THE RELATIVE PREDICTIVE STRENGTH OF DIFFERENT LENDING TECHNOLOGIES

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Abstract

Using a proprietary database of lending decisions to small and medium-sized enterprises (SMEs), the paper investigates how banks cope with adverse selection dilemma. Based on an intertemporal framework spanning over ex-ante decision period and ex-post check period, we qualify wrong and correct lending decisions. To this end, we disentangle the role of hard and soft information within the loan decision processes, and explore the predictive power of the different lending technologies. Empirical evidence suggests that both hard information and relationship lending variables are significant in predicting correct choices, as well as in increasing the probability of errors, because of adverse selection effect and soft budget constraint problems. Findings suggest that adverse selection can be better controlled by a durable bank-firm relationship, as well as by an atomistic loan decision process, at the local level. Differently, a loan decision-making exclusively based on hard-financial information may lead to adverse selection errors.

Keywords: Adverse selection; Lending technologies; SMEs; Relationship lending; Soft and hard information.

JEL classification: G21; G28; L25; O12; O16

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1. Introduction

Funding of small and medium-sized enterprises (SMEs) in recent years has become a significant topic for scholars and policymakers. Motivation of this interest is largely due to the relevance of SMEs, which account for the majority of firms in many countries. As an example, in Italy, they represent the 99.6% of the manufacturing sector in 2014 (OECD Factbook 2014).

Reinforcement for this interest is inspired by the well-known pecking-order theory (Myers and Majluf, 1984), suggesting that SMEs are more financially constrained, respect to large firms, because they are opaque (Berger and Udell, 1998 and Cole et al., 2004). This opaqueness implies that self-financing is the dominant financial source for SMEs, and among external finance banks are their largest financing source. For Italian SMEs, self-financing and bank loans measure, respectively, 65.5% and 49.1% of their total financing sources (Ministry of Economic Development Report, 2015).

As for bank finance, minor banks appear more sensitive than large banks to the relevance of SMEs to territorial economic growth (Berger et al., 2004). In this respect, a special role is played by minor banks represented by local cooperative banks (CBs) that at the national level in 2014, count for the 57% of the entire national system. CBs are non-profit, cooperative financial institutions governed by their membership on a one-member-one vote basis, with eligibility for membership defined by the CB's common bond. CBs are small and characterized by self-governance, and the principle of mutuality, i.e. their activity is biased in favour of its members as well as the moral, cultural and economic development of the local community (Ayadi et al., 2010).

Taking into account this special role of CBs in reducing the SMEs' opaqueness and financial constraints this paper contributes at understanding lending decision processes, and exploring the role of information used by banks to take lending decisions. The main aim of the paper is to analyze the relative power of different lending technologies in predicting the quality of loan decisions. To our knowledge, this paper is one of the first attempt to run an extensive "horse race" on the predictive power of different lending technologies in terms of their ability to predict firm outcomes – i.e., correctly predict downgrades and avoid falsely predicting downgrades

We refer to most recent theoretical paradigms on bank-firm relationship that overcome some traditional dichotomies of lending process definitions. First, those based on the association between *types* of banks with *types* of firms (DeYoung et al., 2004; Berger and Udell, 2006; Berger and Black, 2011). Second, those based on counter-position of a relationship-based versus transaction-based lending approaches (Berger and Udell, 2006). Finally, those based on opposition of soft information, largely obtained thanks to personal knowledge (Boot, 2000), against hard information, considered neutral and easily transferable across time and space (Udell, 2008).

Precisely, in the context of the paradigm of *lending technologies* defined by Berger and Udell (2006, p.2946) as "a unique combination of primary information source, screening and underwriting policies/procedures, loan contract structure, and monitoring strategies/mechanisms", we qualify lending technologies on the basis of the informative content that characterises the relative lending processes. Therefore, our main aim is to test the relative predictive strength of different lending technologies over all loans and not on the subset of loans where they would likely be the primary underwriting technology. Moreover, we do not want to introduce an ordinal classification among the different lending technologies, but to assess their predictive power in a context characterised by complementarity rather than substitutability among them.

To this purpose, we propose a bank-specific archetype of four lending technologies referred to small banks specialized in SMEs' loans. We associate to each technology a mixed combination of hard and soft information that banks expect to exploit: from the '*financial statement lending'*, that is entirely based on hard information, up to the '*relationship lending*', that is entirely based on soft information.

By disentangling hard and soft information within each lending technology, we are able to capture its specific role in affecting correctness of banking choices. Any lending decision, especially when borrower's opaqueness intensifies, such as the case of SMEs credit market, is exposed to an adverse selection dilemma.

To this aim, within a panel structure, we set probit models in order to estimate which, among the different lending technologies of our bank-specific archetype, is significantly able to predict loan quality grade: i.e. granting loans to ex-post bad credit quality borrowers or granting loans to ex-post good credit quality borrowers.

Results indicate that when the decision exploits just accounting information, i.e. hard data banks are induced to rise credit availability with an increasing probability of adverse selection errors. As for relationship lending technologies, mainly based on soft information, results suggest that being a long-standing customer of a bank, and operating intensively, may help the bank to overcome adverse selection problem, mainly when the loan decision process is individually and autonomously managed by the local loan officer. However, being an exclusive customer (a sort of house-bank customer) induces the bank in the error of soft-budget constraint.

The paper is organized as follows. The next section reviews the literature on bank lending paradigms to SMEs and presents the intertemporal framework used to classify lending decisions. The third section presents the data and methodology. The fourth one describes the bank-specific lending technologies and control variables used in the empirical section. Section fifth illustrates the results while the sixth section reports the robustness tests. The final section concludes and discusses some policy implication and future development of this study.

2. Theoretical framework

2.1. Small business credit availability and relationship lending

From a theoretical perspective, SMEs opacity implies that banks face difficulties in evaluating both small firms' capacity and their willingness to serve debt, because of their uncertain business profitability and their likely moral hazard behaviours (De la Torre et al., 2010). Hence, impersonal or arms-length lending processes, based on objective and transparent information, may result to be less effective/adapt for SMEs than relational lending processes, that tend to be better exploited by small banks. Coherently, the so-called 'current paradigm' suggests an association of *types* of lending banks with *types* of firms (DeYoung et al., 2004; Berger and Udell, 2006; Berger and Black, 2011), and brings about a dichotomy of lending process, generally correlating with bank dimensions: a relationship versus a transaction-based lending (Bartoli et al., 2013). An inevitable deduction is a different kind of information handled within these lending processes: soft versus hard information. On the one hand, relationship lending primarily depends on soft information (Boot, 2000 and Stein, 2002), which is mainly a qualitative information, such as the personal knowledge of the firm owner and its management as well as the assessments of the SMEs future prospects. On the other hand, the so-called transaction lending is based on hard information[1], i.e. a quantifiable and easily stored information that can be produced and communicated over long distances (Udell, 2008). A more recent stream of the literature (Udell, 2008, Berger and Udell, 2006; Berger and Black, 2011; Berger, 2015; Udell, 2015) indicates fallacies of an ‘optimal' lending technology in convincingly describe the lending production process of a bank. In this respect, we define a lending technology as a process a lending technology based on soft and hard information content that characterises the relative lending processes.

To address the informational opacity problem, a new paradigm emerges suggesting that it does not exist only a transaction lending technology. Rather, there are many different types of transactions lending technologies quite dissimilar because of different degree of hard information all but one of them is well suited for funding opaque SMEs. Some Authors (see Berger, 2012 and Udell, 2015) identify different types of lending technologies based on different mix of soft and hard information adapted to lend to both opaque and transparent SMEs. As in the previous paradigm (Berger and Udell, 2006), the relationship lending technology relies on soft information gathered over time through contact with the firm, the entrepreneur, and the local community, and through the provision of multiple services.

A different mix of soft and hard information characterize lending technologies; thus, they can change over time and across countries. Improvements in information and financial technology reformed boundaries of soft information, allowing even some forms of "hardening" the information used for SMEs loans. Theory (Petersen and Rajan, 2002 among others) argues that the developments in information processing and telecommunication technologies have improved banks' abilities to process and transmit over longer distance hard quantitative information about loans customers. Some lending technologies such as small-business credit scoring may have facilitated the ability of banks to increase the distance between small business borrowers and their banks. Nonetheless, the recent technological changes have not had such an effect in improving the processing and transmission of soft-information that persists to

[1] Even if in literature there is not an unconfutable dichotomy between the two types of information some characteristics can be unequivocally connected to hard information: i) it is almost recorded as numbers; ii) the collection method need not be personal; iii) it is objectively comparable over time. In summary, hard information is "easily concentrated into a fixed set of numbers that uniformly communicate there relevant information" (Petersen, 2004 – p. 9).

be strictly related to the personal discretionary judgement of the local loan officer in a sort of judgmental lending technology (Berger, 2015 – p. 303).

2.2. A lending paradigm reformulation

We propose a bank-specific paradigm based on a selection of lending technologies that are typically exploited by banks specialized in SMEs loans. We associate each specific lending technology with a graduation of hard/soft information that we expect being exploited by banks in dealing with that peculiar lending process. In fact, theory argues that a different processing of hard and soft information characterize different lending technologies (Berger, 2015 and Udell, 2015). Authors in other studies – Berger et al. (2005) and DeYoung et al. (2008) – focus also on the role played by hard information – summarized in the credit scoring technologies – and soft information usually associated to relationship lending technologies on firm's loan default and find that hard-information lending approaches may outperform soft-information lending approaches in "long-distance" situations.

Consistent with empirical validation, we disentangle nuances of hard and soft information along through the four lending technologies assumed as a sort of archetype for small cooperative banks (CBs) specialized in SMEs loan activity. As from Berger and Black (2011) and Berger (2015) we refer to: 1) financial statement lending, 2) small business credit scoring, 3) asset based lending, and 4) relationship lending (see Table 1).

Table 1: Lending technologies and information nuances

Lending technologies	Lending procedures/information	Typology of information	
Financial Statement L	Balance-sheet ratios	Hard	
Small Business Credit Scoring	Anomalies track-record	Hard & Soft	
Asset Based Lending	Collateral	Hard & Soft	
Relationship lending	Loan officer-entrepreneur contact & hierarchical decision process	Soft	

To each lending technology, we relate an increasing degree of soft information, since the financial statement lending is completely hard-information based. While Berger and Udell (2006) base their financial statement technology on audited statements prepared by a reputable accounting firm according to widely accepted accounting standards such as GAAP, we define a financial statement technology as a technology based on accounting ratio based on information collected from SMEs financial statements. In some way, our financial ratios are more in line with Kallberg, and Udell, G. F. (2003).

The *small-business credit scoring* in Berger and Udell (2006) is a transaction technology based primarily on hard information about the SME's owner as well as the firm. The owner information is primarily personal consumer data obtained from consumer credit bureaus. This is combined with data on the SME collected by the financial institution and often from commercial credit bureaus. In our case we build a score based on a regional statistical model for credit anomalies for CBs.[2] This credit-scoring index is based on the borrower position with respect to both the internal bank history and the system data (Central Credit Register).[3] From a technical point of view, this index is objective, however at least marginally each bank can manipulate the internal history of the borrower introducing a discretionary evaluation. Presence or absence of collateral and personal guarantees justify the *asset-based lending* technology. As for *relationship lending* technology, it relies on soft information gathered though contract over time with the firm, i.e. the duration of the relationship, the number of operation collected over time, the house bank or multi-lending firm attitudes as well as the *judgment lending* based on single personal – local loan officer, the bank manager or the board chair experience – decisions.

2.3. *Intertemporal classification of lending decisions*

Some literature explores the role of hard and soft information in defining SMEs credit risk, i.e. the probability to lend to bad quality customers. Most of these studies consider how relationship information, or soft information often embedded in credit ratings, are able to predict the likelihood of lending to bad/risky SMEs (Agarwal and Hauswald, 2010; Agarwal et al., 2011).

Our paper contributes at understanding how soft/hard information affects default prediction, but it mainly investigates how lending procedures, in their multifaceted components, affect the correctness of banking choices. The information asymmetries problem characterizing the relationship between

[2] The Italian CB system is composed of an associative structure and a corporate system. The associative structure is subdivided into three levels: local (CBs), regional (Regional Federations) and national (Federcasse). The individual CBs are associated with the Regional Federations (representing one or more regions), which in turn are members of Federcasse, the Italian Federation of CBs. Federcasse represents and protects the rights of its associated banks, offering them legal, fiscal, and organizational assistance. The Statistical default model used to obtain the small-credit scoring technology for each CB is processed at the regional Federation level.

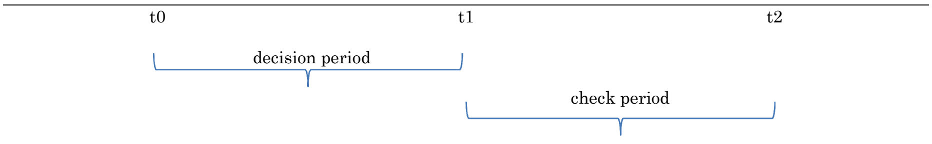
[3] The Central Credit Register is an information system on the debt of the customers of the banks and financial companies supervised by the Bank of Italy. The Bank of Italy collects information on customers' borrowings from the intermediaries and notifies them of the risk position of each customer vis-à-vis the banking system. Source: Bank of Italy.

borrowers and banks typically falls into the adverse selection dilemma for lenders especially within the SMEs perimeter, where opaqueness intensifies. From a time structure perspective, similarly to Hauswald and Marquez (2006), we set an intertemporal framework to classify correctness of lending decisions, which may consist in either *right* or *wrong* lending choices. Distinction of right decisions against errors arises following a two-dimension perspective that meet lending choices, at a given time, with evolution of SMEs' creditworthiness, in the subsequent period.

At a given point of time, the screening and lending decision under the dilemma of adverse selection can be either favourable (the bank grants the loan) or unfavourable (the bank rejects the loan) for the SME. Banks would expect to deny lending to bad borrowers, indeed. Choices are reasonably based on bank's creditworthiness predictions, within the concurring influence of information, policies, procedures, and contractual structures, i.e. within a given lending technology. In a period *following* the decision period, the observation of SME creditworthiness in terms of probability of default, allows to appreciate the correctness of these choices.

Hence, our intertemporal system of classification is developed over a two-period time horizon, which is defined by three points in time t = 0, 1, 2. At t=0, banks face uncertainty about the quality of borrowers. During the ex-ante *decision period*, from t0 to t1, banks run their screening of borrowers' credit risk. At t=1, banks shape their lending decisions, i.e. they either offer or deny credit/trust. During the subsequent ex-post *check period*, from t1 to t2, banks observe the quality of outstanding credit lines, based on whatever happened to borrowers. At t=2 banks know the true quality of borrowers (Figure 1).

Figure 1: Time structure to classify lending choices



Information on decisions taken (to offer/deny credit) in a decision period, and borrowers' credit quality *after* these decisions (good or bad credit quality), allows to theoretically classifying lending choices taken by banks, as summarized in Figure 2. We assume that a 'bad' lending decision is taken when: 1) bank *offers* credit (offers trust) to customers/positions that are going to hold a bad quality in the future; 2) bank *denies* credit (denies trust) to customers/positions that are going to hold a good quality in the future.

Conversely, we assume that a 'good' lending decision is taken when: 1) bank *offers* credit (offers trust) to customers/positions that are going to hold a good quality in the future; 2) bank *denies* credit (denies trust) to customers/positions that are going to hold a bad quality in the future.

Figure 2: Classification of lending choices

		Borrowers' credit quality ('check period')	
		Good quality	Bad quality
Lending choices ('decision period')	The bank *denies* credit/trust	FP type I error	TP Right decision
	The bank *offers* credit/trust	TN Right decision	FN type II error

Note: Consider that label of cells depends on the hypothesis that is to be tested. Here, we set the hypotheses coherently with adverse selection paradigm, in line with Hauswald and Marquez (2006). The null hypotheses is that banks expect to deny lending to bad borrowers.

Overall, our intertemporal system of classification indicates two typologies of 'good choices' for the bank, within the adverse selection dilemma: either, the lender is successful in denying credit/trust to customers which in the future would worsen their credit quality (True Positive - TP); or, the bank exploits a return-opportunity by lending to customers' that would show a good credit in the future (True Negative - TN).

Conversely, False Positive-FP and False Negative-FN positions in Figure 2 are bad choices, and technically represent *errors*. Priors of prudent lending behaviors, due to adverse selection, indicate a type I error (FP), when the bank denies credit/trust to those which-will-be good quality borrowers, thus causing rejection of acceptable credit risk. The False Negative (FN) case is a type II error, and it represents a severe error, because the bank is unsuccessful in managing the adverse selection dilemma: it did not rejected loans, i.e. offered credit/trust, to a (transformed into) bad quality position.

Credit market is typically featured by lending competition and banks compete for borrowers, as theoretically conceived by Hauswald and Marquez (2006). Therefore, type I errors (FP) cannot be attributed as decisions that fall uniquely under the responsibility of lenders: rejection of (future) good credit quality borrowers may be a bank's decision and it would represents an error. Nevertheless, this situation may also be caused by customers' willingness to select a different lender, as a bank's competitor. Coherently, the analysis of causes of bad lending choices uniquely refers to false negative-FN, i.e. type II errors, where responsibilities are unambiguously assigned to lenders.

3. Data and methodology

3.1. Data set of SMEs lending choices

Over last decades, deregulation, technological change and increased competition have partially changed bank market structure without however undermine the role of small banks, which preserve both at the international and national level a primary role in the financing of opaque SMEs. A good proxy for small banks in Italy is the category of CBs, which in the 2014 numerically count for the 57% of the national system.

We exploit a proprietary dataset of the whole credit lines offered by 20 CBs operating at the level of an Italian Region (Marche), corresponding to the archive of the entire population of their customers, existing at June 2013, June 2014 and June 2015. This unique and comprehensive dataset is composed by credit line positions of legal entities in 2013 - 2014 - 2015 banks' archive. In terms of contractual typologies, we retain self-liquidating loans that are credit transactions with a form of predetermined redemption and revocable loans that correspond to overdrafts. These rules return a final restricted dataset of N=9,898 credit lines positions, distributed among the 20 CBs as described in Table 1A.

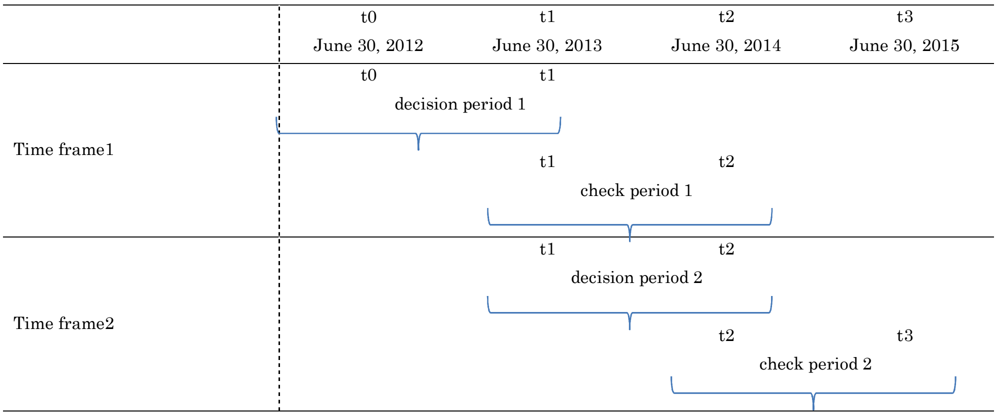
3.2. Empirical classification of lending decisions

Here we apply to empirical data our intertemporal system for classification of lending decisions. Our dataset offers the dollar value of credit lines (CL) that are offered by the 20 banks to their customers in the form of legal entities, at June 30th 2012 (CL_{12}), at June 30th 2013 (CL_{13}) and at June 30th 2014

(CL_{14}). Moreover, we received the internal rating (IR) that was assigned by banks to their customers at the date June 30^{th} 2013 (IR_{13}) at the date June 30^{th} 2014 (IR_{14}) and at the date June 30^{th} 2015 (IR_{15}).

The data obtained enable to analyse the decision and the check period in a panel dimension. In particular, we have two decision periods, the first one from June 2012 to June 2013; the second one from June 2013 to June 2014; and two check periods, the first one from June 2013 to June 2014; the second one from June 2014 to June 2015 (Figure 3).

Figure 3: Decision and check periods



Information on whether a bank offered or denied credit/trust is obtained by comparing dollar values of credit lines between June 2012 and June 2013 in time frame 1, and between June 2013 and June 2014 in time frame 2.

Specifically, a bank is considered to *deny* credit/trust to a customer if one of these alternatives occurs:

i) positive dollar values of credit line, declined to zero at the end of the decision period, i.e. $CL_{1t-1}>0$ and $CL_{1t}=0$, that is the code to indicate the position has been closed;

ii) positive dollar values of credit line decreased during the decision period: $CL_{1t}<CL_{1t-1}$, but excluding when this decrease is due to be 'waiting to be confirmed', i.e. $CL_{1t}\neq 1$;

iii) the credit line remained in a condition 'waiting to be confirmed' from the beginning to the end of the 'decision period': $CL_{1t}=CL_{1t-1}$ and $=1$.

Conversely, a bank is considered to *offer* credit/trust to a customer if one of these alternatives occurs:

i) positive dollar values of credit line increased in the decision period: $CL_{1t} > CL_{1t-1}$;

ii) positive dollar values of credit line, existent at the start of the decision period and confirmed at the end of the same decision period: $CL_{1t} = CL_{1t-1}$ and $\neq 0$;

iii) positive dollar values of credit line, existent at the start of the decision period, are moved into a condition 'waiting to be confirmed': $CL_{1t-1} > 0$ and $CL_{1t} = 1$, that is the code to indicate the position is 'under evaluation for confirmation'.[VV1]

Based on the dataset of N=9,898 credit lines positions, and following the above empirical instructions, we have N=6,217 positions where banks offered credit/trust, and N=3,681 where banks refused credit/trust.

The second step in classifying lending decisions and in filling up the theoretical classification matrix of Figure 2 is to observe the actual credit quality that is manifested in the 'check period'. A 'positive evolution' of credit quality is assigned to a customer/position if its internal rating increased, or remained unchanged, between 2013 and 2014 in time frame 1 or between 2014 and 2015 in time frame 2: $IR_{14} \geq IR_{13}$ or $IR_{15} \geq IR_{13}$. A 'negative evolution' of credit quality is assigned to a customer/position if its internal rating decreased between 2013 and 2014 or between 2014 and 2015 ($IR_{14} < IR_{13}$ or $IR_{15} \geq IR_{14}$), or declined to zero ($IR_{14}=0$ or $IR_{15}=0$, i.e., default condition).[VV2]

Based on these rules, we have N=7,916 with a 'positive evolution' of credit quality, and N=1,982 with a 'negative evolution' of credit quality.

Therefore, all the information is now available to draw the empirical distribution for good choices (TN and TP) and bad choices (FP and FN), as reported in Table 3.

Table 3: Typologies of lending decisions by sub-samples of positions

	Time frame1		Time frame2		Total	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
True Negative - TN	2,456	56.7	2,768	49.7	5,224	52.8
False Negative - FN	446	10.3	547	9.8	993	10.0

True Positive - TP	336	7.8	653	11.7	989	10.0
False Positive - FP	1,096	25.3	1,596	28.7	2,692	27.2
Total	4,334	100.0	5,564	100.0	9,898	100.0

3.3. Econometric models

Along with the hypothesis that banks would expect to deny lending to bad borrowers, we set two domains of choices in order to outline the multivariate investigation: the first domain is on the error side, the second one is on the correctness side of decisions. Firstly, we define a domain 1, which includes errors of lending to ex post bad customers (FN – Error of type II), against the alternative correct decision, i.e. denying credit to ex post bad customers (TP). Then, we delimit a domain 2, which comprehends the correct decisions of lending to ex post good customers (TN), against the alternative wrong decision, i.e. lending to ex post bad customers (FN).

We set a frame of models to investigate how lending technologies, with the embedded information, is able to significantly predict our domains of lending choices. We define this probit scheme of models:

Models J (Mj): $\Pr\ (Y_j = 1 \mid L, C)$ (1)

where J indicates the domain of analysis (domain 1 or 2), and designates the specific category of choices to be explored, based on the categorical (1-0) Y_j variable:

i) when j is 1, we refer to the domain 1 of errors, where we analyze variables that are able to predict errors against the correct choice that could have been alternatively taken. Y_1 is equal 1 for FN; Y_1 is equal 0 for TP;

ii) when j is 2, we refer to domain 2 and we explore the right choice, against the wrong choice that could be selected alternatively. Y_2 is equal 1 for TN; Y_2 is equal 0 for FN.

In frames of Models J, we test the significance of matrix L, which includes variables approximating the different lending technologies proposed in our theoretical framework. C is the matrix that includes control variables.

Note that variables included in matrix L refer to an ex-ante period, compared to the dependent variable Y_j that relies on outcomes based on an ex-post information. Therefore, we override concern for endoneity, and estimations of Models J indicate how lending technologies differently affect the likelihood of errors, or of correct lending decisions.

Due to estimation formalization, all variables are included in a comprehensive vector X and model (1) is presented as follows:

Models J (Mj): $\Pr\ (Y_j = 1 \mid X) = \Phi(X'\beta)$ (1.bis)

where Pr denotes probability and Φ is the cumulative distribution function of a standard normal distribution. Parameters, indicated by the vector ß, are estimated by maximum likelihood.

4. Description of the variables

4.1. Lending technologies

The first lending technology is the *financial statement lending* defined as a transaction technology, which relies primarily on ratios based on firms' financial statements (Udell, 2015). In addition, the literature on bank default risk base the predictors' index on balance-sheet data (Bugeja, 2015).

In this respect, to approximate financial statement lending we posit one of the principal measure of companies' financial distress probability, i.e. the version of the Z-Score model developed by Altman (1983) for private non U.S. corporates suitable for manufacturing and non-manufacturing firms (the so called Z"-Score [EM] Model). Each company was given a score (Z"-SCORE [EM]) composed by a discriminant function of four variables weighted by coefficients. Analytically, the Z"-Score [EM] Model is estimated as (Altman, Hatzell and Peck, 1995).

$$Z'' - \text{SCORE [EM]} = +3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (2)$$

where the first ratio, Working capital/Total assets ratio (X1), is a measure of the net liquid assets of the firm relative to the total asset; X2 is a measure of cumulative profitability and refers to the earned surplus of a firm over its entire life; the EBIT/Total assets ratio (X3) is a measure of the true productivity or profitability of the assets of a firm, not affected by any tax or leverage factors; finally X4 shows how much the firm's assets can decline in value (measured by book value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent.

This model measures the probability of a company entering bankruptcy within a 12-mounth period or in other terms a measure of firms' financial health. Higher values of the Z"-Score [EM] indicates a lower financial distress risk.

Among the different version of the Z-Score model developed by Altman, the Z"-Score [EM] has been chosen for several reason. First of all, very few Italian firms are public; moreover, it has been shown that the Z"-Score model applied to non-U.S. companies is far more robust than the other models (Altman & Hotchkiss, 2006). Altman himself uses the Z"-score in order to assess the financial health of non U.S. corporates (Altman, 2000 – p. 26) and concludes that this model is also useful within an industry where the type of financing of assets differs greatly among firms and important adjustments, like lease capitalization, are not made (Altman, 2000 – p. 27). Last but not least, several contributes[4] show that the original coefficients are extremely robust across countries and over time.

The second lending technology is the *small business credit scoring* that rests on the evaluation of customer track record. This variable – named CREDIT SCORING – is a variable computed by the common risk management system, shared by the 20 CBs, following internal guidelines. This track record is an internal informational tool based on the inventory and processing of two principal type of information that occurred on a monthly basis, within the 24 months before the banking decision. The first type of information is linked to the evaluation of the risk position of each customer vis-à-vis the overall banking system as supplied by the Central Credit Register of the Bank of Italy. The second type on information rests on data obtained through the verification of the bank internal information on each customer in terms of renewal, overdue, overdraft. The higher the small business CREDIT SCORING variable, the higher the frequency of 'anomalies' of SMEs; the lower the variable, the higher is the

[4] For an extensive review of the literature, see Bellovary, Giacomino, Akers (2007).

absence of 'anomalies'. The variable stands in the range 0-3. Three stands for 'relevant anomaly'; two stands for 'attention condition'; one for 'observation condition'; zero stands for 'no anomalies'.

The third lending technology is the asset based lending. In the paper, the role of the collateral is proxied by the variable COLLATERAL. The variable identifies the relationship between credit granted and the degree of guarantee coverage respect the amount of credit granted. The variable has been constructed by identifying five classes stemming from the combination of the amount of credit granted and the amount of collateral required. In particular, the first class indicates the situation of maximum trust, which is expected when credit has been granted but no collateral has been required. The opposite situation of minimum trust is associated to the presence of collateral in the absence of credit granted. All the other combinations stand in the between of these two extremes. Moreover, to control for the degree of personal responsibility of an individual or entity for the debt in the event of default of the company, we insert the variable PERSONAL GUARANTEE, which is a dummy variable equals 1 in case of legal form that entails unlimited personal liability, and 0 otherwise.

The fourth lending technology is the *relationship lending technology* approximating the relation between the bank and the borrower. In the main empirical literature the most used variable to proxy the bank-firm relationship is based on the information that bank can accumulate on the borrower history (see for example Petersen and Rajan, 1994 and Berger and Udell, 1995). This behavior is facilitated if the relation is continuous and repeated over time. In this respect in our paper, we introduce two variables catching these aspects. The variable DURATION measures the difference, on a time basis, between the date of the customer opening record and the date in which the credit line has been approved. This variable is useful to test the effect of the intensification of the length of the relationship between banks and firms on the probability to take the right decision in the loan evaluation process. Moreover, to catch the idea that the accumulated information process follow a non-monotonic path (Diamond, 1991 and Berger and Udell, 1995), the length enters the model also as a square root of the number of year the firm has a relationship with the bank, SQR_DUR. In our paper, the hausbank-status, or in other terms the relevance of the main bank is measured by the variable EXCLUSIVITY. This variable is computed as the ratio between the credit granted by the bank and the amount of credit granted by the overall banking system. As the degree of bank concentration increases, banks pay attention in taking the right decision, however as outlined in the literature a greater bank exposure can expose the bank to the risk of soft-budget constraint; i.e. banks may provide liquidity insurance to firms also in situation of unexpected deterioration of borrower rating (Elsas and Krahnen, 1998). In terms of the number of bank relationship, the variable MULTI-LENDING tests whether the number of banking relationships can affect the probability to take right loan decisions. MULTI-LENDING is a categorical variable that identifies the number of banks with which the company operates. Based on the Bank of Italy Credit Register information, the variable has been constructed by dividing the number of banks in 3 classes: class 1 if the number of banks with which the company operates is lower or equal to three, class 2 if the number of banks is between four and seven and finally, class 3 if the number of banks is greater or equal to seven. Another measure used in the literature to assess the intensity of the relationship between bank and borrowers is given by "multiple interactions with the same customer over time and/or across products" (Boot, 2000, p. 10). In this respect, we consider the variable INTENSITY that measures the maximum number of operations associated to every single customer in logarithm term. In relation to the hierarchical level of the lending decision process, we insert a *judgemental variable* named BOARD. The variable BOARD is a dummy variable equals 1 in case of collective decision taken by the board of directors and 0 otherwise (i.e. when the decision is made at branch level or taken directly by CEO/general manager, or also by the president). This variable is used however differently with respect to the prevalent literature, due to the particular typology of banks involved in our analysis. In the literature, similar variables are used in order to control for physical (Degryse and Ongena, 2005), functional (Alessandrini et al., 2009) and hierarchical distance (Stein, 2002) between bank and firm. Banks involved in our analysis are small local banks operating in the context of one Italian region, on a provincial basis. On the one hand, these banks are local and definitively very close to SMEs; on the other, they are characterised by few management/hierarchical levels. In this respect, the BOARD variable, here, indicates the collegiality of the decision process, in the attempt to capture the role of a collective judgment in predicting correctness of choices.

4.2. Control variables

We insert three control variables. First, we control for bank size by classes of total asset – BANK SIZE. Given that we are working on a sample of small local banks, but of different sizes, we insert this control variable in order to verify if relative larger banks show a different/greater ability to process information related to customers. We identify 4 size classes: class 1 to which belongs banks with total asset (TA) between 0 and 300 mln euro; class 2 banks with total asset between 300 and 500 mln euro; class 3 banks with total asset between 500 and 700 mln; class 4 banks with total asset greater than 700 mln euro.

Then, we insert the log of LOAN SIZE in order to control for the economic importance of loan size on the quality of lending decision. In case of larger loan size banks may be more exposed to different interferences in making right decisions; the same interferences can lead banks towards wrong decisions.

Finally, we insert the variable OVERDRAFT FACILITIES which is constructed as a dummy variable equals 1 in case of overdraft, and 0 in case of self-liquidating loans, the latter referred to the standard and typical Italian self-liquidating technology for which the bank grants usually a short-term loan based on the promise that a borrower's customer will regularly pay its debt. The variable captures the risk profile of the two mentioned lending technologies and could signal the development of a different (more careful and precise) lending process associated to overdraft facilities than in case of self-liquidating loans.

A list of the variables used is presented in Table A.2. of the Appendix.

5. Results

Based on our formulation of the lending paradigm, Tables 4 and 5 show evidence of the effect of each technology on correctness of banking choices. With respect to each domain, we offer four model specifications (columns M1-M4, of Tables 4 and 5) based on technologies indicated in Table 2. The fifth specification (column M5) includes the complete model estimation. All specifications include control variables.

As for the financial statement technology, column (1) of Tables 4&5, suggests that the probability of default of the borrower, i.e. the Z”-SCORE [EM] does not significantly affect the adverse selection dilemma of domain 1. Differently, it positively affects correct decisions of domain 2, i.e. the Z”-SCORE [EM] increases the probability to lend to ex-post good borrowers against ex-post bad ones.

Table 4: Results by domain 1

Dependent variable: Y1=1, false negative; 0, true positive

Variable	M1	M2	M3	M4	M5
Constant	-1.6456***	-1.0258***	-2.1575***	-1.6010***	-2.0279***
Z”-SCORE [EM]	0.0096				0.0174*
CREDIT SCORING		-0.2804***			-0.3150***
COLLATERAL			0.2034***		0.3225***
INTERNAL GUARANTEE			0.0437		0.0067
DURATION				-0.0369**	-0.0419**
DUR_SQR				0.2325**	0.2991***
INTENSITY				-0.2052***	-0.2148***
EXCLUSIVITY				0.5979***	0.7366***
MULTI-LENDING				-0.0585	-0.0456
BOARD				0.2585**	0.3449***
BANK SIZE	-0.0197	-0.0046	-0.0279	-0.0542	-0.0581
LOAN SIZE	0.1331***	0.1315***	0.1376***	0.1235***	0.1147***
OVERDRAFT FACILITIES	0.6009***	0.6350***	0.6166***	0.4806***	0.5351***
Observations	1,920	1,920	1,920	1,920	1,920
Wald chi2	66.81	70.99	80.78	85.29	94.69
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	2538.383	2494.451	2507.623	2474.243	2365.18
BIC	2571.743	2527.812	2546.543	2535.404	2448.582
LR test	10.14	12.92	9.45	8.00	8.78

This Table shows results of estimations of probit model [1] where the dependet variable is the categorial variable Y1, that is 1 indicating errors of lending to ex post bad customers (false negative – Error II),and 0 indicating the alternative correct decision, i.e. denying credit to ex post bad customers (true positive).

* Statistically significant parameters at 0.10 confidence levels; ** Statistically significant parameters at 0.05 confidence levels; *** Statistically significant parameters at 0.01 confidence levels.

Column (2) of Tables 4&5 adds the credit scoring technology. Results suggest that as the SCORING increases the probability of error of type II decreases, inferring that qualified internal customer behaviour with respect to both the bank and the system helps to control for the adverse selection dilemma. At the same time, as the CREDIT SCORING increases, the bank improves its capacity to correctly choose borrowers that will conserve a good quality in the future.

Table 5: Results by domain 2

Dependent variable: Y2=1, true negative; 0, false negative

Variable	M1	M2	M3	M4	M5
Constant	2.6162***	-1.9603***	3.5249***	4.4049***	-0.7872*
Z”-SCORE [EM]	0.0544***				0.0281**
CREDIT SCORING		1.3608***			1.3998***
COLLATERAL			-0.2051***		-0.0890*
INTERNAL GUARANTEE			0.1072		0.0057
DURATION				0.0888***	0.0561***
DUR_SQR				-0.3071**	-0.2587**
INTENSITY				-0.1607***	-0.0198
EXCLUSIVITY				-0.1306	-0.1607
MULTI-LENDING				-0.2922***	-0.2602***
BOARD				-0.8510***	-0.3649***
BANK SIZE	0.0753*	0.0497	0.0841*	0.051	0.0521
LOAN SIZE	-0.0933***	-0.0027	-0.1002***	-0.0398	0.0027
OVERDRAFT FACILITIES	-0.0438	0.0528	-0.0271	-0.1159	0.0364
Observations	6,217	6,217	6,217	6,216	6,216
Wald chi2	26.1	153.91	23.87	84.01	129.56
Prob > chi2	0.0000	0.0000	0.0002	0.0000	0.0000
AIC	5289.522	4382.326	5296.838	5204.058	4326.977
BIC	5329.933	4422.736	5343.838	278.142	4428
LR test	142.57	65.61	148.02	147.79	69.06
/ lnsig2u	1.2450***	0.4934**	1.3071***	1.5108***	0.6527**

This Table shows results of estimations of probit model [2] where the dependet variable is the categorial variable Y2, that is 1 indicating the correct decisions of lending to ex post good customers (true negative), against the alternative wrong decision, i.e. lending to ex post bad customers (false negative).

* Statistically significant parameters at 0.10 confidence levels; ** Statistically significant parameters at 0.05 confidence levels; *** Statistically significant parameters at 0.01 confidence levels.

Column (3) of Tables 4&5 introduces the asset based lending technology measured with both the external COLLATERAL (physical collateral such as real estate) and PERSONAL GUARANTEE (i.e. personal guarantees by business representatives). The results suggest that COLLATERAL does not reduce the adverse selection problem but accrue the bank moral hazard behaviour. The literature associates to the collateral the acceptation to be an incentive for lenders as a substitute for (Manove, Padilla, and Pagano 2001) or as a complement to (Rajan and Winton 1995, Boot 2000, Longhofer and Santos 2000) screening and monitoring efforts. Our results appear in line with such literature, suggesting that as COLLATERAL increase the probability to commit error of type II increases, as well as the probability to choose correctly good customers decreases. As for the PERSONAL GUARANTEE, it does affect neither the probability of Error II, nor the probability of right choices.

Column (4) of Tables 4&5 introduces some variables that proxy the relationship lending technology (DURATION, DUR_SQR, INTENSITY, EXCLUSIVITY, MULTI-LENDING and BOARD). The greater the knowledge of the customer the bank has cumulated thanks to the length of the relationship (DURATION) the more its capability to control the adverse selection problem (Petersen and Rajan, 1994 and Berger and Udell, 1995). The negative sign of this variable in Table 4, and its positive sign in Table 5, suggest that the bank can overcome its selection problem, thanks to a deeper knowledge of its customers that allows both a reduction of errors and an increase of good decisions. The positive sign of DUR_SQR in Table 4 and correspondingly the negative sign in Table 5 confirm the non-monotonic path of duration on the probability to select correctly its customers (Diamond, 1991 and Berger and Udell, 1995). As for INTENSITY is concerned, results suggest that as the number of operations the customer underwrites with the bank, the better is its capability to choose correctly the customer with a negative impact on the probability to make errors of type II (Table 4). However, as the number of the operations increases, the probability the bank selects good customer decreases (Table 5). The large number of operations the firm entails with the bank may hide an opportunistic behaviour; in this perspective, INTENSITY cannot be considered a guarantee of creditworthiness *tout court*. As for the EXCLUSIVITY, the positive sign of Table 4 suggests that, as the firm becomes a hausbank-customer, the bank incurs in the risk of soft-budget constraint increasing the probability of errors-type II. Being an exclusive customer may induce the bank in the renewal of line of credit even when the firm is not credit worthy, suffering for an intense adverse selection problem (Elsas and Krahnen, 1998). Differently the exclusive relation does not play any statistical significant role in the determining the probability of choosing customers correctly. The variable MULTI-LENDING does not significantly affect the probability of errors-type II (Table 4), but holding many bank-relationships may worsen the probability to choose correctly its customers (Table 5). Keeping in mind the computation of the dependent categorical Y2 variable, we deduce that the increase of the number of banks from which customers receive loans causes an increase of the probability of lending to ex post bad firms, instead of lending to ex post good companies. Finally, the variable BOARD signals that a collegial decision does not help the bank to solve the adverse selection problem as suggested by the positive sign of the variable in Table 4 and the negative sign in Table 5. Sharing decisions, and mainly the related professional responsibilities, may induce a moral hazard behaviour, thus having this decisional process not always optimal for small local banks. This would suggest that the atomistic decision taken by a single operator can better guide towards more prudent choices, both reducing errors and increasing correct decisions.

Column (5) of Tables 4&5 summarize in a complete specification model all the above considerations. Results are confirmed, with two exceptions. On the one hand, the financial statement technology variable becomes statistical significant also in domain 1 (Table 4), with a negative sign of the parameter. As the Z"-SCORE [EM] increases, i.e., the firm sits far away from any concern of default, the probability that the bank may choose ex-post bad customers increases. This evidence definitively confirms the risk of adverse selection for the bank: when the quality of the firm seems to be good, due to an apparent satisfying accounting condition, the bank tends to increase its credit availability, with the risk to be captured by its customer (so called, soft-budget constraint).

On the other hand, the variable INTENSITY becomes statistically non-significant in the domain 2 (Table 5). Since its inception, this variable showed a multifaceted role, in supporting avoidance of errors, as well as inducing a decrease in the likelihood of correct choices because of possible opportunist behavior of customers. Therefore, we address a specific investigation, including interaction effects, and precisely DURATION*INTENSITY, MULTI-LENDING*INTENSITY and EXCLUSIVITY*INTENSITY.

Table 6: Results with interaction effects

	Domain 1 False negative vs. True positive		Domain 2 True negative vs. False negative	
Variable	M1	M2	M1	M2
Constant	-1.7781***	-2.2341***	4.2406***	-0.8169*
Z"-SCORE [EM]		0.0175*		0.0285**
CREDIT SCORING		-0.3137***		1.4006***
COLLATERAL		0.3187***		-0.0830*
INTERNAL GUARANTEE		0.0102		0.0023
DURATION	-0.0480**	-0.0529**	0.0753***	0.0477**
DUR_SQR	0.2609**	0.3266***	-0.2571**	-0.2303**

INTENSITY	-0.1299	-0.1047	-0.092	0.0041
EXCLUSIVITY	0.5065***	0.7904***	0.4427**	0.1249
MULTI-LENDING	0.0561	0.064	-0.3513***	-0.2894***
DURATION * INTENSITY	0.0035	0.0037	0.0028	0.0027
MULTI-LENDING * INTENSITY	-0.0607*	-0.0590*	0.0387	0.0152
EXCLUSIVITY * INTENSITY	0.0469	-0.0413	-0.3900***	-0.1935**
BOARD	0.2584**	0.3412***	-0.8441***	-0.3716***
BANK SIZE	-0.0606	-0.062	0.0449	0.0494
LOAN SIZE	0.1239***	0.1136***	-0.0428	0.0005
OVERDRAFT FACILITIES	0.4737***	0.5252***	-0.1236	0.0312
Observations	1,920	1,920	6,216	6,216
Wald chi2	87.8	97.62	81.61	130.14
Prob > chi2	0.00000	0.00000	0.00000	0.00000
AIC	2475.494	2367.479	5196.187	4327.8
BIC	2553.335	2467.56	5290.475	4449.028
LR test	7.73	8.19	149.74	70.39
/ lnsig2u	-0.7902	-0.697	1.4355***	0.6642***

* Statistically significant parameters at 0.10 confidence levels; ** Statistically significant parameters at 0.05 confidence levels; *** Statistically significant parameters at 0.01 confidence levels.

Columns (1&3) of Table 6 show results for domain 1 and 2, respectively, considering only the relationship lending variables. As for domain 1, all the variables hold their sign and their statistical significance. Moreover, the negative sign of MULTI-LENDING*INTENSITY suggests that as the intensity increases as well as the number of bank relations, the bank can better select its customers, i.e. the probability of error of type II decreases. An increase in the number bank operations improves the knowledge of the firm by the bank, decreasing the probability of errors, and this is true even if the firm increases its number of bank relations. As for domain 2, the variable INTENSITY is not statistically significant when considered alone. Taking into consideration both INTENSITY and EXCLUSIVITY, as the intensity increases, as well as the exclusivity of the relationship, an opportunistic behavior by the firm is revealed. Consequently, the bank is less likely to correctly select its customers.

6. Robustness

In order to deal with statistical pitfalls of multiple discriminant analysis (MDA) used in computation of Altman's Z-Score, we use two alternative models of financial distress as robustness check: Zmijewski (1984) and Ohlson (1980) models[5]. In fact, on one hand Ohlson (1980) uses logit analysis, which overcomes several statistical problems inherent in the MDA approach, including the assumptions that the financial ratios of bankrupt and non-bankrupt groups are normally distributed and have the same variance-covariance matrix. On the other hand, as argued by Zmijewski (1984 - p.59), studies "typically estimate financial distress prediction models on non-random samples. Estimating models on such samples can result in biased parameter and probability estimates if appropriate estimation techniques are not used". Thus we use the Zmijewski model, which is calibrated to a random sample in order to deal with this phenomena.

The Zmijewski ZM-Score is a combination of three financial ratios:

$$ZM - score = -4.336 - 4.513\left(\frac{NI}{TA}\right) + 5.679\left(\frac{TL}{TA}\right) + 0.004\left(\frac{CA}{CL}\right) \qquad (3)$$

where TA is total asset, TL: total liabilities; CL: Current liabilities; CA: Current Asset; NI: net income. A higher ZM-score is associated with a higher financial distress risk.

In addition to the previous model, we use also the Ohlson O-Score model. Ohlson (1980) selected nine independent variables that he thought should be helpful in predicting bankruptcy without providing theoretical justification for the selection. We follow the implementation of Ohlson (1980) by Griffin and Lemmon (2002) and compute the O-score as:

$$O - score = -1.32 - 0.407\log(TA) + 6.03\left(\frac{TL}{TA}\right) - 1.43\left(\frac{WC}{TA}\right) + 0.0757\left(\frac{CL}{CA}\right) - 2.37\left(\frac{NI}{TA}\right) - 1.83\left(\frac{FFO}{TA}\right) + 0.285(D_{Loss}) - 1.72(D_{TL-TA}) - 0.521\left(\frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}\right) \qquad (4)$$

where TA is total asset, WC: working capital; TL: total liabilities; CL: Current liabilities; CA: Current Asset; NI: net income; FFO: Funds from operations; D_{Loss}: dummy variable equals 1 if the company realized a net loss in the last two years; D_{TL-TA}: dummy variable taking value of 1 if total liabilities are

[5] As the primary purpose of this study is to examine the impact of financial distress in correctness of lending decisions, we rely only on previously published financial distress models, rather than attempt to develop a new model of financial distress that isolates from the scope of the paper.

higher than total assets. As in the case of ZM-Score, a higher O-score is associated with a higher financial distress risk. Results are presented in Table 7. As for the other technologies, all the main results hold. Table 7 demonstrates that our major empirical findings remain qualitatively unchanged.

Table 7: Robustness check

* Statistically significant parameters at 0.10 confidence levels; ** Statistically significant parameters at 0.05 confidence levels; *** Statistically significant parameters at 0.01 confidence levels.

	Domain 1 Dep. var. Y1 False negative vs. True positive				Domain 2 Dep. var. Y2 True negative vs. False negative			
Variable	M1	M2	M3	M4	M1	M2	M3	M4
Constant	-1.9989***	-2.1156***	-2.3740***	-2.4258***	-0.52	-0.5905	-0.3944	-0.6064
ZM-SCORE	-0.0401***	-0.0397***			-0.0585***	-0.0588***		
O-SCORE			-0.0227*	-0.0228*			-0.0587***	-0.0597***
CREDIT SCORING	-0.3142***	-0.3114***	-0.2618***	-0.2604***	1.2939***	1.2970***	1.2998***	1.3146***
COLLATERAL	0.3749***	0.3684***	0.3472***	0.3457***	-0.0896**	-0.0847*	-0.0539	-0.0498
INTERNAL GUARANTEE	0.0548	0.0568	0.0494	0.0478	0.0405	0.0376	-0.0357	-0.0417
DURATION	-0.0429**	-0.0557**	-0.0507**	-0.0414	0.0417**	0.0355*	0.0806***	0.0737***
DUR_SQR	0.3029***	0.3342***	0.3322**	0.3045**	-0.1940**	-0.1730*	-0.3805***	-0.3583***
INTENSITY	-0.2231***	-0.1669	-0.1792***	-0.1389	-0.0095	0.0363	-0.0403	0.0869
EXCLUSIVITY	0.7540***	0.7538***	0.7120***	0.6022**	-0.1634	0.0626	-0.0423	0.2638
MULTI-LENDING	-0.0342	0.0505	-0.0192	0.0197	-0.2697***	-0.2749***	-0.2344***	-0.1871**
DURATION * INTENSITY		0.0043		-0.0025		0.002		0.0024
MULTI-LENDING * INTENSITY		-0.0444		-0.0189		0.0005		-0.0324
EXCLUSIVITY * INTENSITY		-0.0101		0.0606		-0.1547*		-0.1943*
BOARD	0.3671***	0.3661***	0.5347***	0.5274***	-0.3314***	-0.3387***	-0.5178***	-0.5393***
BANK SIZE	-0.0797*	-0.0831*	-0.0262	-0.0274	0.0474	0.0451	0.1007**	0.0997**
LOAN SIZE	0.1140***	0.1127***	0.1034***	0.1050***	0.0092	0.0083	-0.0142	-0.0155
OVERDRAFT FACILITIES	0.5499***	0.5380***	0.5207***	0.5217***	0.0517	0.0479	0.0199	0.0154
Observations	1,789	1,789	1,425	1,425	5,958	5,958	4,607	4,607
Wald chi2	79.17	82.24	82.64	82.74	124.05	123.81	109.40	107.33
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	2182.552	2186.055	1770.971	1776.135	4073.681	4076.549	3266.844	3269.47
BIC	2264.893	2284.864	1849.9	1870.85	4174.068	4197.014	3363.374	3385.306
LR test	6.82	6.32	7.76	7.88	50.01	51.14	61.22	63.23
/ lnsig2u	-0.6323	-0.6937	-0.6793	-0.6649	0.4515	0.4697*	0.6492**	0.6888**

7. Conclusions

Novelty of this paper is the investigation of determinants of the quality of banking choices. Quality is defined at the micro-level, by using an intertemporal perspective based on the SMEs bank loans positions. The 'good' is distinguished by a 'bad' lending decision by comparing the choice that is taken in a given time, i.e., offering/denying credit, with the creditworthiness of this position ex-post, i.e., one year later the lending decision is taken.

Given this statement, we shed light on if and how hard information and/or relational information predict, alternatively, either errors or correct choices, against the opposite correct /wrong decision, respectively.

Confirming that all lending technologies are based on hard and soft information (Berger and Black, 2011), our findings suggest that both sides of information work as complementary in explaining the quality of lending choices. Nevertheless, both 'extreme' of hard-soft nuances of information systematically reveal merits and pitfalls, due to their nature. As for hard information, mainly contained in the financial statement technology, we find evidence that when a bank decision process is exclusively based on this technology, adverse selection problems may arise. When accounting ratios sounds to support the bank from any concern of default, a condition of soft-budget constraints may encourage the bank to grant loans to firms that are on the point to worsen their creditworthiness. As for soft information, some interesting results emerge from the so-called judgmental technology. If the validation loan process is taken at the collegial level, the risk of adverse selection increases, induced by an indirect moral hazard effect stimulated by a shared risk-redistribution responsibility among more people. Differently, a direct responsibility of the decision, recognized in charge of either single branch director, or bank president, or CEO, is shown to lead to better outcomes, decreasing the probability of errors, as well increasing the probability of correct choices.

From a policy perspective, implications of our results suggest that at the local level the personal knowledge of the firm continues to pay a role in supporting the quality of banking choices, while financial ratio technology, even if objective and transparent, continues to be insufficient to complete the knowledge of SMEs. In this respect, and given the regulatory reform that is reviewing the corporate structure of CBs in Italy (Decree-Law 14 February 2016, n. 18), our results suggest not to forget values and merits of soft information embedded in the bank-borrower relationship at the local level.

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Appendix

Table A1 - Dataset of credit lines by class of bank

Size class by range of millions of euro	Number of banks	First period		Second period		Total	
		Freq.	Percent	Freq.	Percent	Freq.	Percent
0-300	5	371	8.6	359	6.5	730	7.4
300-500	5	1,130	26.1	1,046	18.8	2,176	22.0
500-700	5	1,430	33.0	2,178	39.1	3,608	36.5
700-99999	5	1,403	32.4	1,981	35.6	3,384	34.2
Total	20	4,334	100.0	5,564	100.0	9,898	100.0

Table A.2 - Variables names, definitions and measures

Variable	Definition	Measure
Matrix L – Lending technologies		
Z''-SCORE [EM]	Altman Z-Score computed for private, manufacturing, non-manufacturing firms and emerging market.	The score is composed by a discriminant function of four variables weighted by coefficients. As the score increases the borrower firm quality increases i.e. it increases the distance from the default zone
ZM-SCORE	Zmijewski ZM-Score	The score is a combination of three financial ratios. A higher ZM-score is associated with a higher financial distress risk
O-SCORE	Ohlson O-Score model	The score is a 9 factor linear combination of coefficient-weighted financial ratios. A higher O-score is associated with a higher financial distress risk
SCORING	Small business credit scoring is a variable computed by the single bank according to the internal guidelines. Track record analysis rest on two principal type of information. The first one is linked to the evaluation of the risk position of each customer vis-à-vis the overall banking system. The second one rests on information obtained through the verification of the bank internal data in terms of renewal, overdue, overdraft.	The original variable disclosed by the single bank has been reclassified into 4 classes. The variable stands in the range 0-3. 0 stands for relevant anomaly; 1 stands for attention; 2 for observation; 3 stands for no anomalies
COLLATERAL	Degree of collateral coverage respect the amount of credit granted	Categorized variable that identify the relationship between credit granted and degree of collateral coverage. The variable has been constructed by identifying 5 classes: class 1 maximum trust [credit granted but no collateral required]; class 5 minimum trust [presence of collaterals and absence of credit granted].
INTERNAL GUARANTEE	Degree of personal responsibility of an individual or entity for the debt in the event of default of the company	Dummy variable equals 1 in case of legal form that entails unlimited liability and 0 otherwise
DURATION	Duration of the bank-borrower relationship.	Duration measured as the distance expressed on a time basis between the customer opening record and

		the date in which the credit line has been approved
DUR_SQR	Square root of Duration	To control for a potential nonlinearity of the effect of duration on relationship lending
EXCLUSIVITY	Degree of bank-firm relationship	Continuous variable calculated as the ratio between the credit granted by the bank and the amount of credit granted by the total banking system.
MULTI-LENDING	The variable can be considered as a proxy of the degree of sharing of information on that particular customer as presented in the Central Credit Register	Categorized variable that identify the number of banks with which the company operates. The variable has been constructed by dividing the number of banks in 3 classes. Class 1 if the number of banks with which the company operates is <= 3; class = 2 if the number of banks between 4 and 7 and finally class = 3 if the number of banks> = 7
INTENSITY	The variable can be considered as a proxy of commercial liveliness since it approximates the activities of cross-selling undertaken by the bank on that particular customer	Log of the maximum number of operations associated to every single customer
BOARD	Dummy variable that expresses the degree of collegiality of the decision	The variable equals 1 in case of collective decision taken by the board of directors and 0 otherwise (i.e. when the decision is made at branch level or taken directly by CEO/general manager or by president)
Matrix C – Control variables		
BANK-SIZE	Bank size by classes of total asset	Categorized variable. 4 classes identified. Class 1 banks with total assets (TA) between 0 and 300 mln euro; class 2 TA between 300 and 500 mln; class 3 TA between 500 and 700 mln; class 4 TA greater than 700 mln euro
LOAN SIZE	Loan size	Log of loan size
OVERDRAFT FACILITIES	Variable expression of the different degree of risk associated to the different lending technologies that implies the development a more careful and precise lending process.	Dummy variable equals 1 in case of overdraft facilities and 0 otherwise (i.e. mainly self-liquidating loans)