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Bank Loan Deterioration: Is It All Fault of the Crisis?

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Abstract

Despite the recent academic focus on the effects of the crisis on bank loan quality, a fully satisfying analysis of their causes is still missing, likely because of a lack of detailed information on bank-borrower relationships and the way loan decisions are taken within banks. Thanks to the availability of a large dataset provided us by a regional Italian bank for the three calendar years 2010-2012, we are able to describe changes occurred in the bank loan quality of 3,103 firms, primarily small- and medium-sized firms. Besides a generalized deterioration of the loan quality due to the crisis, our findings show that the loan quality (as measured by each loan rating) is largely influenced by how information is processed and used at the different hierarchical levels within the bank at the time of loan decisions. More specifically, the deterioration of loan quality increases as the loan approval decision is made at higher levels of the lending-decision hierarchy, while it decreases with the firm age, size and the proximity of firms to the bank. The latter result supports the primacy of relationship-lending technology relative to transaction-based lending technology.

Keywords: SMEs funding; Relationship lending, Bank-loan policies.
JEL Classification Numbers: G21, G24, O16

1. Introduction

This paper aims at analyzing the changes in the quality of bank loans, as measured by each loan rating, by studying how information is processed and used at the different hierarchical levels within the bank at the time of loan decisions. Thanks to the availability of a large dataset provided us by a regional Italian bank for the three calendar years 2010-2012, we are able to describe changes occurred in the bank loan quality of 3,103 firms, primarily small- and medium-sized firms (SMEs), located in the same region where the bank has its headquarter. In economies with a bank-based financial industry, it is vital to understand how banks select the firms to which they will lend, and whether the lending process is efficient and contributes to the country competitiveness.

Italy's Non Performing Loans (NPLs) ratio stood at 13.3 % at the end of 2012 from a record low of 5.0 % in Jun 2008. The deep recession that has hit the Italian economy in 2009 and lengthy credit recovery procedures severely impaired Italian banks' balance sheets and loan quality and, then, have contributed to the high volume of NPLs in Italy's banking system (Bank of Italy, 2017). In 2015, following the adoption by the E.U. in 2014 of the *Bank Recovery and Resolution Directive* (BRRD), the Italian Government and the Bank of Italy (the resolution authority for the Italian banking system) acted to resolve the situation of crisis at four banks under special administration: *Cassa di Risparmio di Ferrara*, *Banca delle Marche*, *Cassa di Risparmio della Provincia di Chieti* and *Banca Popolare dell'Etruria e del Lazio*.[1] Following the resolution decision, the academic and political discussion made clear that the generalized increased in the stock of NPLs and its consequences on banks' balance sheets were the result of the business cycle together with inadequate bank managers and/or organizational forms (Visco, 2018).[2] Indeed, the effect of a change in the probability of an uncertain loan to become non performing is extremely costly for the banking system (Maggi and Guida, 2011). Leaving aside issues concerned with fraud and misconduct allegations by managers, some of the banks with the most severely impaired balance sheets and loan quality may lay the blame on themselves for the mismatch between their lending-decision hierarchy and their lending technology.

Relationship and transaction-based technologies are the two main lending technologies. Nowadays, the literature on these two technologies is huge and we make no attempt to provide an exhaustive list of the literature in this area, but we only recall their main characteristics in the next paragraphs.

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[1] These were small or medium-sized banks whose total market share came to about 1 per cent of system-wide deposits. The solution adopted guaranteed the business continuity and financial recovery of the four banks, in the interests of the local economies in which they were located. It fully protected the savings that households and firms hold in the form of deposits, current accounts and ordinary bonds, it preserved the jobs of all the banks' employees and required no public funds. The banks' cumulative losses, valued in a very conservative way, were absorbed first of all by the riskiest investment instruments: shares and subordinated bonds. The involvement of shareholders and subordinated bondholders is an express prerequisite for the orderly solution of banking crises under the BRRD, which was transposed into Italian law by Legislative Decree nr. 180/2015 of 16 November.

[2] Angelini et al. (2017) show that macroeconomic conditions explain almost 90% of the NPLs flows observed since 2008, while actual or potential criminal behavior by bank managers seems to account for 4% to 8% of total defaults observed among non-financial corporations.

On the one hand, transaction-based lending technologies are primarily based on borrowers' hard quantitative information, such as the strength of the financial statement or the value of their assets, which are relatively easy to document and transfer (Berger and Udell, 2006). On the other hand, relationship lending is extended primarily based on borrowers' soft qualitative information, such as the entrepreneurs' characteristics including skill and integrity, which are difficult to verify (Uchida et al., 2006, Cole et al., 2004).

When banks develop close relationships with borrowers over time, they are able to gather propriety information about firms through repeated interactions (Boot, 2000). Therefore, banks can extend loans at favorable contract terms and provide firms with better access to finance (Boot and Thakor, 1994; Petersen Rajan, 1995). The main drawback of relationship lending is that it could give rise to hold-up problems and the consequent extraction of rents from firms (Sharp 1990; Rajan, 1992).

It is typically assumed that relationship lending technologies help to reduce information asymmetries between firms and banks by the close contact between the two parties. Therefore, firms that are especially exposed to high information problems (opaque firms), such as small-sized companies, should choose a relationship bank. Indeed, key elements defining the SMEs' relationship banking, such as concentration, length, and mutual trust, may constitute a real help to access appropriate financing, at reasonable costs and requirements (Badulescu, 2012). In the continental European bank-based system, there is evidence that SMEs with longer bank relationships have enhanced access to loans, but at the same time they bear a higher cost for their debt. Moreover, the existence of trust between the firm and the bank improves access to financing and reduces borrowing costs, whereas it increases the likelihood that guarantees will have to be provided (Hernández-Cánovas and Martínez-Solano, 2010), especially for female-owned firms (Calcagnini et al., 2015).

Banks that choose to emphasize relationship lending may be organized quite differently from banks that do not (Berger and Udell, 2002). It may be the case that, some or all of the four above mentioned banks grew up *too much fast*: the process of merging among local and small-sized banks generated interregional financial players, but their financial culture did not change as fast as their size. These new financial intermediaries likely kept using relationship technologies to provide credit to firms at the lower levels of the bank hierarchy, while top managers were still familiarizing with transaction-based lending technologies and were unable to fully implement effective lending policies when the financial crisis hit the world economy.

The organizational structure of banks could have implications for the financing of small businesses and entrepreneurial firms. The existing evidence shows that the organization of lending institutions is important for the use and transmission of information, as well as credit availability for small businesses (Bellucci et al., 2017). Notwithstanding the huge production of theoretical and applied work, no generalized consensus can be found on which of the two lending technologies guarantees the best loan applicant selection and, therefore, the lower loan default probability. However, by means of detailed credit register information for Italian banks, Bolton et al. (2016) find that a firm financed by transaction-based lending technologies has a higher probability of going into default.

Further, two main issues are concerned with lending technologies.

First, soft information deteriorates as it is transmitted to others within the hierarchy of the lending institution. However, banks can avoid diluting soft information by delegating lending authority to the same agent that collects it, i.e., the loan officer (Uchida and Udell, 2012). We can assume that the relationship lending technology is more important at the bank branch/loan officer level, while transaction-based lending technologies are used at higher levels of the bank hierarchy.

Second, bank lending technologies are thought to be either relationship or transaction-based. Indeed, banks are more likely a combination of both technologies, with transaction-based lending technologies playing an increasing role in larger banks (Bartoli et al. 2013).

This paper is related to Calcagnini at al. (2018) and uses detailed information provided by an Italian regional bank on over 16,000 lending decisions and 3,000 firms between 2010 and 2012. The information set contains, among others, data on each loan status and who took the loan decision. We also have information on the physical distance between the bank and its customers. Specifically, we can control if the bank, or one of its branches, is located in the same municipality of the customer firm. Further, the regional bank is large enough to account for the presence of both types of lending technologies. Finally, the bank database has been also integrated with firms' balance sheet items to control for information potentially not fully captured by other bank variables, such as firm ratings. This paper is also related to Marchetti and Pozzolo (2018) who emphasize the role of bank organization on the lending decisions. Indeed, they find that banks with internal organization that allows for a better use of soft information, because for instance they have a smaller number of hierarchical decisional levels – granted relatively more credit than other banks. Further, they also find that smaller firms also experienced a stronger reduction in credit supply from those same banks that have an internal organization that is less suitable to the transfer of soft information.

In Calcagnini at al. (2018) we estimated a Probit model of the probability of loan default. Even though results were satisfactory, one likely drawback of that empirical work is the limited number of loan defaults: 3 in 2010 (i.e., 0,14% of firms), 10 in 2011 (i.e., 0,49% of firms), 66 in 2012 (i.e., 4,13% of firms). To obtain more robust results, in this paper we first turn our attention to determinants of changes in firm ratings between 2010 and 2012, and then we estimate a Probit model where the dependent variable is 1 if the rating status deteriorated and 0 otherwise. In both models, the set of explanatory variables includes variates that indicate who decided on each single loan, together with conditioning variates reflecting the presence of different guarantee types (collateral and personal guarantees), the firm age, size, and leverage, the initial debt levels, total number of loan applications of each firm, whether the firm is a new customer and bank branches are located in the same municipality of the customer firm, the presence of financial services, apart from lending, whether the firm belongs to the corporate portfolio of the bank year, industry, loan-type, size-branch dummies.

Empirical results show that, *ceteris paribus*, firm ratings deteriorated less when the decision to approve a loan application was taken by the loan officer at the bank branch level. This result supports our assumption that the relationship lending technology is more effective at the lowest level of the lending institution hierarchy, and finds further strength by the fact that rating deteriorations were smaller whenever the customer firm was located within the same municipality of the bank branch. In other words, the higher up in the bank hierarchy the lending decision was made by transaction-based technologies, the larger was the rating deterioration during the 2010-2012 period.[3] This result was mitigated by the use of more information provided to the bank by older and larger firms.

Overall, our findings are consistent with those of Calcagnini et al. (2018), and Brighi et al. (2017) who 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. On the contrary, a loan decision-making process based exclusively on hard financial information of SMEs may lead to adverse selection errors. Our results are favorable to relationship lending technologies, but they also show that transaction-based technologies were not effectively used by higher levels of the bank hierarchy.

Our empirical results may also provide support to bank regulation proposals that restrict the universal banking model and have a more clear-cut separation between commercial and investment banking businesses (Gambacorta, 2016).[4]

The rest of the paper is organized as follows. In Section 2, we briefly describe the unique dataset and our model, while in Section 3 we discuss the estimation results. Section 4 concludes.

2. Data and Methodology

2.1 Data

We use a unique proprietary dataset that provides information on all loans extended by a regional Italian bank to firms, mainly to small-and medium-sized enterprises (SMEs), over the period 2010 -2012. We combine the bank loan data with balance-sheet data taken from the dataset AIDA for the firms located (registered office) in the same region of the bank headquarter.[5] After the matching, the dataset with non-missing observations contains 16,460 approved loan applications for 3,072 firms.

[3] As for the two lending technologies, with respect to their relative efficiency in the allocation of resources, it would be more appropriate to compare their benefits and costs and not simply their effect of firm ratings. Indeed, assuming that transaction-based lending technologies are cheaper than relationship technologies, if the savings from the former are large enough to compensate the additional costs associated with worse ratings, transaction-based lending technologies should be preferred to relationship technologies.

[4] Indeed, while banks that do business by relationship lending technologies likely offer more business stability in exchange for less efficiency, banks that use transaction-based lending technologies are associated with the provision of cheaper loans (at least in good times), but with higher business instability. Initiatives of structural banking refer to the "Volcker rule" in the U.S. and to the proposals of the Vickers Commission for the U.K.. In Europe, there is no agreement on the idea to revise the model of universal banking, as banks should be free to choose which business model to adopt. See Gambacorta and van Rixtel (2013) for a survey on the main reforms.

[5] AIDA covers 1 million Italian companies, and contains their detailed accounting information following the scheme of the 4th Directive CEE, plus indicators and trade description; information on ownership and managers and scanned images of accounts with additional notes. The cost of using this additional source of information was the drop in the number of observations (from 17,641 firms and 136,095 loan records to 3,425 customers and 18,658 loan records).

Thus, the final sample excludes micro firms, and those located outside the region. Finally, the bank provided us with information related to the presence of guarantees and other services only for the matched sample of firms. More importantly, each loan/firm is keyed to a rating status that goes from performing exposures, to a default probability of 100 percent. However, as rating are reconsidered every six months, we exclude from our analysis the loans deliberated from July 2012 to December 2012, as for these loans the rating variation is necessary equal to zero.[6] Therefore, our regression sample contains 3,103 unique firms and 15,110 loans.

Table 1 shows the number of firms, loans and the number of loans (firms), whose rating worsened during the period. Our data show that in all the three years a significant percentage of loans (and firms) experienced a deterioration of rating. This evidence is coherent with the dynamics of the Italian economy. Italy entered a recession in 2011, mainly as a consequence of the sovereign debt crisis in the euro area. The worsening of the cyclical phase was particularly intense in the second half of 2011, when a contraction of economic activity began and continued in 2012.[7] Therefore, the worsening of the financial turmoil made the provision of banks more difficult, impacting on lending policies to the private sector (Bank of Italy, 2012 and 2013).

Table 1: Number of firms, loans, and rating deterioration

	Firms	Loans	Rating deterioration: Loans (firms)	
			Absolute values	Percentage values
2010	2,324	7,441	2850 (905 firms)	38.3 (38.9)
2011	2,134	5,623	2033 (797 firms)	36.1 (37.3)
2012	1,141	2,046	706 (343 firms)	34.5 (30.1)

Source: Our calculations on the regional bank data.

2.2 Organizational Design

Our bank data contains information on the hierarchic power to approve a loan application. In the database, there are originally twenty different levels represented by either one person or a committee. We grouped these twenty decisional levels in six pseudo loan managers/committees and, correspondently, created six dummy variables as follows: *Board*, *General Director/CEO; Vice General Director/Vice CEO*; *Headquarter Managers*; *Area Managers*; *Branch Managers*.

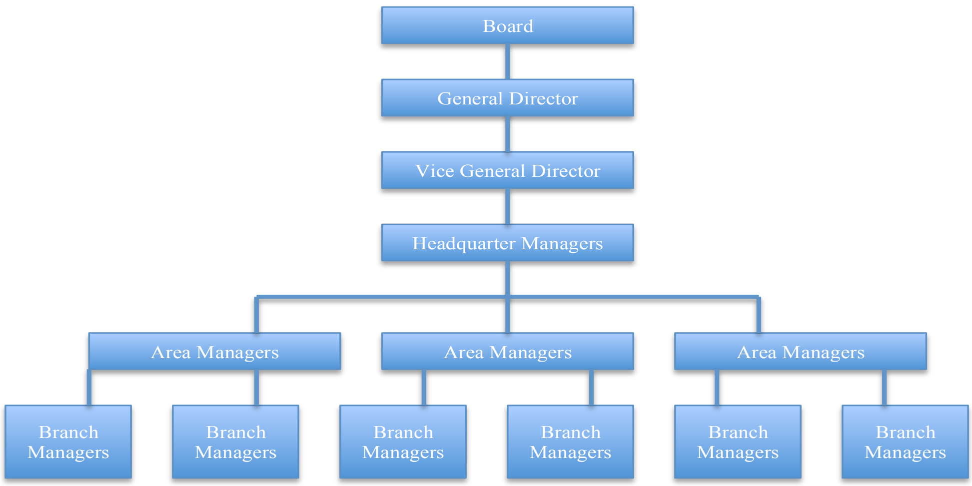
Figure (1) provides an illustration of the managerial hierarchy of the bank. In total there are six management levels with employees at each layer comparable in terms of their responsibilities, discretionary power, experience, and salary. The top four layers, starting with *Headquarter Managers*, constitute the senior management team and are mainly focused in business development. The lower ranked employees consist of *Area Managers* and *Branch Managers* and are mainly involved on the

[6] Some bank data are available only for the restricted sample, and are information related to the presence of guarantees, and to other services. The Appendix describes why and how we used a smaller database to estimate Models 1 and 2.
[7] Italy GDP fell by 2.4 percent in 2012.

operation side of lending. Every ranked employee has a credit origination limit and that limit increases with the rank of the official.

Each level has a specified approval limit depending on the size of the loan, and on firm rating. In case the loan falls out of the branch manager's limits, it is sent either to the *Area Manager*, *Headquarter Managers*, or higher decisional levels for approval.

Figure 1- Internal Organizational Design



The *Board*, the *General Director*, the *Vice General Director* and the *Headquarter Managers* operate from the central office. Below the central office there are the *Area Managers*, which represent distinct geographical zones across the region. Within each zone there may be some different area offices. Finally, under each area office there are a number of *Branch Managers*. Branches may be of different size: large, medium and small, according to the number of employees.

In fact, the organizational structure of the bank is such that all applications are first filed at a local bank branch. If the loan request is above certain threshold, the assessment of the loan application prepared by the loan officer at the local branch is passed along to senior managers at the bank headquarters for a further analysis and final decision.

2.3 Methodology

To examine the impact of different bank lending technologies on loan performance, we estimate two models.

Model 1 assumes that the variation of rating, *Delta Rating*$_{ij}$, depends on a set of independent variables and a constant term as follows

$$Delta\ Rating_{ij} = \beta_0 + \sum_{k=1}^{5} \beta_k H_{ij} + \sum_{m=6}^{15} \beta_m F_{ij} + \sum_{h=16}^{20} \beta_h L_{ij} + IFE_j + TFE_i + \varepsilon_{ij} \quad (1)$$

Model 2 assumes that the conditional probability that the firm rating deteriorates, pr_{ij} (*Deterioration=1*), depends on a set of independent variables and a constant term as follows

$$pr_{ij} = \Pr(Deterioration_{ij} = 1|X) = \Phi(X\beta) \qquad (2)$$

where

$$X\beta = \beta_0 + \sum_{k}^{5} \beta_k H_{ij} + \sum_{m=6}^{15} \beta_m F_{ij} + \sum_{h=16}^{20} \beta_h L_{ijt} + IFE_j + TFE_i + \varepsilon_{ij}$$

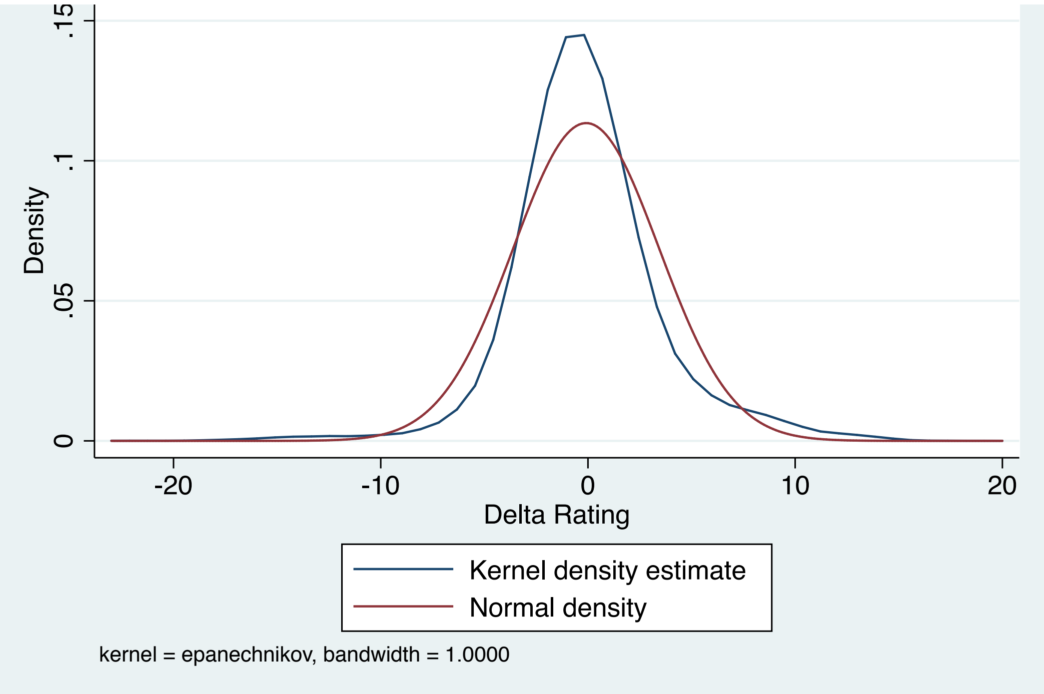
Φ=(.) is a cumulative distribution function (CDF), which is assumed to be Normal.

The indexes *i,* and *j* refer to loan applications and firms, respectively. H_{ij} contains information on who evaluated the loan within the bank and F_{ij} and L_{ij} are vectors of (respectively) firm-specific and loan application-specific variables. IFE_j and TFE_i are industry and time fixed-effects dummy variables, respectively, and ε_{ij} is the error term that is assumed to be independent and identically distributed.

In Model 1, our dependent variable, *Delta Rating*, is a discrete variable equal to the difference between the rating at the end of our period of observation (end 2012) and the month at which the loan is deliberated.[8] In the bank database, each loan/firm is keyed to a rating status from '1', i.e., performing exposures, to '24' that correspond to a default probability of 100 percent.

Figure 2 shows the distribution of *Delta Rating*. We note that the distribution is slightly left biased, thus, as expected, the numbers of rating deterioration are larger than those of rating improvements.

Figure 2- Kernel density estimate of Delta Rating



Three sets of variates might potentially affect the rating status variation and deterioration.

[8] Observations of loans deliberated in the last six months of 2012 are not included in the sample used to estimate Models 1 and 2.

The first set, the vector *H*, contains information on the hierarchic power to approve a loan application. Thus, the vector *H* contains six dummy variables as follows: *Board,*[9] *General Director*/CEO; *Vice General Director*/*Vice* CEO; *Headquarter Managers*; *Area Managers*; *Branch Managers*.

The second set, the vector *F*, contains firm-specific characteristics. They are: a) the firm's size as measured by (the log of) their sales, *Log(Sales)*, at the time of the loan approval; b) the firm's age as measured by (the log of) years from foundation, *Log(Age)*, at the time of the loan approval; c) the firm's leverage, *Leverage*, at the time of the loan approval; d) the firm's proximity to the bank as measured by the dummy variable *Municipality*, which takes the value of one if the branch and the firm are located in the same municipality, and zero otherwise; e) the demand by the firm for *Other Services* provided by the bank that, in our case, are mainly represented by financial services, apart from lending, such as securities accounts. The securities accounts mostly contain treasury bonds. The metric *Other Services* is a dummy variable that is equal to one when the firm demands these services and zero otherwise, and is intended to capture the scope of the bank-borrower interaction (Cole and Wolken, 1995). The association between this relationship characteristic and a loan performance might be dominated by either a reduction in asymmetric information and an enhancement of mutual trust or the exacerbation of hold-up problems (or mitigation of possible soft budget) originating from the preferential position of the bank. Furthermore, the presence of a securities account owned by the firm could weaken the bank's incentive to screen firms' investment projects, affecting negatively the loan performance (Manove, Padilla and Pagano, 2001); f) the number of granted loans, *Granted Loans*, the firm has obtained along the three-year period. This variable measures the number of (positive) interactions the firm and the bank have during the period. In general, we observe that the loans in our sample are frequently renegotiated by the bank, both to adjust interest rates to changing policy or interbank rates, and to reflect various changes in the economic conditions; g) similarly, we also control for those firms that obtain loans in all the three years by means of a dummy variable, *Firm123*, which takes the value of 1 if it is the case; h) Ono and Uesugi (2009) observe that the composition of the lender's portfolio might also be relevant for collateral requirements. We extend their idea by adding a variable, *Portfolio*, which takes the value of 1 if the bank considers the borrower as part of its corporate market and 0 if it is part of the small business market. The assignment to one of the two segments depends on borrowers' business strategy, type of industry, and their demand for services; i) we also control for the presence of a new bank customer, for which the bank assigns a rating for the first time. The *New Customer* variable is equal to 1 when the firm is a new customer, and 0 otherwise.

We also added in our empirical equation industry fixed effects, as defined according to the ATECO 2007 classification (ISTAT, 2009). The 48% of firms are in the Manufacturing industry, 20% in the Construction industry, and the 14% in the Wholesale and retail trade industry.

[9] The bank President, i.e., the President of the Board of Directors, has the authority to approve a loan under unique circumstances and at short notice.

The third set of variates, the vector *L*, contains loan- and branch-specific characteristics. They are: a) the firm rating at the time of the loan approval, *Initial Rating*, a step variable and runs from 1 to 24 (higher values correspond to higher default probabilities); b) the (log of) amount of credit granted by the bank before the new loan application is approved *Log(Initial Debt)*; c) the presence of guarantees assisting the loan. Specifically, *Collateral* is a dummy variable, which takes the value of one if the loan is backed by collateral and zero otherwise; *Personal Guarantees* is a dummy variable, which takes the value of one if the loan is backed by personal guarantee and zero otherwise; *Personal and Collateral* is a dummy variable, which takes the value of one if the loan is assisted by both personal guarantees and collateral and 0 otherwise. As shown in Table 3, 5.4% of loans are assisted by *Collateral*, while 21% of loans are assisted by *Personal Guarantees*. The 5.3% of loans are secured by both types of guarantees. Furthermore, we have information on the *Loan Type*, which can be line of credit, loan, mortgage, or composite loan (as a result of a combination of the first three loan types). As shown in Table 3, 76% of loans are lines of credit according to which the bank establishes the maximum amount of the loan that the firm can borrow. The firm can access funds from the line of credit at any time, as long as it not exceeds the maximum amount granted. Thus, this loan type is mainly used to finance firm short-term needs of credit to run its business. Loans are the 9.8% of total loans, while mortgages are 2.5%. The latter are always assisted by collateral and are granted to finance firm's real investments, such as the acquisition of machinery or plants. Finally, we control for the size of the branch office by means of three dummy variables, *Large*, *Medium*, and *Small*, which take the value=1 if the branch size falls in that specific category, and zero otherwise. The 47% of applications are made at *Medium*-size Branch offices.

Finally, we control for time fixed effects.

Variable description and summary statistics are shown in Table 2 and Table 3, respectively.

Table 4 shows the number of rating deterioration by decisional level: the percentage of rating deterioration increases as long as the lending decision is taken at higher hierarchical levels and it is significantly larger when the decision is taken by the *Board* than by the other decisional levels.

Descriptive statistics suggest a negative relationship between the hierarchy of bank loan approval and loan performance, which is worth exploring.

Table 2. Variable Definitions

VARIABLE	DEFINITION	SOURCE
	Dependent variables	
Delta Rating	A discrete variable, which is equal to the difference between the firm rating at the end of 2012 and the firm rating at the time the loan is granted.	Bank Data
Deterioration	A dummy variable equal to 1 (and 0 otherwise) if the rating deteriorates at the end of the period; that is if the variable Delta Rating is greater than zero.	Bank Data
	Decisional levels	
Board	A dummy variable equal to 1 (and 0 otherwise) if the loan was deliberated by one of the following original decisional authorities: 'President'; 'Board of Directors'; 'Executive Committee'; 'Credit Committee';	Bank Data
General Director	A dummy variable equal to 1 (and 0 otherwise) if the loan was deliberated by the Chief Executive Officer (CEO) of the bank.	Bank Data
Vice General Director	A dummy variable equal to 1 (and 0 otherwise) if the loan was deliberated by the Vice CEO	Bank Data
Headquarter managers	A dummy variable equal to 1 (and 0 otherwise) if the loan was deliberated by one of the following authorities: 'Supervisor debt collection'; 'Supervisor credit area'; 'Delegate Supervisor credit area'; 'Supervisor of the loan service'; 'Delegate of the loan service'.	Bank Data
Area managers	A dummy variable equal to 1 (and 0 otherwise) if the loan was deliberated by one of the following authorities: 'Area Supervisor'; 'Delegate area supervisor'; 'Delegate Territorial Manager loan service'; 'Territorial Manager loan service'; 'Area Delegate Manager'; 'Area Manager'	Bank Data
Branch managers	A dummy variable equal to 1 (and 0 otherwise) if the loan was deliberated by one of the following managers: 'Branch Manager1'; 'Branch Manager2'; 'Branch Manager3'	Bank Data
	Firm Characteristics	
Log(Sales)	A continuous variable, which measures the (log) of firm sales in the year of application in thousands of euros.	AIDA
Log(Age)	A continuous variable, which measures the (log) of firm age in the year of application.	AIDA
Leverage	A continuous variable, which measures the (log) of firm leverage in the year of application in thousands of euros.	
Portfolio	A dummy variable equal to 1 when the firm belongs to the corporate portfolio of the bank, and 0 if it belongs to the small business portfolio.	Bank Data
New Customer	A dummy variable equal to 1 (and 0 otherwise) when the firm is a new customer.	Bank Data
Municipality	A dummy variable equal to 1 (and 0 otherwise) if the branch and the firm are located in the same municipality.	AIDA
Other Services	A dummy variable equal to 1 (and 0 otherwise) when the firm demands other services to the bank.	Bank Data
Granted Loans	A discrete variable, which identifies the number of loans obtained from the bank by the firms in the three years.	Bank Data
Firm123	A dummy variable equal to 1 (and 0 otherwise) when the firm obtains credit from the bank in all the three years.	Bank Data
Industry Fixed Effects	21 dummy variables, which identify the sector of firm activity according to the ATECO2007 classification.	AIDA
	Loan Characteristics	
Initial Rating	A step variable, which measures the customer rate at the time (month) the loan is granted. Rating goes from 1 to 24 according to the bank's range of the probability of default. It is equal to 1 if the default probability is *very low*, 24 if the default probability is *very high*.	Bank Data
Log(Initial Debt)	A continuous variable that measures the (log) amount of credit granted by the bank before the new application is approved.	Bank Data
Collateral	A dummy variable equal to 1 (and 0 otherwise) if the loan is assisted by collateral.	Bank Data
Personal Guarantees	A dummy variable equal to 1 (and 0 otherwise) if the loan is assisted by personal guarantees.	Bank Data
Personal and Collateral	A dummy variable equal to 1 (and 0 otherwise) if the loan is assisted by personal guarantees and collateral.	Bank Data
Loan Type	4 dummy variables, which identify the type of loan: "Line of Credit", "Loans", "Mortgages", "Composite Loans".	Bank Data
Branch size	4 dummy variables, which identify the size of the branch: "small", "medium", "large", "not available".	Bank Data

Table 3. Summary statistics of the regression sample

The table presents summary statistics for the sample used in the analysis. Description of the variables is provided in Table 2. The sample consists of 15,101 observations.

Variable	Mean	Max	Min	Sd
		Dependent Variables		
Delta Rating	-0.086	19	-22	3.516
Deterioration	12.235	24	1	3.586
		Decisional Levels		
Board	0.049	1	0	0.215
General Director	0.044	1	0	0.206
Vice General Director	0.116	1	0	0.321
Headquarter Managers	0.152	1	0	0.359
Area Managers	0.337	1	0	0.473
Branch Managers	0.301	1	0	0.459
		Firm Characteristics		
Log(Sales)	7.939	13.421	-4.510	1.148
Log(Age)	2.523	4.663	0	0.873
Leverage	20.396	924.820	-960.420	71.096
Municipality	0.653	1	0	0.476
Other Services	0.308	1	0	0.462
Granted Loans				
		Loan and Bank Characteristics		
Initial Rating	12.235	24	1	3.586
Log (Initial Debt)	12.861	18.919	0	2.772
Collateral	0.054	1	0	0.226
Personal Guarantees	0.210	1	0	0.408
Personal and Collateral	0.053	1	0	0.225
Lines of Credit	0.757	1	0	0.429
Loan	0.098	1	0	0.298
Mortgages	0.025	1	0	0.157
Composite Loan	0.119	1	0	0.324
Large-size branch	0.345	0	1	0.476
Medium-size branch	0.467	0	1	0.499
Small-size branch	0.167	0	1	0.373
Size not available	0.021	0	1	0.143

Table 4. Hierarchy of bank loan approval and loan deterioration

Decisional Level	Deterioration		Percentage of Deterioration
	No (Deterioration = 0)	Yes (Deterioration = 1)	
Board	351	382	52.11%
General Director	338	334	49.70%
Vice General Director	966	794	45.11%
Headquarter Managers	1,406	895	38.85%
Area Managers	3,370	1,726	33.87%
Branch Managers	3,087	1,458	32.08%
Total	9,521	5,589	36.99%

3. Empirical Strategy and Discussion of Results

This paper aims at studying the relationship between who, within a bank, approves a loan and its performance. Given the review of the literature and the data available, we have enough information upon which to base the following

Portmanteau Hypothesis: *If lending technologies are used effectively at all hierarchical levels, changes in firm ratings should not be affected by who, within a bank, approves a loan.*

Table 5 shows OLS estimates of Model 1, while in Table 6 we report the Probit estimates of Model 2.

3.1 Hierarchy levels

Our key variables are decisional levels; thus, we first focus our attention to the estimated coefficients of the hierarchic variables. In both Table 5 and 6, the *Branch Managers* variable is the excluded dummy, so the estimated coefficients of the other decisional level variables may be interpreted as differences with respect to this missing binary variable. Results show that for all decisional levels, apart the *Area Managers*, which is the closest one to the *Branch Managers*, both the rating (negative) variation and the rating deterioration are higher with respect to the loans granted by the bottom of the decisional hierarchy. Furthermore, as shown in both Tables, the probability is larger as long as the decisional level increases, suggesting that relationship lending technologies are more effective than transaction-based lending technology. This finding is overall confirmed in the estimates in which we control for all other firm- and loan- characteristics. In other words, the probability of deterioration is significantly larger if the loan decision is taken by the *Board* than by a branch loan officer, after controlling for several conditional issues of the loan approval, such as the firm risk (rating). This finding suggests that default probabilities are higher in the presence of transaction-based lending technologies, which are typically employed at the highest decisional levels.

3.2 Control variables

Further, the estimated effects of the presence of guarantees and financial services, apart from lending (such as a securities account) are the opposite of those expected: they both tend to be associated with a lager rating deterioration. In the former case, the presence of personal guarantees and the contemporaneous presence of collateral and personal guarantees likely identify the riskier firms, while in the latter security accounts play the role of one among other secondary sources of repayment, since we already control for the presence of guarantees (collateral and personal guarantees). Therefore, the information content of the *Other Services* variable is not consistent with the predictions of transaction-based technologies, according to which a subset of assets may be used as one source of repayment in the case of loan default, and our results show that, on average, firms with securities account were, likely, also low-quality customers (Berger and Udell, 2006). Another explanation of the positive relationship between loan defaults and the presence of *Other Services* refers to the possibility that the bank's incentive to screen firms' investment project is weaken in the presence of securities accounts owned by the firms. This *lazy* bank behavior will likely result, on average, in higher loan default rates (Manove, Padilla and Pagano, 2001).

The negative sign of the coefficient of the dummy variable *Municipality*, which has value equal to one if the firm is locate in the same commune of the bank or one of its branches, provides support for relationship lending technologies that help to reduce information asymmetries between firms and banks by the close contact between the two parties. This finding is consistent with recent empirical evidence which shows that

Our results are favorable to relationship lending technologies, but they also show that transaction-based technologies were not effectively used by higher levels of the bank hierarchy.

Table 5: Rating variation and decisional levels

The table shows estimated coefficient of OLS estimation of Model 1, followed by robust standard errors in parentheses. Description of the variables is provided in Table 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

VARIABLES	(1)	(2)	(3)	(4)
Board	1.670***	0.951***	0.838***	0.377**
	(0.155)	(0.166)	(0.170)	(0.161)
General Director	1.226***	0.932***	0.812***	0.371**
	(0.163)	(0.161)	(0.166)	(0.163)
Vice General Director	0.924***	0.740***	0.599***	0.366***
	(0.100)	(0.105)	(0.113)	(0.110)
Headquarter Managers	0.469***	0.330***	0.172*	0.079
	(0.087)	(0.088)	(0.095)	(0.093)
Area Managers	0.057	0.030	-0.031	-0.034
	(0.069)	(0.068)	(0.072)	(0.071)
Initial Rating	-0.069***	-0.111***	-0.139***	-0.137***
	(0.008)	(0.009)	(0.009)	(0.009)
Log (Sales)		-0.024	-0.120***	0.048
		(0.033)	(0.040)	(0.041)
Age		-0.249***	-0.315***	-0.303***
		(0.037)	(0.042)	(0.041)
Leverage		0.003***	0.003***	0.002***
		(0.000)	(0.000)	(0.000)
Municipality		-0.642***	-0.598***	-0.620***
		(0.060)	(0.059)	(0.059)
Other Services		0.503***	0.430***	0.424***
		(0.063)	(0.063)	(0.062)
Log (Initial Debt)		0.172***	0.128***	0.094***
		(0.015)	(0.016)	(0.016)
2011		-0.035	-0.012	-0.012
		(0.062)	(0.062)	(0.060)
2012		-0.048	-0.066	0.017
		(0.072)	(0.072)	(0.070)
Portfolio			0.620***	0.567***
			(0.078)	(0.077)
New Customer			0.021	0.023
			(0.149)	(0.149)
Granted loans			0.018***	0.021***
			(0.002)	(0.002)
Firm123			0.828***	0.746***
			(0.067)	(0.066)
Collateral			-0.206	-0.256
			(0.185)	(0.182)
Personal Guarantees			0.424***	0.328***
			(0.083)	(0.081)
Personal and Collateral			0.435***	0.295*
			(0.153)	(0.152)
Constant	0.455***	-0.129	0.593	-0.997*
	(0.108)	(0.319)	(0.376)	(0.542)
Industry fixed effects	no	No	no	yes
Loan type effects	no	no	yes	yes
Brach size effects	no	no	yes	yes
Observations	16,328	15,110	15,110	15,110
Firms	3,286	3,103	3,103	3,103
Adj. R-squared	0.022	0.055	0.086	0.148

Table 6: Rating deterioration and decisional levels

The table shows estimated coefficient of Probit estimation of Model 2, followed by robust standard errors in parentheses. Description of the variables is provided in Table 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

VARIABLES	(1)	(2)	(3)	(4)
Board	0.556***	0.443***	0.378***	0.205***
	(0.048)	(0.053)	(0.057)	(0.059)
General Director	0.479***	0.412***	0.341***	0.187***
	(0.049)	(0.053)	(0.057)	(0.059)
Vice General Director	0.339***	0.335***	0.264***	0.176***
	(0.034)	(0.037)	(0.040)	(0.041)
Headquarter Managers	0.180***	0.181***	0.107***	0.068*
	(0.032)	(0.034)	(0.036)	(0.037)
Area Managers	0.044*	0.017	-0.022	-0.036
	(0.026)	(0.027)	(0.029)	(0.030)
Initial Rating	-0.017***	-0.036***	-0.041***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)
Log (Sales)		-0.018*	-0.071***	-0.008
		(0.010)	(0.013)	(0.014)
Log (Age)		-0.144***	-0.156***	-0.159***
		(0.013)	(0.015)	(0.016)
Leverage		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
Municipality		-0.268***	-0.246***	-0.257***
		(0.022)	(0.023)	(0.024)
Other Services		0.059**	0.024	0.021
		(0.023)	(0.024)	(0.025)
Log (Initial Debt)		0.043***	0.032***	0.019***
		(0.005)	(0.005)	(0.005)
2011		-0.094***	-0.094***	-0.099***
		(0.023)	(0.024)	(0.024)
2012		-0.135***	-0.156***	-0.131***
		(0.033)	(0.034)	(0.035)
Portfolio			0.286***	0.288***
			(0.029)	(0.030)
New Customer			0.162***	0.173***
			(0.056)	(0.057)
Granted loans			0.301***	0.274***
			(0.026)	(0.026)
Firm123			0.301***	0.274***
			(0.026)	(0.026)
Collateral			-0.052	-0.063
			(0.066)	(0.069)
Personal Guarantees			0.132***	0.094***
			(0.030)	(0.031)
Personal and Collateral			0.034	-0.020
			(0.053)	(0.055)
Constant	-0.242***	0.132	0.432***	0.141
	(0.039)	(0.102)	(0.123)	(0.198)
Industry fixed effects	no	no	No	yes
Loan type effects	no	no	Yes	yes
Brach size effects	no	no	Yes	yes
Observations	16,328	15,110	15,110	15,110
Firms	3,286	3,103	3,103	3,103

4. Conclusion

In this study we use a unique dataset from a regional Italian bank to provide new evidence on how the hierarchical distance between a loan officer and the bank president affect the performance of bank loans. The theory on information sharing suggests that it becomes more difficult for a subordinate to share information with his boss when the subordinate is lower in the lending-decision hierarchy. When the loan-approval decision is made at higher levels of the hierarchy, information collected by the subordinates is likely to receive less weight in the decision process, resulting in inferior loan outcomes.

Our empirical results show that the probability of rating deterioration increases with the hierarchical position of the decision-maker. This is supportive of the idea that relationship lending technologies are more effective at the lowest level of the lending institution hierarchy. We also find that the probability of deterioration is lower when the borrower is located in the same municipality as the bank branch to which the borrower applied. This finding demonstrates that the physical distance between borrower and lending still matters, at least for Italian SMEs.

Our results about the different response of default probabilities to relationship and transaction-based lending technologies may also provide support to structural bank regulation initiatives, mainly in the U.S. and U.K., as a response to the global financial crisis.

Appendix: Database construction

The database was constructed by means of the following steps:

1. Extraction of all deliberated loan records from the original database provided by the regional bank for the period 1/1/2010 − 31/12/2012: nr. 273,699 loans, for a total of nr. 109,148 customers;
2. From the total number of loans, we dropped those (nr. 56,148) for which the delta debt (i.e.: the variation between the initial debt and the requested amount of final debt) was equal to zero. These records usually refer to internal procedures the bank uses to control its clients. Thus, the final dataset at this stage contains 217,551 records and 100,825 customers, of which 17,641 are firms and 136,095 the corresponding records;
3. In the next step we merged the database with information (balance sheet data) coming from the AIDA (Italian company information and business intelligence) dataset for the Region where the bank headquarters are located. AIDA covers 1 million Italian companies, and contains their detailed accounting information following the scheme of the 4th Directive CEE, plus indicators and trade description; information on ownership and managers and scanned images of accounts with additional notes. The cost of using this additional source of information was the drop in the number of observations (from 136,095 to 18,658 loan records and from 17,641 to 3,425 firms);
4. The bank provided information on the presence of guarantees and on the presence of other services only for the matched sample.

References

Agarwal S., and Hauswald R., (2010). Distance and Private Information in Lending, *Review of Financial Studies*, 23: 2757–2788.

Alessandrini P., Calcagnini G., and Zazzaro A., (2008). Asset restructuring strategies in bank acquisitions: Does distance between dealing partners matter? *Journal of Banking & Finance*, 32(5): 699 – 713.

Alessandrini P., Presbitero A.F., and Zazzaro A., (2009). Banks, distances and firms' financing constraints, *Review of Finance*, 13(2): 261 – 307.

Angelini P., Bofondi M. and Zingales L., (2017) The origins of Italian NPLs, draft, Bank of Italy and University of Chicago.

Badulescu D., (2012). SMEs Relationship Banking: Length, Loyalty, Trust. Do SMEs get something in Return? *International Journal of Economics and Management Engineering* Vol:6, No:6, 1038-1045.

Bank of Italy (2017). Banche e istituzioni finanziarie: finanziamenti e raccolta per settori e territori. Roma

Bank of Italy (2017). Annex, https://www.bancaditalia.it/media/views/2017/npl/, Roma

Bank of Italy (2013). Relazione Annuale sull'anno 2012. Roma.

Bank of Italy (2012). Relazione Annuale sull'anno 2011. Roma.

Bartoli F., Ferri G., Murro P., and Rotondi Z., (2013). Sme financing and the choice of lending technology in Italy: Complementarity or substitutability? *Journal of Banking & Finance*, 37(12): 5476 – 5485.

Berger A.N., and Udell G.F., (2002), Small business credit availability and relationship lending: the importance of bank organisational structure. *The Economic Journal*, 112: F32-F53.

Berger A.N., and Udell G.F., (1992). Some evidence on the empirical significance of credit rationing, *Journal of Political Economy*, 100(5): 1047 – 1077.

Berger A.N., and Udell G.F., (2006). A more complete conceptual framework for sme finance, *Journal of Banking & Finance*, 30(11): 2945 – 2966.

Berlin M., and Mester L. J. (1999). Deposits and relationship lending, *The Review of Financial Studies*, 12(3): 579 – 607.

Bolton P., Freixas X., Gambacorta L., and Mistrulli P.E., (2016). Relationship and transaction lending in a crisis. *The Review of Financial Studies*, 29(10): 2643 – 2676.

Boot A.W.A. and Thakor A.V, (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, 20: 503 – 529.

Boot A. W. A. (2000) Relationship banking: What do we know? *Journal of Financial Intermediation*, 9(1): 7 – 25.

Brighi P., Lucarelli C., and Venturelli V. (2017). Predictive strength of lending technologies in funding smes. *Mimeo*.

Calcagnini G:, Cole R., Giombini G., and Grandicelli G., (2018). Hierarchy of bank loan approval and loan performance. *Economia Politica: Journal of Analytical and Institutional Economics*, 35(3), pp. 935-954.

Calcagnini G., Farabullini F., Giombini G. (2014). The impact of guarantees on bank loan interest rates, *Applied Financial Economics*, 24: 397 – 412.

Calcagnini G., G. Giombini, and E. Lenti. (2015). Gender Differences in Bank Loan Access. An Empirical Analysis, *Italian Economic Journal*, 1: 193-217.

Cole, R., L. Goldberg, and L. White (2004). Cookie Cutter vs. Character: The Micro Structure of Small Business Lending by Large and Small Banks, *Journal of Financial and Quantitative Analysis*, 39: 227 – 250.

Cole, R., and J. D. Wolken, (1995) Financial services used by small businesses: evidence from the 1993 National Survey of Small Business Finances, Federal Reserve Bulletin, Board of Governors of the Federal Reserve System (U.S.), issue Jul, 629-667.

Gambacorta L., (2016). Relationship and transaction lending: New evidence and perspectives. *Emerging Markets Finance and Trade*, 52(1): 70 – 75.

Gambacorta, L., and A. van Rixtel. 2013. Structural bank regulation initiatives: Approaches and implications. BIS Working Papers 412, Bank for International Settlements, Basel.

Guida R., Sabato V. (2017). Relationship Lending and Firms'Leverage: Empirical Evidence in Europe, *European Financial Management*, Vol. 23, No. 4, 2017, 807–835. DOI: 10.1111/eufm.12109

Hernández-Cánovas, G. & Martínez-Solano P., (2010). Relationship lending and SME financing in the continental European bank-based system, *Small Bus Econ* 34: 465-482. DOI: 10.1007/s11187-008-9129-7

ISTAT (2009). Classificazione delle attività economiche Ateco 2007. Metodi e Norme n. 40. ROMA.

Liberti, J. M., and Mian A. R., (2009). Estimating the Effect of Hierarchies on Information Use, *Review of Financial Studies*, 22: 4057 – 4090.

Maggi B., Guida M. (2011). Modelling non-performing loans probability in the commercial banking system: efficiency and effectiveness related to credit risk in Italy, *Empir Econ*, 41: 269–291. DOI: 10.1007/s00181-010-0379-2

Manove M., Padilla A. J. And M. Pagano (2001). Collateral versus project screening: a model of lazy banks, *RAND Journal of Economics*, 32 (4): 726–744.

Marchetti J D and Pozzolo A.F., (2018). Bank organization and credit supply at difficult times: Evidence from the Lehman Crisis. Paper presented at the La 59.ma Riunione Scientifica Annuale (RSA) della Società Italiana degli Economisti, Bologna 25-27 October.

Ono A., and I. Uesugi. (2009). Role of Collateral and Personal Guarantees in Relationship Lending: Evidence from Japan's SME Loan Market, *Journal of Money, Credit and Banking* 41, 935-960.

Petersen M. A. and Rajan R. G., (1995). The effect of credit market competition on lending relationships, *The Quarterly Journal of Economics*, 110(2): 407 – 443.

Qian J., P. E. Strahan and Z. Yang (2015). The Impact of Incentives and Communication Costs on Information Production and Use: Evidence from Bank Lending, *The Journal of Finance*, 70(4): 1457 – 1493.

Rajan R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt, *The Journal of Finance*, 47(4): 1367 – 1400.

Sharpe S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships, *The Journal of Finance*, 45(4): 1069 –1087.

Skrastins J., and Vig V. (2019). How Organizational Hierarchy Affects Information Production, *The Review of Financial Studies*, Volume 32, Issue 2, 1 February, pp. 564–604.

Uchida H., Udell G.F., and Yamori N. (2006). Sme financing and the choice of lending technology. Technical Report 06-E-025, RIETI Discussion Paper Series 06-E-025.

Uchida H., Udell G.F., and Yamori N. (2012). Loan officers and relationship lending to smes, *Journal of Financial Intermediation*, 21(1): 97 – 122.

Visco I. (2018). Anni difficili. Dalla crisi finanziaria alle nuove sfide per l'economia, *Il Mulino*.