Debt restructuring with multiple bank relationships*

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Abstract

When the debt of a firm in distress is dispersed, a restructuring agreement is difficult to reach because of free rider problems among lenders. Some features in bank lending may reduce these difficulties. Banks come across each other frequently and can behave strategically in devising the restructuring plan. We model this setting as a repeated game, wherein players can threaten to introduce a punishment in the future stages of the game in case of free riding behavior. As the number of lending banks grows large, 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. Our empirical analysis shows that the restructuring probability initially tends to increase with the number of lending banks, and then the relation is reversed: coordination problems prevail as soon as the number of lending banks is larger than a threshold, estimated in four banks. Our theoretical model and empirical results give a new rationale to the common feature of multiple banking relations.

JEL: G21, G33

Keywords: banks, debt restructuring, number of creditors.

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), firms located in 20

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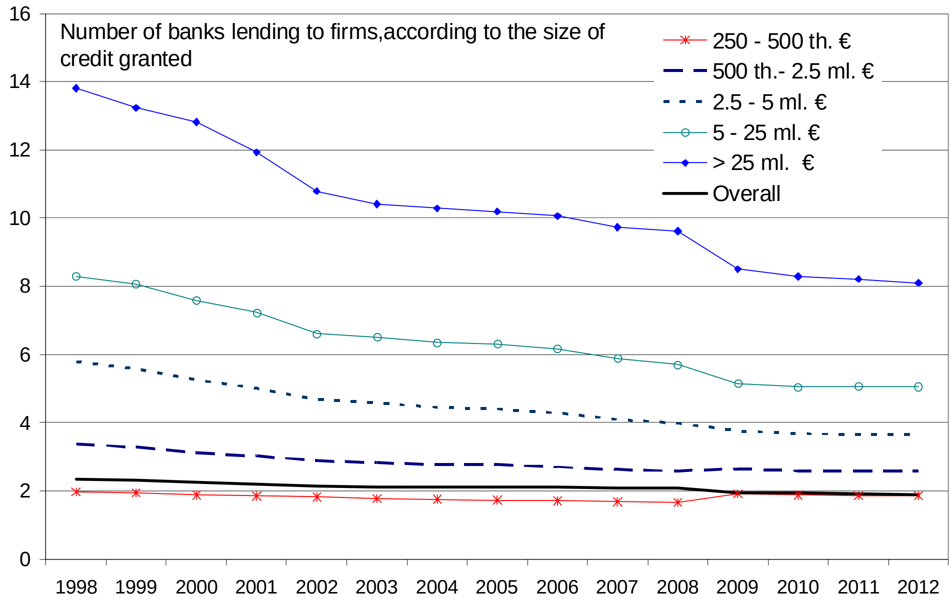

Figure 1: Multiple bank borrowing by firms. Source: Bank of Italy, Statistics on line.

countries 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 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 millions, and 4 banks for loans up to 5 millions; 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.

The theoretical literature explains this behavior as aimed at reducing the information monopoly held by the relationship bank, which in turn may be translated into some form of rent extraction (Sharpe, 1990; Rajan, 1992). The bank may also misbehave during the restructuring phase (Guiso and Minetti, 2010). Therefore, firms try to reduce the bank's bargaining 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, since the conflicts among many creditors may convey liquidation even if this is not economically efficient (Bolton and Scharfstein, 1990, 1996; Bulow and Shoven, 1978; Gertner and Scharfstein, 1991; White, 1989). Considering this theoretical background, it is even more puzzling that especially risky firms, with a higher probability of default, tend to have a higher number of lending banks (Ongena, Tumer-Alkan and von Westernhagen, 2007; Godlewski, Lobez, Statnik and Ziane, 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 banks framework.

In this paper, we put forward some propositions that could account for the diffusion of multiple banking. We consider the case when the debt of a firm in distress is dispersed among many banks. In this situation, a restructuring agreement is difficult to reach because of free rider problems among lenders. We first model the "restructuring game" as a one-shot game with complete information among the lending banks. We show that, when more than one bank is lending to the distressed firm, the liquidation solution is more likely since the non-cooperative strategy strictly dominates.

However, there are some features in bank lending that may help to reduce this coordination risk. Differently from dispersed bond-holders, banks are non-atomistic creditors that can act strategically. Recent theoretical contributions have shown that banks do interact strategically (Hertzberg, Liberti and Paravisini, 2011; Ogura, 2006; Fluet and Garella, 2007). Therefore, even considering that multiple banking is a restraint in the renegotiation process, still banks may behave very differently from dispersed public creditors or a large pool of uniform lenders. They can meet and discuss over the best solution for the firm. More important to our analysis, they can threat a punishment in case of free riding behavior.

We add these features by considering a game repeated through time. Every stage of the game corresponds to a decision on a different firm in distress, whose outstanding debt should be restructured by the lending banks. Repetition gives the possibility to introduce a punishment in case of free-riding behavior. By following 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, participating in restructuring negotiations, grows large, since the chance of meeting again another bank in another negotiation table grows as well. Thus, we reach the conclusion that the likelihood of a 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 necessarily reduces the chance of an agreement leading to some debt forgiveness, due to coordination problems among them.

The argument we use resembles that of multimarket contact put forward 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 the other markets where the two firms compete. In our setting, the repetition of the game trough time and 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 public debt restructuring.

We analyze empirically the validity of our theoretical predictions by estimating the probability of bank-debt restructuring. This is not an easy choice, for many reasons. The prospects of the firms are difficult to evaluate in a distress situation because hard information is less reliable. Of course, banks have many advantages with respect to outside financiers. They have proprietary information about the firm characteristics, gathered through repeated interaction 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.

In the analysis, 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 the decision. We want to test whether an increase in this number has a positive impact on the restructuring probability, as predicted by our model. To this aim, the Italian case is a particularly 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, Garella and Guiso, 2000). We control for the economic and financial situation of the firm, the industry it belongs to and its location. Then, we proceed to verify the impact of these variables on the workout success and overall survival probability.

We focus on the role of relations with the banking system, leaving aside industry or firm-specific causes that brought about the distress. Further, we consider explicitly only financial restructuring, in order to highlight the role of banks in this process, controlling for anticipated profit opportunities by introducing balance-sheet ratios before the reorganizations. We introduce also firm fixed or random effects in various robustness checks.

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 outstanding debts. We focus on doubtful loans ("*incagli*"), a condition in which the borrower is insolvent, but – unlike 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 the firms at an early stage of the distress, we consider all those firms that were reported as doubtful for the first time in 2007. Therefore, these are essentially the population of Italian firms that in 2007 were unable to repay their debt but that were judged to have still the possibility to recover by their lending banks. These data have been combined with information concerning relations with the banking system, balance-sheet data, and records from firms' official registers to assess whether these firms have gone bankrupt or have been liquidated in the following years.

Our results show 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. four banks). This empirical finding is consistent with our model: it shows that a larger number of creditors can have a positive impact on the likelihood of cooperation among them; however, after some threshold this impact is more than offset by coordination problems. The empirical analysis provides other interesting findings, although not directly implied by our 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. The size of the firm increases the probability of restructuring and improves the likelihood of survival. Banks tend to restructure the outstanding debt of those firms they are more involved in. Dispersed debt increases the restructuring probability. These results are robust to various specifications of the dependent variable and to different econometric techniques.

The paper is organized as follows. Section 2 presents the model. Section 3 performs the empirical analysis, while Section 4 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 a two-period time span (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 may 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 initial outstanding debt.[1] In turn, if the workout is unsuccessful, the investment brings zero return and the firm is liquidated.

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 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

[1] 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).

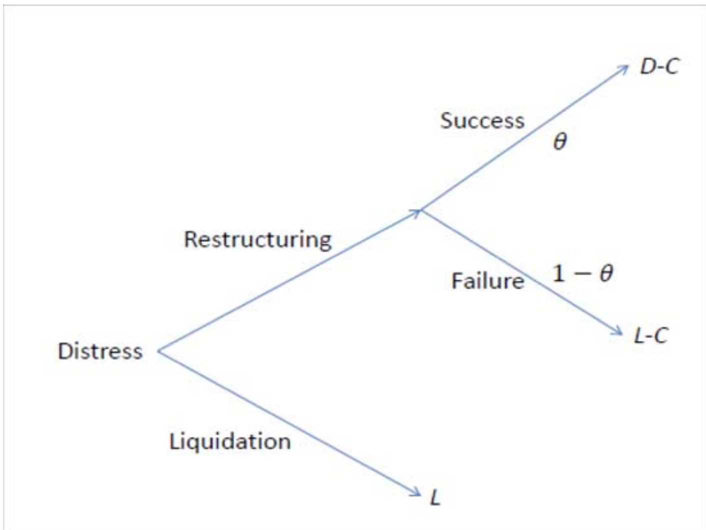

Figure 2: The decision tree of the restructuring choice

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, the liquidation is the only option left, and the liquidation value L is lower than x (and D), essentially because of distressed selling.[2] 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 payoff involved in the decision process.

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.[3] In case of unsuccessful restructuring, the liquidation value is reduced by the deadweight loss of the new credit extended to finance the workout.

[2] 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.

[3] 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.

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.

Figure 3 represents the payoffs of the different strategies. We assume that the outcomes are common knowledge and that the two banks act simultaneously. To keep things simple, we focus on pure strategies only.

	Bank 1		
		$NotCo$	Co
Bank 2	$NotCo$	$\frac{L}{2}, \frac{L}{2}$	$\frac{V_r}{2} - C, \frac{V_r}{2}$
	Co	$\frac{V_r}{2}, \frac{V_r}{2} - C$	$\frac{V_r - C}{2}, \frac{V_r - C}{2}$

Figure 3: The payoffs of the two-bank game
(The first payoff in each cell is that of bank 1)

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:

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

If $\theta \geq \widehat{\theta}$, then one bank has an incentive to bear the full cost of bailing out the firm, given that the other bank holds-out. If $\theta < \widehat{\theta}$, 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 $(\widehat{\theta})$ for the success probability of the workout, such that:*

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

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

Notice also that $\widehat{\theta} = 2\theta^*$. This implies that there is a range of values for the probability of success, namely $\widehat{\theta} > \theta \geq \theta^*$, 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.

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 $t_0, t_{1,...}$. 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 in the future, 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 other "bargaining tables" in some future periods 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 $\theta < \widehat{\theta}$, 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 a future period (what we denote as "termination probability") is a decreasing function of N. It makes sense to 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. We denote the termination probability with $p(N)$, where $p'(N) < 0$.

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.

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 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 the current 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 then possible to define a new threshold for the success probability of the workouts, i.e.

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

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

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

Proposition 3 *In the sequential restructuring game, there exists a threshold level $\widetilde{\theta}$ for the success probability of the workout, such that the equilibrium path with cooperation is sustained iff $\theta \geq \widetilde{\theta}$, 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 to reach a cooperative outcome, and thus to avoid 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 considers the case of a large number of dispersed bondholders, who have a clear incentive to hold-out in a one-shot game. Our contribution is to show 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.

Finally, we check whether the sequential game improves upon the one-shot game, 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 $\widetilde{\theta}$ with the value $\widehat{\theta}$ previously obtained. Using Equations (5) and (4), where of course 2 must be substituted with N, we have that $\widetilde{\theta} < \widehat{\theta}$ if and only if

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

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.*

3 The empirical evidence on debt rescheduling

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. They might eventually develop into bad loans, or recover their financial stability.

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. Accordingly, we build our dataset starting from lending banks' reports on the firms classified as doubtful loans.[4]

In order to avoid selection biases, our dataset includes the whole population of firms that enter distress 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) to assess the ultimate development of firms' conditions (i.e. workout success or liquidation). Furthermore, by choosing 2007, we are able to select those firms that were

[4] This strategy is similar to the one followed by Brunner and Krahnen (2008), Franks and Sussman (2003), Couwenberg and De Jong (2004), who start from a sample of financially distressed firms as directly defined by their lending banks.

already in distress before the burst of the financial crisis, hence avoiding the effects of the so-called "moratorium".[5] In 2007, 5,716 firms operating in the industrial and service sectors have been reported 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, thus reducing our sample to 3,073 firms, 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.[6] In this way, we define the population 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 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 of Commerce (Cerved data set). This further reduces our observations to 2,894 firms. These data have been matched with the Credit Register data base (CR hereafter), which reports firms' individual relations with the lending banks, in order to have information about the type of credit relations these firms have developed with the banking system. Only loans greater than 75,000 Euros are recorded in CR. Due to the matching, the number of firms further 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. Distressed firms in the sample are rather small, both with respect to total assets and sales; on average, they record 4 million Euros of sales and around 6 million of total assets; the medians are even lower, around 1 and 1.6 million, respectively. The year before the distress event, returns on productive activities were already deteriorated, but still positive: earnings before interest payments, depreciation taxes and amortization (Ebitda) were 0.6 percent of total assets. On average they were lower than the interest payments, which were around 3.6 percent of total assets; however, the median firm still managed to cover the interest expenses, since the latter were 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). Firms are highly indebted. 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.

[5] 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 the 2007 as a benchmark, we are able to select firms in distress to which the traditional restructuring instruments apply.

[6] 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.

Table 3 describes the type of relation 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 thousands for the median, respectively). Firms in the sample maintain relations with approximately 3.7 banks (3 for the median). This is in line with the evidence reported in Detragiache, Garella and Guiso (2002), according to which 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 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.

Table 4 reports the outcome of the crisis. More than one fourth of the sample restructures the outstanding credit lines (28 percent, 693 firms out of 2,489), either by means of an extension of debt maturity, or by obtaining new loans. 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.

3.2 Variables definition

The first question we address concerns the determinants of debt restructuring. Banks are the main source of external finance for Italian firms. In our sample they represent more than 80 percent of total financial debt (96 percent for the median firm), and more than 40 percent of total debt.[7]

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), 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. With these interventions, banks make borrowers' financing constraint less stringent, thus improving their survival probability. We do not consider other types of restructuring, such as debt equity-swaps, lender syndicate or others, which are very uncommon for SMEs in distress.

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.

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

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 assume 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 (*#banks*) with which a firm has credit relations. 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 the retaliation threat is more difficult to carry out and free riding becomes prevailing.

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 it is positive or negative, we use the index squared. As an alternative, we also focus on the index proposed by Hannan (1997) and used in Ongena, Tümer-Alkan and von Westernhagen (2007), which modifies the Herfindahl-Hirschman concentration Index (HHI) to reduce its correlation with the number of banks. 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

$$HHI_{jt} = \frac{V_{jt}^2}{N_{jt}} + \frac{1}{N_{jt}}.$$

The first term on the r.h.s. provides a measure of share inequality. Hence, by subtracting the inverse of the number of banks ($1/N_{jt}$) from the HHI, we obtain the Share Inequality Index (SII), which we use in our estimates.

Main bank. We control for the type of bank that has the major share in lending to the distressed firm. The idea is that local banks may be more prone to debt renegotiation in case of distress, because they are deeply rooted in the economy they belong to and have strong linkages with their customers.

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's characteristics. We control for the anticipated going-concern value of the firm, 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 crisis. 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), again using the score with one year lag with respect to the distress event.

Finally, we introduce the firm size (*log of total assets*), and sector and regional dummies. Table 5 reports descriptive statistics for the variables used in the estimates.

3.3 Restructuring probability

3.3.1 The baseline model

The primary goal of our empirical analysis is to assess the probability of restructuring. Accordingly, our dependent variable ($RESTR$) is a dummy taking value 1 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 0 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:

$$prob\,(y=1)_{i(between\ t\ \ and\ \ t+3)} = \Phi\left(a_i + \beta X_i + \gamma B_i + L_i + e_i\right) \tag{7}$$

where Φ denotes the standard cumulative normal distribution, and X_i a set of controls describing a firm's overall economic and financial situation. 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; 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 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 (7) 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.

The 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 fairly few differences in the size of marginal effects. The likelihood of restructuring is higher for larger firms. It is improved for those firms with a healthier economic and financial situation before the distress event, thus suggesting that economic efficiency is preserved.

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 on an overall estimated probability of around 30 percent.

Because of the possible presence of collinearity among the variables, 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 variables are introduced and the dispersion in lending shares is measured by the share inequality index. 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 relations 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.

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.[8] This result can be explained by the possible mutual control mechanism among banks having similar lending shares, which reduces free riding incentives in the restructuring process. Conversely, when bank lending shares are asymmetric, the banks with higher share are less exposed to the retaliation threat by smaller banks, because of their larger bargaining power. For this reason, large banks might be able to adjust the restructuring process to their own advantage (Guiso and Minetti, 2010), thus unsettling the cooperative behavior towards an agreement solution.[9] 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. However, 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 be even more relevant and can partially account for the lack of evidence on our collateral variable.[10]

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), we find that cooperative banks are more prone to renegotiate their loans with respect to the benchmark (large bank corporations). The impact is rather high, improving the likelihood of restructuring by 8 percentage points. Conversely, when the main bank is specialized in long-term financing, the restructuring probability is reduced (by about 9 percentage points).

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

[9] This result is consistent also with the insurance motive put forward by Carletti, Cerasi and Daltung (2007), according to which banks diversify their loans portfolio and share monitoring efforts by means of multiple lending.

[10] This is in line with the evidence reported in Davydenko and Franks (2006), 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 UK, where the bank's ability to realize assets upon default his much higher.

As far as balance-sheet variables are concerned, the restructuring probability is higher when the firm had 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., moving total assets from 700 thousand to 4 million Euros), the overall restructuring probability increases by 7 percentage points. Larger firms may simply be "too big to fail" or they might have a stronger bargaining power. Besides, the bank might decide to restructure a doubtful loan to postpone the emergence of a loss on a big position, which might negatively affect the bank's solvency and, in this way, the cost of funds. 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 recent diffusion of large-scale distribution.

3.3.2 Panel data specifications

To check the robustness of the results obtained with our baseline specification, we exploit also the time series dimension of our dataset by means of a panel specification including random effects. The restructuring variable is now computed annually in each of the three years following the distress event. Since data are now organized in a panel, this specification accounts for the individual unobserved characteristics of the firms in the sample and for the potential reversibility of the restructuring decision. 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 a further deterioration of its economic situation. These changes are overlooked by the analysis of the three-year 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, according to the specification:

$$prob\,(y=1)_{i,t} = \Phi\left(a_i + \beta X_{i,t-1} + \gamma B_{i,t-1} + L_i + u_i + e_{i,t}\right) \tag{8}$$

where u_i is a firm specific random disturbance constant through time, independent from the error term $e_{i,t}$ and from the regressors. With respect to the previous specification, we also introduce time dummies since both the dependent variable and the regressors vary each year. Some of the changes in the regressors within the three year window may be endogenously determined, because of reverse causation effects. To restrain these potential endogeneity problems, we lag all the regressors. We run a maximum likelihood estimation of the previous specification.

Table 7 reports our results. 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. As for as the going concern value of the firm, both the leverage ratio and the profitability are highly significant. Interest payments are now significant and with a positive impact. Most likely, given the level of debt, higher interest payments leave more room to renegotiation interventions. The number of banks has an initial positive impact, which is reverted beyond a given threshold. The maximum restructuring probability is now reached with around three banks, when the overall probability rises to 19.9 percent from 16.2 percent on average. The skewness is slightly significant (at the 10 percent level) and negative, while the share inequality index is strongly significant and negative, confirming that asymmetric lending shares tend to hinder debt restructuring. Collateral is also slightly significant with a negative impact in the first three specifications, but not in our preferred one (Column [5]). This result seems to support the so called 'lazy bank' hypothesis proposed by Manove, Padilla and Pagano (2001), according to which well secured banks tend to intervene less in case of financial distress essentially because of their improved bargaining position with respect to other creditors (Bester, 1994). However, the evidence is too weak to draw clear-cut conclusions.

3.4 New finance following financial distress

Our panel data allow also to investigate the quantity of new loans granted to the firm in each of the three years following the distress event. In doing so, 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 actual 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 quantity 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).[11] More precisely, we focus on a system GMM estimator,

[11] 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

according to the following specification:

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

where the dependent variable is the logarithm of the quantity of credit granted to each firm, $i = 1, \ldots n$, X_{it} is the vector of strictly exogenous covariates, W_{it} is a vector of endogenous covariates, u_i are the panel-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. These lags are introduced for all the variables 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 (when considered). Standard errors are made robust to heteroskedasticity and to serial correlation. Finally, having fixed effects, we do not include time-invariant firm dummies – such as those on the sector of activity, the area of location and, in one specification, the type of the main bank (although these characteristics could in principle change, they are in fact essentially time-invariant).

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 8 reports our results, which confirm the qualitative findings obtained with the specifications discussed in the previous sections. The various specifications fulfil the standard tests. 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, as well as the type of the main bank. However, this latter variable is not changing over time. Hence, we drop it in our second specification, which is our preferred one (Column [2]). Our results confirm that the credit granted is higher as the number of banks increases and credit concentration decreases. As already noted, however, the relation appears to be non-linear and it starts to decrease after a threshold, which is around 3 banks (in specifications [2] and [3]) or 4 banks (in specification [1]). The quantity of the new loan granted to firms in distress is greater the larger the borrowing firm is and the higher the Ebitda and Intangible assets over total assets are. When focusing on Z scores instead of balance sheet indices (Column [3]), our results show that new loans are much lower towards firms that are classified as very risky.

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.

3.5 Survival and restructuring

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

We rely on a binary response model in which we consider jointly the two outcomes: default (either through liquidation or formal bankruptcy procedures) versus successful restructuring. At this stage, the endogeneity of the default outcome with respect to the restructuring decision is a clear source of bias: if a bank decides not to restructure outstanding debt, at the same time it may also file for bankruptcy and the two decisions are simultaneously determined. In order to deal with this issue, we consider a system of two equations, the first one of which defines the probability of firm's survival and the second the restructuring decision; i.e.

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

with $(\varepsilon_1, \varepsilon_2) \approx N(0,1)$ and $corr(\varepsilon_1, \varepsilon_2) = \rho_{12}$, and where $1(.)$ is equal to 1 if the relation inside the brackets holds true.

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

$$prob\left(y_1 = 1, y_2 = 1\right) \approx \Phi_2\left(x_{1i}\beta_1, x_{2i}\beta_2, \rho_{12}\right), \tag{10}$$

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. Table 9 reports our estimates. The correlation between the survival equation and the restructuring equation (ρ_{12}) is positive and significant. Restructuring improves the likelihood of survival. The likelihood ratio test confirms that we have to take into account the correlation among the two phenomena when studying the survival probability. However, if banks are capable of screening ex-ante the successful firms, then they would solely restructure outstanding debt of viable enterprises. As a consequence, one needs to take into account this element also in the first stage, when restructuring decisions are taken. Yet, the results for the restructuring equation remain essentially unchanged with respect to our previous specifications. 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. At the same time, the size of the firm increases the likelihood to survive. The relations with the banking system maintain some explanatory power. A higher bank share increases the survival probability. The same is true for the number of banks, at least up to a certain 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 bank-ratio 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 10 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; 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.

4 Concluding Remarks

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 rider 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 cannot 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 prediction of our model focusing on the impact of the number of lending banks on the restructuring probability by means of a unique data set, which has information on the population of Italian firms at the very beginning of distress. Our findings confirm our theoretical prediction and convey a number of interesting insights into the restructuring process. On the one hand, 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. On the other hand, reaching an agreement on the restructuring plan becomes more difficult when more than four banks are involved. 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. Given the number of banks, dispersed debt improves the probability of restructuring, most likely because symmetric lending shares may represent a mutual control mechanism, which reduces the free riding incentive in the restructuring process. When lending shares are asymmetric, banks with higher lending shares are less exposed to the retaliation threat by smaller banks and, therefore, they might follow an opportunistic behavior. Overall, our theoretical and empirical results on the number of banks and credit concentration give a new rationale to the common feature of multiple banking relations.

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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)

	t-1			T		
	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 (1) / 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)
(Thousand of Euros or ratios)

	t-1			t			t+1		
	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 - Default and liquidation
(Number of firms and frequencies)

Firms which	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 5 - Sample statistics

Variables	N	mean	p50	Sd
Bank-ratio	2186	0.445862	0.43728	0.222232
# banks (in logs)	2489	1.006983	1.098612	0.767408
(# 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

Table 6 - Debt restructuring in the three years following the distress event.
Probit model. Average marginal effects and standard errors of the marginal effects

The dependent variable is a dummy, equal to 1 if the firm has obtained either an increase in the long-term maturity of its loans or the grant of a new loan in the three years following the distress event. Average marginal effects and standard errors of the marginal effects are reported in the table. 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)
# 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)
(# 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)	
Zscore - fragile firms (t-1)						0.01856
						(0.04923)
Zscore - 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
Estimated overall probability	0.3026	0.3103	0.3089	0.2985	0.2994	0.2899
Count R2	0.718	0.721	0723	0.720	0.720	0.723
BIC	2619.9	2605.8	2580.4	2581.0	2582.0	2563.0
AIC	2489.1	2469.2	2438.7	2438.8	2439.8	2432.3

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

Table 7 -Yearly debt restructuring decisions. Panel data probit model.
Average marginal effects and standard errors of the marginal effects.

The dependent variable is a dummy, equal to 1 if the firm has obtained either an increase in the long-term 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.
Average marginal effects and standard errors of the marginal effects are reported in the table. Discrete changes from the base levels are reported for dummy variables.

	[1]	[2]	[3]	[4]	[5]	[6]
Bank-ratio (t-1)	0.05409*	0.06008**	0.06182**	0.06307**	0.06305**	0.07651***
	(0.02777)	(0.02781)	(0.02780)	(0.02771)	(0.02771)	(0.02796)
# banks (t-1)	-0.00422	0.06327***	0.06009***	-0.00804	0.11738***	0.13031***
	(0.01073)	(0.02235)	(0.02241)	(0.02651)	(0.02459)	(0.02492)
(# banks)^2 (t-1)		-0.03360***	-0.02788***	-0.02624***	-0.05398***	-0.06121***
		(0.00977)	(0.01021)	(0.00983)	(0.01054)	(0.01066)
Skewness ^{2} (t-1)			-0.01262*			
			(0.00683)			
Herfindahl-Hirschman (t0)				-0.16084***		
				(0.03216)		
Share Inequality Index (t0)					-0.15958***	-0.18451***
					(0.03171)	(0.03150)
Collateral (t-1)	-0.03536*	-0.03788*	-0.03637*	-0.02838	-0.02831	-0.03125
	(0.01932)	(0.01934)	(0.01934)	(0.01932)	(0.01932)	(0.01956)
Long-term banks (1/0)	-0.05161**	-0.04872**	-0.04771**	-0.04527*	-0.04505*	-0.04889**
	(0.01994)	(0.02036)	(0.02048)	(0.02086)	(0.02088)	(0.02079)
Popular banks (1/0)	0.01748	0.01710	0.01704	0.01730	0.01745	0.01155
	(0.01534)	(0.01527)	(0.01524)	(0.01520)	(0.01520)	(0.01516)
Cooperative banks (1/0)	0.08374***	0.08474***	0.08451***	0.07798***	0.07794***	0.08222***
	(0.02264)	(0.02256)	(0.02251)	(0.02201)	(0.02201)	(0.02278)
Foreign banks (1/0)	-0.07920	-0.07703	-0.07519	-0.07578	-0.07583	-0.07018
	(0.04954)	(0.05117)	(0.05212)	(0.05275)	(0.05264)	(0.05711)
Size (log of firm's assets, t-1)	0.03476***	0.03815***	0.03833***	0.03991***	0.03991***	0.04786***
	(0.00578)	(0.00586)	(0.00585)	(0.00585)	(0.00585)	(0.00569)
Debt over assets (t-1)	-0.11159***	-0.10713***	-0.10502***	-0.09965***	-0.09931***	
	(0.02554)	(0.02556)	(0.02557)	(0.02518)	(0.02518)	
Intangibles / total assets (t-1)	-0.06161	-0.06130	-0.06269	-0.06392	-0.06447	
	(0.05391)	(0.05381)	(0.05373)	(0.05349)	(0.05348)	
Ebitda / assets (t-1)	0.00204***	0.00204***	0.00200***	0.00185***	0.00184***	
	(0.00046)	(0.00045)	(0.00045)	(0.00045)	(0.00045)	
Interest payments /assets(t-1)	0.10827***	0.10440***	0.10225***	0.09287**	0.09245**	
	(0.03822)	(0.03841)	(0.03834)	(0.03841)	(0.03843)	
Zscore – fragile firms						-0.00988
						(0.03197)
Zscore - risky firms						-0.05356*
						(0.03041)
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
Estimated overall probability	0.1559	0.1628	0.1637	0.1616	0.1623	0.1682
BIC	4886.9	4883.4	4888.5	4866.4	4866.1	4874.6
AIC	4716.3	4706.3	4704.8	4682.7	4682.4	4704.5

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

Table 8 - New credit granted to distressed firms.
System GMM panel data estimation

The dependent variable is the *log of the new credit granted* to firms in distress in the three years after the distress event. System GMM estimates of the coefficients and standard errors are reported in the table.

Dependent variable: credit granted (in logs)	[1]	[2]	[3]
	b/se	b/se	b/se
L1. credit granted (in logs)	0.86070***	0.83640***	0.79333***
	(0.02429)	(0.02196)	(0.02950)
Bank-ratio	-0.52879	1.09973	1.94324
	(1.24924)	(1.46564)	(1.74165)
# banks	4.26958***	5.45309***	4.73088***
	(1.47482)	(1.45398)	(1.72797)
(# banks)^2	-1.64763**	-2.43382***	-2.03041**
	(0.68832)	(0.71807)	(0.81925)
Share Inequality Index	-4.21528***	-5.35047***	-5.35261***
	(1.10910)	(0.97630)	(1.32548)
Collateral	0.84373	0.00689	-1.36139
	(0.79204)	(0.80982)	(0.91387)
Popular banks (1/0)	-0.70649		
	(0.69448)		
Cooperative banks (1/0)	0.03735		
	(0.58641)		
Foreign banks (1/0)	1.98226		
	(1.78145)		
Size (log of firm's assets)	0.16707	0.36419***	0.25453
	(0.13504)	(0.14122)	(0.17288)
Debt over assets	0.02036	0.03233	
	(0.02422)	(0.02389)	
Intangibles over total assets	0.98613*	1.09733**	
	(0.52991)	(0.55965)	
Ebitda over assets	0.01221***	0.01224***	
	(0.00209)	(0.00245)	
Interest payments over assets	-0.08577	-0.08349	
	(0.10989)	(0.13997)	
Zscore – fragile firms			-1.54958
			(1.95159)
Zscore - risky firms			-5.22794***
			(1.90165)
Year = 2008	-0.72597***	-0.82804***	-0.28514
	(0.20102)	(0.19276)	(0.24453)
Year =2009	-0.15470	-0.12574	0.30440
	(0.13885)	(0.14982)	(0.19147)
Year =2010	-0.13943	-0.19002	0.16672
	(0.11652)	(0.13058)	(0.16398)
Constant	-1.49344	-3.17930***	2.24982
	(0.93194)	(1.04456)	(2.49030)
N. obs.	3404	3404	3404
N. firms	1543	1543	1543
N. instruments	114	114	114
Arellano-Bond test for AR(1) (p-value)	0.000	0.000	0.000
Arellano-Bond test for AR(2) (p-value)	0.543	0.659	0.152
Hansen test of overid. restrictions (p-value)	0.328	0.548	0.169

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

Table 9 -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 stared.

The dependent variable for the restructuring equation is a dummy, equal to 1 if the firm has obtained either an increase in the long-term maturity of its loans or the grant of a new loan in the three years following the distress event. Average marginal effects and standard error of the marginal effects are reported in the table

	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)
# banks (t0)	0.08068*	0.27292*	0.21665*
	(0.04439)	(0.03883)	(0.03299)
(# 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		
Rho $_{12}$	0.647286***		
	(0.026722)		
chi2	252		
BIC	5351.2		
AIC	5061.1		

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

Table 10 - 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**
# banks (t0)	-0.06136 *	0.27292*
(# 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