UNIVERSITÀ CATTOLICA DEL SACRO CUORE
Dipartimento di Economia e Finanza

Working Paper Series

Debt restructuring with multiple bank relationships

Angelo Baglioni, Luca Colombo, Paola Rossi

Working Paper n. 77

January 2019

UNIVERSITÀ CATTOLICA del Sacro Cuore

Debt restructuring with multiple bank relationships

Angelo Baglioni
Università Cattolica del Sacro Cuore

Luca Colombo
Università Cattolica del Sacro Cuore

Paola Rossi
Banca d'Italia

Working Paper n. 77
January 2019

Dipartimento di Economia e Finanza
Università Cattolica del Sacro Cuore
Largo Gemelli 1 - 20123 Milano – Italy
tel: +39.02.7234.2976 - fax: +39.02.7234.2781
e-mail: dip.economiaefinanza@unicatt.it

Debt restructuring with multiple bank relationships*

Angelo Baglioni† Luca Colombo‡ Paola Rossi§

Abstract

When the debt of firms in distress is dispersed, a restructuring agreement is difficult to reach because of free riding. We develop a repeated game in which banks come across each other frequently, allowing them to threaten a punishment in case of free riding. As the number of lending banks grows, the chance of meeting again a bank and of being punished for free riding increases, improving the likelihood of cooperation. Looking at Italian firms in distress, we find that the restructuring probability increases with the number of banks up to a threshold - three banks - beyond which coordination problems prevail.

JEL: G21, G33

Keywords: banks, debt restructuring, number of creditors

---

*The opinions expressed are those of the authors and do not necessarily reflect those of the Bank of Italy. We wish to thank Raffaello Bronzini, Vittoria Cerasi, Ettore Croci, Silvia Del Prete, Marcello Pagnini, Carlotta Rossi, Paolo Sestito, the participants at the Workshop on Credit and Financial Institutions Agglomeration (Bank of Italy, Rome, 30 January 2015), at the Italian Economic Society (Bocconi University, October 2015) and two anonymous referees for suggestions and comments to a previous version of the paper. Remaining errors are our own.

†Università Cattolica, Largo A. Gemelli 1, I-20123 Milano. Phone: +39.02.7234.4024; fax: +39.02.7234.2781; e-mail: angelo.baglioni@unicatt.it

‡Università Cattolica, Largo A. Gemelli 1, I-20123 Milano. Phone: +39.02.7234.2637; fax: +39.02.7234.2781; e-mail: lucava.colombo@unicatt.it

§Banca d'Italia, Research Division Milan Branch. Phone: +39.02.72424.342; e-mail: paola.rossi@bancaditalia.it

1 Introduction

Bank lending is an important source of external finance, frequently the only one available to small- and medium-sized enterprises to fund their activity and investments. Tight bank-firm relationships are assumed to ease financial constraints of firms without access to capital markets (Boot, 2000). This is true especially in difficult times, when the firm cannot meet its obligations and it has to renegotiate its debt contracts to avoid bankruptcy (Rajan, 1992; Bolton and Freixas, 2000).

Despite the relevance of relationship lending, one common feature in many countries is multiple borrowing from many banks. According to Ongena and Smith (2000), focusing on a sample including 20 countries, firms have an average of 5.6 banking relationships. In Qian and Strahan (2007), who compare 43 countries, the number of banks ranges between 4 and 7 according to the country legal origin (English or German). In Italy, the average number of banks for non-financial firms is 3 when bank lending is between 500 thousands and 2.5 million euro, and 4 for loans up to 5 million euro; considering higher values of total loans, the number of banks becomes very large (up to 8 banks, see Figure 1) and the first lender covers less than 40 per cent of the total bank debt.[1]

The theoretical literature explains this behavior as aimed at reducing the information monopoly held by the main bank, which may translate into some form of rent extraction (Sharpe, 1990; Rajan, 1992) and induce misbehavior phenomena during the restructuring phase (Guiso and Minetti, 2010). Firms want to reduce the bank's monopoly power by diversifying the sources of external finance and by increasing the number of lending banks. Yet, the diversification in bank financing comes at the cost of increasing coordination risk in case of distress, since the conflicts among many creditors may convey liquidation even when this is not economically efficient (Bolton and Scharfstein, 1990, 1996; Bulow and Shoven, 1978; Gertner and Scharfstein, 1991; White, 1989). Considering this theoretical

[1] Bank of Italy's statistics concerning firms reported in the Credit Register (Centrale dei rischi) with total loans larger than 75,000 Euros and one or more credit relationships.

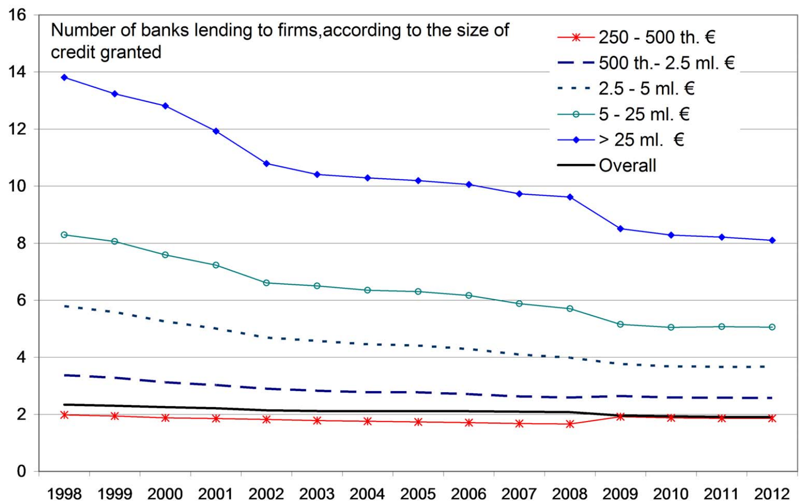

Figure 1: Multiple bank borrowing by firms. (Source: Bank of Italy, Credit Register Data)

background, it is even more puzzling that especially risky firms – those with a higher probability of default – tend to have a higher number of lending banks (Ongena *et al.*, 2012; Godlewski *et al.*, 2010).

As a matter of fact, while multiple bank relationships are widespread across countries, the actual effect of this choice on debt restructuring in case of financial distress is still an open question and very few papers address the coordination problem in a multiple bank framework.

In this paper, we provide a novel rationale for the diffusion of multiple banking focusing on a simple "restructuring game" modeled as a one-shot game with complete information among lending banks. We show that when the debt of a firm in distress is dispersed among many banks, a restructuring agreement may be difficult to reach because of the existence of free riding problems among lenders. Indeed, the liquidation solution is prevalent since the non-cooperative strategy is strictly dominant. However, there are some features in bank lending that may help reducing this coordination risk. Differently from dispersed bond-holders, banks are non-atomistic creditors acting strategically. Indeed, recent theoretical contributions have highlighted that banks interact strategically (Hertzberg *et al.*, 2011; Ogura, 2006; Fluet and Garella, 2007). In this perspective, and recalling that multiple banking is a restraint in the renegotiation process, banks may behave very differently from dispersed public creditors or large pools of uniform lenders. They can meet and discuss how to deal with a firm's financial distress. More important to our analysis, they can threat a punishment in other credit relationships in case of free riding behavior.

We embed these features in our theoretical model by considering a game repeated through time. Every stage of the game corresponds to a decision on a different firm in distress, the outstanding debt of which should be restructured by the lending banks. Repeated interaction gives the possibility to introduce a punishment in case of free-riding behavior. By adopting a classical trigger strategy (each bank cooperates until the other defects and afterwards it defects forever, thus forcing the liquidation of distressed firms), free riding becomes unprofitable whereas cooperation is rewarded. A central result of our model is that the threat of punishment becomes more relevant as the number of banks lending to a firm (and participating in the restructuring negotiation) grows large, since the chance of meeting again another bank of the same pool on another negotiation table grows as well. Thus, the likelihood of debt restructuring, avoiding an inefficient liquidation of a distressed firm, increases with the number of lending banks. This result contrasts with the traditional view that a large number of creditors reduces the chances of an agreement leading to debt forgiveness, due to coordination problems. Needless to say, as the number of banks involved in a credit relationship increases, coordination problems play a role as well, introducing a trade-off between coordination costs and the benefits of mitigating free riding.

The argument we use resembles that of multimarket contact proposed by Bernheim and Whinston (1990), according to whom multimarket contacts between two rival firms improve collusive outcomes since any deviation is punished not only in the market where it occurs but also in all other markets where the two firms compete. In our setting, the repetition of the game over different firms in distress improves the incentive to cooperate. Of course, this is true only if creditors are likely to meet again in the future and if they do not discount the value of the next encounter too much. In Axelrod's (1984) words "the future must have a sufficiently large shadow". This is a reasonable assumption as long as bank lending is concerned, while it is difficult to reconcile with publicly held debt restructuring.

Our key contribution is to test empirically the theoretical predictions of our simple model by estimating the probability of bank-debt restructuring. A restructuring choice is problematic, as firms' prospects are difficult to evaluate in a distress situation when hard information is likely to be less reliable. Of course, banks have many advantages compared to outside financiers. They have proprietary information about the firm characteristics, gathered through repeated interactions with the entrepreneur along the credit relationship, and they are better equipped to monitor borrowers than other creditors, especially when small and medium-sized enterprises are involved.

We focus on the role of firms' relationships within the banking system. We are especially interested on how the number of banks affects the capability of firms in financial distress to renegotiate outstanding debt and to successfully overcome the crisis, after controlling for the different aspects that may affect this decision. In particular, we want to test whether an increase in the number of banks has a positive impact on the probability of restructuring (at least up until coordination problems become predominant), as predicted by our theoretical model, or has a negative impact, as predicted by standard theory. In other words, we want to highlight the trade-off between the incentive to cooperate stemming from the strategic interactions among banks and the coordination problems that arise when the number of banks increases. To this aim, the Italian case – on which we focus – is an especially interesting one: on the one hand, bank-debt is the main source of external finance; on the other hand, multiple borrowing from many banks is widespread also among small-and medium-sized enterprises (Detragiache *et al.*, 2000).

We control for the economic and financial situation of the distressed firms by introducing balance-sheet ratios before the reorganization, and we introduce dummies for the sector of activity of the firm and its location. We also use firm fixed or random effects in various robustness checks. Finally, we verify the impact of these variables on the workout success and the firm's overall survival probability. We consider explicitly only financial restructuring in order to highlight the role of banks in this process, controlling for anticipated profit opportunities.

Our empirical analysis has been performed on the population of about 2,400 Italian firms facing distress in 2007. To build our dataset we start from banks' reports of borrowers facing distress. For regulatory reasons, banks have to report firms that encounter difficulties in repaying their debts, as long as the amount extended to the firm exceeds 75,000 Euros. We focus on doubtful loans (*incagli*), a condition in which the borrower is insolvent, but – unlike with bad loans (*sofferenze*) – this situation is assumed to be only temporary by the bank. We classify these firms as financially distressed. In order to include in our data those firms that are at an early stage of distress, we consider all firms that were reported as doubtful for the first time in 2007. Therefore we consider all Italian firms, with outstanding bank debt above the censoring threshold, that were unable to repay their debts in 2007, but that still had the possibility to recover according to their lending banks. These data have been combined with information concerning relationships with the banking system, balance-sheet data, and records from firms' official registers to assess whether the considered firms have gone bankrupt or have been liquidated in the following years.

We find that the probability of restructuring increases with the number of lending banks, although the impact is not linear and it becomes negative above a threshold (i.e. three banks). Consistently with our theoretical predictions, this finding suggests that the presence of a larger number of creditors can have a positive impact on the likelihood of cooperation among them, even though – after a threshold – this impact is more than offset by coordination problems. Our empirical analysis provides other interesting insights, although not directly implied by the theoretical model. Banks help firms with a better economic and financial situation – in terms of returns on industrial production and leverage ratio – before the distress event. Firm size is positively correlated with the probability of restructuring and it improves the likelihood of survival. Banks tend to restructure the outstanding debt of those firms for which bank financing is prevailing, so that the coordination problems with other types of creditors are lower. We also control for the concentration of debt among banks lending to the firm, finding that dispersed debt increases the probability of restructuring. One possible explanation for this result is that symmetric lending shares represent a mutual control mechanism, which improves the restructuring process by reducing the free riding incentive. This explanation is consistent with the insurance motive put forward by Carletti *et al.* (2007), according to which multiple lending allows banks to diversify their loans portfolio and share monitoring efforts.

Overall, we show that banks maintain their special role in firm financing also in difficult situations and when a firm's debt is dispersed among many banks, as they improve coordination in debt restructuring processes. However, this result is mitigated and eventually overturned when more than three banks are involved. Our findings are robust to various specifications of the dependent variable and to different econometric techniques.

The paper is organized as follows. Section 2 presents a stylized model highlighting our basic intuition, while Sections 3 and 4 test its empirical relevance. Section 5 deals with the outcome of the restructuring process, either liquidation or survival. Section 6 concludes.

2 A simple model of the restructuring decision

2.1 The basic decision problem with a single bank

We consider a firm that has an investment project to be completed in two periods (t_1 and t_2). The investment is financed by issuing only bank debt (D), which encompasses both the principal and interest payments and which will come to maturity at the end of the second period. We assume that the project cannot be partially liquidated.

As in Rajan (1992), at the end of the first period the investment starts generating cash flows and it becomes clear whether it will be successful or problematic. In good times, the returns are high, covering current expenses in t_1 and ensuring both debt repayments and extra profits for the entrepreneur in t_2. In contrast, in bad times, returns are not large enough to pay back current expenses in t_1 – such as wages or the costs of intermediate inputs. The low level of returns also signals the possibility that the firm will not be able to repay its debt due in t_2. Hence, the firm enters in financial distress and it must ask the bank for help. The bank can decide to rescue the firm by providing the additional funds needed to keep the firm going and to carry out the investment project. The bank either grants a new loan to assure survival, or it liquidates the firm: we focus our attention on this choice. At the end of the second period, if the workout is successful, the firm obtains a return (at most) equal to the value of the initial outstanding debt.[2] In turn, if the workout is unsuccessful, the investment brings zero return and the firm is liquidated.[3]

There are two possible cases. First, the bank does not refinance the firm and goes for liquidation. The liquidation value, $L > 0$, is lower than the outstanding bank debt: $L < D$. Hence, the bank suffers a loss in case of liquidation and it recovers only a known and previously identifiable

[2] We do not consider higher returns, essentially because of the financial distress situation in which the firm is operating. This is a common framework in previous research on debt restructuring (see, among others, Detragiache and Garella 1996).

[3] We assume that the entrepreneur prefers to avoid default, both because of its stigma and to retain the ability to invest and profit in the future.

portion of its initial loan.

Second, the bank refinances the firm, allowing it to continue its activity. It is reasonable to assume that the outcome from carrying out the workout plan presents further uncertainties, stemming from the distressed situation in which the firm is operating. Thus, the workout brings a positive return x in date t_2, with a probability of success equal to θ. This return is (at most) equal to the outstanding debt D, whereas the residual profits to equity-holders are zero, i.e. $x \leq D$. The bank can recover its initial loan, but it loses the new financing granted in the workout, i.e. the new loan is assumed to be junior with respect to the outstanding debt. For the sake of simplicity, and without loss of generality, we can assume that the relation between x and D holds with equality: $x = D$. If the workout fails, liquidation is the only option left, and the liquidation value L is lower than x (and D), essentially because of distressed selling.[4] Hence, the value of the firm under the restructuring hypothesis (V_r) is

$$V_r = \theta D + (1 - \theta)L,$$

with $L < D$.

As mentioned above, in order to obtain this restructuring value, new funds must be invested in the firm, representing the cost (C) of the restructuring option. Hence, the actual expected profit for the bank from restructuring is $V_r - C$. Figure 2 reports the extensive form representation of the payoffs obtained by the bank under different scenarios.

In the debt restructuring case, the bank has the possibility to receive a higher percentage of its credit than in the case of liquidation ($D - C > L$), although with some degree of uncertainty.[5] In case of unsuccessful restructuring, the liquidation value is reduced by the deadweight loss of the

[4] For the sake of simplicity, we assume that the liquidation value L is the same either if the firm is liquidated in t_1 – as a consequence of financial distress, or in t_2 – following an unsuccessful restructuring.

[5] This framework is in line with actual evidence about workout losses. For Italy, Generale and Gobbi (1996) estimate that banks lose about 20 per cent of their claims in private reorganizations, as against up to 80 percent in court-supervised bankruptcy procedures.

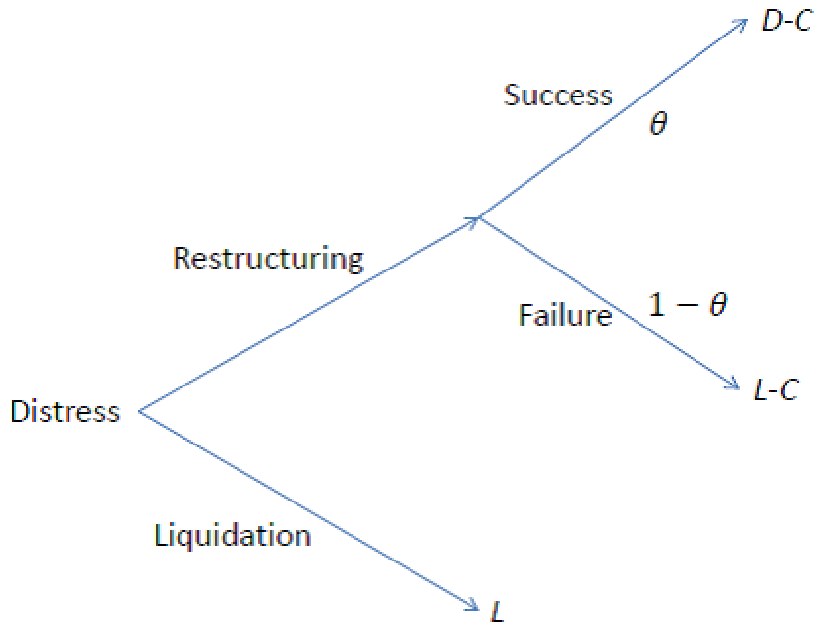

Figure 2: The bank's restructuring choice

new credit extended to finance the workout.

In order to analyze the restructuring versus liquidation decision, we assume that the bank is risk-neutral. Risk neutrality is usually considered a reasonable assumption to describe a well diversified bank (Rajan, 1992; Bannier, 2007; Detragiache, 1995). Hence, the bank participates to the restructuring process only if the expected profit from restructuring is higher than the liquidation value that could be obtained by liquidating the firm in t_1:

$$V_r - C \geq L. \tag{1}$$

This condition allows us to derive a probability threshold for which the bank is indifferent between restructuring or liquidating the firm in t_1 that is equal to

$$\theta^* = \frac{C}{D-L}. \tag{2}$$

As long as the probability of success of the workout is greater or equal than this threshold, i.e. $\theta \geq \theta^*$, the bank refinances the firm with the new loan, while if $\theta < \theta^*$ the firm is liquidated.

2.2 The coordination problem with several banks

Assume now that Condition (1) holds, so that it is efficient ex-ante for the single bank to restructure the debt and bail out the firm. It is then interesting to ask what are the consequences if more than one bank is financing the firm. A coordination problem arises among the lending banks, who should decide whether to restructure or not. The problem occurs because each bank is better off if it gains from restructuring without carrying the associated costs. Hence, each bank has an incentive to hold-out from any possible agreement, leaving the other banks to carry the whole burden of the procedure. This is a classical prisoner's dilemma situation. The consequence might be the liquidation of the firm, even though it is not the Pareto optimal solution.

To better highlight this coordination problem, we focus here on the simple two-bank case. The reasoning can be easily extended to the more general case in which the number of banks is $N > 2$, a case we study in the next Sub-section, dealing with the repeated game. Let us consider two banks, each lending $\frac{D}{2}$ to a distressed firm, so that each bank has one half of the total outstanding debt. Each of them has to decide in t_1 whether to provide the new funds needed to bail out the firm: we label these two different strategies as Cooperate (Co) and Not Cooperate ($NotCo$) respectively. The outcomes of their decisions can be described as follows.

1. Both banks cooperate, sharing the cost of bailing out the firm ($\frac{C}{2}$ each), in exchange of

one-half of the restructured firm's value ($\frac{V_r}{2}$).

2. Both banks do not cooperate: the firm is liquidated, and each bank gets $\frac{L}{2}$.

3. One bank cooperates and the other does not: the first bank bears the full cost of restructuring (C), while it gets only one-half of the restructured firm's value ($\frac{V_r}{2}$); the second bank gets one-half of the restructured firm's value ($\frac{V_r}{2}$) without bearing any restructuring cost. In other words, the latter bank adopts a typical free-riding behavior.

Table 1 represents the game between the two banks in normal form. We assume that the outcomes are common knowledge and that the two banks act simultaneously. Furthermore, we only focus on pure strategies.[6]

Table 1: The two-bank game (the first payoff in each cell is that of bank 1)

		Bank 2	
		$NotCo$	Co
Bank 1	$NotCo$	$L/2, L/2$	$V_r/2, V_r/2 - C$
	Co	$V_r/2 - C, V_r/2$	$(V_r - C)/2, (V_r - C)/2$

It is immediate to see that (Co, Co) cannot be a Nash equilibrium, since $\frac{V_r}{2} > \frac{V_r - C}{2}$: if one bank cooperates, the other one has a clear incentive to free ride. To see whether either $(NotCo, Co)$, or $(Co, NotCo)$ can be an equilibrium, we need to check the inequality

$$\frac{V_r}{2} - C \geq \frac{L}{2}, \tag{3}$$

which enables us to define the following threshold for the success probability of the workout:

$$\hat{\theta} = \frac{2C}{D - L}. \tag{4}$$

[6]We are mainly interested in situations where there exists a unique equilibrium in dominant strategies.

If $\theta \geq \hat{\theta}$, then one bank has an incentive to bear the full cost of bailing out the firm, given that the other bank holds-out. If $\theta < \hat{\theta}$, to the contrary, the dominant strategy for each bank is $NotCo$, so the Nash equilibrium is $(NotCo, NotCo)$. This discussion allows us to state the following Proposition 1.

Proposition 1 *There exists a threshold level ($\hat{\theta}$) for the success probability of the workout, such that:*

(a) if $\theta \geq \hat{\theta}$, the two-bank game has two Nash equilibria in pure strategies: $(NotCo, Co)$ and $(Co, NotCo)$;

(b) if $\theta < \hat{\theta}$, the two-bank game has a unique Nash equilibrium in pure strategies: $(NotCo, NotCo)$.

Notice also that $\hat{\theta} = 2\theta^*$. This implies that there is a range of values for the probability of success, namely $\hat{\theta} > \theta \geq \theta^*$, such that Condition (1) is met but Condition (3) is not. This observation immediately leads to the following Proposition 2.

Proposition 2 *There exists a range of values of the success probability of the workout, such that a single bank lender allows for restructuring, while two banks fail to coordinate and liquidate the firm.*

Therefore, there are circumstances in which, even if restructuring is economically efficient – i.e. the expected continuation value of the firm net of the restructuring cost is larger than the liquidation value (Condition (1) holds), the firm is restructured if only one bank is lending and it is liquidated if multiple banks are lending, due to a coordination failure among them. Because of free riding, the liquidation outcome is more likely with several lending banks than with a single bank.[7]

[7] When $\theta \geq \hat{\theta}$, we have multiple equilibria. We could introduce a rule to select the equilibrium such that, for instance, one requiring banks to move sequentially. Alternatively, since banks jointly have an incentive to hold in, they can also find a different agreement. A common solution to improve cooperation is to introduce a majority rule. Restructuring procedures, both court supervised and out-to-court, usually require that the majority of debt-holders participate in the agreement. Therefore, the decision of each debt-holder is pivotal to the agreement and a free-riding behavior will jeopardize the restructuring outcome. As a result, they will cooperate more easily. We will show in the next section that repetition can lead to a similar outcome.

2.3 A multistage game with many distressed firms

We now study the general case in which $N \geq 2$ banks have to decide whether to allow for debt restructuring in a sequential game. We assume that there are many distressed firms in the market, and we extend the previous model to allow for an infinite time horizon, with periods denoted by $t_0,t_{1,\ldots}$. When a bank decides whether to cooperate or not in t_0, it considers the likelihood of meeting again any of the other $N-1$ banks when the decision about restructuring will have to be made for some other distressed firms. In other words, it has to consider the chance of repeating the game on on other "negotiation tables" with any of the banks with which they are currently playing the restructuring game. We investigate whether this sequential game can lead to some improvements over the one shot game introduced above, by increasing the chance of an efficient restructuring being undertaken. Therefore, we focus here on the case in which $\theta < \hat{\theta}$, so that the Nash equilibrium of the one-shot game is $(NotCo, NotCo)$.

We also assume that the probability that any of the N banks playing the game in t_0 will not meet any of the other $N-1$ banks in each future period (denoted by $p(N)$) is a decreasing function of N: $p'(N) < 0$. In other words, we assume that the larger is the number of banks currently playing the restructuring game, the higher is the likelihood of playing again the same game with some of them, when other firms will enter financial distress. This assumption can be justified by considering that the total number of banks in the population (say P) is assumed to be fixed (i.e. the size of the market for bank loans is given). If N banks currently play the restructuring game (where of course $N \leq P$), for each of them the probability of playing again the game with any of the other $N-1$ banks in a single future period is equal to $\frac{N}{P}$.[8] This problem can be considered equivalent to the following simple example. Consider an urn with P balls, from which N balls

[8]More in details, given that bank a has currently played the restructuring game, the probability of potential future interactions of bank a with the other $(N-1)-$banks corresponds to the combinations of $(N-1)-$elements that can be drawn without repetition from the population of $P-$banks, out of all the possible encounters of $N-$elements that

are extracted and then replaced into the urn. Now consider another extraction: the probability of extracting one of the balls that was previously extracted is $\frac{N}{P}$, which is trivially increasing in N. Equivalently, the probability of not extracting any of them is decreasing in N. This reasoning can be easily extended to a sequence of extractions, where the probability of extracting a ball already extracted in a previous trial follows a Binomial distribution.

As it is standard in sequential games of this kind, we let each participating bank play a "grim trigger strategy", namely: play Co in t_0 and in all future periods as long as all other banks do the same, and switch to $NotCo$ in period t_k and in all following periods if any of the other banks plays $NotCo$ in period t_{k-1}. Notice that the threat of punishing a deviation from the cooperative behavior with a non-cooperative behavior forever is credible, since $(NotCo, NotCo)$ is the equilibrium (in dominant strategies) of the stage game. Importantly (we will be back on the point later on in this Section), we assume that if a bank in a renegotiation pool encounters again a bank that has been deviating in a previous pool, the information about the deviating bank becomes available to all banks participating in the current renegotiation table – and only to them, so that knowledge is local.

We first determine the payoff of each bank along the equilibrium path, where all banks cooperate in all stages of the restructuring game. In each stage, the payoff is $\frac{V_r - C}{N}$, since each bank receives a share $\frac{1}{N}$ of the expected continuation value of the firm and it pays the same share of the restructuring cost, namely the new funds to be injected in the distressed firm. For all future periods t_k (with $k = 1, 2...$), this payoff is multiplied by a factor $\frac{(1-p)}{(1+r)^k}$, where $(1-p)$ is the probability of playing again the game and $\frac{1}{1+r}$ is the discount factor, computed with the market interest rate r. Easy

can be drawn from the $P-$banks, i.e.

$$\frac{\binom{P-1}{N-1}}{\binom{P}{N}} = \frac{\frac{(P-1)!}{(P-1-(N-1))!(N-1)!}}{\frac{P!}{(P-N)!N!}} = \frac{\frac{(P-1)!}{(P-N)!(N-1)!}}{\frac{P!}{(P-N)!N!}} = \frac{N}{P}.$$

calculations show that the term $\left[1 + \frac{(1-p)}{(1+r)} + \frac{(1-p)}{(1+r)^2} + ...\right]$ can be written as $\left[1 + \frac{(1-p)(1-r)}{r}\right]$. By letting $\frac{(1-p)(1-r)}{r} = \gamma$, we can then write the bank payoff from cooperation as: $(1+\gamma)\frac{(V_r - C)}{N}$.

The payoff from deviation can be computed as follows. A bank playing $NotCo$ in some periods receives $\frac{V_r}{N}$ in that period, since it does not pay for the restructuring costs, and it gets $\frac{L}{N}$ in all future periods, since the grim punishment will be triggered by all other banks. By considering again that all future payoffs must be multiplied by the factor $\frac{(1-p)}{(1+r)^k}$ (with $k = 1, 2...$), the overall payoff from deviation can be written as $\frac{V_r}{N} + \gamma\frac{L}{N}$.

By comparing the payoffs from cooperating and from deviating, it is immediate to see that the following inequality must hold for the equilibrium path to be sustained

$$(1+\gamma)\frac{(V_r - C)}{N} \geq \frac{V_r}{N} + \gamma\frac{L}{N}.$$

It is worth noting that in the above equation we should add the payoff that a bank would get if it does not meet again (for a given number of periods, or forever) any of the banks it is currently playing with, weighted by the appropriate discounted probability. However, as this term would appear on both sides – being obtained both if a bank currently either cooperates or deviates – it can be neglected.

It is then possible to derive a new threshold for the success probability of the workouts, i.e.

$$\tilde{\theta} = \frac{(1+\gamma)C}{\gamma(D-L)}, \tag{5}$$

such that banks cooperate if $\theta \geq \tilde{\theta}$ and deviate otherwise.

Easy calculations show that $\frac{\partial\tilde{\theta}}{\partial\gamma} < 0$ and $\frac{\partial\gamma}{\partial N} > 0$, so that $\frac{\partial\tilde{\theta}}{\partial N} = \frac{\partial\tilde{\theta}}{\partial\gamma}\frac{\partial\gamma}{\partial N} < 0$. The above discussion is summarized in the following Proposition 3.

Proposition 3 *In the sequential restructuring game, there exists a threshold level* $\tilde{\theta} = \frac{(1+\gamma)C}{\gamma(D-L)}$, *with* $\gamma = \frac{(1-p)(1-r)}{r}$, *for the success probability of the workout, such that the equilibrium path with cooperation is sustained iff* $\theta \geq \tilde{\theta}$, *and it is decreasing in the number of banks participating in the game.*

This is the central result of our model. As the number of banks negotiating for restructuring the debt of a distressed firm grows larger, the likelihood of reaching a cooperative outcome, thus avoiding an inefficient liquidation, increases. The rationale behind this result relies on the threat of being punished by some other banks in case of free-riding, which becomes more severe as the number of banks grows larger. It is important to note that the result in Proposition 3 contrasts with the traditional view of the literature on debt restructuring, arguing that an agreement allowing for restructuring is more difficult to reach with a large number of creditors due to the emergence of coordination problems among them. This literature generally finds that a large number of dispersed bondholders have a clear incentive to hold-out in a one-shot game. Instead, our contribution shows that creditors (having a chance to meet again in other restructuring games) take into account the threat of being punished for free-riding, which can offset the immediate gains from free riding. Furthermore, this threat turns out to be more powerful the larger the number of creditors that are likely to meet in the future.

It is crucial to stress the importance of the assumption that all banks involved in a renegotiation know about the presence of a bank among them that behaved as a free rider in a previous renegotiation. In general, one may question that a bank meeting again a deviator has an incentive to report her information to the other (unaware) banks involved in the renegotiation, hence triggering the punishment. Indeed, a bank might decide to hide her information so that a cooperative arrangement could be implemented. In abstract terms, this is an instance of the well known debate on the applicability of the Folk Theorem when agents are involved in infrequent trades. The key problem is the presence of imperfect observability – an agent (i.e. bank) possessing information about previous trades that are not known by others – which establishes a fundamental difference with respect to standard repeated games where all relevant information is common knowledge across agents (and for which cheating immediately triggers retaliation by the 'victim'). Kandori (1992) has shown that the Folk Theorem holds under these circumstances – independent of the matching rule and of the population size – provided that each player observes the 'label' attached (based on the player's behavior in previous trades) to each agent in the local community she is currently dealing with; i.e. there is local monitoring.[9] In our setup, we can immediately appeal to Kandori's result exactly thanks to the assumption that all banks in a renegotiation pool at any given point in time are informed – by a bank that met the deviator in the past – about a former deviation by any other banks in the pool.[10]

Finally, we check whether the sequential game improves upon the one-shot game when banks follow a trigger strategy to punish free riding, by lowering the threshold level for the success probability of the workout above which banks are induced to cooperate. To do so, we compare the new threshold $\tilde{\theta}$ with the value $\hat{\theta}$ previously obtained. Using Equation (4) – with N instead of 2 – and Equation (5), we have that $\tilde{\theta} < \hat{\theta}$ if and only if

$$\frac{(1+\gamma)C}{\gamma(D-L)} < \frac{NC}{(D-L)},$$

[9]As stated by Kandori (1992, p.65), the informal enforcement mechanism supporting cooperation in this case relies on the threat of punishment strategies triggering a 'contagious' defection process. Ellison (1994) has shown that contagious punishments may support cooperation even in setups with anonymous random matching, in which players are unable to recognize their opponents.

[10]A subsequent literature (see e.g. Ali and Miller, 2016) investigated the conditions under which cooperation can be supported if information disclosure within a community is only voluntarily shared, showing that ostracism (i.e. excluding deviating agents and cooperating with the others) may be self-defeating and it should be tempered by forgiveness to facilitate cooperation. This approach can not be immediately applied to our setup, as ostracism would not be possible in our framework. Indeed, cooperation by all banks (but for the deviating one) would result in a firm's debt being renegotiated, hence eliminating the possibility of punishing the deviating bank, whose loans would be repaid in full.

which is equivalent to

$$\frac{r}{(1-p)(1-r)} < N - 1. \tag{6}$$

It is easy to see that Condition (6) is more likely to be met (i) the lower is r – i.e. the longer is the time horizon of the banks participating in the restructuring game, (ii) the smaller is the 'termination' probability p, and (iii) the larger is the number of banks N (as N grows large, the l.h.s in (6) decreases since $p'(N) < 0$, and of course the r.h.s. increases). While the first finding is consistent with the standard result that in a sequential game the cooperative path can be sustained provided players' time horizon is sufficiently long, the last one – summarized by the following proposition – is a specific feature of our model and reinforces the key message of Proposition 3.

Proposition 4 *The larger is the number of creditors, the more likely is that the sequential game allows for a cooperative outcome under scenarios in which a one-shot game would lead to the inefficient liquidation of a firm in financial distress.*

Proposition 4 implies that, since the probability of efficient debt restructuring is increasing in the number of lending banks, all banks that are active in the economy should be involved in all lending relationships. This is obviously too extreme and follows directly from the absence of coordination costs in the model. It is straightforward to note that in the presence of such costs there will be a maximum number of banks above which coordination problems would prevail over cooperation incentives.[11]

[11] Adding coordination costs to our theoretical model is a straightforward extension. We dispose of this additional complication to neatly isolate the benefits of cooperation among lenders in debt restructuring decisions, which are the novel addition to a literature that has extensively investigated the role of coordination issues.

3 Debt restructuring: An empirical analysis

The empirical analysis aims first of all at assessing the validity of the main prediction of the model in Section 2, namely that an increase in the number of lending banks makes it more likely that the bank debt of a distressed firm will be restructured, thus allowing the firm to survive and possibly to recover. Of course, the advantage of the multiple bank relationship enlightened by our model must be balanced with the coordination problems that we have not explicitly modeled, but that have obvious implications. Therefore, we expect a non-linear relationship between the number of lending banks and the debt restructuring probability. Moreover, our dataset enables us to test the impact of additional variables, among which the ratio of bank debt over total debt, the degree of concentration in bank lending shares, as well as the economic and financial conditions of the borrowing firms. As we shall see below, these variables add interesting information about the likelihood of debt restructuring and the role of multiple banking relationships.

3.1 Data description

Italian banks are required to report to the Bank of Italy detailed information on non-performing loans (classified in the two sub-categories of bad and doubtful loans) for regulatory purposes. Bad loans are extended to insolvent borrowers against whom the procedures of debt collection and collateral repossession are initiated. Conversely, 'doubtful' (or 'sub-standard') loans refer to borrowers who are not timely paying back their debt but whose economic prospects suggest that they might recover their solvency within a reasonable time period. Hence, they are natural candidates to enter our dataset of financially distressed firms. The doubtful loans might either develop into bad loans, or the corresponding borrowing firms may recover their financial stability.

We build our dataset starting from lending banks' reports on the firms classified as doubtful loans in the Credit Register data base (CR hereafter), which reports firms' individual relationships with the lending banks.[12] Only loans larger than 75,000 Euros are recorded in the CR. Since banks have to report doubtful loans as long as the amount extended to a firm exceeds 75,000 Euros, above this censoring threshold we have information on the population of Italian firms that are not repaying their debts in a given moment.

To avoid selection biases, our dataset includes those firms that are reported as distressed within a particular year, unconditional of the firm type or the outcome of distress. We choose 2007 as our reference year in order to allow for enough time following the crises (we have data up until 2012). Furthermore, by choosing 2007, we are able to select those firms that were already in distress before the burst of the financial crisis, hence avoiding the effects of the so-called "moratorium".[13] In 2007, 3,073 firms operating in the industrial and service sectors have been reported for the first time as distressed by at least one bank. We consider only firms that have been classified by their lending banks as financially distressed for the first time in that year in order to make sure that firms enter our data at the onset of the crisis or, at least, when it has been initially accounted for.[14] In this way, we define a sample of Italian firms that did not pay back the principal or the interests on their debts towards the banking system for the first time in 2007, but that might reasonably recover their financial stability in a limited period of time. Our data follow these firms for the three following years.

In order to gather information about firms' economic and financial conditions, we use annual balance sheet data and the records of firms' legal situation available through the Italian Chambers

[12]This strategy is consistent with the one adopted by Brunner and Krahnen (2008), Franks and Sussman (2005), Couwenberg and De Jong (2006), who start from a sample of financially distressed firms as directly defined by their lending banks.

[13]In 2009, the Ministry for the Economy and Finance, the Italian Banking Association and the Italian Business Associations signed an agreement allowing for the suspension of principal repayments on some forms of debt held by small and medium-sized enterprises (renewed in February 2012). However, these measures were not applied to firms already in distress before the crisis. Therefore, by choosing 2007 as a benchmark, we are able to select firms in distress to which the traditional restructuring instruments apply.

[14]To our purposes, the onset of the crisis corresponds to the first year the firm has been reported as financially distressed by at least one bank.

of Commerce (Cerved dataset). As a consequence of the matching, the number of firms in our sample decreases to 2,489. Table 1 shows the composition of the sample by sector of activity, while Table 2 reports descriptive statistics about balance-sheet indices. On average, distressed firms in the sample record 4 million Euros of sales and around 6 million of total assets; the medians are lower, around 1 and 1.6 million, respectively. The year before the distress event, returns on productive activities are already deteriorated, but still positive: earnings before interest payments, depreciation taxes and amortization (Ebitda) were 0.6 percent of total assets. On average they are lower than the interest payments, which are around 3.6 percent of total assets; however, the median firm still manages to cover the interest expenses, since the latter are around 3.1 percent of total assets against an Ebitda on assets of 4.7 percent. The situation worsens the following year (the year of the distress), when operating profits on average become negative. They do not cover debt-service obligations also for the median firm. Total returns on assets become strongly negative (-13,2 percent). Total liabilities are nearly equal to total assets for the median firm, and even higher for the average. About one fourth of the firms in the sample has a negative net worth, thus confirming the severity of their crisis. Banks cover more than 80 percent of financial liabilities (more than 96 percent for the median), and more than 40 percent of total debts.[15]

Table 3 describes the type of relationship between the firms in the sample and the banking system. The year before the distress, credit extended is around 2.3 million Euros on average, while credit granted is 2.8 million (650 and 700 thousand for the median, respectively). Firms in the sample maintain relationships with approximately 3.7 banks (3 for the median). This is consistent with the evidence reported in Detragiache *et al.* (2002), whose paper focuses on large firms and reports that the median firm has 5 lending relationships and the mode is 3 banks. It is also consistent with the Bank of Italy's statistics on the number of banks, according to which

[15]The other major source of borrowing is trade credit.

non financial firms whose credit granted is between 2.5 and 5 million of Euros have on average 4.3 lending banks (2.7 when the credit granted is between 500 thousand and 2.5 million Euros – see Figure 1 in Section 1).

Lending shares are fairly concentrated, with an Herfindahl-Hirschman concentration index of 0.55. Real collateral is around 26 per cent of total credit extended, a percentage that does not include personal guarantees. One year after the distress event, the number of banks tends to decrease and the concentration index rises.

3.2 Variables definitions

Banks are the main source of external finance for Italian firms. We study how lending banks contribute to the workout of financially distressed firms, adopting credit decisions such as a maturity rescheduling or the granting of new loans. Following the taxonomy introduced by Brunner and Krahnen (2008), used also in Micucci and Rossi (2017), we consider a firm to have restructured outstanding loans if one of the following two conditions has occurred in the three years following the distress event: (i) total loans granted have increased, (ii) the long term credit granted by lending banks has increased.[16] With these interventions, banks make borrowers' financing constraints less stringent, thus improving their survival probability. We do not consider other types of restructuring, such as debt equity-swaps, lender syndicates or others, which are very uncommon for SMEs in distress. In our dataset, 27.8% of firms in distress have seen their bank debt restructured (see Table 4).

The dependent variable is defined by looking at the three years following the distress event, whereas all the regressors are calculated in the year of distress or the year before.[17] Therefore all

[16] These interventions correspond to what Brunner and Krahnen (2008, page 431) define as "loosening of the borrower's financial constraints".

[17] Using different time lags does not change the results reported in the paper.

the regressors are predefined with respect to the restructuring decision.

Our interest is mainly focused on the impact of the variables that describe the type of relationship between a firm and its lending banks on the probability of debt restructuring. To pin down this multifaceted relationship between borrowing firms and their lenders and to control for firm characteristics, we focus on the covariates listed below.

Bank debt. We consider a variable (bank ratio) defined as the ratio between bank debt and total outstanding debt of the firm (including trade credit). We expect that better coordination is achieved if a large part of outstanding debt is held by banks.

Number of lending banks. We introduce the number of banks (n. banks) with which a firm has credit relationships. We allow for possible non-linearities in this relation, by also considering the number of banks squared. It is sensible to assume that there is a threshold beyond which free riding prevails over the retaliation threat. Both variables are defined either at the moment of distress or the year before, to limit possible endogeneity problems.

Credit concentration. We measure debt dispersion among lending banks by means of an index of skewness in lending shares across the banks lending to the firm. Since we are interested in the degree of skewness, regardless of whether it is positive or negative, we use the index squared. We also focus on the Herfindahl-Hirschman concentration Index (HHI), as modified by Hannan (1997) (and used in Ongena *et al.*, 2012) to reduce the correlation of the index with the number of banks. More precisely, the HHI is defined as $HHI_{jt} = \sum_{i=1}^{n} s_{ijt}^2$, where s_{ijt} is the share of credit granted by bank i to firm j at time t on overall credit granted by the n-lending banks to firm j. Hannan (1997) decomposes the HHI as follows:

$$HHI_{jt} = \frac{V_{jt}^2}{N_{jt}} + \frac{1}{N_{jt}}, \tag{7}$$

where V_{jt} denotes the coefficient of variation of the credit granted to the firm and N_{jt} denotes the number of banks. Furthermore, observing that the first term on the right hand side of (7) provides a measure of share inequality, by subtracting the inverse of the number of banks $(1/N_{jt})$ from the expression of HHI_{jt}, we obtain a third index – the Share Inequality Index – that we also use in our estimates.

Main bank. We control for the type of bank that has the major share in lending to the distressed firm by means of a set of dummies that control for the type of main bank lending to each firm in the sample. We explicitly control for Long-term banks (banks that are generally specialized in granting long-term loans), Popular banks, Cooperative banks, Foreign banks. The benchmark is represented by large bank corporations, defined according to the Bank of Italy classification. The idea behind this classification is that local banks tend to intervene more easily in favor of firms in financial distress. This may reflect either the fact that they are deeply rooted in the economy they belong to and have strong linkages with their customers, or that they are subject to the risk of being 'captured' by the local community, thus delaying liquidation of the distressed firm even when this is the most efficient solution (Berger and Udell, 2002).

Collateral. We account for the value of collateral posted by the firm (normalized on total loans), since the degree of collateralization may account for different banks' behavior.

Firm characteristics. We control for the anticipated value of the firm as a going-concern, introducing several balance-sheet indices to pin down the economic situation and financial position of each firm, as well as the existence of intangible assets. In particular, we use the ratios of total liabilities, intangible assets, Ebitda and interest payments over total assets. To limit potential endogeneity problems, these ratios are calculated in the year before the distress. As a robustness check we use also different time lags, such as two year lags or the average in the three years before the distress event, without significant differences in the results. In some specifications, we also use the Altman's Z-score (as calculated by Cerved Group) to catch the ex-ante probability of default of the distressed firm (Altman, 1968), using the score with one year lag with respect to the distress event. Finally, we control for firm size (log of total assets), and add sectoral and regional dummies.

In Section 4 we consider every single credit relationship between a firm in our sample and its lending banks. At this stage, having loan-level data, we are able to look directly at the number of interactions among banks. To do so, we introduce the following additional covariates.

Probability to meet again among banks. This variable – which will be precisely defined in Section 4 – is a proxy of the probability to meet again the same group of banks in a different restructuring table towards a different firm.

Leader. In loan-level data, this variable is defined as a dummy that controls whether the bank is the main bank lending to the observed firm (i.e. the bank with the highest share in total lending).

Bank's balance sheet variables. We control for the degree of capitalization of the bank, its liquidity and credit risk, introducing in the estimates the solvency ratio (capital over total loans), the liquidity ratio (retail deposits over total loans) and a risk ratio (non-performing loans over total loans).

Table 4 reports all descriptive statistics for the variables used in the empirical analysis and Table 5 the correlations among such variables.

3.3 Restructuring probability

3.3.1 The baseline model

The primary goal of our empirical analysis is to assess the probability of restructuring at the firm level. Accordingly, our dependent variable (RESTR) is a dummy taking value one if the firm obtains (a) an increase in total credit granted, or (b) a maturity extension at least once in the three years following the distress event; and value zero otherwise. As noted in Sub-section 3.1, around

28 percent of the firms in our sample obtain one of these interventions.

At this stage, data are organized as a cross-section with a limited dependent variable and we estimate a probit model of the type

$$prob\,(y=1)_{i(between\ t\ \ and\ t+3)} = \Phi\left(a_i + \beta_1 X_i + \beta_2 \gamma B_i + \beta_3 L_i + e_i\right), \tag{8}$$

where Φ denotes the standard cumulative normal distribution, and X_i a set of controls describing a firm's overall economic and financial situation (firm size, debt/assets, intangibles/assets, Ebitda/assets, interest payments/assets, Altman's Z-score). These controls are evaluated the year before the distress event, since these are the balance-sheet information that each bank has at its disposal at the moment of distress. B_i are the characteristics of the relationship of the firm with the banking system defined at the moment of distress (bank debt, number of lending banks, credit concentration, collateral, type of main bank); L_i are dummies to control for the localization (macro-regions) and the sector of activity of the firm; e_i denotes the model error term. The dependent variable is defined by looking at the three years after the distress event; as a consequence, all the regressors are predefined with respect to the restructuring decision.

Table 6 shows the results of Model (8) and reports the marginal effects on restructuring probability of unit changes in the relevant explanatory variables, as well as of discrete changes from the baseline levels in case of dummy variables. Because of the possible presence of collinearity, we introduce the number of lending banks, its squared value and the index of asymmetry (or concentration index) one by one in Columns 1-5 of Table 6. Our preferred specification is reported in Column [5], where all the covariates are introduced and the dispersion in lending shares is measured by the share inequality index. In Column [6] we use the Z-score variable instead of balance-sheet indices to capture the economic situation of the firm and its prospects.

Overall, our estimates show that all the variables describing the type of relationship with the banking system have a relevant impact on the restructuring probability. The main results are confirmed across different specifications, with only few differences in the size of marginal effects. The likelihood of restructuring is higher for larger firms. It is improved for those firms with healthier economic and financial conditions before the distress event, thus suggesting that economic efficiency is preserved. More in details, the ratio of bank loans over total borrowing is highly significant and positive. Banks tend to help those firms they are more involved in. Moving from the first to the third quartile of the distribution of this variable (approximately from 28 to 60 percent in the ratio of bank debt to total debt), the restructuring probability is increased by 5 percentage points out of an overall estimated probability of around 30 percent.

Consistently with the prediction of our theoretical model, the number of banks has a direct and positive impact on the restructuring probability. Yet, this impact is non-linear, as the coefficient of the squared term is statistically significant and negative (Columns [2]-[5]). Considering the average marginal effects of Column [5], the maximum restructuring probability is reached when the firm has relationships with four banks and the estimated restructuring probability rises to 38 percent (against an estimated average of 30 percent). Therefore, the probability tends to rise with the number of banks up to a certain threshold, beyond which it starts declining, which suggests that problems of coordination among banks tend to dominate beyond this threshold.[18]

The skewness index has a negative sign but it is not statistically significant. However, when we introduce the share inequality index, this has a negative and statistically significant impact: given the number of banks, dispersed held debt increases the probability of debt restructuring, while concentrated debt tends to reduce it.[19] This result can be explained by the possible mutual control mechanism among banks having similar lending shares, which reduces free riding incentives in the

[18]Similar results are reached using dummies for the number of banks, with a maximum at around three banks.

[19]An interaction term between the number of banks and the concentration index is never significant.

restructuring process. This explanation is consistent with the insurance motive put forward by Carletti *et al.* (2007), according to which banks diversify their loans portfolio and share monitoring efforts by means of multiple lending. Conversely, when bank lending shares are asymmetric, the banks with higher shares are less exposed to the retaliation threat by banks with smaller shares, because of their larger bargaining power. For this reason, large banks might be able to bend the restructuring process to their own advantage (Guiso and Minetti, 2010), thus unsettling the cooperative behavior towards an agreement solution. In principle, this effect might be compensated by an opposite incentive: a main bank, holding a large share of firm debt, might be induced to behave as a single lender, since it bears most of the consequences of the liquidation/continuation decision, so it might be induced to allow for restructuring. Our empirical findings show that this second effect is weaker than the former.

Collateral – defined as the value of real guarantees (mainly real estate) pledged to the bank over the value of outstanding loans – is never significant in our specifications. However, we do not have information on the personal guarantees pledged by the entrepreneur, which might also be relevant and can partially account for the lack of evidence on our collateral variable.[20]

Considering the characteristics of the main bank lending to each firm in the sample (i.e. the bank with the highest share in total lending), cooperative banks have a higher probability of restructuring (8 percentage points higher than the benchmark, represented by large banks corporations). Conversely, when the main bank is specialized in long-term financing, the restructuring probability is reduced (by about 9 percentage points).[21]

As far as balance-sheet variables are concerned, the restructuring probability is not surprisingly

[20]This is in line with the evidence reported in Davydenko and Franks (2008), who show that in France personal guarantees are used more often than real estate as collateral, since banks can size them directly against cumbersome procedures required in court supervised collateral sales. The opposite is true for Germany and the UK, where the bank's ability to realize assets upon default is much higher.

[21]These banks are generally specialized in granting long-term loans to finance firms' investments or to support firms operating in particular fields, such as construction or agriculture. They have only deposits with 18-months-maturity or more, with the exclusion of sight deposits.

higher when the firm has better economic performances before the distress. Profitability is strongly significant with the expected signs: a higher Ebitda before the distress increases the likelihood of debt restructuring. On the contrary, highly leveraged firms have a lower restructuring probability (significant at the 10 percent level). When introducing the Z-score variables instead of balance-sheet indices (in Column 6), the likelihood of restructuring is lower for risky firms, but the corresponding variables are not statistically significant.

The size of the firm has a strong positive effect: the bigger the firm, the higher the probability to restructure. Moving from the first to the third quartile of the distribution of this variable (i.e., increasing total assets from 700 thousand to 4 million Euros), the overall restructuring probability increases by 7 percentage points. Large firms might have a stronger bargaining power, or the bank might decide to restructure a doubtful loan to postpone the emergence of a loss, which is higher the larger is the distressed firm. Intangible assets are never significant, as well as the cost of debt.

As far as the sector of activity is concerned (the corresponding coefficients are not reported in the Tables), our benchmark is the 'food and beverages' industry. With respect to this benchmark, the probability to restructure is significantly lower for firms operating in the 'textile' and 'other manufacturing' sectors, the latter encompassing the wood and furniture industry. These traditional manufacturing industries have endured a long standing structural crisis, following the fierce competition from low-price producers in emerging countries, which may account for our results. The other significant difference (yet at the 10 percent level) is detected for firms operating in the 'Commerce' sector. These are usually very small firms, characterized by a significant market turnover, and negatively affected by the diffusion of large-scale distribution.

3.3.2 Robustness: Debt restructuring for firms' sub-samples

In the previous analysis we consider the whole sample of distressed firms, which gives us an overall picture of the restructuring probability at firm level. We now correlate more precisely our estimates to the theoretical model put forward in the previous Section by considering different sub-samples of firms (Table 7). First, we select only those firms that are reported as doubtful by at least one-third of the lending banks, thereby restricting our analysis to those cases where there is consensus on the difficulties of the firm (column [1]). Then, we drop from this sample all the firms that have just one lending relationship, as our main goal is to investigate the impact of the interactions among different banks (columns [2], [3] and [4]). Finally, we consider only those firms that are still in distress after three years since the beginning of the crisis. To select those firms, we consider a Z-score at t+3 corresponding to fragile or risky firms (i.e. equal or higher than 6; see column [5]).

While the number of firms considered in the estimates decreases progressively across the various specifications, yet our results are fairly stable and similar to those discussed above. The overall probability of restructuring is now slightly lower than in the whole sample: it increases with the number of banks up to around three banks and then it decreases. This result is consistent across all the various sub-samples used in the robustness exercise. The regressor capturing the level of collateral is now significant and positive, pointing to an improved probability of obtaining help from the pool of lending banks when pledging more collateral.

3.3.3 Robustness: Checking for firms' heterogeneity

In this sub-section, we check the robustness of our results to a setup in which the restructuring variable is computed for each of the three years following the distress event. This specification accounts for the individual unobserved characteristics of the firms in the sample and for the potential reversibility of the restructuring decision. For instance, one firm may receive help one year but the following year this decision is changed because of bad news about the long-term perspective of the firm, or because there is a further deterioration of its economic situation, or again because the firm exits the market. These changes are overlooked by the analysis of the three-years window. To take into account that error terms might be correlated within firms, we use a probit model with individual random effects to catch firms' heterogeneity. We also introduce time dummies since both the dependent variable and the regressors vary each year, and we consider all the regressors with a one-year lag to limit possible endogeneity problems. Table 8 reports our results. In doing the exercise, we consider the whole sample (columns [1]-[2]), the sub-sample of those firms that are considered as doubtful by at least one third of their lending banks (columns [3]-[4]), and the sub-sample of firms that have multiple credit relationships and are considered as doubtful by at least one third of their lending banks. Overall, our main findings are confirmed; the marginal effects concerning the relation with the banking system are lower, and the estimated overall probability of restructuring is around 16 percent per year. Such probability decreases in the sub-samples. Indeed, the maximum restructuring probability is reached with around three banks considering the whole sample (when the overall probability rises to 19 percent from 16 percent on average), while it is slightly lower – around 2.5 banks – for the sub-sample of firms that have multiple credit relationships and are considered as doubtful by at least one third of their lending banks.

3.3.4 Robustness: New finance following financial distress

To further check the robustness of the results obtained with our baseline specification, we investigate a different dependent variable defined as the quantity of new loans granted to the firm in each of the three years following the distress event, which are 2008, 2009 and 2010. In doing so, we exploit the time series dimension of our dataset by means of a panel specification. We need to take into account that error terms might be correlated within firms and therefore the quantity of new credit granted will depend upon the current level of the credit granted to the firm. Furthermore, the changes in some of the variables of interest in the three years following the distress event (such as the number of banks) may be affected by the volume of credit the firm wants to obtain, therefore being possibly endogenous. To properly face these issues, we consider a dynamic panel data specification, following Arellano-Bond (1991) and Blundell and Bond (1998).[22] More precisely, we focus on a system GMM estimator, according to the following specification

$$y_{i,t} = \alpha y_{i,t-1} + \beta_1 X_{it} + \beta_2 B_{it} \beta_2 + u_i + d_t + e_{it}, \tag{9}$$

where the dependent variable is the logarithm of the quantity of credit granted to each firm $i = 1, \dots n$; X_{it} is a vector of strictly exogenous covariates; B_{it} is a vector of endogenous covariates (detailed below); u_i are the firm-level fixed effects (that may be correlated with the covariates); d_t is a set of time dummies, and e_{it} is the model error term.

The estimation of the system GMM requires to set the variables to be instrumented and the number of lags to be included in the instruments' matrix. We use lags between $t3$ and $t5$ for the GMM instruments (we have data on the firms in the sample since 2003). These lags are introduced for all the covariates that pin down the relation with the banking system, which might be affected by the changes in the dependent variable (i.e. number of banks, concentration, share of bank debt over total debt, collateral, type of the main bank). Standard errors are made robust to heteroskedasticity and to serial correlation. Finally, having firm-level fixed effects, we do not include time-invariant firm variables – such as those on the sector of activity, the area of location and, in one specification,

[22]The Arellano-Bond's estimator uses first-differences to remove the firm's specific fixed effect and uses internal instruments (i.e. past levels of the variables included in the empirical model) to deal with the endogeneity of the lagged dependent variable and other covariates. The Blundell and Bond system estimator (System GMM) improves the efficiency of the Arellano-Bond's model by estimating jointly a regression in first differences and a regression in levels, using lagged levels as instruments for the regression in differences and lagged differences as instruments for the regression in levels.

the type of the main bank (although these characteristics could in principle change, they are in fact essentially time-invariant). We keep all the firms in our sample, considering also defaulted firms as long as we have data on their situation, even though the number of firms actually considered is reduced automatically because of the lags used in the estimates.

We consider the standard Arellano-Bond test for autocorrelation of the first and second order on the idiosyncratic errors. We check the validity of our specification by computing the Hansen test of over-identification, which tests whether the set of instruments is orthogonal to the error process (i.e. the exogeneity of the instrument).

Table 9 shows our results, which are reported both for the whole sample (columns [1]-[3]), and for the sub-sample of those firms that have multiple credit relationships and are considered as doubtful by at least one third of their lending banks (columns [4]-[6]), i.e. those firms we considered in the previous robustness exercise (Sub-section 3.3.2). The various specifications fulfill the standard tests: the Hansen test of over-identification restrictions supports the validity of the instruments; the test of the second order AR(2) is verified (whereas, as expected, the AR(1) is not), which satisfies the requirement that the second lag is not correlated with the error term to assure that GMM estimators are consistent.

The results confirm the qualitative findings discussed previously. The new credit granted (in logs) presents a clear persistency, given that the lagged dependent variable is significantly different from zero. The bank debt ratio loses its relevance. The type of the main bank is significant only for the sub-sample of firms that have multiple lending relationships and are reported as doubtful by at least one third of the lending banks (column [4]). Our results confirm that the credit granted is higher as the number of banks increases and credit concentration decreases. As already noted, the relation appears to be non-linear and it starts to decrease after a threshold, which is again around three banks. This threshold is slightly lower in specification [5], when it is about 2.5 banks. The amount of the new loan granted to firms in distress is greater the larger the borrowing firm and the higher the Ebitda. Intangibles increase the new loan granted, but only in the whole sample, and Z-scores are never significant.

4 An extension: Loan level data

In this section we further investigate whether the key result of our theoretical model – namely a positive correlation between the restructuring probability and the number of banks – depends upon the probability of meeting in the future with the same group of banks lending to a particular firm.

This type of analysis requires to rely on more granular data than those used in our baseline specification, which focuses on the total bank debt of each firm rather than on the debt a firm has with each bank. To overcome the problem, we consider loan level data, implying that the number of observations for each firm is now equal to the number of banks that are lending to it. Importantly, the restructuring probability needs now to be defined (admittedly less accurately) for each single lending bank rather than for each firm as in our baseline specification (see the definition of restructuring provided in Sub-section 3.2), entailing that the results in this Section are not directly comparable with those in Sub-section 3.3.1.[23]

In order to build a proxy for the probability that each bank meets again the same group of lending banks in the future, we define different groups of banks lending to a firm and, for each of these groups, we compute the number of credit relationships they have in common within the sample. For the sake of simplicity, we limit our attention to specific groups of three banks (two in the case of just two lending banks) up to the sixth lending bank (ordered by credit granted) for each firm, following a simple rule: the group consisting of the first, second and third bank; the one

[23]The lower accuracy of such definition is what prompted us not to consider it in our baseline specifications.

composed by the second, third and fourth bank, and so on up to the sixth bank.[24] Obviously such a variable does not consider all the future possible interactions among the banks lending to a specific firm, and it is therefore an imperfect (underestimating) proxy for the probability we are interested in. As expected, in our sample, the obtained probability is correlated positively and significantly with the number of banks with which each firm has a credit relationship (see Table 5).[25]

Having data both at firm – and bank – level, we control also for bank characteristics using balance sheet ratios (such as solvency, liquidity and risk, as defined in Sub-section 3.2). To take into account that the error term might be correlated within firms, we use a probit model with individual random effects to catch firms' heterogeneity, according to the specification

$$prob\,(y=1)_{(between\ t\ \ and\ t+3),i,b} = \Phi\left(a_i + \beta_1 X_{i,t-1} + \beta_2 B_{i,b,t-1} + \beta_3 E_{b,t} + \beta_4 L_i + u_i + e_{i,t}\right), \quad (10)$$

where the restructuring probability is defined for each lending bank and Φ denotes the standard cumulative normal distribution; $B_{i,b,t-1}$ are the characteristics of firm i relationship with lending bank b defined one year before the distress (the probability that the bank meets again another bank belonging to the same pool of lending banks, the number of lending banks and its squared value, the level of collateral); $E_{b,t}$ is a set of controls for the bank (solvency, liquidity, and risk ratios). $X_{i,t-1}$ is a set of controls describing firm i's overall economic and financial situation (firm size, debt/assets, intangibles/assets, Ebitda/assets, interest payments/assets, Altman's Z-score), evaluated the year before the distress event; L_i are dummies to control for the localization (macro-regions) and the sector of activity of firm i; u_i is the error term that control for firms' heterogeneity; $e_{i,t}$ denotes the residual error term. The dependent variable is defined by looking at the three years after the

[24] This number is normalized with the number of total credit relationships each bank of every group has individually within the sample.

[25] A side estimate, not reported but available upon request, confirms the positive and significant correlation between the number of banks and the probability to meet again in the future among banks.

distress event. As a consequence, all the regressors are predefined with respect to the restructuring decision.

Table 10 reports our results. The first column reports the results for the whole sample; columns [2] and [3] consider only firms with multiple lending relationships and whose debt has been reported as doubtful by at least one third of the lending banks at the distress event. Finally, having data at loan level, we can focus on the sub-sample of banks that have reported the loan as doubtful (column [4]). To check the robustness of our results, and to account for further heterogeneity as well as for all possible distortions from omitted variables, we estimate the previous relationships for the same sub-samples also using a linear probability model and introducing firm fixed effects, or both firm and bank fixed effects (Table 11).

The results from the probit model (Table 10) show that the probability of a pool of lending banks to meet again in the future is highly significant in every specification and it has a positive impact on the probability to restructure outstanding debt. The latter increases by 2.4 percentage points moving from the first to the third quartile of the distribution of the variable that measures the probability of meeting again the same group of banks in the future. Since the overall estimated probability is around 24 percent, the estimated impact is quantitatively relevant.

The number of banks and its squared value show the same signs as before, but they are no longer statistically significant and are therefore dropped in column [3]. This finding reinforces our *a priori* conjecture that the interactions among lending banks play an important role. Collateral is significant and positive, whereas the dummy for the main bank (Leader) is positive but its significance is weak. Bank balance sheet variables show that higher liquidity, solvency and lower credit risk improve the probability that the bank restructures its loans. The estimates are fairly stable across the different specifications, in spite of the fact that the number of observations varies significantly across the different sub-samples.

Table 11 reports our results for the linear probability model (considering the same sub-samples as in Table 10), with firm fixed effects (columns [1]-[3]) or both firm- and bank- fixed effects (columns [4]-[6]). Our main results are confirmed, although the probability to meet in the future banks belonging to the same pool of lenders has now a much larger impact on the probability to restructure outstanding debt. The corresponding coefficient is particularly large for the sub-sample of banks that reported the firm as a doubtful borrower (columns [3] and [6]), suggesting that classifying the firm as doubtful is an important signal, perhaps the first move in a restructuring game.[26]

5 Survival and restructuring

Finally, having investigated the determinants of the restructuring decision, we focus on its effect on workout success versus liquidation (either through formal bankruptcy procedures, or private asset selling), controlling for the firms that eventually obtain to restructure their outstanding debt.

Table 12 reports the outcome of the crisis for the financially distressed firms in the sample. The final year we consider is 2010. Around 54 percent of the firms in the sample survives (1,345 firms), while 46 percent either goes bankrupt or it is liquidated. The share of successful firms rises to 85 percent among those who have restructured, while it is 42 percent for the others. In this Section we address the relation between the restructuring decision and the survival outcome.

Theoretically, restructuring and survival may be jointly determined. Banks should be able to select ex-ante, by means of their screening activity, the firms most likely to survive. If the lending bank can reasonably predict which firm will survive, it will restructure only outstanding debt of

[26] Yet, the interaction among banks raises the issue of a potential bias in favor of the restructuring process: banks may be induced to agree to a restructuring plan to avoid the 'stigma' of a non-cooperative behavior, even though each bank would have preferred to liquidate the firm. This explanation should be thoroughly considered, since it could add a new rationale to the sometime observed zombie lending behavior (Caballero *et al.*, 2008; Schivardi *et al.*, 2017).

those firms with a higher probability of survival. Yet, this decision will affect the survival outcome itself, for two possible motives: i) the firm will not have enough funds to finance its activity and, ii) if a bank decides not to restructure outstanding debt, at the same time, it may file for bankruptcy. As a consequence, the two decisions may be simultaneously determined.

The endogeneity of the default outcome with respect to the restructuring decision is a possible source of bias. In order to deal with this issue, we consider a system of two equations using a binary response model that jointly considers the two outcomes, the first defining the probability of firm's survival and the second the restructuring decision, i.e.

$$\begin{array}{rl} probability\ of\ survival & y_1 = 1\left(\beta_1 x_1 + \varepsilon_1 > 0\right) \\ probability\ of\ restructuring & y_2 = 1\left(\beta_2 x_2 + \varepsilon_2 > 0\right), \end{array}$$

with $(\varepsilon_1, \varepsilon_2) \approx N(0,1)$ and $corr(\varepsilon_1, \varepsilon_2) = \rho_{12}$, and where the indicator function $1(.)$ takes value 1 if the inequality inside the brackets holds true.

To estimate this two-equations model, we consider a bivariate probit model of the type

$$prob\left(y_1 = 1, y_2 = 1\right) \approx \Phi_2\left(\beta_1 x_{1i}, \beta_2 x_{2i}, \rho_{12}\right), \tag{11}$$

where Φ_2 is the bivariate normal cumulative distribution function, and ρ_{12} is the correlation between the two events. Consistent and asymptotically efficient parameter estimates can be obtained by maximum likelihood estimation of the bivariate probit model, using the same set of covariates as in Equation (8). Table 13 reports our estimates. The correlation between the survival equation and the restructuring equation (ρ_{12}) is positive and significant: as expected, restructuring improves the likelihood of survival and we have to take into account the correlation among these two phenomena when studying the survival probability. However, ex-post survival probability may affect also the restructuring decision if banks are capable to detect successful firms ex-ante. As a consequence, because in the bivariate probit model the restructuring equation is estimated jointly with the survival equation, the results on the restructuring probability might be affected with respect to our previous specifications. Nonetheless, the results for the restructuring equation remain essentially unchanged, confirming our previous analysis.

Focusing on the survival equation, the balance-sheet ratios go in the expected direction: higher profits before the distress event improve the likelihood of survival. Analogously, the size of the firm increases the likelihood to survive. The relation with the banking system maintains some explanatory power: when banks are the main creditors, the survival probability is improved. As before, survival increases with the number of banks, but only up to a threshold.

When considering jointly the probabilities of restructuring and survival – i.e. the event of a successful restructuring (Column 3) – the relation with the banking system proves crucial. A high number of lending banks is very important in affecting positively the overall outcome, although the relationship is again non linear. The joint probability of successful restructuring increases up to 3.5 banks, beyond which it begins to reduce. This notwithstanding, it is important to stress that the joint probability of success is given by the product of two components: (i) the probability to survive, conditional on having restructured, and (ii) the probability of restructuring; i.e.

$$prob\,(y_1 = 1, y_2 = 1) = prob\,(y_1 = 1 \mid y_2 = 1) \times prob\,(y_2 = 1)$$

In Table 14 we report the marginal effects of our covariates on these two different probabilities. Column [1] highlights the impact of our main variables on the probability to survive conditional on having restructured, and Column [2] the impact on the probability to restructure. The impact of the relation with the banking system on the joint probability of a successful restructuring process is driven essentially by the restructuring equation. In the second stage, the residual impact on the survival probability conditional on restructuring is negligible (and negative as far as the number of banks is concerned). Overall, the estimated conditional probability to survive for firms that have restructured is 89 percent, against 48.1 percent for those firms that have not restructured their debt.

6 Concluding remarks and policy implications

In this paper, we investigate the role of strategic interaction among banks in the decision of restructuring their loans towards firms in financial distress. On the one hand, the existence of free riding problems increases the difficulties in finding a restructuring agreement. On the other hand, banks are very different lenders than bond-holders and this difference should be accounted for. Bond-holders are dispersed and are unable to coordinate their actions, while banks are non-atomistic debt-holders: each bank has a bargaining power against the firm, as obvious, but also against the other lending banks. The starting point of our analysis is the observation that usually the pool of lending banks consists of a finite number of lenders, who have more than one distressed firm to face and to restructure. Therefore, they come across each other frequently over time. As a consequence, coordination might be improved by the threat of future punishment in case of free riding behavior. As the number of lending banks increases, the chance of meeting again another bank in some other restructuring negotiations and of being punished for free riding increases, thus pointing to improved likelihood of the cooperative solution. Quite obviously, also coordination problems become larger as the number of banks grows larger. Hence, we expect to see a critical number of banks above which the probability of restructuring starts decreasing.

We test empirically the key prediction of our model focusing on the impact of the number of lending banks on the restructuring probability by means of a unique dataset, which has information on the population of Italian firms at the beginning of their distress spell. Our findings confirm our theoretical prediction and convey a number of interesting insights into the restructuring process. Increasing the number of banks improves initially the restructuring outcome and the access to new loans and, through these effects, the probability of survival, at least up to a threshold. However, reaching an agreement on the restructuring plan becomes more difficult when more than three banks are involved.

To better understand whether the obtained positive correlation between the restructuring probability and the number of banks depends upon the probability of meeting in the future with the same group of banks lending to a particular firm, we also rely on loan-level data. Our results based on such data confirm that the probability of the same banks interacting again in the future (on a different renegotiation table) has a positive effect on the probability to restructure outstanding debt. Interestingly, banks tend to restructure the outstanding debt of those firms for which bank financing is prevailing. The ratio of bank debt over total outstanding debt is very strong in influencing both the decision of debt rescheduling and the probability of successfully overcoming the crisis and surviving, even after controlling for the financial and economic situation of the firm before the distress event. For a given number of banks, dispersed debt improves the probability of restructuring. One possible explanation is that symmetric lending shares represent a mutual control mechanism, which reduces the free riding incentive in the restructuring process.[27] When lending shares are asymmetric, banks with higher lending shares are less exposed to the retaliation threat by banks with smaller shares and, therefore, they might follow an opportunistic behavior. Overall, our theoretical and empirical results on the number of banks and credit concentration give

[27]This is in line with the insurance motive put forward by Carletti *et al.* (2007).

a new rationale to the commonly observed feature of multiple banking relations.

The paper has far reaching policy implications. Banks maintain their special role in firm financing also when firms are in financial distress and their debt is dispersed among many banks, a situation in which the debt is more difficult to restructure because of free riding problem. This is because banks may act strategically, thus improving the restructuring probability of a firm in financial distress even when more than one lender is involved in the process. However, this result fades away rapidly and multiple banking relationships become detrimental to the restructuring process when more than three banks are involved. Being this the case, a limited number of lending banks should be sufficient to avoid information monopoly by the main bank as well as to assure a fair valuation in case of distress.

Conversely, however, the strategic interactions among (a limited number of) banks raise the issue of a potential bias in favor of the restructuring process. Banks may be induced to agree to a restructuring plan to avoid the 'stigma' of a non-cooperative behavior, even though each bank would have preferred to liquidate the firm. This possibility could add a new rationale to the sometimes observed 'zombie lending' behavior (Caballero *et al.*, 2008; Schivardi *et al.*, 2017). We do not explore this issue. However we show that strategic interaction among banks is a force that might improve cooperation in favor of a restructuring agreement, but it may be also harmful if the decision is taken not only considering the single firm but also the situation of other firms in distress.

Lender coordination through privately negotiated arrangements may be improved also by the design of the institutional framework. In Italy, the insolvency regime has been repeatedly reformed and recently (October 2017) new measures to facilitate the early emergence of the crisis, as well as out-of-court restructuring procedures, have been introduced. On this point, by properly accounting for the tension between the benefits of strategic cooperation and the costs of coordination, our model emphasizes the relevance of a common ground among lending banks to reach a balanced agreement, where both the firm's situation and its evaluation by lending banks are common knowledge within the pool of lending banks.

References

Ali, S. Nageed and D. Miller, (2016), "Ostracism and Forgiveness", *American Economic Review*, Vol. 106, pp. 2329-2348.

Altman, E.I., (1968), "Financial Ratios Discriminant Analysis and the Prediction of Corporate Bankruptcy", *The Journal of Finance*, Vol. 23, pp. 589-609.

Arellano, M. and S. Bond, (1991), "Some tests of specification for panel data: Monte carlo evidence and an application to employment equations.", *Review of Economic Studies*, Vol. 58, pp. 277–97.

Axelrod, R., (1984), *The Evolution of Cooperation*, Basic Books, New York.

Bannier, C., (2007), "Heterogeneous multiple bank financing: does it reduce inefficient credit-renegotiation incidences?", *Financial Markets and Portfolio Management*, Vol. 21, pp. 445-470.

Berger, A. N., and G. F. Udell, (2002), "Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure", *The Economic Journal*, Vol. 112, n. 477, pp. F32-F53.

Bernheim, B. D. and M. D. Whinston, (1990), "Multimarket Contact and Collusive Behavior", *RAND Journal of Economics*, Vol. 21, pp. 1-26.

Bester, H. (1994), "The Role of Collateral in a Model of Debt Renegotiation", *Journal of Money Credit & Banking*, Vol. 26, pp. 72-86.

Blundell, R. and S. Bond, (1998), "Initial conditions and moment restrictions in dynamic panel data models.", *Journal of Econometrics*, Vol. 87, pp. 115–143

Bolton, P., and X. Freixas (2000), Equity, Bonds, and Bank Debt: Capital Structure and Financial Market Equilibrium Under Asymmetric Information, *Journal of Political Economy*, Vol. 108, pp. 324-51.

Bolton, P. and D. S. Scharfstein, (1990), "A theory of predation based on agency problems in financial contracting, *American Economic Review*, Vol. 80, pp.93-106.

Bolton, P. and D. Scharfstein, (1996), "Optimal debt Structure and the Number of Creditors", *Journal of Political Economy*, Vol. 104, pp. 1-25.

Boot, A.W.A. (2000), "Relationship Banking: What Do We Know?", *Journal of Financial Intermediation*, Vol. 9, pp. 7–25.

Brunner, A. and J.P. Krahnen, (2008), "Multiple Lenders and Corporate Distress: Evidence on Debt Restructuring", *Review of Economic Studies*, Vol. 75, pp. 415-42.

Bulow, J. I. and J. B. Shoven, (1978), "The Bankruptcy Decision", *Bell Journal of Economics*, Vol. 9, pp. 437-56.

Caballero, R., T. Hoshi and A. K. Kashyap (2008), "Zombie Lending and Depressed Restructuring in Japan", *American Economic Review*, Vol. 98, No. 5.

Carletti, E., V. Cerasi, and S. Daltung, (2007), "Multiple-bank lending: Diversification and free-riding in monitoring", *Journal of Financial Intermediation*, Vol. 16, pp. 425–51.

Couwenberg, O. and A. De Jong (2006), "It Takes Two To Tango: An Empirical Tale Of Distressed Firms and Assisting Banks", *International Review of Law and Economics*, Vol. 26, pp. 429-454.

Davydenko, S. A. and J. R. Franks, (2008), "Do Bankruptcy Codes Matter? A Study of Defaults in France, Germany and the UK", *The Journal of Finance*, Vol. 63, No. 2, pp. 565-608.

Detragiache, E., (1995), "Adverse selection and the costs of financial distress", *Journal of*

Corporate Finance, Vol. 1, pp. 347-365.

Detragiache, E. and P. Garella, (1996), “Debt Restructuring with multiple creditors and the role of exchange offers”, *Journal of Financial Intermediation*, Vol. 5, pp. 305-336.

Detragiache, E., P. Garella and L. Guiso, (2000), “Multiple versus single banking relationships: Theory and evidence”, *The Journal of Finance*, Vol. 55, pp. 1133-1161.

Ellison, G., (1994), “Cooperation in the Prisoner’s Dilemma with Anonymous Random Matching”, *Review of Economic Studies*, Vol. 61, pp. 567-588.

Fluet, C. and P. G. Garella, (2007), “Relying on the Information of Others: Debt Rescheduling with Multiple Lenders”, Development Working Papers 232, Centro Studi Luca d’Agliano.

Franks, J. R and O. Sussman, (2005) “Financial Distress and Bank Restructuring of Small to Medium Size UK Companies”, *The Review of Finance*, Vol. 9, No 1, pp. 65–96.

Generale, A. and G. Gobbi, (1996), “Il recupero dei crediti: costi, tempi e comportamenti delle banche”, Banca d’Italia, Temi di discussione del Servizio Studi, n. 265, Roma.

Gertner, R. and D. Scharfstein, (1991) “A Theory of Workouts and the Effects of Renegotiation Law”, *The Journal of Finance*, Vol. 46, 1189-1222.

Godlewski, C.J., F. Lobez, J-C. Statnik and Y. Ziane, (2010), “Better borrowers, fewer banks?”, IFS-Institut de Finance de Strasbourg working paper, February.

Guiso, L. and R. Minetti, (2010), “The Structure of Multiple Credit Relationships: Evidence from U.S. Firms”, *Journal of Money, Credit and Banking*, Vol. 42, pp. 1037-1071.

Hannan, T. H., (1997), “Market Share Inequality, the Number of Competitors, and the HHI: An Examination of Bank Pricing”, *Review of Industrial Organization*, Vol. 12, pp. 23-35.

Hertzberg, A., J. M. A. Liberti, and D. Paravisini, (2011), “Public Information and Coordination: Evidence from a Credit Registry Expansion”, *The Journal of Finance*, Vol. 66, pp. 379–412.

Kandori, M., (1992), “Social Norms and Community Enforcement”, *Review of Economic Stud-*

ies, Vol. 59, pp. 63–80.

Manove, M., A. J. Padilla and M. Pagano, (2001), "Collateral vs. project screening: a model of lazy banks", *Rand Journal of Economics*, Vol. 32, pp.726-44.

Micucci, G. and P. Rossi, (2017), "Debt Restructuring and the Role of Banks' Organizational Structure and Lending Technologies", *Journal of Financial Services Research*, Vol. 51, pp. 339-361.

Ogura, Y., (2006), "Learning from a rival bank and lending boom", *Journal of Financial Intermediation*, Vol. 15, pp. 535–555.

Ongena, S. and D.C. Smith (2000), "What Determines the Number of Bank Relationships? A Cross-country Evidence", *Journal of Financial Intermediation*, Vol. 9, pp. 26-56.

Ongena, S., G. Tümer-Alkan and N. von Westernhagen (2012), "Creditor concentration: an empirical investigation", *European Economic Review*, Vol. 56, pp. 830-847.

Qian, J. and P. E. Strahan, (2007), "How laws and institutions shape financial contracts: the case of bank loans", *The Journal of Finance*, Vol. 62, pp. 2803-2834,.

Rajan, R. G. (1992), "Insiders and outsiders: the choice between informed and arm's-length debt", *The Journal of Finance*, Vol. 47, pp. 1367-1399.

Schivardi F., E. Sette and G. Tabellini (2017), "Credit Misallocation During the European Financial Crisis", LUISS Guido Carli -School of European Political Economy Working paper, No 3/2017.

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

White M. J., (1989), "The corporate bankruptcy decision", *Journal of Economic Perspectives*, Vol. 3, pp. 129-153.

Table 1 – Sector of activity and area of location of firms in the sample

Sector	n. firms	%
Food and beverages	158	6.35
Textile and shoes	143	5.75
Chemicals	113	4.54
Metal and Machinery	343	13.78
Other manufacturing firms	166	6.67
Construction	491	19.73
Commerce sector	559	22.46
Other Services	516	20.73
Area:		
North West (1/0)	822	33.03
North East (1/0)	293	11.77
Centre (1/0)	690	27.72
South (1/0)	684	27.48
Total	2,489	100.00

Table 2 – Balance-sheet ratios (at the distress event and one year earlier)
(Thousand of Euros or ratios)

	2006			2007		
	n. obs.	Mean	median	n. obs.	Mean	Median
Total assets	2186	7020	1895	2489	6278	1668
Total sales	2186	5029	1200	2489	4248	919
Ebitda / tot. Assets	2186	0.006	0.047	2489	-0.074	0.024
Interest payments / tot. Assets	2186	0.036	0.031	2489	0.056	0.038
Roa	2186	-0.028	0.029	2489	-0.132	0.012
Total debt / tot. assets	2186	0.916	0.902	2489	1.132	0.928
Bank debt / total debt	2186	0.446	0.437	2488	0.429	0.419
Bank debt / financial debt	2173	0.849	0.974	2470	0.836	0.961

Table 3 – Relationship with the banking system (at the moment of distress)
(Thousands of Euros or ratios)

	2006			2007			2008		
	n. obs.	mean	median	n. obs.	mean	median	n. obs.	mean	median
Total credit extended	2489	2345	648	2489	2307	599	2264	2155	565
Total credit granted	2489	2812	708	2489	2347	551	2264	1663	300
Number of lending banks	2489	3.728	3	2489	3.689	3	2264	3.274	2
Herfindahl-Hirschman index in lending shares	2489	0.549	0.500	2489	0.602	0.527	2263	0.658	0.603
Real collateral (as % of total credit extended)	2483	0.257	0.070	2485	0.268	0.064	2259	0.290	0.072
Share of bad loans over total credit extended	2483	0	0	2485	0.039	0	2259	0.239	0

Table 4 – Sample statistics

Variables	n. obs.	mean	p50	Sd
Data at firm level				
Restructuring (1/0)	2489	0.278425	0	0.448314
Bank-ratio	2186	0.445862	0.43728	0.222232
n. banks (in logs)	2489	1.006983	1.098612	0.767408
(n. banks)^2 (in logs squared)	2489	1.602694	1.206949	1.781976
Skewness [2]	2489	0.529946	0.08482	1.046253
Herfindahl-Hirschman	2489	0.601739	0.526627	0.31895
Share Inequality Index	2489	0.124121	0.053728	0.19167
Collateral	2483	0.256765	0.070378	0.326285
Size (log of firm's assets, t-1)	2489	7.449304	7.419381	1.367602
Debt over assets (t-1)	2186	0.915676	0.90168	0.463049
Intangibles / total assets (t-1)	2186	0.054693	0.010052	0.111613
Ebitda / assets (t-1)	2186	0.60697	4.678276	28.65828
Interest payments / assets (t-1)	2186	0.035628	0.031127	0.03329
Z-score	2488	2.772508	3	0.492501
Data at loan level				
Restructuring (1/0)	6932	0.2517311	0	0.4340389
Bank solvency	6932	0.1310923	0.1190391	0.054046
Bank liquidity	6932	0.6690447	0.6414914	0.2979938
Bank risk	6932	0.0878235	0.0687986	0.0568538
Prob. to meet again among banks	6932	1.783208	1.390131	2.090289

Table 5 – Correlations

Data at firm level

	Restructuring	Bank -ratio	n. banks (in logs	n. banks (in logs squared)	Herfindahl-Hirschman	Share Inequality Index	Collateral
Restructuring	1						
Bank-ratio	0.1115	1					
n. banks (in logs)	0.1362	0.1683	1				
(n. banks)[2] (in logs squared)	0.1008	0.1712	0.9364	1			
Herfindahl-Hirschman	-0.1805	-0.1132	-0.8368	-0.7426	1		
Share Inequality Index	-0.0381	0.0639	0.2429	0.1058	0.2362	1	
Collateral	0.0473	0.2723	-0.1678	-0.1505	0.2105	0.0677	1
Size (log of firm's assets, t-1)	0.1661	-0.001	0.6375	0.6368	-0.4834	0.1756	0.0614
Debt over assets (t-1)	-0.0817	-0.0935	-0.1089	-0.0942	0.124	0.0158	-0.0184
Intangibles / total assets (t-1)	-0.0284	0.012	-0.0359	-0.0301	0.0313	-0.0149	-0.0887
Ebitda / assets (t-1)	0.0813	0.0578	0.0735	0.0638	-0.1095	-0.0561	-0.0218
Interest payments / assets (t-1)	-0.0349	0.1674	-0.0484	-0.0543	0.0371	-0.0031	-0.0565
Z-score	-0.1383	-0.0322	0.0572	0.0506	-0.0355	0.0402	-0.1369

	Size (log of firm's assets, t-1	Debt over assets (t-1)	Intangibles / total assets (t-1)	Ebitda / assets (t-1)	Interest payments / assets (t-1)	Z-score
Size (log of firm's assets, t-1)	1					
Debt over assets (t-1)	-0.2049	1				
Intangibles / total assets (t-1)	-0.026	-0.0108	1			
Ebitda / assets (t-1)	0.1589	-0.3959	-0.0164	1		
Interest payments / assets (t-1)	-0.286	0.4882	-0.0413	-0.2698	1	
Z-score	-0.0813	0.1663	0.054	-0.0932	0.1824	1

Data at loan level

	Restructuring	Prob. to meet again among banks	n. banks (in logs)
Restructuring	1		
Prob. to meet again among banks	0.0221	1	
n. banks (in logs)	-0.0106	0.4064	1

Table 6 – Probit model for debt restructuring at firm level. Baseline specifications

The dependent variable is a dummy, equal to 1 if the firm has obtained either an increase in the maturity of its loans or the grant of a new loan in the three years following the distress event (between t and t+3). The table reports average marginal effects and standard errors of the marginal effects; discrete changes from the base levels are reported for dummy variables.

	[1]	[2]	[3]	[4]	[5]	[6]
Bank-ratio (t0)	0.14487***	0.16191***	0.16438***	0.17628***	0.17532***	0.18754***
	(0.04896)	(0.04894)	(0.04896)	(0.04870)	(0.04868)	(0.04672)
n. banks (t0)	0.04387**	0.19354***	0.19209***	0.02264	0.27955***	0.29180***
	(0.01825)	(0.03670)	(0.03670)	(0.04796)	(0.03893)	(0.03893)
(n. banks)^2 (t0)		-0.07100***	-0.06633***	-0.05030***	-0.10558***	-0.11073***
		(0.01514)	(0.01569)	(0.01553)	(0.01610)	(0.01612)
Skewness ^{2} (t0)			-0.01231			
			(0.01102)			
Herfindahl-Hirschman (t0)				-0.33705***		
				(0.05964)		
Share Inequality Index (t0)					-0.32627***	-0.34817***
					(0.05861)	(0.05738)
Collateral (t0)	0.04302	0.03776	0.04000	0.05189	0.05181	0.05101
	(0.03383)	(0.03389)	(0.03394)	(0.03374)	(0.03373)	(0.03354)
Long-term banks (1/0)	-0.09700**	-0.09053**	-0.08846**	-0.07464*	-0.07474*	-0.07541*
	(0.03598)	(0.03658)	(0.03681)	(0.03785)	(0.03784)	(0.03798)
Popular banks (1/0)	-0.00383	-0.00638	-0.00655	-0.00415	-0.00397	-0.00538
	(0.02405)	(0.02389)	(0.02387)	(0.02374)	(0.02374)	(0.02374)
Cooperative banks (1/0)	0.08345**	0.08398**	0.08468**	0.07713**	0.07782**	0.07477**
	(0.03462)	(0.03455)	(0.03456)	(0.03409)	(0.03410)	(0.03457)
Foreign banks (1/0)	0.06204	0.08140	0.08321	0.07468	0.07333	0.06689
	(0.14214)	(0.14491)	(0.14437)	(0.13925)	(0.13937)	(0.13836)
Size (log of firm’s assets, t-1)	0.03287***	0.04043***	0.04070***	0.04712***	0.04695***	0.05199***
	(0.01035)	(0.01042)	(0.01042)	(0.01043)	(0.01043)	(0.00978)
Debt over assets (t-1)	-0.11063*	-0.10582*	-0.10401*	-0.08270	-0.08339	
	(0.05716)	(0.05721)	(0.05713)	(0.05668)	(0.05670)	
Intangibles / total assets (t-1)	-0.11571	-0.10934	-0.11104	-0.10825	-0.11082	
	(0.09081)	(0.08980)	(0.08980)	(0.08912)	(0.08918)	
Ebitda / assets (t-1)	0.00253***	0.00246***	0.00243***	0.00197**	0.00198**	
	(0.00082)	(0.00081)	(0.00081)	(0.00080)	(0.00080)	
Interest payments / assets (t-1)	0.03605	0.02217	0.02838	-0.02880	-0.02696	
	(0.40514)	(0.41170)	(0.41133)	(0.39559)	(0.39549)	
Z-score - fragile firms (t-1)						0.01856
						(0.04923)
Z-score - risky firms (t-1)						-0.02345
						(0.04663)
Constant	yes	Yes	Yes	Yes	yes	Yes
Industrial dummies	yes	Yes	Yes	Yes	yes	Yes
Regional dummies	yes	Yes	Yes	Yes	yes	Yes
n. firms	2,182	2,182	2,182	2,182	2,182	2,166
Estimated overall probability	0.2917	0.2868	0.2895	0.2895	0.2904	0.2767
Count R^2	0.718	0.721	0.723	0.720	0.720	0.723
BIC	2619.9	2605.8	2612.2	2581.0	2582.0	2563.0
AIC	2489.1	2469.2	2469.9	2438.8	2439.8	2432.3

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7 –Probit model of debt restructuring for sub-samples of firms

The dependent variable is a dummy, equal to 1 if the firm has obtained either an increase in the maturity of its loans or the grant of a new loan in the three years following the distress event (between t and t+3). The table reports average marginal effects and standard errors of the marginal effects; discrete changes from the base levels are reported for dummy variables.

	[1]	[2]	[3]	[4]	[5]
	Considered doubtful by at least one third of the lending banks	Only with multiple-banks and doubtful by at least one third of the lending banks	Multiple- banks and doubtful by at least one third of the lending banks; with z-score	Multiple- banks; doubtful by at least one third of the lending banks; more lags in balance-sheet variables	Still in distress in *t+3* (z-score>=6); doubtful by at least one third of the lending banks in *t*
Bank-ratio (t-1)	0.18010***	0.14093**	0.16223***	0.16038*	0.18173**
	(0.04944)	(0.06584)	(0.06162)	(0.08266)	(0.09162)
n. banks (t-1)	0.28472***	0.26679**	0.28541**	0.28781*	0.26031***
	(0.04372)	(0.12936)	(0.13019)	(0.15297)	(0.08029)
(n. banks)^2 (t-1)	-0.13595***	-0.13282***	-0.13991***	-0.11794**	-0.11585***
	(0.02095)	(0.04606)	(0.04641)	(0.05290)	(0.03746)
Share Inequality Index (t0)	-0.26211***	-0.33129***	-0.35468***	-0.28560***	-0.22734**
	(0.05795)	(0.06774)	(0.06617)	(0.08275)	(0.10740)
Collateral (t-1)	0.06039*	0.12131***	0.10355**	0.10384*	0.01100
	(0.03321)	(0.04525)	(0.04447)	(0.05694)	(0.06285)
Long-term banks (1/0)	-0.10459**	-0.09128*	-0.09402*	-0.09778	-0.16178**
	(0.03785)	(0.04846)	(0.04816)	(0.05484)	(0.07180)
Popular banks (1/0)	-0.01640	-0.02117	-0.02398	-0.03419	0.00839
	(0.02561)	(0.03164)	(0.03125)	(0.03888)	(0.05040)
Cooperative banks (1/0)	0.04274	0.02758	0.03808	0.01662	0.02873
	(0.03511)	(0.04482)	(0.04543)	(0.05696)	(0.05814)
Foreign banks (1/0)	-0.05936	-0.02180	0.00403		
	(0.16844)	(0.21010)	(0.22139)		
Size (log of firm's assets at t-1) (a)	0.04016***	0.05193***	0.05299***	-0.00415	0.02892
	(0.01096)	(0.01402)	(0.01307)	(0.01923)	(0.02124)
Debt over assets (t-1) (a)	-0.05777	-0.04286		-0.14416	-0.06569
	(0.05334)	(0.07672)		(0.10982)	(0.10026)
Intangibles / total assets at t-1 (a)	-0.12009	-0.20239		-0.03179	-0.24260
	(0.09078)	(0.12277)		(0.17075)	(0.17042)
Ebitda / assets at t-1 (a)	0.00219***	0.00303***		0.00361**	0.00381**
	(0.00080)	(0.00108)		(0.00154)	(0.00165)
Interest payments /assets at t-1 (a)	-0.05215	0.26538		-0.20749	-1.01597
	(0.38641)	(0.67015)		(1.01015)	(1.03512)
Z-score – fragile firms			0.08430		
			(0.16278)		
Z-score - risky firms			-0.01146		
			(0.16015)		
Constant	yes	yes	yes	yes	Yes
Industrial dummies	yes	yes	yes	yes	Yes
Regional dummies	yes	yes	yes	yes	Yes
n. firms	1,714	1,179	1,178	801	687
Estimated overall probability	0.2506	0.2857	0.2643	0.3092	0.4861
Count R^2	0.763	0.727	0.729	0.722	0.643
BIC	1909.6	1418.8	1413.6	1023.5	1015.7
AIC	1.773.4	1291.9	1296.9	911.1	906.9

* significant at 10%; ** significant at 5%; *** significant at 1%. (a) In column [4] it is the average between t-3 and t-1.

Table 8 –Yearly debt restructuring decisions at firm level. Panel data probit model

The dependent variable is a dummy, equal to 1 if the firm has obtained either an increase in the maturity of its loans or the grant of a new loan in each of the three years following the distress event. All the estimated equations include regional, sector and year dummies. The table reports average marginal effects and standard errors of the marginal effects; discrete changes from the base levels are reported for dummy variables.

	[1]	[2]	[3]	[4]	[5]	[6]
	Whole sample		Considered doubtful by at least one-third of the lending banks		Only with multiple-banks and doubtful by at least one-third of the lending banks	
Bank-ratio (t-1)	0.06305**	0.07651***	0.06795**	0.08229***	0.07138*	0.09693**
	(0.02771)	(0.02796)	(0.02759)	(0.02794)	(0.03912)	(0.03792)
n. banks (t-1)	0.11738***	0.13031***	0.11195***	0.12247***	0.15006*	0.18220**
	(0.02459)	(0.02492)	(0.02785)	(0.02833)	(0.08614)	(0.08697)
$(\text{n. banks})^2$ (t-1)	-0.05398***	-0.06121***	-0.06986***	-0.07806***	-0.08792***	-0.10363***
	(0.01054)	(0.01066)	(0.01427)	(0.01448)	(0.03269)	(0.03296)
Share Inequality Index (t0)	-0.15958***	-0.18451***	-0.11555***	-0.13564***	-0.14901***	-0.17761***
	(0.03171)	(0.03150)	(0.03169)	(0.03168)	(0.03797)	(0.03804)
Collateral (t-1)	-0.02831	-0.03125	-0.02091	-0.02432	0.00077	-0.00847
	(0.01932)	(0.01956)	(0.01870)	(0.01898)	(0.02671)	(0.02675)
Long-term banks (1/0)	-0.04505*	-0.04889**	-0.04480*	-0.04847*	-0.03872	-0.03823
	(0.02088)	(0.02079)	(0.02078)	(0.02073)	(0.02706)	(0.02777)
Popular banks (1/0)	0.01745	0.01155	0.01858	0.01132	0.01027	0.00212
	(0.01520)	(0.01516)	(0.01631)	(0.01613)	(0.02070)	(0.02025)
Cooperative banks (1/0)	0.07794***	0.08222***	0.07337***	0.07465***	0.06405**	0.06206**
	(0.02201)	(0.02278)	(0.02365)	(0.02442)	(0.03088)	(0.03154)
Foreign banks (1/0)	-0.07583	-0.07018	-0.01002	-0.0037	0.00549	0.01
	(0.05264)	(0.05711)	(0.09477)	(0.10134)	(0.11630)	(0.12243)
Size (log of firm's assets, t-1)	0.03991***	0.04786***	0.03810***	0.04609***	0.04125***	0.04799***
	(0.00585)	(0.00569)	(0.00617)	(0.00603)	(0.00826)	(0.00788)
Debt over assets (t-1)	-0.09931***		-0.07911***		-0.09210***	
	(0.02518)		(0.02511)		(0.03560)	
Intangibles / total assets (t-1)	-0.06447		-0.01509		0.04029	
	(0.05348)		(0.05194)		(0.06989)	
Ebitda / assets (t-1)	0.00184***		0.00145***		0.00149**	
	(0.00045)		(0.00044)		(0.00059)	
Interest payments /assets(t-1)	0.09245**		0.07197*		0.29099	
	(0.03843)		(0.03815)		(0.32719)	
Z-score – fragile firms		-0.00988		0.0552		0.08338
		(0.03197)		(0.05539)		(0.07176)
Z-score - risky firms		-0.05356*		0.02717		0.05124
		(0.03041)		(0.05457)		(0.07050)
Constant	yes	Yes	Yes	Yes	Yes	Yes
Industrial dummies	yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	yes	Yes	Yes	Yes	Yes	Yes
Year dummies	yes	Yes	Yes	Yes	Yes	Yes
n. firms	2478	2464	1,951	1,937	1,417	1,406
n. obs.	5218	5129	3,987	3,898	2,648	2,602
Estimated overall probability	0.1623	0.1682	0.1247	0.1253	0.1343	0.1345
BIC	4866.1	4874.6	3454.6	3449.9	2471.5	2457.3
AIC	4682.4	4704.5	3278.5	3287	2306.8	2304.8

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9 – System GMM panel data. New credit granted to distressed firms

The dependent variable is the *log of the new credit granted* to firms in distress in each of the three years following the distress event. System GMM estimates of the coefficients and standard errors are reported in the table. Standard errors are robust to heteroskedasticity and serial correlation.

	Whole sample			Only with multiple-banks and doubtful by at least one third of the lending banks		
	[1]	[2]	[3]	[4]	[5]	[6]
L1. credit granted (in logs)	0.82376***	0.83755***	0.81195***	0.77049***	0.78602***	0.74490***
	(0.02442)	(0.02239)	(0.02986)	(0.04232)	(0.04087)	(0.05394)
Bank-ratio	1.46932	2.24133	3.03648**	-0.02015	1.40661	0.60149
	(1.30561)	(1.40246)	(1.45321)	(1.45980)	(1.71065)	(1.56164)
n. banks	5.94194***	5.45191***	4.88609***	4.15713**	4.79661**	5.20011***
	(1.48843)	(1.48935)	(1.47993)	(1.75958)	(1.90890)	(1.85872)
(n. banks)^2	-2.67804***	-2.56363***	-2.04144***	-1.90989**	-2.72502***	-2.76967***
	(0.71688)	(0.73783)	(0.69988)	(0.84329)	(0.96670)	(0.92300)
Share Inequality Index	-5.42486***	-5.38165***	-5.91016***	-4.29136***	-5.12861***	-5.43535***
	(0.95062)	(0.98561)	(1.26861)	(1.06043)	(1.12303)	(1.45742)
Collateral	-0.03937	-0.37410	-0.36871	-0.40255	-0.90439	-0.63671
	(0.76830)	(0.77425)	(0.87891)	(1.04586)	(1.07553)	(1.23119)
Long-term banks (1/0)	-1.41435			-2.73025*		
	(1.44461)			(1.40230)		
Popular banks (1/0)	-0.37171			1.25198		
	(0.71112)			(1.06618)		
Cooperative banks (1/0)	0.11185			2.14880*		
	(0.75816)			(1.12961)		
Foreign banks (1/0)	2.49820			14.73336		
	(2.46275)			(15.60607)		
Size (log of firm's assets)	0.40784***	0.42447***	0.34131**	0.48573***	0.53395***	0.53019***
	(0.14562)	(0.14170)	(0.16808)	(0.17281)	(0.17996)	(0.16809)
Debt over assets	0.03472	0.03565		0.06093*	0.09577***	
	(0.02404)	(0.02469)		(0.03576)	(0.03517)	
Intangibles over total assets	1.15536**	1.04203*		-0.07218	-0.88342	
	(0.56635)	(0.55100)		(0.92025)	(0.89178)	
Ebitda over assets	0.01189***	0.01227***		0.01426***	0.01428***	
	(0.00236)	(0.00244)		(0.00499)	(0.00483)	
Interest payments over assets	-0.04308	-0.08621		-3.73068*	-4.07261*	
	(0.11421)	(0.15210)		(2.22988)	(2.35933)	
Z-score – fragile firms			5.43354			-1.42881
			(4.08756)			(4.58331)
Z-score - risky firms			3.25283			-2.90139
			(3.69681)			(4.38167)
Year = 2008	-0.82366***	-0.89463***	-0.50740**	-0.81140***	-0.85010***	-0.38205
	(0.18785)	(0.19398)	(0.19957)	(0.30824)	(0.30429)	(0.30202)
Year =2009	-0.13642	-0.13180	0.01942	0.04860	0.24463	0.35775
	(0.14680)	(0.15077)	(0.16196)	(0.23130)	(0.23099)	(0.22972)
Year =2010	-0.20200	-0.18548	-0.04600	-0.20254	-0.07057	0.14137
	(0.12947)	(0.13023)	(0.14345)	(0.17820)	(0.17805)	(0.19075)
Constant	-3.48523***	-3.79340***	-6.99782*	-2.76940*	-2.89748**	-0.01182
	(1.07298)	(1.02191)	(4.08064)	(1.50012)	(1.42321)	(4.62737)
Firm fixed effects	yes	yes	yes	yes	yes	yes
n. obs.	3,416	3,418	2,886	1,676	1,678	1,424
n. firms	1,545	1,546	1,340	817	818	719
Arellano-Bond test for AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond test for AR(2) (p-value)	0.797	0.614	0.200	0.873	0.793	0.750
Hansen test of overid. restrictions (p-value)	0.328	0.523	0.671	0.346	0.117	0.385

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10 – Loan level data, panel estimation. Probit model with random effects by firm

The dependent variable is a dummy equal to 1 if the bank lending to the firm has granted either an increase in the maturity of the loan, or a new loan in the three years following the distress event (between t and t+3). The table reports average marginal effects and standard errors of the marginal effects; discrete changes from the base levels are reported for dummy variables.

	Whole sample	Only multiple-banks and firms that were considered as doubtful by at least one third of the lending banks		Only multiple-banks and only banks that considered the firm as doubtful in *t*
	[1]	[2]	[3]	[4]
prob. to meet again among banks	0.00829***	0.00949**	0.00972**	0.00944**
	(0.00311)	(0.00408)	(0.00385)	(0.00474)
n. banks (t0)	0.03497	0.08559	—	—
	(0.02824)	(0.07684)		
(n. banks)^2 (t0)	-0.00803	-0.01418	—	—
	(0.00964)	(0.02458)		
Leader (1/0)	0.04084***	0.03315*	0.02553	0.02688
	(0.01373)	(0.01772)	(0.01734)	(0.02290)
Collateral (t0)	0.09863***	0.12151***	0.11478***	0.13421***
	(0.01783)	(0.02495)	(0.02467)	(0.03231)
Bank solvency	0.47708***	0.56124***	0.54449***	0.07743
	(0.09694)	(0.13489)	(0.13434)	(0.16336)
Bank liquidity	0.15330***	0.14907***	0.14713***	0.14576***
	(0.01888)	(0.02755)	(0.02748)	(0.03614)
Bank risk	-0.39091***	-0.58231***	-0.58649***	-0.51131***
	(0.09970)	(0.14357)	(0.14300)	(0.19725)
Size (log of firm's assets, t-1)	0.00261	-0.00067	0.01022	0.00815
	(0.00658)	(0.00918)	(0.00758)	(0.00908)
Debt over assets (t-1)	-0.06240**	-0.07719*	-0.07410*	-0.05950
	(0.03054)	(0.04478)	(0.04460)	(0.05293)
Intangibles / total assets (t-1)	0.07089	0.14645*	0.14204*	0.12909
	(0.05902)	(0.07763)	(0.07725)	(0.10119)
Ebitda / assets (t-1)	0.00002	0.00033	0.00033	-0.00004
	(0.00036)	(0.00052)	(0.00051)	(0.00060)
Interest payments / assets (t-1)	0.55081**	1.02592**	1.11837***	0.38656
	(0.27352)	(0.40520)	(0.40220)	(0.48457)
Constant	Yes	yes	yes	yes
Industrial dummies	Yes	yes	yes	yes
Regional dummies	Yes	yes	yes	yes
Firm random effects	Yes	yes	yes	yes
n. obs.	6,936	3,643	3,643	2,391
n. firms	2,139	1,167	1,167	1,540
Estimated overall probability	0.232	0.246	0.244	0.224
BIC	7781.9	4272.0	4260.6	2858.4
AIC	7610.8	4117.0	4118.0	2725.5

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11 – Loan level data, panel estimation. Linear probability model with fixed effects by firm or fixed effects by firm and bank

	Fixed effect by firm, only with multiple-banks			Fixed effect by firm and bank, only with multiple-banks		
	Whole sample	Doubtful by at least one third of the lending banks	Only banks that considered the firm as doubtful	Whole sample	Doubtful by at least one third of the lending banks	Only banks that considered the firm as doubtful
	[1]	[2]	[3]	[4]	[5]	[6]
prob. to meet again among banks	0.04458**	0.05890***	0.08691**	0.04075**	0.05792***	0.10365***
	(0.01981)	(0.02204)	(0.03634)	(0.01729)	(0.018604)	(0.034401)
Leader (1/0)	0.03882***	0.03024	-0.01108	0.039030***	0.035421*	-0.002218
	(0.01461)	(0.01860)	(0.03553)	(0.014523)	(0.018119)	(0.03647)
Collateral (t0)	0.09817***	0.10469***	0.11164*	0.038392	0.055070	-0.05869
	(0.02548)	(0.03459)	(0.06689)	(0.028247)	(0.03666)	(0.077343)
bank solvency	0.66082***	0.64895***	-0.07590			
	(0.14801)	(0.21884)	(0.26976)			
bank liquidity	0.16961***	0.17252***	0.20703***			
	(0.02592)	(0.03255)	(0.05637)			
bank risk	-0.47918***	-0.48080***	-0.69123**			
	(0.11217)	(0.15073)	(0.30388)			
Constant	-0.01381	-0.01573	0.02972			
	(0.04842)	(0.05650)	(0.08622)			
Fixed effects by firm	Yes	yes	yes	yes	yes	yes
Fixed effects by bank	No	no	no	yes	yes	yes
n. obs.	6,431	3,643	2,391	6,431	3,643	2,391
n. firms	1,634	1,167	1.540	1,634	1,167	1.540
R^2	0.031	0.032	0.028	0.210	0.281	0.3904

* significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by firm.

Table 12 – Default and liquidation
(Number of firms and frequencies)

Firms that	have restructured		have not restructured		total sample	
	n. obs.	%	n. obs.	%	n. obs.	%
Survive	591	85.28	754	41.98	1,345	54.04
Exit from the market	101	14.72	1,042	58.02	1,144	45.96
Total	693	100.00	1,796	100,00	2,489	100.00
% of the sample	27.84		72.16		100.00	

Table 13 – Survival and restructuring. Biprobit model

The dependent variable for the survival equation is a dummy equal to 1 if, in 2012, the firm is still in activity, equal to 0 if the firm has left the market or a default/liquidation procedure has started.
The dependent variable for the restructuring equation is a dummy, equal to 1 if the firm has obtained either an increase in the maturity of its loans, or it has been granted a new loan in the three years following the distress event. The table reports average marginal effects and standard errors of the marginal effects.

	Marginal effects and standard errors of the marginal effects		Marginal effects for joint probability Survival=1 & restructuring=1
	Survival eq.	Restructuring eq.	
	[1]	[2]	[3]
Bank-ratio (t0)	0.14096**	0.17112**	0.15375**
	(0.05469)	(0.04847)	(0.04098)
n. banks (t0)	0.08068*	0.27292*	0.21665*
	(0.04439)	(0.03883)	(0.03299)
(n. banks)^2 (t0)	-0.06718***	-0.10479***	-0.09036***
	(0.01853)	(0.01612)	(0.01377)
Share Inequality Index (t0)	-0.24710***	-0.33821***	-0.29764***
	(0.06105)	(0.05884)	(0.04911)
Collateral (t0)	0.06149	0.05632	0.05360
	(0.03758)	(0.03330)	(0.02810)
Long-term banks (1/0)	-0.04700	-0.07030	-0.05980
	(0.04967)	(0.03844)	(0.03208)
Popular banks (1/0)	0.02317	-0.00978	-0.00289
	(0.02674)	(0.02361)	(0.02013)
Cooperative banks (1/0)	0.05669	0.06886	0.06303
	(0.03640)	(0.03393)	(0.02939)
Foreign banks (1/0)	-0.19559	0.07840	-0.01583
	(0.14427)	(0.13405)	(0.10186)
Size (log of firm's assets, t-1)	0.03384***	0.04848***	0.04235***
	(0.01135)	(0.01023)	(0.00864)
Debt over assets (t-1)	-0.00618	-0.03207	-0.02480
	(0.02936)	(0.03989)	(0.03098)
Intangibles / total assets (t-1)	-0.08504	-0.09254	-0.08490
	(0.09923)	(0.08885)	(0.07467)
Ebitda / assets (t-1)	0.00093*	0.00219*	0.00179*
	(0.00049)	(0.00074)	(0.00057)
Interest payments /assets(t-1)	0.36452	-0.05710	0.03025
	(0.41872)	(0.38046)	(0.31494)
Constant	Yes		
Industrial dummies	Yes		
Regional dummies	Yes		
Year dummies	No		
ϱ_{12}	0.647286***		
	(0.026722)		
χ^2	252		
BIC	5351.2		
AIC	5061.1		

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 14 – Marginal effects on restructuring and survival probabilities

	[1]	[2]
	Marginal effects for probability of survival=1, conditional on restructuring=1	Marginal effects for probability of restructuring=1
Bank-ratio (t0)	0.02184**	0.17112**
n. banks (t0)	-0.06136 *	0.27292*
(n. banks)^2 (t0)	-0.00060 ***	-0.10479***
Share Inequality Index (t0)	-0.02215***	-0.33821***
Collateral (t0)	0.01726	0.05632
Long-term banks (1/0)	0.00138	-0.07030
Popular banks (1/0)	0.01913	-0.00978
Cooperative banks (1/0)	0.01081	0.06886
Foreign banks (1/0)	-0.22590	0.07840

* significant at 10%; ** significant at 5%; *** significant at 1%.

Working Paper del Dipartimento di Economia e Finanza

1. L. Colombo, H. Dawid, *Strategic Location Choice under Dynamic Oligopolistic Competition and Spillovers*, novembre 2013.
2. M. Bordignon, M. Gamalerio, G. Turati, *Decentralization, Vertical Fiscal Imbalance, and Political Selection*, novembre 2013.
3. M. Guerini, *Is the Friedman Rule Stabilizing? Some Unpleasant Results in a Heterogeneous Expectations Framework*, novembre 2013.
4. E. Brenna, C. Di Novi, *Is caring for elderly parents detrimental to women's mental health? The influence of the European North-South gradient*, novembre 2013.
5. F. Sobbrio, *Citizen-Editors' Endogenous Information Acquisition and News Accuracy*, novembre 2013.
6. P. Bingley, L. Cappellari, *Correlation of Brothers Earnings and Intergenerational Transmission*, novembre 2013.
7. T. Assenza, W. A. Brock, C. H. Hommes, *Animal Spirits, Heterogeneous Expectations and the Emergence of Booms and Busts*, dicembre 2013.
8. D. Parisi, *Is There Room for 'Fear' as a Human Passion in the Work by Adam Smith?*, gennaio 2014.
9. E. Brenna, F. Spandonaro, *Does federalism induce patients' mobility across regions? Evidence from the Italian experience*, febbraio 2014.
10. A. Monticini, F. Ravazzolo, *Forecasting the intraday market price of money*, febbraio 2014.
11. Tiziana Assenza, Jakob Grazzini, Cars Hommes, Domenico Massaro, *PQ Strategies in Monopolistic Competition: Some Insights from the Lab*, marzo 2014.
12. R. Davidson, A. Monticini, *Heteroskedasticity-and-Autocorrelation-Consistent Bootstrapping*, marzo 2014.
13. C. Lucifora, S. Moriconi, *Policy Myopia and Labour Market Institutions*, giugno 2014.
14. N. Pecora, A. Spelta, *Shareholding Network in the Euro Area Banking Market*, giugno 2014.
15. G. Mazzolini, *The economic consequences of accidents at work*, giugno 2014.
16. M. Ambrosanio, P. Balduzzi, M. Bordignon, *Economic crisis and fiscal federalism in Italy*, settembre 2014.
17. P. Bingley, L. Cappellari, K. Tatsiramos, *Family, Community and Long-Term Earnings Inequality*, ottobre 2014.
18. S. Frazzoni, M. L. Mancusi, Z. Rotondi, M. Sobrero, A. Vezzulli, *Innovation and export in SMEs: the role of relationship banking*, novembre 2014.
19. H. Gnutzmann, *Price Discrimination in Asymmetric Industries: Implications for Competition and Welfare*, novembre 2014.
20. A. Baglioni, A. Boitani, M. Bordignon, *Labor mobility and fiscal policy in a currency union*, novembre 2014.
21. C. Nielsen, *Rational Overconfidence and Social Security*, dicembre 2014.
22. M. Kurz, M. Motolese, G. Piccillo, H. Wu, *Monetary Policy with Diverse Private Expectations*, febbraio 2015.
23. S. Piccolo, P. Tedeschi, G. Ursino, *How Limiting Deceptive Practices Harms Consumers*, maggio 2015.
24. A.K.S. Chand, S. Currarini, G. Ursino, *Cheap Talk with Correlated Signals*, maggio 2015.
25. S. Piccolo, P. Tedeschi, G. Ursino, *Deceptive Advertising with Rational Buyers*, giugno 2015.

26. S. Piccolo, E. Tarantino, G. Ursino, *The Value of Transparency in Multidivisional Firms*, giugno 2015.
27. G. Ursino, *Supply Chain Control: a Theory of Vertical Integration*, giugno 2015.
28. I. Aldasoro, D. Delli Gatti, E. Faia, *Bank Networks: Contagion, Systemic Risk and Prudential Policy*, luglio 2015.
29. S. Moriconi, G. Peri, *Country-Specific Preferences and Employment Rates in Europe*, settembre 2015.
30. R. Crinò, L. Ogliari, *Financial Frictions, Product Quality, and International Trade*, settembre 2015.
31. J. Grazzini, A. Spelta, *An empirical analysis of the global input-output network and its evolution*, ottobre 2015.
32. L. Cappellari, A. Di Paolo, *Bilingual Schooling and Earnings: Evidence from a Language-in-Education Reform*, novembre 2015.
33. A. Litina, S. Moriconi, S. Zanaj, *The Cultural Transmission of Environmental Preferences: Evidence from International Migration*, novembre 2015.
34. S. Moriconi, P. M. Picard, S. Zanaj, *Commodity Taxation and Regulatory Competition*, novembre 2015.
35. M. Bordignon, V. Grembi, S. Piazza, *Who do you blame in local finance? An analysis of municipal financing in Italy*, dicembre 2015.
36. A. Spelta, *A unified view of systemic risk: detecting SIFIs and forecasting the financial cycle via EWSs*, gennaio 2016.
37. N. Pecora, A. Spelta, *Discovering SIFIs in interbank communities*, febbraio 2016.
38. M. Botta, L. Colombo, *Macroeconomic and Institutional Determinants of Capital Structure Decisions*, aprile 2016.
39. A. Gamba, G. Immordino, S. Piccolo, *Organized Crime and the Bright Side of Subversion of Law*, maggio 2016.
40. L. Corno, N. Hildebrandt, A. Voena, *Weather Shocks, Age of Marriage and the Direction of Marriage Payments*, maggio 2016.
41. A. Spelta, *Stock prices prediction via tensor decomposition and links forecast*, maggio 2016.
42. T. Assenza, D. Delli Gatti, J. Grazzini, G. Ricchiuti, *Heterogeneous Firms and International Trade: The role of productivity and financial fragility*, giugno 2016.
43. S. Moriconi, *Taxation, industry integration and production efficiency*, giugno 2016.
44. L. Fiorito, C. Orsi, *Survival Value and a Robust, Practical, Joyless Individualism: Thomas Nixon Carver, Social Justice, and Eugenics*, luglio 2016.
45. E. Cottini, P. Ghinetti, *Employment insecurity and employees' health in Denmark*, settembre 2016.
46. G. Cecere, N. Corrocher, M. L. Mancusi, *Financial constraints and public funding for eco-innovation: Empirical evidence on European SMEs*, settembre 2016.
47. E. Brenna, L. Gitto, *Financing elderly care in Italy and Europe. Is there a common vision?*, settembre 2016.
48. D. G. C. Britto, *Unemployment Insurance and the Duration of Employment: Theory and Evidence from a Regression Kink Design*, settembre 2016.
49. E. Caroli, C.Lucifora, D. Vigani, *Is there a Retirement-Health Care utilization puzzle? Evidence from SHARE data in Europe*, ottobre 2016.
50. G. Femminis, *From simple growth to numerical simulations: A primer in dynamic programming*, ottobre 2016.
51. C. Lucifora, M. Tonello, *Monitoring and sanctioning cheating at school: What works? Evidence from a national evaluation program*, ottobre 2016.

52. A. Baglioni, M. Esposito, *Modigliani-Miller Doesn't Hold in a "Bailinable" World: A New Capital Structure to Reduce the Banks' Funding Cost*, novembre 2016.
53. L. Cappellari, P. Castelnovo, D. Checchi, M. Leonardi, *Skilled or educated? Educational reforms, human capital and earnings,* novembre 2016.
54. D. Britto, S. Fiorin, *Corruption and Legislature Size: Evidence from Brazil*, dicembre 2016.
55. F. Andreoli, E. Peluso, *So close yet so unequal: Reconsidering spatial inequality in U.S. cities*, febbraio 2017.
56. E. Cottini, P. Ghinetti, *Is it the way you live or the job you have? Health effects of lifestyles and working conditions,* marzo 2017.
57. A. Albanese, L. Cappellari, M. Leonardi, *The Effects of Youth Labor Market Reforms: Evidence from Italian Apprenticeships*; maggio 2017.
58. S. Perdichizzi, *Estimating Fiscal multipliers in the Eurozone. A Nonlinear Panel Data Approach*, maggio 2017.
59. S. Perdichizzi, *The impact of ECBs conventional and unconventional monetary policies on European banking indexes returns*, maggio 2017.
60. E. Brenna, *Healthcare tax credits: financial help to taxpayers or support to higher income and better educated patients? Evidence from Italy*, giugno 2017.
61. G. Gokmen, T. Nannicini, M. G. Onorato, C. Papageorgiou, *Policies in Hard Times: Assessing the Impact of Financial Crises on Structural Reforms*, settembre 2017.
62. M. Tettamanzi, *E Many Pluribus Unum: A Behavioural Macro-Economic Agent Based Model*, novembre 2017.
63. A. Boitani, C. Punzo, *Banks' leverage behaviour in a two-agent New Keynesian model*, gennaio 2018.
64. M. Bertoni, G. Brunello, L. Cappellari, *Parents, Siblings and Schoolmates. The Effects of Family-School Interactions on Educational Achievement and Long-term Labor Market Outcomes*, gennaio 2018.
65. G. P. Barbetta, G. Sorrenti, G. Turati, *Multigrading and Child Achievement*, gennaio 2018.
66. S. Gagliarducci, M. G. Onorato, F. Sobbrio, G. Tabellini, *War of the Waves: Radio and Resistance During World War II*, febbraio 2018.
67. P. Bingley, L. Cappellari, *Workers, Firms and Life-Cycle Wage Dynamics*, marzo 2018.
68. A. Boitani, S. Perdichizzi, *Public Expenditure Multipliers in recessions. Evidence from the Eurozone*, marzo 2018.
69. M. Le Moglie, G. Turati, *Electoral Cycle Bias in the Media Coverage of Corruption News*, aprile 2018.
70. R. Davidson, A. Monticini, *Improvements in Bootstrap Inference*, aprile 2018.
71. R. Crinò, G. Immordino, S. Piccolo, *Fighting Mobile Crime*, giugno 2018.
72. R. Caminal, L. Cappellari, A. Di Paolo, *Linguistic skills and the intergenerational transmission of language*, agosto 2018.
73. E. Brenna, L. Gitto, *Adult education, the use of Information and Communication Technologies and the impact on quality of life: a case study*, settembre 2018.
74. M. Bordignon, Y. Deng, J. Huang, J. Yang, *Plunging into the Sea: Ideological Change, Institutional Environments and Private Entrepreneurship in China*, settembre 2018.
75. M. Bordignon, D. Xiang, L. Zhan, *Predicting the Effects of a Sugar Sweetened Beverage Tax in a Household Production Model*, settembre 2018.
76. C. Punzo, L. Rossi, *The Redistributive Effects of a Money-Financed Fiscal Stimulus*, gennaio 2019.
77. A. Baglioni, L. Colombo, P. Rossi, *Debt restructuring with multiple bank relationships*, gennaio 2019.