4) and the presence of audited statement (columns 5 and 6). We find that only older, larger and audited firms have more trade credit than bank credit in cases of mismatch.[7] In fact, the interaction term *SOFT * LT_TRANS* is positive and significant only in columns 2, 4 and 6. Moreover, the interaction term *SOFT * LT_REL* is significant and negative for older and larger firms. These results suggest that these firms have better access to bank credit and can more easily substitute relationship bank credit for trade credit, whereas younger, smaller firms must continue to use trade credit.

5.2. Bank-firm relation characteristics

De Bodt *et al.* (2015) show that a potential consequence of mismatching is the increase in the number of banks approached by firms, to find other banks that are able to evaluate them correctly. What happens when a firm already has a large pool of banks? To test this idea, we split our sample in two subsamples based on number of banks and run Equation (1) on each subsample. Table A7 provides the results. Column 1 corresponds to the results for subsamples in which firms have pools of three banks or less, and column 2 displays results in which firms have pools of more than three banks. The interaction term *SOFT * LT_TRANS* is positive and

[7] We split the sample using the mean value for age (30.247 years) and size (138.405 employees). As a robustness check, we use as threshold 50 employees. Results, available upon request, are qualitatively similar.

significant only when the firm has a pool of three banks or fewer (Column 1). That is, only opaque firms with a small pool of banks increase their portion of trade credit, because they substitute trade credit for relationship credit in cases of mismatching. This result supports our idea that opaque firms with large banking pools favor credit from other banks over trade credit.

Concerning the length of relationship, the literature shows that transmitting information takes time and is costly for firms and that firms, emitting soft information, can be “informally capture” by their bank (Sharpe, 1990; Rajan, 1992). Thus, we can suppose that firms, which already develop a long relationship with their bank, will be less able to switch to another bank and are more incline to switch to trade credit. The results confirm this hypothesis. Splitting our sample depending on the length of relationship (Table A7 columns 3 and 4), we find that substitution is only done by firms which have few years of relationship (below or equal to 2 years) with their bank.[8]

5.3. Banks characteristics

Berger *et al.* (2005) prove that larger national banks have an advantage in managing hard information and that smaller local banks have an advantage in managing soft information because of their respective decision-making organizational structures. However, Ferri and Murro (2015) find that the impact of mismatch on credit rationing is larger when the main bank is a local bank. In line with Ferri and Murro (2015) we expect that trade credit is more relevant for firms with a local bank as a main bank. In columns 1-2 of Table A8, we split the sample according to the nature of the main bank. The findings confirm the hypothesis: the coefficient of the interaction between soft information and transactional lending technology is significant only when the main bank is local. This seems to corroborate the role of switching costs as, on average, the firms with a local main bank have longer relationships with their main banks (Ferri and Murro, 2015).

In columns 3-4 of Table A8, we study the role of loan officer turnover. The literature underlines that banks can avoid diluting soft information by delegating lending authority to the same agent that collects it, the loan officer (Stein, 2002; Liberti and Mian, 2009). Thus, we expect that rationing conditional on mismatch may be less probable for banks with infrequent loan officers' turnover. Indeed, Hertzberg *et al.* (2010) show that a rotation policy of loan officers in a bank

[8] As a robustness check, we split the sample using as a threshold 5 years. The results, available upon request, are qualitatively similar.

is linked to the lending technology used by the bank. However, the results show that the presence of turnover in the bank does not seem to affect the substitution between bank credit and trade credit for firms in mismatch (the interaction term *SOFT * LT_TRANS* is significant in columns 3 and 4).

5.4. Economic and social characteristics

Finally, economic and social environment can also affect the use of trade credit through different way (e.g., trust in banks, judicial efficiency, and economic development). We split our sample depending on the location of the firm in Italy (North, Center or South). The three Italian macro-regions differ significantly in terms of socio-economic development (D'Onofrio et al., 2018). The North of Italy includes those regions with the highest levels of per capita GDP, while the South is poorer and is the area with lower levels of trust (Guiso et al., 2004; Murro and Peruzzi, 2018). Table A9 columns 1 to 3 displays our results. We can note that the substitution is mostly effective in the North and the Center of Italy, but not in the South. This suggests that the substitution is possible where the local economic environment is high.

Guiso *et al.* (2004) show that the social capital also have an important impact on the financial development in the different areas in Italy: a high social-capital leads to a more important financial development in the area. To capture this effect, we use Guiso *et al.* (2004) measure (see Table A1 for a description) then we split our sample depending on the mean Social value (columns 4 and 5 Table A9). We can see that firms emitting soft information have a higher part of trade credit in case of mismatching only in area with a high social capital, confirming the relevance of socio-economic conditions for the access to alternative sources of credit.

6. Endogeneity of match and trade credit

We are aware that our estimation may be affected by a potential endogeneity problem. We assume that opaque firms, which are in case of mismatching, increase their level of trade credit as they are more credit rationed by the bank. However, the level of trade credit can also drive the relation between the firm and its bank. Opaque firms with a high level of trade credit either can decide not to emit soft information, due to its cost, or can be less careful in their bank choice. Moreover, credit-constrained firms could have an incentive to rely on more trade credit to send a signal to banks and improve their access to bank credit (Minetti et al., 2018).

We deal with this potential endogeneity using an instrumental variable regression. As we need to solve our endogeneity issue on both our soft indicator and our lending technology indicators, we consider six instrumental variables. First, following Ferri and Murro (2015), we use an index of self-confidence of the firm. The index of self-confidence is an average of the dummies constructed on the characteristics 7, 8, 9, 10, 11, 12 and 14 from the question "*Which characteristics are key in selecting your main bank?"* (Table 2). As explained by the authors, this variable captures "the importance that a firm places on the ex-ante transactional features of its bank". Thus, higher is the value of this variable lower is the needs to emit soft information for the firm. Moreover, as additional instruments, we use the: provincial quantity of banks' M&A over the 2002–2006 period, the loan officer turnover, the functional distance between hierarchical levels in the province over the 2000–2005 period (Alessandrini *et al.*, 2010) and the average of our transactional and relationship lending indicators at provincial level.

Banks' mergers and acquisitions lead to change the strategy of the bank. Therefore, a high level of M&A in the province implies high potential changes in the structure of the bank leading to a possible mismatch (Ferri and Murro, 2015). We also use the functional distance between hierarchical levels for the banks in the same province of the firm. This variable is equal to the number of branches operating in the province, each weighted by the logarithm of one plus the kilometric distance between the capital of that province and the capitals of provinces where parent banks are headquartered (Alessandrini *et al*., 2010). A high functional distance leads to deteriorate the potential use of soft information by the bank so can lead to a change in the lending technology used by the bank. Finally, we use the average level of our transactional and relationship proxies at provincial level (*Province LT_TRANS* and *Province LT_REL*). These variables are used to capture potential local effect on the technology used by the bank (Caprio *et al.*, 2007).

Table A10 displays our results. The first part of the table reports results concerning our three endogenous variables. We can note that an important loan officer turnover leads to increase the probability that the bank use a transactional lending technology, but decrease the use of relationship lending. Which is consistent with Hertzberg *et al.* (2010) results. Functional distance also affect negatively the use of relationship technologies. Concerning our soft indicator, the Self-Confident index decreases the use of soft information, which is consistent with Ferri and Murro (2015).

Now, if we turn to the second part of the table, we can note that our interaction indicator *SOFT*LT_TRANS* is positive and significant in all columns. This means that the more opaque the firm, the stronger the effect of transactional on the use of trade credit. Interestingly, our interaction indicator *SOFT*LT_REL* is negative and significant in all columns, suggesting that a good matching between an opaque firm and a relational bank reduces the use of trade credit. Therefore, our results seem to be robust also when we account for the possible endogeneity issues.

7. Conclusion

The motivation of firms to use trade credit has been an important puzzle in finance. There are currently two main explanations: real operations and financial. This study is part of the latter group, pertaining to the strength of firm–supplier relationships formalized by Uchida *et al.* (2013), who show that trade creditors can act as relationship lenders. With this article, we go a step further to ask whether trade credit can substitute for relationship credit when firms cannot otherwise find such credit. Using an Italian database, we find strong evidence that firms that use soft information, faced with transactional banks, have greater portions of trade credit in their global debt. Trade creditors, acting as relationship lenders, are better able to evaluate firms than transactional banks and offer better credit conditions; thus opaque firms, mismatched with their banks, substitute trade credit for bank credit. Moreover, we find (weak) evidence that these opaque firms decrease their portions of trade credit when they face relationship banks. Our results hold only for larger and older firms, confirming Klapper *et al.*'s (2012) results. Older and larger firms may more easily substitute bank credit for trade credit when their banks do not correctly evaluate them. We also show that this substitution depends on several parameters. The number of relationships with banks and the length of the relationship with the main bank reduces the probability that an opaque firm in mismatch uses trade creditor, suggesting the relevance of switching costs. Finally, economic development and high level of social capital increase the substitution effect.

This paper might warrant some policy actions that lower switching costs for the firms, but that not exogenously reduce the relevance of relationship lending for the banks. Such policies would help reduce the financial frictions for the firms through bank or trade credit.

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Table A1 – Variables description

Variable definition and source.

Variable	**Description**
Dependent variables	
TC/TL	Ratio of firm's trade credit to total loans as of the end of December 2006
TC/TA	Ratio of firm’s trade credit to total assets as of the end of December 2006
TC/STL	Ratio of firm’s trade credit to total short-term loans as of the end of December 2006
DPO	Days payable outstanding (average trade payable/cost of goods sold) * 360
Variables of interest	
SOFT	We use the following question of the Survey: ‘‘Which characteristics are key in selecting your main bank?’’ In answering this question, the firm was required to give a value, with descending order of importance, from 1–4, to the two following characteristics (among others): ‘‘The bank knows you and your business’’ and ‘‘You have frequent contacts with the credit officer at the bank.’’ The variable Soft is a dummy that takes value one if the firm chose the highest value for both the above two characteristics. (Bartoli *et al.*, 2013).
LT_TRANS	Global index for transactional lending technology; we use a question available in the Survey: ‘‘In your view, which criteria does your bank follow in granting loans to you?’’ In answering this question, the firm was required to give a weight, from 1 (very much) to 4 (nil) to 15 factors. LT_TRANS, is an average of six dummy variables that take a value of 1 if the firm answered “1” to lending factors 1, 2, 3, 4, 5, 6, and 8 respectively. (Bartoli *et al.*, 2013).
LT_FS	Index for financial statement technology; LT_FS is an average of four dummy variables that take a value of 1 if the firm answered “1” to lending factors 1, 2, 3, and 4 respectively (same question as LT_TRANS).
LT_RE	Index for real estate technology; LT_RE is a dummy equal to 1 if the firm answered “1” to lending factor 5 (same question as LT_TRANS).
LT_OF	Index for other fixed-asset technology; LT_OF is an average of four dummy variables that take a value of 1 if the firm answered “1” to lending factors 6 and 8 (same question as LT_TRANS).
LT_REL	Index for relationship lending technology; we use a question available in the Survey: ‘‘In your view, which criteria does your bank follow in granting loans to you?’’ In answering this question, the firm was required to give a weight from 1 (very much) to 4 (nil) to 15 factors. LT_REL, is an average of six dummy variables that take a value of 1 if the firm answered “1” to lending factors 9, 10, 11, 13, 14, and 15 respectively. (Bartoli *et al.*, 2013).
MAINTRANS	1 if LT_TRANS is larger than the 75% percentile of the distribution and LT_REL is lower than 75%
MAINREL	1 if LT_REL is larger than the 75% percentile of the distribution and LT_TRANS is lower than 75%
Control variables	
Firm variables	
LEVERAGE	Ratio of firm's total loan to total asset as of the end of December 2006/1,000
Firm Age	Log(1 + firm age)
PROFIT	Log(1+ Profit of the firm as the end of December 2006)

FA/TA	Ratio of firm's fixed assets to total assets as the end of December 2006
Firm Size	Log(1 + firm number of employees)
CORPORATION	1 if the firm is a corporation
GROUP	1 if the firm belongs to a group
CONSORTIUM	1 if the firm is member of a consortium
AUDIT	1 if the firm has certified accounting statement
Credit Rationed	Dummy takes a value of 1 if the firm answers "yes" to the question ''In 2006 would your firm have wished a larger amount of loans at the prevailing interest rate agreed with the bank?'' and "yes" to at least one of the following two questions: ''In 2006, did the firm demand more credit than it actually obtained?'' and/or ''To obtain more credit, were you willing to pay a higher interest rate?'' (Survey of Italian Manufacturing Firms)
Rel. Length	Log(1 + length of the relationship between the firm and the bank)
Log(Bank)	Log(1 + number of banks the firm deals with)
Province	Set of dummies for each Italian province (in Italy there are 110 provinces)
Sector	Set of dummies equal to 1 if the firm belongs one of six sectors: agriculture, wholesale, construction, industrial production, service, transport
Bank variables	
NATIONAL BANK	1 if the main bank is either a national bank or a foreign bank; 0 if the main bank is a smaller-sized cooperation mutual bank, a larger-sized cooperative banks, a saving bank, or other type of bank
Macroeconomic variables	
GDP	Log of the value of the GDP in the province as of the end of December 2006
HHI	Hirschman-Herfindahl Index calculated using the number of branches per bank in every province
Loans/Deposit	Ratio of deposits in loans at provincial level
Social Capital	Voter turnout at the province level for all the referenda before 1989. (Guiso *et al.*, 2004)
Civil suits	Average number of civil suits pending in the judicial district in 1998–2000, per 1,000 inhabitants (Herrera and Minetti, 2007)
Instrumental variables	
Province LT_TRANS	Average value of transactional lending technology for the firms in the province.
Province LT_REL	Average value of relationship lending technology for the firms in the province.
L.O. Turnover	1 if the loan officer of the firm's main bank changes during the 2001–2006 period.
Banks' M&A	Total number of merger and acquisitions in the province during the period 2002–2006. (SBBI)
Functional distance	Average banks' functional distance between hierarchical levels in the province during the period 2000-2005, as (Alessandrini *et al.*, 2010).
Self-Confident	Average of the dummies constructed on the characteristics 7, 8, 9, 10, 11, 12 and 14 from the question in Table 2.

Table A2 – Sample summary statistics

	Full Sample		**Analysis Sample**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Firm characteristics				
TC/TL	0.273	0.235	0.203	0.199
TC/TA	0.627	0.587	0.433	0.453
TC/STL	0.325	0.33	0.227	0.247
DPO	104.858	112.706	86.088	92.825
Number of Bank	4.985	3.901	5.592	4.271
Rel. Length	2.688	0.705	2.717	0.676
Firm Age	28.783	23.922	30.247	23.063
Profit	8.794	1.518	8.967	1.908
FA/TA	0.266	0.178	0.279	0.183
Firm Size (number of employees)	87.686	314.701	138.405	474.925
LEVERAGE	0.006	0.359	0.025	0.777
CORPORATION	0.949	0.219	0.967	0.176
GROUP	0.188	0.391	0.256	0.437
CONSORTIUM	0.032	0.177	0.033	0.179
Financial information				
SOFT			0.087	0.282
LT_TRANS			0.130	0.241
LT_REL			0.123	0.258
Credit Rationed			0.062	0.241
AUDIT			0.244	0.429
NATIONAL BANK			0.353	0.478
Macroeconomic variables				
GDP	10.220	0.188	10.221	0.182
HHI	0.097	0.036	0.099	0.037
Loans / Deposit	1.943	0.586	1.915	0.569
Civil Suits	0.003	0.005	0.003	0.005
Social Capital	0.846	0.054	0.847	0.055
Instrumental variables				
Province LT_TRANS			0.131	0.081
Province LT_REL			0.123	0.089
L.O. Turnover			0.267	0.443
Banks' M&A			0.251	0.301
Functional distance			2.873	0.825
Self-Confident			0.147	0.272
Observations	4,504		962	

Table A3

Correlation Matrix

The table provides the pairwise correlation matrix. The number in brackets indicates the p-value of the test of significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	TC/TL	TC/TA	TC/STL	DPO	SOFT	LT_REL	LT_TRANS
TC/TL	1.0000						
	[0.0000]						
TC/TA	0.9344***	1.0000					
	[0.0000]	[0.0000]					
TC/STL	0.9451***	0.8810***	1.0000				
	[0.0000]	[0.0000]	[0.0000]				
DPO	0.7994***	0.7945***	0.7693***	1.0000			
	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
SOFT	0.0214	0.0110	0.0133	0.0811**	1.0000		
	[0.5051]	[0.7313]	[0.6805]	[0.0116]	[0.0000]		
LT_REL	0.0346	0.0335	0.0394	0.0579*	0.2062***	1.0000	
	[0.2814]	[0.2964]	[0.2209]	[0.0720]	[0.0000]	[0.0000]	
LT_TRANS	0.0379	0.0384	0.0480	0.0512	0.1922***	0.6404***	1.0000
	[0.2379]	[0.2317]	[0.1364]	[0.1117]	[0.0000]	[0.0000]	[0.0000]

Table A4

Determinants of the Portion of Trade Credit in Total Loan

These regressions show the impact of the use of soft information and of lending technologies, divided into four indicators, on the quantity of trade credit in total loan. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

	(1)	(2)	(3)	(4)	(5)
	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	-0.052	-0.060*	-0.024	-0.033	-0.052
	[0.105]	[0.097]	[0.460]	[0.303]	[0.140]
LT_REL	0.014	0.043	-0.001	0.007	0.027
	[0.765]	[0.304]	[0.981]	[0.872]	[0.567]
SOFT * LT_REL	-0.240*	-0.085	-0.115	-0.041	-0.252*
	[0.072]	[0.394]	[0.257]	[0.698]	[0.063]
LT_TRANS	-0.003				
	[0.947]				
SOFT * LT_TRANS	0.390***				
	[0.005]				
LT_FS		-0.035			-0.047
		[0.280]			[0.166]
SOFT * LT_FS		0.181*			0.185**
		[0.052]			[0.042]
LT_RE			0.019		0.030
			[0.528]		[0.357]
SOFT * LT_RE			0.207**		0.175*
			[0.014]		[0.061]
LT_OF				0.010	0.008
				[0.839]	[0.871]
SOFT * LT_OF				0.129	0.021
				[0.215]	[0.846]
Credit Rationed	-0.001	-0.006	0.001	0.000	-0.003
	[0.966]	[0.834]	[0.962]	[0.998]	[0.923]
AUDIT	0.004	0.006	0.004	0.004	0.005
	[0.807]	[0.698]	[0.827]	[0.812]	[0.763]
Log(bank)	-0.028*	-0.028*	-0.030*	-0.027	-0.030*
	[0.087]	[0.097]	[0.070]	[0.103]	[0.067]
Rel. Length	-0.003	-0.006	-0.002	-0.003	-0.004

	[0.776]	[0.614]	[0.859]	[0.775]	[0.728]
Firm Age	0.037***	0.037***	0.036***	0.036***	0.037***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
PROFIT	0.002	0.002	0.001	0.002	0.001
	[0.740]	[0.717]	[0.801]	[0.711]	[0.789]
FA/TA	0.038	0.039	0.034	0.040	0.033
	[0.300]	[0.286]	[0.360]	[0.281]	[0.372]
Firm Size	-0.002	-0.003	-0.001	-0.003	-0.001
	[0.810]	[0.747]	[0.893]	[0.720]	[0.889]
LEVERAGE	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
CORPORATION	0.056	0.052	0.059	0.050	0.061*
	[0.124]	[0.157]	[0.109]	[0.166]	[0.098]
GROUP	-0.020	-0.019	-0.022	-0.020	-0.020
	[0.264]	[0.291]	[0.229]	[0.284]	[0.281]
CONSORTIUM	-0.031	-0.027	-0.036	-0.026	-0.034
	[0.412]	[0.478]	[0.334]	[0.509]	[0.363]
NATIONAL BANK	0.016	0.015	0.016	0.015	0.017
	[0.313]	[0.348]	[0.291]	[0.356]	[0.273]
GDP	0.956**	0.933**	0.975**	0.945**	0.976**
	[0.017]	[0.020]	[0.015]	[0.017]	[0.017]
HHI	16.971***	16.907***	17.267***	16.437***	17.819***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]
Loans/Deposit	0.556***	0.563***	0.567***	0.542***	0.587***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Civil Suits	82.221***	83.166***	83.569***	84.781***	82.517***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Province Indicators	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes
Constant	-12.885***	-12.638***	-13.125***	-12.695***	-13.221***
	[0.005]	[0.006]	[0.004]	[0.005]	[0.004]
Observations	962	962	962	962	962
R^2	0.145	0.140	0.144	0.138	0.148
Adjusted R^2	0.027	0.022	0.026	0.020	0.027

Table A5

Robustness Tests

These regressions show the impact of the use of soft information and of lending technologies on the use of trade credit (measured by three proxies). We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	TC/TA	TC/STL	DPO	TC/TL	TC/TA	TC/STL	DPO
SOFT	-0.058	-0.102	-8.383	-0.039	-0.043	-0.080	6.873
	[0.174]	[0.158]	[0.609]	[0.173]	[0.249]	[0.208]	[0.666]
LT_REL	-0.000	0.033	4.451				
	[0.999]	[0.751]	[0.812]				
SOFT * LT_REL	-0.187	-0.457	-63.782				
	[0.310]	[0.144]	[0.336]				
LT_TRANS	0.008	0.040	-4.725				
	[0.887]	[0.723]	[0.811]				
SOFT * LT_TRANS	0.328*	0.699**	156.501**				
	[0.088]	[0.031]	[0.027]				
MAINREL				-0.048	-0.069	-0.076	-24.785
				[0.251]	[0.160]	[0.406]	[0.137]
SOFT * MAINREL				-0.134**	-0.174**	-0.376**	-81.184***
				[0.041]	[0.045]	[0.012]	[0.005]
MAINTRANS				-0.028	-0.032	-0.053	-13.777
				[0.224]	[0.262]	[0.326]	[0.151]
SOFT * MAINTRANS				0.154***	0.146*	0.302**	64.366**
				[0.008]	[0.060]	[0.021]	[0.036]
Control Variables	All	All	All	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-15.106**	-26.411***	-4.7e+03***	-13.494***	-15.659**	-27.868***	-5.0e+03***
	[0.016]	[0.007]	[0.005]	[0.004]	[0.013]	[0.005]	[0.003]
Observations	962	962	962	962	962	962	962
R^2	0.129	0.147	0.166	0.145	0.132	0.148	0.168
Adjusted R^2	0.009	0.030	0.052	0.028	0.013	0.031	0.054

Table A6 – Firm characteristics

These regressions show the impact of the use of soft information and of lending technologies on the quantity of trade credit in total loan, splitting the sample according to some firm characteristics. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

	By number of employees		By firm age (year)		By Audited	
	≤ mean	> mean	≤ mean	> mean	Not Audited	Audited
	(1)	(2)	(3)	(4)	(5)	(6)
	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	0.006	-0.093**	0.080	-0.116***	-0.031	-0.296***
	[0.910]	[0.032]	[0.277]	[0.001]	[0.397]	[0.000]
LT_REL	0.036	0.004	-0.019	0.006	-0.020	0.169
	[0.649]	[0.947]	[0.780]	[0.922]	[0.697]	[0.335]
SOFT * LT_REL	0.086	-0.327***	0.103	-0.352***	-0.167	-0.194
	[0.646]	[0.005]	[0.576]	[0.001]	[0.326]	[0.423]
LT_TRANS	0.074	-0.071	0.092	-0.036	0.041	-0.085
	[0.316]	[0.302]	[0.225]	[0.572]	[0.457]	[0.429]
SOFT * LT_TRANS	-0.059	0.604***	-0.181	0.679***	0.255	0.743***
	[0.775]	[0.000]	[0.392]	[0.000]	[0.148]	[0.001]
Control Variables	All	All	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.908	-68.303*	-1.579	-15.373**	-14.812***	-30.017
	[0.822]	[0.069]	[0.924]	[0.013]	[0.003]	[0.370]
Observations	470	492	419	543	727	235
R^2	0.247	0.251	0.226	0.259	0.165	0.391
Adjusted R^2	0.027	0.057	-0.008	0.084	0.018	-0.011

Table A7 – Firm-Bank Relationship

These regressions show the impact of the use of soft information and of lending technologies on the quantity of trade credit in total loan, splitting the sample according to some characteristics of the firm-bank relationship. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

	By number of banks		By Length of Relationship	
	≤ 3 banks	> 3 banks	≤ 2 years	> 2 years
	(1)	(2)	(3)	(4)
	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	-0.075	-0.047	-0.019	-0.107
	[0.256]	[0.254]	[0.630]	[0.112]
LT_REL	0.050	0.023	-0.011	0.054
	[0.552]	[0.701]	[0.841]	[0.625]
SOFT * LT_REL	-0.306	-0.184	-0.208	-0.127
	[0.176]	[0.329]	[0.182]	[0.561]
LT_TRANS	-0.075	0.002	-0.003	-0.010
	[0.334]	[0.971]	[0.956]	[0.934]
SOFT * LT_TRANS	0.537**	0.321	0.369**	0.260
	[0.026]	[0.112]	[0.026]	[0.342]
Control Variables	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes
Constant	2.024	-11.306**	-12.365**	-33.736
	[0.928]	[0.032]	[0.010]	[0.157]
Observations	350	612	718	244
R^2	0.322	0.198	0.168	0.341
Adjusted R^2	0.072	0.029	0.016	-0.040

Table A8 – Bank characteristics

These regressions show the impact of the use of soft information and of lending technologies on the quantity of trade credit in total loan, splitting the sample according to some characteristics of the main-bank of the firm. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

	By Bank type		By Turnover	
	National	Local	No Turnover	Turnover
	(1)	(2)	(3)	(4)
	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	-0.050	-0.054	-0.047	-0.027
	[0.294]	[0.291]	[0.223]	[0.729]
LT_REL	-0.067	0.038	0.022	-0.051
	[0.374]	[0.604]	[0.690]	[0.624]
SOFT * LT_REL	-0.150	-0.222	-0.244	-0.376
	[0.462]	[0.183]	[0.164]	[0.119]
LT_TRANS	0.079	-0.047	0.009	0.028
	[0.355]	[0.462]	[0.883]	[0.775]
SOFT * LT_TRANS	0.274	0.440**	0.351*	0.531*
	[0.208]	[0.010]	[0.052]	[0.058]
Control Variables	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes
Constant	-9.175	-10.397	-13.806**	23.788
	[0.193]	[0.524]	[0.014]	[0.628]
Observations	340	622	705	257
R^2	0.331	0.160	0.190	0.281
Adjusted R^2	0.066	-0.012	0.040	-0.076

Table A9 – Economic Environment

These regressions show the impact of the use of soft information and of lending technologies on the quantity of trade credit in total loan, splitting the sample according to the socio-economic conditions of the province in which the firm is located. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

	By Area			By Social Capital	
	North	Center	South	≤ mean	> mean
	(1)	(2)	(3)	(4)	(5)
	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	-0.067*	0.002	0.121	-0.077	-0.050
	[0.065]	[0.985]	[0.396]	[0.244]	[0.183]
LT_REL	-0.028	0.145	0.058	-0.069	0.044
	[0.588]	[0.218]	[0.699]	[0.425]	[0.398]
SOFT * LT_REL	-0.189	-0.748**	-0.343	0.052	-0.388***
	[0.206]	[0.019]	[0.577]	[0.850]	[0.000]
LT_TRANS	0.025	-0.109	-0.091	-0.010	-0.003
	[0.630]	[0.418]	[0.571]	[0.905]	[0.959]
SOFT * LT_TRANS	0.371**	0.547*	0.018	0.143	0.521***
	[0.021]	[0.058]	[0.977]	[0.632]	[0.000]
Control Variables	All	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes
Constant	-109.704***	40.485	11.057***	18.560	-63.826**
	[0.000]	[0.811]	[0.003]	[0.760]	[0.011]
Observations	688	166	108	287	675
R^2	0.116	0.260	0.552	0.275	0.116
Adjusted R^2	0.024	0.023	0.160	0.044	0.018

Table A10 – IV Regression

These regressions show the impact of the use of soft information and of lending technologies on the quantity of trade credit in total loan, using an IV approach. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ (as indicated in brackets).

First stage IV regress			
	(1)	(2)	(3)
	LT_TRANS	LT_REL	SOFT
Instrumental variables			
Province LT_TRANS	0.326	-1.644	
	[0.699]	[0.319]	
Province LT_REL	-0.099	1.619	
	[0.881]	[0.244]	
L.O. Turnover	0.033**	-0.035**	
	[0.018]	[0.011]	
Banks' M&A	-0.401	0.182	
	[0.200]	[0.677]	
Functional distance	0.004	-0.142*	
	[0.932]	[0.078]	
Self-Confident			-0.234***
			[0.000]
Control	All	All	All
Observations	962	962	962
R^2	0.642	0.648	0.203
Adjusted R^2	0.593	0.600	0.095

Second stage IV regression				
	(1)	(2)	(3)	(4)
	TC/TL	TC/TA	TC/STL	DPO
SOFT*	-0.075	-0.043	-0.392	-40.424
	[0.663]	[0.848]	[0.319]	[0.586]
LT_TRANS*	0.168*	0.152	0.409*	78.504*
	[0.084]	[0.196]	[0.066]	[0.056]
SOFT* # LT_TRANS*	-1.122**	-1.156*	-2.394**	-525.707**
	[0.017]	[0.067]	[0.036]	[0.019]
LT_REL*	-0.096	-0.106	-0.161	-61.188*
	[0.261]	[0.304]	[0.413]	[0.081]
SOFT* # LT_REL*	1.089**	1.168**	2.364**	614.799***
	[0.011]	[0.043]	[0.022]	[0.003]
Control	All	All	All	All
Observations	962	962	962	962
R^2	0.142	0.128	0.148	0.165
Adjusted R^2	0.024	0.009	0.031	0.052