Passing the Parcel ? Relationship Banking at the Onset of Financial Distress

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Abstract

This paper explores banks' behaviour in the five years prior to a firm's financial distress. We construct a model of bank competition where new banks will often refinance loans that a firm's current banks do not want to renew. The model predicts that existing banks will be more frequently able to exit their loans if the firm has collateral or a good rating. Using bank–firm level credit data we test this model and document that indeed, banks with long standing relationships strategically terminate lending relationships at losses at the expense of less informed banks, well before those firms approach default. The number of banks continuously increases until about one year before the default, allowing inside banks that have been present in the firm's capital for a long time to reduce their exposure. As predicted this effect is stronger for firms with a good credit rating prior to bankruptcy.

Keywords: *relationship banking, moral hazard, bankruptcy*

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1 Introduction

A large literature analyzes the interaction of relationship banks with borrowers in financial distress (Beck, Degryse, De Haas, & van Horen (2018), Schäfer (2019), Li, Lu, & Srinivasan (2019)), but little evidence exists on the strategies of relationship lenders before a firm's default. In this paper we observe how lending decisions evolve in a period of five years before a firm's default and analyze how this evolution depends on public information about the firm's creditworthiness.

Our sample is based on credit registry data and contains all French private firms that experienced an event of default between 2013 and 2017. We identify the banks that already had a long running lending relationship with these firms in the period preceding these five years and show that these banks see their relative share of the firm's bank loans drop significantly during the five years leading to default. This is possible because new banks enter the lending pool and - at least partially - replace the banks with a long relationship history. Overall, until up to about 12-months before a firm's default, the number of bank relationships increases and, simultaneously, the share of loans held by the relationship lenders decreases. Only in the last year before default does the number of banks decrease and the lending share of the remaining banks stabilize. None of these effects can be observed for firms that do not default.

These observations are not inconsistent with the idea that banks with long relationships and private information can provide inter-temporal insurance and make efficient decisions for firms in financial distress or during economic downturn.[1]. However, our results caution against a too pollyannaish view of relationship banking. When a firm enters bankruptcy, often banks with long standing relationships and private information will not be present any more or only have a negligible exposure. Banks seem to acquire information about a borrower in order to identify and exit risky loans early, rather than to help firm in financial distress. The well-documented positive effects of long standing banking relationships might be limited to the cases where the relationship bank did not manage to exit their loans on time.

It might be surprising that banks willing to exit a lending relationship are able to find competitors that will refinance their loans. However, this is perfectly consistent with theories of relationship lending first developed by Sharpe (1990) and Rajan (1992), where, consistent with empirical findings (Ioannidou & Ongena, 2010), the information acquired during their lending relationship allows banks to increase their interest rates. Rajan (1992) as well as von Thadden (2004) explicitly model the competition between better informed relationship banks and outside banks and demonstrate that this increase in interest rates enables outside banks to compete successfully. Non-informed competitors will suffer from an adverse selection effect, because they will win the competition for all firms that the existing banks want to exit. However, they will also be able to win the competition for loans to many sound firms and the high interest rate on these loans will compensate their losses from the under-performing firms.

[1] See Deyoung, Gron, Torna, & Winton (2015) and P. G. Berger, Minnis, & Sutherland (2017) for US market and Jimenez, Ongena, Peydro, & Saurina (2012), Bolton, Freixas, Gambacorta, & Mistrulli (2016) and Banerjee, Gambacorta, & Sette (2021) for the European market, among others

To generate sharper predictions, we adapt a model in the spirit of Rajan (1992) and von Thadden (2004) to analyze how competition is influenced by firm characteristics. We show that the availability of positive public information and firms' assets to be used as collateral to secure loans will reduce the risk of adverse selection for the outsider bidder, and therefore increase the proportion of bad firms that will be refinanced by outside lenders.

Our model also predicts that relationship banks will not be able to exit all their lending relationships with bad firms. In particular, if the informational advantage of the current bank is too high, outside banks will refrain from making an offer.

To test the model prediction we use the credit rating that is assigned by the Banque de France, the French central bank, to all firms in our sample as proxy for public information about the firm's credit quality. Consistent with our model, we show that the substitution of old by new lenders before firms enter financial distress is faster and more complete for firms that are better rated during the years prior the default.

We then use the fraction of tangible asset to investigate the role of collaterals on banks' behaviours. We demonstrate that, in line with our prediction, during the five years before default, the proportion of loans from relationship lenders decreases faster and the number of banks increases more, if the firm has a higher proportion of fixed assets. These results are also consistent with previous papers that have shown that lenders with weaker relationships with the firm are more likely to require collateral (A. N. Berger & Udell (1995), A. N. Berger, Scott Frame, & Ioannidou (2011)).

Our findings demonstrate the importance of private information in lending and the value of this information in making long term forecasts about a firm's success. By documenting that this information can be used by banks to exit risky loans at the expense of less informed creditors, we illustrate the large information asymmetries that exist across different lenders and provide a new explanation for why private information is valuable for banks. A bank with private information is able to exit loans early and will generate a much higher expected return than bank that remains a lender at the time of the firm's default. Our results add a range of implications to the literature on relationship banking and the use of private information in lending (Petersen & Rajan, 1994; A. N. Berger, Miller, Petersen, Rajan, & Stein, 2005; Detragiache, Tressel, & Gupta, 2008; Agarwal & Hauswald, 2010; Bharath, Dahiya, Saunders, & Srinivasan, 2011). In contrast to most of this literature, we demonstrates that information can also have negative consequences for the firm. This might explain why some firms are reluctant to disclose too much information to their banks. However, it is important to remember that our results only hold for the average bank. Previous, literature has shown that banks that define themselves as relationship banks implement different lending strategies and it might very well be that there is a strong heterogeneity in behavior for the banks in our sample. In addition, we only focus on firms that eventually fail, but not on firms that go through a period of financial distress from which they successfully emerge. We cannot exclude that relationship banks can identify firms that will fail in any case, even if the bank provides financial support. Helping these firms would be useless and the fact that relationship banks try to exit these loans does not mean that they will not provide support to firms that have the potential to survive. Both of these questions warrant future research.

Our result are also relevant for the literature on the effect of information on competition between banks.[2] A number of papers have argued that uninformed banks benefit from information generated by relationship banks (Carletti, Cerasi, & Daltung, 2007) and possibly free-ride on creditworthiness tests carried out by existing banks (Petriconi, 2015). The effect we document here runs counter to this intuition. At least in the long run, the informational advantage of the existing banks makes it more dangerous for less informed banks to propose a loan. Actually the fact that private information by inside banks makes poaching of borrowers by competitors more difficult could be one of the reasons for why banks might want to acquire this private information. We also show that credit risk analysis relating on publicly available hard information such as the rating scheme provided by the Banque de France has limits and that banks can beat these ratings by using private and presumably soft information.

Our empirical results on the increase in the number of borrowers are related to the small literature on the number of lending relationships initiated by Ongena & Smith (2000). More recently a range of papers suggest that the number of banks can be seen as a negative indicator of a firm's financial situation. In this regard, we add to the literature on borrowing concentration.

[2]Previous works that theoretically investigate the role of information on bank competition are, for example, Pagano & Jappelli (1993); Padilla & Pagano (1997); Hauswald & Marquez (2006); Bennardo, Pagano, & Piccolo (2015)

In particular, our findings are in line with Foglia, Laviola, & Reedtz (1998) and Cosci & Meliciani (2002) who show that the number of banks is positively correlated with increased riskiness of the firm. This also supports Guiso & Minetti (2010), who show that the structure of a bank pool and the division of credits between banks can be seen as a disciplinary tool both for lenders and borrowers.

The literature also provides some potential alternative non exclusive explanations for our findings. In particular, there might exist additional reasons for why relationship lenders do not want to be present when the firm enters financial distress. They might be worried about the bad reputation that comes with the tough measures required in bankruptcy (Taillet and Troege, 2021) or they might not have the necessary know how to restructure the firm. It is also conceivable that the exit of the historical lenders in firms at the onset of financial distress is driven by the firm rather than by the bank's willingness to termiante the relationship. For example, firms that are aware that they will shortly experience financial distress may want to dilute the power of major banks in their pool to prevent coordination between banks and asset appropriation. Alternatively as proposed by Gropp & Guettler (2018), firms of lower quality may prefer selecting transaction banks in order not to be monitored. We cannot exclude these explanations, but we think that is more likely that the relationship bank willingness to reduce its exposure is the primary driver for our observations. Given the ample evidence for the positive effect of the presence of a relationship lender during firms financial distress, firms anticipating bankruptcy should encourage these lenders to stay, rather than cut the relationship.

Finally, our results mirror the *exit* versus *voice* discussion for equity blockholders (Edmans, 2014). Similar to inside banks, holders of large equity blocks can decide to exit these investments if they receive negative information, or intervene actively to increase the value of their holdings again. The relative attractiveness of these two options for blockholders (banks) will depend on the liquidity of the equity (debt) market and their ability to actively influence the value of their investments by monitoring management (providing financial support).

Our paper also has a range of implications for policy makers. Importantely, the finding that the number of bank relationships increases when distressed borrowers display sufficiently positive rating information suggests that a slow reaction of credit rating agencies in predicting firms' default could benefit informed banks. While the literature tends to shed light on the benefits of rating information for uninformed investors, we highlight that in some specific situations such information can indeed favour the more informed creditors.

In addition our results suggest that freely available credit rating information will increase the liquidity of the loan market. This is not necessarily a good thing from a welfare perspective. In particular, if informed lenders are able to make more efficient decision during financial distress (Dahiya, John, Puri, & Ramirez, 2003) and creditor concentration leads to more efficient bankruptcy outcomes (**?**), the fact that relationship banks are able to exit their loan and be subsituted by new creditors will create additional deadweight losses.

The article proceeds as follows. Section 2 presents our model and its empirical predictions. Section 3 describes the data and variables used in our empirical analysis. Section 4 presents results and Section 5 provides robustness checks. Section 6 concludes.

2 The Model

To better understand how an informed bank can convince outside banks to refinance its existing loans and generate sharper predictions about the conditions under which this is likely to happen, we model the competition between two banks for providing a new loan to a firm. The literature on competition between informed and uninformed banks has been pioneered by Sharpe (1990) who assumes that a bank's private information about the quality of a firm prevents competition for a renewal of the credit, and enables the bank to extract *ex post* monopolistic rents from the firm. Building on Broecker (1990) auction model of bank competition with asymmetric information, Rajan (1992) and von Thadden (2004) have recognized that the outsider can compete despite his information disadvantage. They show that insiders and outsiders will compete in mixed strategies, which limits the rents the insider is able to extract. Similar models have since regularly used to model bank competition (e.g. Dell'Ariccia, Friedman, & Marquez (1999), Hauswald & Marquez (2003), Ruckes (2004), Hauswald & Marquez (2006), Amir & Troege (2011)).

In our model, as in Rajan (1992), one of the competitors is an inside bank that has already given a loan with a size that is normalized to one. The other bank is a new outside bank that would like to refinance this loan. The firm's ex ante quality is summarized by the success probability λ. In case of success the firm is returning X, whereas with probability of $1-\lambda$ the firm fails and returns nothing. Importantly, we assume that the inside bank cannot withdraw its loan unless it is refinanced by the outside bank.

We capture the informational advantage of the inside banks by assuming that with probability q_i it receives a perfect signal about the quality of the firm, whereas the outside bank only knows the ex-ante probability of default $1-\lambda$. The outside bank knows the probability of the inside bank having an information advantage, but does not now whether the inside bank has received a signal nor which signal has been received. Both banks can decide to offer a loan to the firm, asking for a repayment of b in case of success. As the investment is normalized to one, this corresponds to an interest rate of $b-1$. The firm will simply accept the lowest interest rate if two loans are offered or if only one banks makes an offer, accept this loan. If no bank makes an offer the inside bank will have to roll over its existing loan. Bidding is assumed to be closed, i.e. each bank does not know if the competitor has made an offer.

2.1 Bidding Equilibrium

The offers made by the inside bank will depend on its signal. If the signal is bad it knows that the firm is going to fail. In this case it will either not offer a loan or propose a loan at the highest possible interest rate X. Profits will be identical in both cases: We will see that if the outside bank makes an offer, it will with probability one be smaller than X and hence inside bank will award the loan in both cases. If the outside bank makes no offer, the inside bank will lose its outstanding loan if it does not roll over the existing loan or lose the newly awarded loan which has the same amount.

In case the inside bank has received a good or an inconclusive signal its bidding strategy will be more complicated. In general, when deciding about the interest rate, a bank faces a trade-off between a higher profit in the case of winning and a higher probability of winning but a lower interest rate. Similar to other auctions with discrete valuations, the model has no equilibrium in pure strategies. If one bank was bidding an interest rate as a pure strategy, the best response of the competitor would be to either slightly undercut this bid, or to ask for the highest possible interest rate. In both cases the first bank's bid was clearly not optimal. To characterize the bidding equilibrium in mixed strategies, bid distributions for the inside bank having received a signal or not and outside bank have to be specified.

The mixed bidding strategy of the inside bank i can be described by the bidding distribution $F_i(b)$ in case the bank has received a good signal, the probability μ_i of making an offer in case no signal has been received and the distribution of the bids $H_i(b)$ in case the bank is bidding without having received a signal. The outside bank o's strategy can be described by the the probability μ_o of making an offer and the distribution of the bids $H_o(b)$ in case the bank is bidding. The profit of the inside bank i having received a good signal and bidding b against bank o, can be calculated as follows:

$$\pi_i^g(b) = (b-1)\left[1 - \mu_o H_o(b)\right], \tag{1}$$

This is simply the profit on the loan that is know to be without risk $(b-1)$ multiplied by the probability $1-\mu_o H_o(b)$ of proposing an interest rate that is lower than the outside bank's rate, given the probability of bidding μ_o and the bid distribution $H_o(b)$. In case the inside bank has not received a signal its profit can be calculated as

$$\pi_i^0(b) = [(1-\lambda)(-1) + \lambda(b-1)][1-\mu_o H_o(b)]. \tag{2}$$

Again this is simply the expected profit from lending at a rate $b-1$ to a firm that will fail with probability $1-\lambda$ multiplied with the probability of winning against the outsider. In case the insider bids X after having received a bad signal, his profit will be zero in case the outsider makes an offer and he will his loan with a loss of 1 in case the outsider does not make an offer, i.e. his expected profits will be

$$\pi_i^b(b) = (1-\mu_o)(-1). \tag{3}$$

The profit of the outsider o, offering a loan at an interest rate of $b-1$ can be obtained with similar reasoning:

$$\begin{aligned} \pi_o(b) = &(1-\lambda) q_i (-1) + \lambda q_i (1-F_i(b))(b-1) \\ &+ (\lambda b - 1)(1-q_i)[1-\mu_i H_i(b)] \end{aligned}$$

In a mixed strategy equilibrium, both banks must be indifferent between bids on the support of their bidding distribution. This condition leads to a set of three equations which have unique solutions.

The precise form of the equilibrium depends on the value of the term $(1-\lambda)\, q_i\,(-1) + (\lambda X + (-1)\,(1-q_i))$. This expression can be understood as the outsider's expected profit if he bids the highest possible interest rate X and always wins the auction except if the inside bank has received a good signal. Only if this expression is positive, the outsider will ever participate in bidding. We can reformulate this condition as $X > \hat{b} := \frac{1-\lambda q_i}{\lambda(1-q_i)}$, or equivalently as $q_i < \hat{q} := \frac{X\lambda - 1}{\lambda(X-1)}$. This demonstrates that the ousider will make an offer in case the maximum interest rate is sufficiently high if the insider's information is sufficiently imperfect. Given that the insider cannot recall his existing loan he will always offer a new credit.

Proposition 1. *(equilibrium strategies) If the inside bank is receiving information with probability q_i the equilibrium is of the following form:*

a) If $\hat{q} \leq q_i$, the insider always bids X and the outsider never makes an offer.

b) For $\hat{q} > q_i$, the insider distributes his bids with

$$F_i\,(b) := \begin{cases} 0 & \textit{for } b \leq \frac{1}{\lambda}, \\ \frac{\lambda b - 1}{\lambda q_i (b-1)} & \textit{for } \frac{1}{\lambda} < b \leq \hat{b}, \\ 1 & \textit{for } b > \hat{b}, \end{cases} \tag{4}$$

in case of receiving a good signal and

$$H_i\,(b) := \begin{cases} 0 & \textit{for } b \leq \hat{b}, \\ \frac{1}{1-q_i}\left(1 - \frac{b-1}{\lambda b - 1}\lambda q_i\right) & \textit{for } \hat{b} < b \leq X, \\ 1 & \textit{for } b > X. \end{cases} \tag{5}$$

in case of an inconclusive signal. In case of a bad signal he bids the highest possible interest rate X. The outsider makes an offer with probability $\mu_o := 1 - \frac{(1-\lambda)q_i}{(X\lambda - 1)}$ distributing his bids with

$$H_o(b) := \begin{cases} 0 & \text{for } b \leq \frac{1}{\lambda}, \\ \frac{1}{\mu_o}\left[\frac{(b\lambda-1)}{(b-1)\lambda}\right] & \text{for } \frac{1}{\lambda} < b \leq \hat{b}, \\ \frac{1}{\mu_o}\left[1 - \frac{(1-\lambda)q_i}{(b\lambda-1)}\right] & \text{for } \hat{b} < b \leq X, \\ 1 & \text{for } b > X, \end{cases} \tag{6}$$

Proof. See Appendix 9.1 □

Figure 1 shows the distribution functions of both banks in case b). Both banks randomize on the same support. Note, that the inside bank's distribution function has a mass point at $b = X$ implying that it is offering the highest possible interest rate X with a strictly positive probability.

Equilibrium profits can be easily calculated by plugging back the equilibrium strategies F_i, H_i, H_o, μ_o back into the profit functions (1), (2) and (3), but are not relevant for our empirical part and will therefore not be reported

We are interested in how frequently the inside bank will be able to exit its lending engagement after having received a bad signal. Clearly if the outside bank is not participating in the competition, i.e. in case *a)* this is not possible. However if the *ex ante* quality of the firm is sufficiently high or if the inside bank's information advantage is sufficiently weak, i.e. $q_i < \hat{q}$, the outside bank will with a certain probability win the competition despite its informational disadvantage. The following corollary states that the probability of the outside bank winning will be higher if the ex ante quality of the firm λ is higher or if the information advantage of the inside bank is lower

Corollary 1. *(Probability of exiting the loan after a bad signal)*
The probability of the informed bank being able to exit after having received a bad signal increases in λ and X.

Proof. In case the insider has a bad signal he will bid X, but with probability $\mu_o := 1 - \frac{q_i(1-\lambda)}{(1-q_i)(X\lambda-1)}$ the outside bank will also make an offer and will win the auction. Deriving μ_o with respect to λ yields $\frac{(X-1)q}{(1-q)(X\lambda-1)^2} > 0$ and deriving with respect to X yields $\frac{(1-\lambda)\lambda q}{(1-q)(\lambda X-1)^2} > 0$, hence the probability of exiting a good loan is increasing with λ and X. □

To sum up our findings: The model demonstrates that the inside bank's informational advantage allows it to increase interest rates in case it refinances the loan. This makes it possible for outside banks to compete successfully, but also enables the inside bank to exit loans to bad firms. Positive publicly available information about the firm's quality increases the inside bank's ability to exit loans in firms for which it has negative private information.

3 Data

We exploit three datasets managed by the French central bank: The French credit registry in which all lending relationships with credit exposure larger than $25,000$ *EUR* are registered with a monthly frequency; The *FIBEN Bilans* dataset, where the firms' accounting information is reported and, lastly, a dataset that includes the listing of defaults of French borrowers that the French central bank collects directly from the bankrutpcy courts all over the country. In this section we describe how the key variables for our emprical analysis are constructed with the above databases.

3.1 Lending relationship variables

The French credit registry encompasses all lending relationships in France between a financial institution and a resident firm. For the purpose of our analysis we exclude loans to financial corporations and we only keep the firms for which we have at least 7 years of observations before its default. The observations are registered on a monthly basis. Hence, in each period, we can observe a newly created bank-firm relationship as well as the change of the borrower's exposure with each of its lenders.

We build the variable $nbbank_{i,t}$ that captures the number of banks that grant a loan to a given firm i at time t. We also use a measure of firms' borrowing concentration that relies on the *Herfindahl–Hirschman Index* (HHI). The *HHI* is defined as: $\sum \frac{bank\_drawn_{i,j,t}}{outloan\_drawn_{i,t}}^2$, that is the sum of the squared shares of the total loan portfolio of firm i owned by each lender at time t. The closer it is to 1, the more concentrated the bank pool. Note that for a firm with a single bank relationship the HHI takes value 1. A potential pitfall of our analysis would be a priori that several of these firms could borrow on the bond market as part of a funding diversification strategy. However, this should not have a large impact on the results since most of the firms in the sample are relatively small (75% have total assets lower than *EUR 1.9m*).

We are especially interested in examining the evolution of the share of bank financing provided by the relationship lender before firms' default. The first approach we use to identify the informed relationship lenders relies on the length of the firm-bank relationship. We consider any bank that had a lending relationship with the firm during the 2 years prior our observation period (i.e. 5 years before default) as a relationship bank. We thus require that the lender interacted with the firm for at least 2-years to be classified as informed lender. This criteria is based on previous evidence that credit relationships of at least 2-years allow a reduction of asymetric information thanks to the banks' aquisition of soft information (López-Espinosa, Mayordomo, & Moreno, 2017). We build the dummy variable *relbank* that takes the value 1 if the observed lending relationship is with a relationship bank and 0 otherwise. The variable *relshare* indicates the fraction of loans granted by relationship banks to firm i at time t. In Section 5, we demonstrate robustness across alternative ways of defining informed lenders.

3.2 Firm data

The *FIBEN* database provides accounting data at firm level from which we build a set of control variables. These variables includes the proportion of debt to equity (*leverage*), total assets, proportion of tangible assets to total assets (*tangprop*), and the *cashratio* that is the firms' amount of cash over total assets. Since loans are reported on a monthly basis, while financial statements are reported annually, we match the latest accounting numbers prior to the loan observed date (e.g. Fiscal Year ending in 03/2016 with loan observed in

05/2016).[3]

The same database allows us to collect the Banque de France' credit ratings. The French central bank assigns a credit rating via its analysts to each firm with sales greater then 0.75 millions or outstanding loans greater than 0.38 millions and make available to all lenders through the public credit registry. The rating scale has 12 levels, going from '3++' that is assigned to firms with the highest credit quality to the rating level P that corresponds to the level of default. These rating are revised by rating analysts and can change any time if an improvement or worsening in the firms' credit quality happens. We map the Banque de France' credit ratings on a numerical scale ($3++=1$, $\dots$, $P=12$), thus the lower the credit rating the highest is the credit quality estimated by the rating analysts. We create the variable *goodrating*, which takes the value 1 if the average rating of the firm in the years before its default is below the sample median.

3.3 Default data

We extract all events of default registered in France between *2013* and *2017*. We observe the date of default as well as the type of default that is reported at firm-event level.

As event of default, we consider both the event of liquidation (*liquidation judiciaire* and restructuring (*redressement judiciaire and autres mesures légales*).The distinction between liquidation and restructuring is similar to the distinction between *Chapter 7* and *Chapter 11* of the United States Bankruptcy

[3]When matching the aforementioned databases, we eliminate data older than 23 months vis-à-vis the observation date.

Code. Indeed, in case of liquidation, no recovery is possible and the firm ceases to exist, while in case of restructuring, the firm's manager can renegotiate the terms of debt with the remaning creditors. The liquidation of firms represents 68% of the events of default, showing that liquidation is rather the rule than the exception as far as bankruptcy proceedings are concerned.

We focus on the first event of default recorded by each firm in the sample. Indeed, even though the firm may survive after the event of restructuring, we consider the first event to be the most discriminant in terms of asymmetrical knowledge between lenders about the state of the firm. We then build the variable TTD, which indicates the number of months between the observation date and the firm default and takes value from 0 to -60, where 0 is when the firm file for bankruptcy.

3.4 Summary statistics

Table 1 presents the summary statistics at firm level that refer to the period going from 5 years prior to the default to the time of bankruptcy filing. We hence consider $245,927$ observations overall over the period. It has to be noted that the default 'Defaillances' database records $263,592$ defaults between 2013 and 2017 but we do not have loan data for the very small firms so they are de facto excluded from the analysis. The firms in our sample contract loans from 3.5 different banks on average (the median number of banks observed amounts to 3) and the average HHI is 0.573. Interestingly, the average share of loans provided by relationship banks is 24.7% but this is impacted by the fact that around 50% of our firm level observations do not have a relationship bank. As far as company size goes, the median amount of *total asset* observed amounts to *EUR* 1,299,000 but the largest amounts to more than *EUR* 4bn. The companies in our sample have low amounts of cash and tangible assets (medians resp. 5.5% and 15.1% of *total assets*). As far as risk perception is concerned, the median Banque de France rating for our firm level observations is 6, which is the sixth best grade on a scale of one to twelve. Any grade above 7 is a grade commensurate with financial difficulties in the foreseeable future, while the worst grade 12 (*P* in the *Banque de France classification*) means that the bank is facing some disciplinary procedure. In our sample, the level of rating assigned to firms 60 months before default is concentrated between the 5+ and 6, which indicates moderate level of risk.

We also compare the metrics for the companies observed five years before default with the same metrics observed the month before default (Table 2 and Table 3). We observe that the median rating has dropped by one notch, the median level of cash to total assets ratio has decreased by 2.1pp to 1.9%, the same can be said about the ratio of tangible assets to total assets with a 0.8pp decrease to 9.5%, while leverage has increased by more than 5pp to 12.8% $<$. We note that in parallel the loans are less concentrated given the 8.2% decrease of the average *HHI*.

4 Empirical analysis

4.1 Number of banks and bank pool concentration

We start our empirical analysis by examining the evolution of the number of bank relationships over the 5-year before the firm's default. The prediction of our model is as follows: if relationship banks possess negative private information about the firm, they act strategically and leave space for new banks to refinance the firm's loans. As a consequence, the number of banks that lend to the firm should increase over time up to the point where all markets become aware of the firm's distress. Similarly, we should observe a decrease in the borrowing concentration measured by the HHI defined in Section 3.

We estimate the following model:

$$Y_{i,t} = \sum_{t} \beta_t \mathbb{1}_{i,t}^{TTD} + \eta_i + \eta_t + \varepsilon_{i,t} \tag{7}$$

where the outcome variables $Y_{i,t}$ are the number of lenders (*nbbank*) and the Herfindhal Index (*HHI*). We regress these variables on a set of dummy variables equal to one t months before the default. We control for leverage, credit ratings, firm' size, the share of tangible assets and the cash ratio. We add firm fixed effects that control for all firm characteristics that are not time-varying in the period analyzed, and year fixed effects that capture aggregate shock in the credit market. In all specifications, standard errors are clustered at the firm level.

We plot in Figure 2 the coefficients of our dummy variables that depict the evolution of the firms' number of lenders. The graph shows an inverted

U-shaped pattern: the number of banks that grant loans to firms increases steadily up to a about one year before the bankruptcy. In the year preceding the default the number of banks that interact with the firms constantly decreases over time.

Figure 3 shows the coefficients of Model 7 using the HHI as outcome. The index follows a clear *U-shaped* pattern before firms' default. Consistently with the results exploiting the number of lenders, the concentration of firms' funding significantly decreases up to the year preceding their bankruptcy.

We provide the estimation of model 7 in the Appendix, Table 11 and Table 12. For sake of brevity, we only report the coefficients of the first dummy variable of the year. We thus omit all other time dummies that are anyway plotted in Figure 1 and 2. Focusing on Table 11, the first dummy variable that turns to be positive and statistically significant is the dummy that corresponds to the 45th month before default, that is about four years before the event. Around this date firms start to increase their bank relationships. All other dummy variables up to the month of default show the expected positive and statistically significant coefficients. Importantly, the month before defaults firms still experience a higher number of relationship with respect to the 60th month before bankruptcy, as shown by the coefficient of the dummy TTD_{-1} in Table 11. However, this coefficient is smaller than the coefficient of dummy TTD_{-13}, which confirms that during the last year, some banks exit the relationship pool. Table 12 shows that in all the four models (column $1-4$), the HHI appears to experience a significant drop 48 months before default, and accelerate three years before default, as shown by the coefficient of TTD_{-37}

that is negative and statistically significant. In the model 3 and 4, in which we add firm and time fixed effects, we clearly observe that the drop in the concentration of funding does not continue up to default. Indeed, the coefficients for months until 3 months before default are statistically significant and higher than the coefficient 13 months before default and in the few months before the event the coefficients of the time dummies are not statistically different from zero.

We then estimate an alternative model that considers a different measure of our main independent variable, i.e. the time to default. We estimate the following equation:

$$Y_{i,t} = \beta TTD + \eta_i + \eta_t + \varepsilon_{i,t} \tag{8}$$

Where TTD is now a continuous variable that captures the number of months until default. We still focus on a period that goes from 60 months before default (dummy omitted in model 7) up to time 0 that corresponds to the date of default, so TTD takes value between -60 to 0. As in model 7, we include leverage, size, rating, the ratio of tangible assets over total assets and the cash ratio as controls, as well as time and firm fixed effects.

Table 4 reports the results when the outcome variable is the number of firms' bank relationships. In column 2 we add our control variables, while in column 3 and 4 we include firm and time fixed effect. Thus, column 4 corresponds precisely to our Model 7. In line with the graphical analysis, the coefficients of the variable TTD show expected positive sign: as default approaches, the number of banks increases. The result holds in all the specifications.

Focusing on column 4, we observe that leverage enters positively in the regression. This positive relationship is in line with previous findings that a larger number of bank relationships is associated with better firms' acces to credit (Gopalan, Udell, & Yerramilli, 2011). Firms that are smaller in size appear to have, on average, less bank relationships, which support previous evidence that the number of relationships increases with the firm's size (see, e.g., Detragiache, Garella, & Guiso (2000) and Farinha & Santos (2002))

In Table 5, we estimate Model 8 using the *HHI* as outcome. We thus regress the index on a continuous variable that captures the time to default (i.e. TTD), ranging from -60 to 0. This variable enters negatively and statistically significant in the model, confirming that once getting close to default firms show less concentrated borrowing. The signs of the coefficients of the control variables are consistent with the ones in Table 4. Larger firms and firms with higher leverage have less concentrated borrowing. Additionally, we see this is also true for firms with higher share of tangible assets. As tangible assets can be used by firms as collateral, this finding is not surprising: collaterals have been found to improve the firms' ability to collect fundings through different lenders (A. N. Berger & Udell (1995), A. N. Berger et al. (2011)).

4.2 Evolution of relationship bank exposure

In this section we test the prediction of the model that relationship banks try to exit loans before the firm default.

We consider the subsample of relationships that each firm has with the informed banks. We run Model 7 and Model 8 using *relshare*, which is the amount of drawn loans granted by the relationship bank over the firms' total loan amount, as outcome variable.

The coefficents of the time dummies of Model 7 are plotted in Figure 4. We find that the share of loans from informed banks constantly decreases over the five years before the default of the borrower, consistent with the prediction that informed bank try to strategically end the relationship with the firm. Table 6 reports the estimates of Eq. 8. The coefficient of the variable TTD is negative and statistically significant at the 1% level in all the specifications, confirming a drop of lending from relationship banks to distressed firms as default approaches. The coefficients of the control variables in column 4 – the model that includes all control variables and fixed effects– suggests that bigger firms rely less, on average, on the relationship lender. This is consistent with results emphasized in Section 4.1 that larger firms tend to differentiate more their funding.

4.3 Public information and bank lending strategy

4.3.1 Firm's credit rating

Focusing on the period preceding the financial distress of the firm, our model predicts that the better the ex-ante credit quality of the firm (i.e. the higher is λ), the higher should be the informed bank's ability to exit the relationship.

We explore the empirical validity of this prediction by using the firm's outstanding credit rating over the years before the bankruptcy filing as proxy for the *ex ante* credit quality of the firm. This proxy is justified by the fact that outside and less informed banks rely on credit ratings for the assesment of the credit quality of the firms and, thus, for their lending decisions (Cahn, Girotti, & Salvadè, 2020).

We start by exploring the effects of rating information on the dynamic of the number of lenders and the exposure of informed banks before firm's default. We compute the average level of the rating for each firm in the period that goes from 5-year to 1-year before the event of default. The choice of excluding the year prior the default is based on our previous finding that emphasizes that in such year the financial distress of the firm is common knowledge. We build the variable *good rating* that takes value 1 when firms have a level of credit rating below the sample mean and 0 otherwise. The fact that a firm had a relative bad rating before the default implies that a signal of the low quality of the borrower was already available to all lenders. The prediction is that in such cases it is more difficult for the firm to attract new lenders and, in turn, the relationship lender is more likely to be stuck with the distressed borrower.

We start with a graphical illustration. We run Model 7 separately for the sample of firms with good and bad rating. Figure 5 plots the coefficient β_t for t between -59 and 0 (expressed in months), where 0 is the time to default. In line with our conjecture, it appers very clearly that the number of lenders strongly increases up to the time of default only for firms that have relatively good credit rating over the period, thus when public information did not incorporate yet the firm's financial distress. We then turn to formal statistical tests. We run Model 8 including the interaction term betwen the variables TTD and *goodrating*. The coefficient of this interaction term captures the differential path of the variable that indicates the number of lenders between firms with bad ratings with respect to firms with good credit ratings. Results are reported in Table 7. Column 2 shows the estimates of the model that includes both control variables and time fixed effects. The key coefficients are the ones of the interaction terms between TTD_t and *goodrating*. In line with the graphical analysis, the coefficients are positive and statistically significant, suggesting that the number of lenders over time increases more for well rated firms.

We next replicate the graphical analysis and the statistical tests using as dependent variable in Eq. 8 the share of loans granted by relationship banks. Figure 6 links the time to default to the exposure of the relationship lender toward the firms depending on the the level of credit ratings. The graphs show that relationship lenders reduce their exposure for firms that appeared to have a good rating in the pre-distress period. The estimates of the regression including the interaction terms between TTD_t and *goodrating* are reported in Columns 3 and 4 of Table 7. The interaction terms are negative, suggesting that the drop in the amount of informed loans are statistically significant more pronounced for firms better rated.

This finding shows that the relationship bank reduces its exposure toward distressed firms when a public signal – the credit rating assigned by a third-party – increases the probability that others, less informed lenders, will be willing to lend to the firm. This allows the informed bank to minimize its potential losses also by delaying the firms default thanks to the presence of other investors.

[Input Table 7]

4.3.2 Availability of collateral

Another reason that could make more willing outside banks to refinance a loan is the availability of information that allows to infer that the firm's loss given default is reasonably low. Indeed, uninformed lenders are more likely to finance borrowers that can pledge collateral (A. N. Berger et al., 2011). In this Section, we distinguish firms based on the share of tangible assets that proxies for the amount of collaterals that firms can pledge. We expect that new lenders are more likely to replace the relationship bank before the default when firms have relative high share of tangibles.

To test this prediction, we regress the number of banks on the variable *TTD*, the variable *tangible* (taking the value 1 if the share of firms' tangible assets is higher than the median share), and their interaction. If, as default approaches, the number of banks increases more for firms that are more able to attract new lenders thanks to their ability to pledge collateral, the coefficient of the interaction term should be positive and statistically significant. Results are reported in Table 8. Column 2 reports our main specification that includes time and firm fixed effects. The interaction term has the predicted sign, suggesting a more pronounced increase of lenders over time for the sample of distressed firms with more tangible assets.

If the number of bank relationships increases more for high-asset tangibility firms, we should then observe that the relationship bank reduces its exposure especially toward those firms. To analyze if this is the case, we regress the amount of loans that a firm has drawn from the relationship bank over the total firm' loans on the TTD variable and its interaction with the variable *tangibles*. If our prediction is correct, the coefficient of the interaction term should be negative and statistically significant. This is confirmed by the results displayed in column 3 and 4 of Table 8.The coefficients of the control variables in column 4 are also in line with our finding. The fact that the relationship share is lower when firms have more tangible assets and when rating levels are high indicates that firms are more likely to be financed by non-relationship banks when they have more tangibles and when the rating information signals that the firm is creditworthy.

We find this result consistent with the previous findings on credit ratings: relationship banks quickly reduce their exposure when they can be replaced by new lenders. Overall, our findings suggest that public information has a strong impact on the ability of the relationship bank to pass the parcel in case of firm's financial distress.

5 Robustness checks

To test the robustness of our empirical results, we conduct two additional analyses. First, we investigate whether our findings are robust to using an alternative definition of relationship bank. Second, we implement a matching approach to compare banks' behaviours towards firms that later will file for bankruptcy with ex-ante similar firms that did not file for bankruptcy.

5.1 Main banks

Our main definition of informed banks relies on the lenght of the bank-firm relationship: the longer the duration of the relationship, the higher the probability that the lender is informed about the firm's credit quality. Another indicator of the amount of information held by the lender is the amount of outstanding loans between the lender and the firm over the total firm's loan outstanding (see, e.g., Petersen & Rajan (1994) and Schenone (2010)). Based on these previous evidence, we classify as informed bank the lender that provides the largest share of credit to the firm 5 years before default (hereafter, *main bank*). We then check whether our previous results are robust to this different classification. We estimate Eq. 8, where the outcome is the variable *mainshare* that identifies the share of firm's loans held by the main banks. Results, reported in Table 9, confirm that the informed bank reduces its exposure over the five years prior the borrower's filing for bankruptcy (see 9), confirming the prediction of the model and our main empirical analysis.

5.2 Comparison with non defaulting firms

To mitigate the concern that our findings could be driven by changes in the demand rather than the supply of credit, we compare the sample of firms that file for bankruptcy with similar firms that do not file for bankruptcy. We perform a propensity score matching in order to identify a control group of bankrupt firms, as in Garcia-Appendini (2011). We consider the sample of defaulted firms and we focus on their characteristics 60 months before the default, which is the beginning of our observation period. We then consider all firms that appeared in the credit registry in those months but that won't file for bankruptcy in the following 5-year. We match –without replacement– each bankrupt firm with a firm that won't file for bankruptcy but has similar credit rating, leverage, total assets, share of tangible assets, number of banks and share of the main bank and operates in the same industry. Table 13 shows the summary statistics of defaulted and non-defaulted firms before and after matching and a t-test to assess the significance of the difference between the two samples. Before the matching procedure, bankrupt firms appear to have worse credit ratings, lower tangible assets, more borrowing diversification and to be smaller in size. However, after the matching procedure all differences between the two samples of firms disappear as shown by the t-tests in column 5.

Focusing on the sample of defaulted firms and the matched control sample, we then apply a slightly modified version of our model 8: We include the dummy *default* that takes value 1 for treated firms (bankrupt firms) and 0 for firms in the control sample (firms that survive), and the interaction of the dummy *default* with the variable TTD. We show results separately by year. We include all control variables used in the previous models and industry fixed effect. The outcome variables we focus on are the number of banks and the share of loans grants by the relationship bank.

The results are summarized in Table 10. The key coefficient is the one of the interaction term. For each year, the results show that firms which will eventually default see the number of banks in their pool rises quicker in the five years before default and the share of their relationship banks decrease at a quicker pace, which validates our core analysis.

6 Conclusion

This paper investigates banks' behaviour in the five years prior the default of their borrowers. The data analysis is guided by a model of bank competition where outside banks refinance the loans that relationship banks do not want to renew. The model predicts that informed banks can easily exit from distressed relationships when positive information about the borrowers' creditworthiness is shared in the credit market.

We employ credit registry data covering a sample of French private firms that experience an event of default between 2013 and 2017. We document a substantial increase in the average number of bank relationships before those firms officially default and, simultaneously, a reduction in the share of loans held by informed banks. Consistent with the prediction of the model, we uncover a large degree of heterogeneity in banks behavior depending on the firms' availability of collateral and outstanding credit rating. In fact, we find that outside banks are more likely to replace the informed bank when borrowers have tangible assets and a good rating before bankruptcy.

Overall, we theoretically and empirically document that public information can affect the fraction of bad loans that are refinanced in the credit market. In doing so, our results lead to important implications for policy makers.

References

Agarwal, S., & Hauswald, R. (2010, July). Distance and Private Information in Lending. *Review of Financial Studies*, *23*(7), 2757–2788.

Amir, R., & Troege, M. (2011). On the effects of banks' equity ownership on credit markets. *Annals of Finance*, *7*(1), 31–52.

Banerjee, R. N., Gambacorta, L., & Sette, E. (2021). The real effects of relationship lending. *Journal of Financial Intermediation*, *48*, 100923.

Beck, T., Degryse, H., De Haas, R., & van Horen, N. (2018). When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics*, *127*(1), 174–196.

Bennardo, A., Pagano, M., & Piccolo, S. (2015). Multiple bank lending, creditor rights, and information sharing. *Review of finance*, *19*(2), 519–570.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial economics*, *76*(2), 237–269.

Berger, A. N., Scott Frame, W., & Ioannidou, V. (2011). Tests of ex ante versus ex post theories of collateral using private and public information. *Journal of Financial Economics*, *100*(1), 85–97.

Berger, A. N., & Udell, G. F. (1995). Relationship Lending and Lines of Credit in Small Firm Finance. *The Journal of Business*, *68*(3), 351–381.

Berger, P. G., Minnis, M., & Sutherland, A. (2017). Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Journal of Accounting and Economics*, *64*(2-3), 253–277.

Bharath, S. T., Dahiya, S., Saunders, A., & Srinivasan, A. (2011). Lending relationships and loan contract terms. *The Review of Financial Studies*, *24*(4), 1141–1203.

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

Broecker, T. (1990, March). Credit-Worthiness Tests and Interbank Competition. *Econometrica*, *58*(2), 429.

Cahn, C., Girotti, M., & Salvadè, F. (2020). Credit ratings and the hold-up problem in the loan market. *Available at SSRN 3072891*.

Carletti, E., Cerasi, V., & Daltung, S. (2007). Multiple-bank lending: Diversification and free-riding in monitoring. , 27.

Cosci, S., & Meliciani, V. (2002). Multiple Banking Relationships: Evidence from the Italian Experience. *The Manchester School*, *70*(S1), 37–54.

Dahiya, S., John, K., Puri, M., & Ramirez, G. (2003). Debtor-in-possession financing and bankruptcy resolution: Empirical evidence. *Journal of Financial Economics*, *69*(1), 259–280.

Dell'Ariccia, G., Friedman, E., & Marquez, R. (1999). Adverse Selection as a Barrier to Entry in the Banking Industry. *The RAND Journal of Economics*, *30*(3), 515–534.

Detragiache, E., Garella, P., & Guiso, L. (2000). Multiple versus single banking relationships: Theory and evidence. *The Journal of finance*, *55*(3), 1133–1161.

Detragiache, E., Tressel, T., & Gupta, P. (2008). Foreign banks in poor countries: theory and evidence. *The Journal of Finance*, *63*(5), 2123–2160.

Deyoung, R., Gron, A., Torna, G., & Winton, A. (2015). Risk overhang and loan portfolio decisions: small business loan supply before and during the financial crisis. *The Journal of Finance*, *70*(6), 2451–2488.

Edmans, A. (2014). Blockholders and Corporate Governance. *Annual Review of Financial Economics*, *6*(1), 23–50.

Farinha, L. A., & Santos, J. A. (2002, April). Switching from Single to Multiple Bank Lending Relationships: Determinants and Implications. *Journal of Financial Intermediation*, *11*(2), 124–151.

Foglia, A., Laviola, S., & Reedtz, P. M. (1998). Multiple banking relationships and the fragility of corporate borrowers q. , 16.

Garcia-Appendini, E. (2011). Supplier certification and trade credit. *Available at SSRN 1795107*.

Gopalan, R., Udell, G. F., & Yerramilli, V. (2011). Why do firms form new banking relationships? *Journal of Financial and Quantitative Analysis*, *46*(5), 1335–1365.

Gropp, R., & Guettler, A. (2018, February). Hidden gems and borrowers with dirty little secrets: Investment in soft information, borrower self-selection and competition. *Journal of Banking & Finance*, *87*, 26–39.

Guiso, L., & Minetti, R. (2010, August). The Structure of Multiple Credit Relationships: Evidence from U.S. Firms. *Journal of Money, Credit and Banking*, *42*(6), 1037–1071.

Hauswald, R., & Marquez, R. (2003). Information Technology and Financial Services Competition. *The Review of Financial Studies*, *16*(3), 921–948.

Hauswald, R., & Marquez, R. (2006). Competition and strategic information acquisition in credit markets. *The Review of Financial Studies*, *19*(3), 967–1000.

Ioannidou, V., & Ongena, S. (2010). "Time for a Change": Loan Conditions and Bank Behavior when Firms Switch Banks. *The Journal of Finance*, *65*(5), 1847–1877.

Jimenez, G., Ongena, S., Peydro, J.-L., & Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, *102*(5), 2301–26.

Li, Y., Lu, R., & Srinivasan, A. (2019). Relationship bank behavior during borrower distress. *Journal of Financial and Quantitative Analysis*, *54*(3), 1231–1262.

López-Espinosa, G., Mayordomo, S., & Moreno, A. (2017). When does relationship lending start to pay? *Journal of Financial Intermediation*, *31*, 16–29.

Ongena, S., & Smith, D. C. (2000). What Determines the Number of Bank Relationships? Cross-Country Evidence. *Journal of Financial Intermediation*, *1*(9), 26–56.

Padilla, A. J., & Pagano, M. (1997). Endogenous communication among lenders and entrepreneurial incentives. *The review of financial studies*, *10*(1), 205–236.

Pagano, M., & Jappelli, T. (1993). Information sharing in credit markets. *The journal of finance*, *48*(5), 1693–1718.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The journal of finance*, *49*(1), 3–37.

Petriconi, S. (2015). Bank Competition, Information Choice and Inefficient Lending Booms. *SSRN Electronic Journal*.

Rajan, R. G. (1992). Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt. *The Journal of Finance*, *47*(4), 1367–1400.

Ruckes, M. (2004). Bank Competition and Credit Standards. *The Review of Financial Studies*, *17*(4), 1073–1102.

Schäfer, L. (2019). “Forgive but Not Forget”: The Behavior of Relationship Banks When Firms Are in Distress*. *Review of Finance*, *23*(6), 1079–1114.

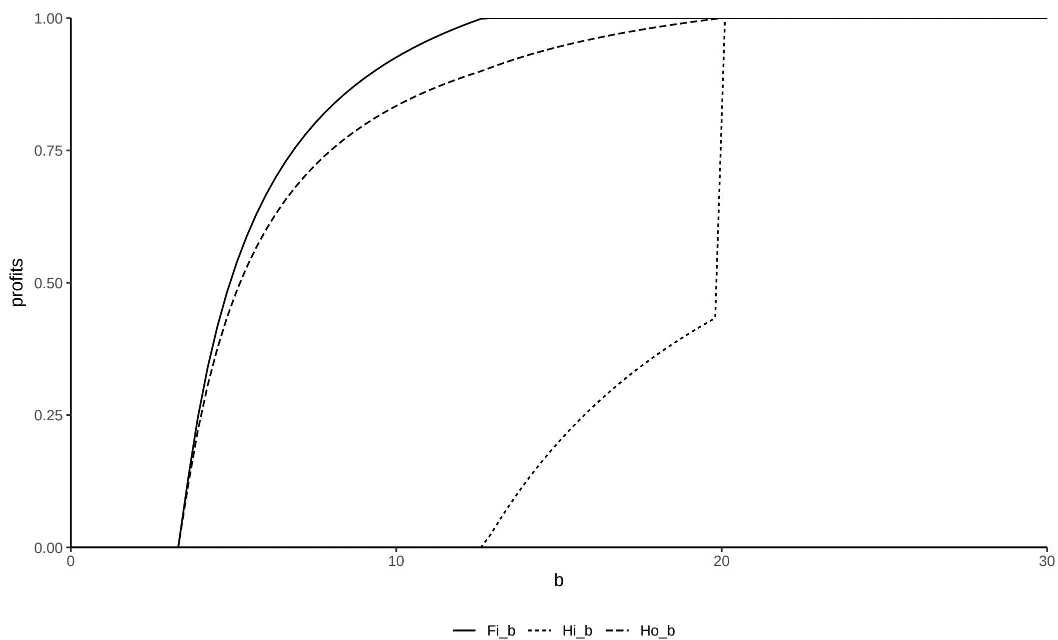
Schenone, C. (2010, March). Lending Relationships and Information Rents: Do Banks Exploit Their Information Advantages? *Review of Financial Studies*, *23*(3), 1149–1199.

Sharpe, S. A. (1990). Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships. *The Journal of Finance*, *45*(4), 1069–1087.

von Thadden, E.-L. (2004). Asymmetric information, bank lending and implicit contracts: The winner's curse. *Finance Research Letters*, *1*(1), 11–23.

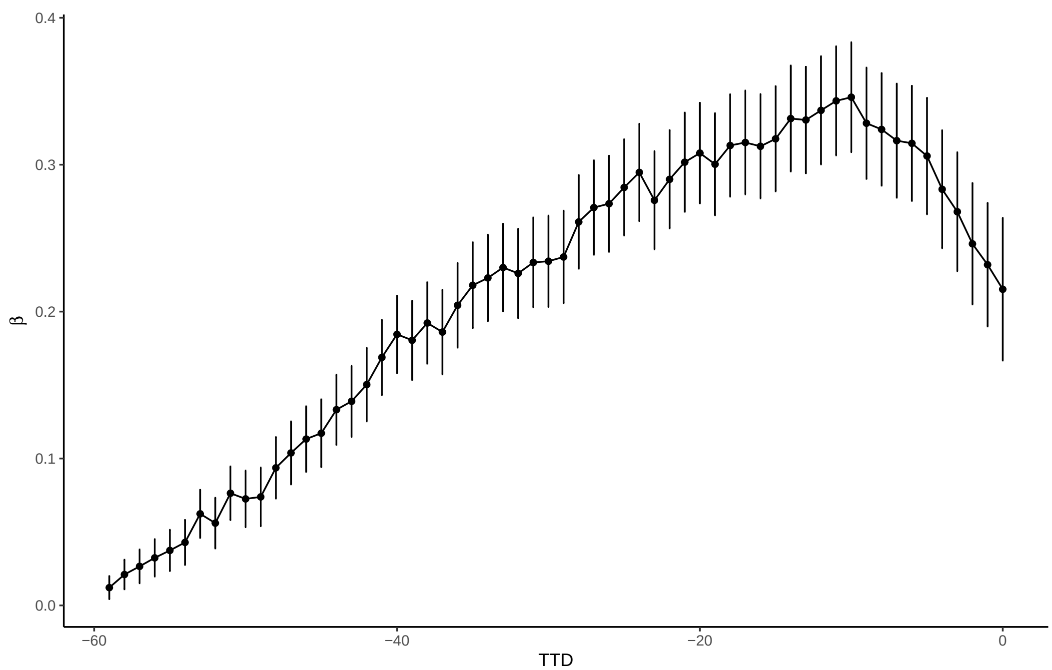
7 Figures

Figure 1: Bid distribution in equilibrium (case b)



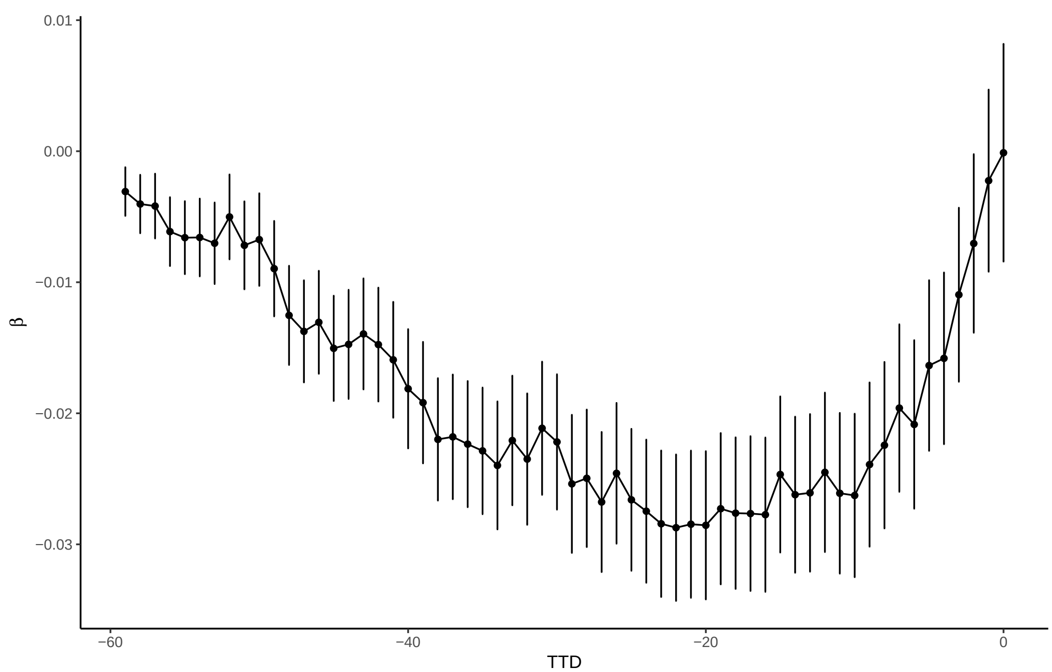
This figure shows the distribution of bids in equilibrium assuming the quality of the signal is good enough (case b) for both inside (*(i)*) and outside (*(o)*) banks.

Figure 2: Number of banks before firms' default



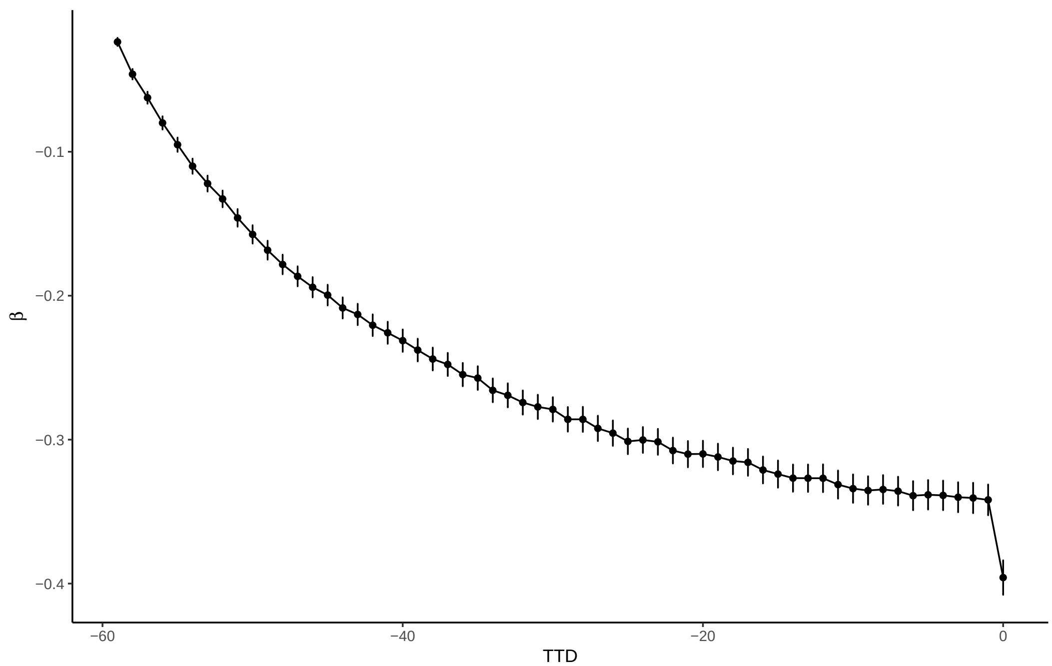
This figure shows the evolution of the number of banks before firms' default. The graph plots the coefficient β_t of the regression $nbbank_{j,t} = \sum_t \beta_t \mathbb{1}^{TTD}_{j,t} + \eta_j + \eta_t + \varepsilon_j$, where t indicates the time to default (TTD) expressed in months and it goes from -59 to 0, where 0 is the time of default.

Figure 3: Concentration of bank borrowing before default



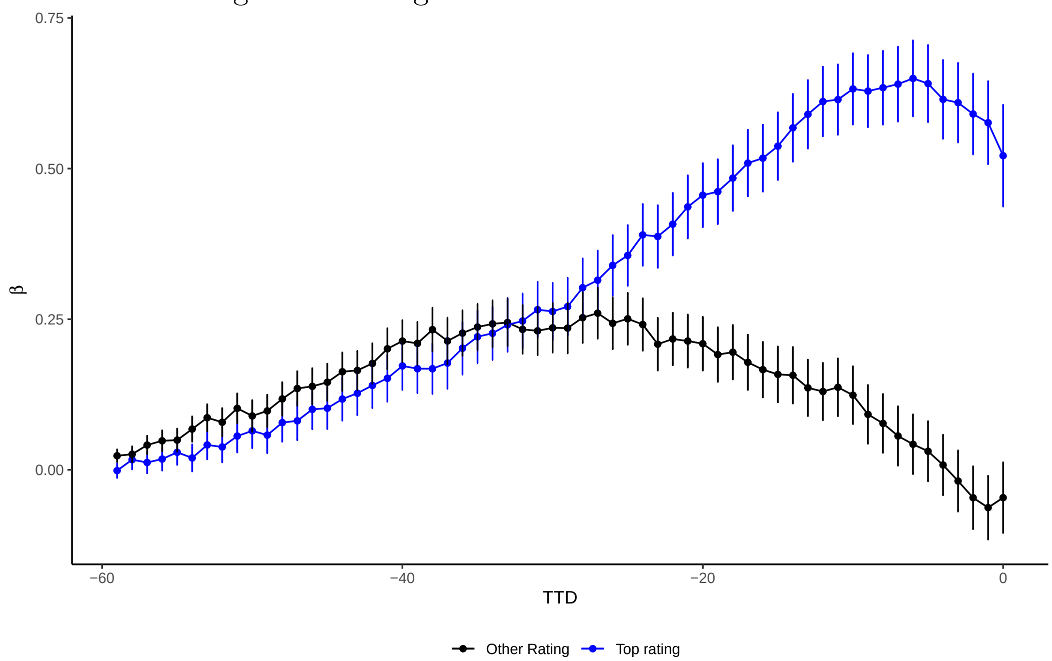
This figure shows the evolution of the concentration of firms' bank borrowing (Herfindahl Index) before firms' default. The graph plots the coefficient β_t of the regression $HHI_{j,t} = \sum_t \beta_t \mathbb{1}_{j,t}^{TTD} + \eta_j + \eta_t + \varepsilon_j$, where t indicates the time to default (TTD) expressed in months. t goes from -59 to 0, where 0 is the time of default.

Figure 4: Share of loans from relationship banks before default



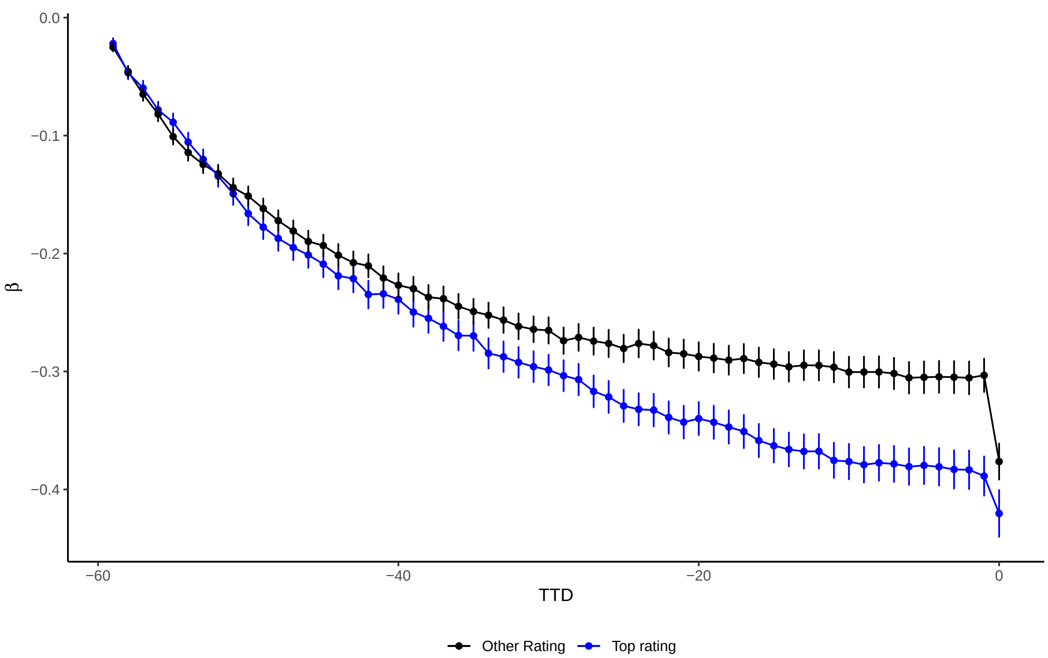
This figure shows the evolution of the share of loans granted by informed lenders. The graph plots the coefficient β_t of the regression $relshare_{j,t} = \sum_t \beta_t \mathbb{1}_{j,t}^{TTD} + \eta_j + \eta_t + \varepsilon_j$, where t indicates the time to default (TTD) expressed in months. t goes from -59 to 0, where 0 is the time of default.

Figure 5: The evolution of the number of banks before firm's default given firms' outstanding credit rating



This figure represents the evolution of the number of bank relationship that a firm has in the 5 years before default depending on the level of firms' credit rating available to all lenders in the credit market. We divide the sample of firms between those with a credit rating level above the sample mean (Top Rating) and those with ratings below the sample mean (Other Rating). As in Figure 2, the graph plots the coefficient β_t of the regression $nbbank_{j,t} = \sum_t \beta_t \mathbb{1}^{TTD}_{j,t} + \eta_j + \eta_t + \varepsilon_j$, where t indicates the time to default (TTD) expressed in months and it goes from -59 to 0, where 0 is the time of default.

Figure 6: Relationship bank share in pool before firm's default given firms' outstanding credit rating



This figure represents the evolution of the share of loans granted by the informed bank in the 5 years before default depending on the level of firms' credit rating available to all lenders in the credit market. We divide the sample of firms between those with a credit rating level above the sample mean (Top Rating) and those with ratings below the sample mean (Other Rating). As in Figure 4, , the graph plots the coefficient β_t of the regression $relshare_{j,t} = \sum_t \beta_t \mathbb{1}_{j,t}^{TTD} + \eta_j + \eta_t + \varepsilon_j$, where t indicates the time to default (TTD) expressed in months and it goes from -59 to 0, where 0 is the time of default.

8 Tables

Table 1: Summary statistics at firm level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
total_asset	245,927	5,348.514	68,796.640	11.000	721.000	1,299.000	2,829.500	4,240,556.000
EBITDA_margin	245,927	−0.011	0.123	−15.086	−0.029	0.008	0.028	2.327
tangprop	245,927	0.151	0.155	0.000	0.046	0.099	0.201	0.995
leverage	245,927	0.128	0.264	−0.734	−0.002	0.108	0.237	22.091
cashratio	245,927	0.055	0.076	0.000	0.004	0.026	0.075	0.734
rating	249,978	6.097	1.746	1	5	6	7	12
outloan_drawn	249,978	1,137.839	6,325.481	0	130	310	777	405,129
outloan_undrawn	249,978	197.652	1,882.328	0	0	19	122	162,785
rel_share	249,978	0.247	0.398	0.000	0.000	0.000	0.542	1.000
nbbank	249,978	3.468	2.484	1	2	3	4	29
HHI	242,015	0.573	0.284	0.062	0.340	0.509	0.865	1.000
multbank	249,978	0.809	0.393	0	1	1	1	1

The table presents firm level summary statistics for our sample of firms having experienced an event of default. The variables total assets, drawn and undrawn credit amounts are all displayed in thousand euros.

Table 2: Summary statistics at firm level 5 years before default

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
total_asset	3,769	5,278.349	70,985.280	114.000	700.000	1,222.000	2,662.000	4,174,790.000
EBITDA_margin	3,769	0.017	0.093	−2.179	0.001	0.021	0.045	2.327
tangprop	3,769	0.152	0.154	0.000	0.048	0.103	0.201	0.995
leverage	3,769	0.096	0.209	−0.595	−0.034	0.074	0.212	0.957
cashratio	3,769	0.071	0.089	0.000	0.007	0.039	0.100	0.598
rating	4,098	5.282	1.609	1	4	5	6	12
outloan_drawn	4,098	1,051.530	6,460.511	0	111.2	284	716.8	276,319
outloan_undrawn	4,098	217.468	2,352.922	0	0	17.5	117.8	128,531
rel_share	4,098	0.506	0.428	0.000	0.000	0.580	1.000	1.000
nbbank	4,098	3.199	2.335	1	2	3	4	21
HHI	3,941	0.608	0.288	0.067	0.357	0.535	1.000	1.000
multbank	4,098	0.773	0.419	0	1	1	1	1

The table presents firm level summary statistics for our sample of firms having experienced an event of default 5 years before default occurs. The variables total assets, drawn and undrawn credit amounts are all displayed in thousand euros.

Table 3: Summary statistics at firm level 1 year before default

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
total_asset	4,097	5,376.922	69,094.240	11.000	720.000	1,308.000	2,889.000	4,240,556.000
EBITDA_margin	4,097	−0.028	0.126	−2.943	−0.049	−0.003	0.018	1.000
tangprop	4,097	0.148	0.156	0.000	0.043	0.095	0.196	0.991
leverage	4,097	0.151	0.390	−0.483	0.020	0.128	0.247	22.091
cashratio	4,097	0.043	0.064	0.000	0.003	0.018	0.057	0.621
rating	4,098	6.600	1.528	1	6	6	7	12
outloan_drawn	4,098	1,161.000	5,405.392	0	146	329.5	805.8	213,985
outloan_undrawn	4,098	188.123	1,200.668	0	0	18	124	41,492
rel_share	4,098	0.164	0.351	0	0	0	0	1
nbbank	4,098	3.626	2.552	1	2	3	5	22
HHI	4,014	0.558	0.281	0.086	0.333	0.502	0.793	1.000
multbank	4,098	0.825	0.380	0	1	1	1	1

The table presents firm level summary statistics for our sample of firms having experienced an event of default 1 year before default occurs. The variables total assets, drawn and undrawn credit amounts are all displayed in thousand euros.

Table 4: Number of banks (continuous TTD)

	Dependent variable:			
	nbbank			
	(1)	(2)	(3)	(4)
TTD	0.007***	0.007***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
leverage		0.594**		1.438***
		(0.277)		(0.135)
rating		−0.030**		−0.010*
		(0.015)		(0.006)
log(total_asset)		1.134***		0.930***
		(0.043)		(0.047)
tangprop		−0.147		0.333
		(0.228)		(0.212)
cashratio		−2.153***		0.517**
		(0.463)		(0.208)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	245,927	245,927	245,927	245,927
R^2	0.003	0.273	0.860	0.869
Adjusted R^2	0.003	0.273	0.858	0.867
Residual Std. Error	2.478 (df = 245925)	2.116 (df = 245920)	0.935 (df = 241819)	0.906 (df = 241814)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table presents the OLS regression coefficients, where the dependent variable is the number of banks and the explanatory variable is the number of months before default, i.e. *TTD*. The variable *TTD* takes value between −60, that indicates 60 months before default and 0 that is the time of default. While we lack the granularity observed in Table 11, this presentation has the advantage of capturing the main effect of the regression in a simplified way. Columns 3 and 4 show results including both year and firm fixed effects.

Table 5: HHI (continuous TTD)

	Dependent variable:			
	HHI			
	(1)	(2)	(3)	(4)
TTD	-0.001^{***}	-0.001^{***}	-0.0004^{***}	-0.0003^{**}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
leverage		-0.049		-0.210^{***}
		(0.032)		(0.020)
rating		0.006^{***}		0.001
		(0.002)		(0.001)
log(total_asset)		-0.079^{***}		-0.091^{***}
		(0.004)		(0.006)
tangprop		-0.014		-0.056^{*}
		(0.027)		(0.029)
cashratio		0.444^{***}		-0.038
		(0.056)		(0.033)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	238,131	238,131	238,131	238,131
R^2	0.003	0.122	0.728	0.737
Adjusted R^2	0.003	0.122	0.723	0.732
Residual Std. Error	0.284 (df = 238129)	0.266 (df = 238124)	0.149 (df = 234029)	0.147 (df = 234024)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table presents the OLS regression coefficients, where the dependent variable is the concentration of firms' bank borrowing (Herfindahl Index) and the explanatory variable is the number of months before default, i.e. *TTD*. The variable *TTD* takes value between −60, which indicates 60 months before default, and 0 that is the time of default. While we lack the granularity observed in Table 11, this presentation has the advantage of capturing the main effect of the regression in a simplified way. Columns 3 and 4 show results including both year and firm fixed effects.

Table 6: Share of relationship banks (continuous TTD)

	Dependent variable:			
	relshare			
	(1)	(2)	(3)	(4)
TTD	-0.005^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
leverage		0.032^{**}		-0.033
		(0.014)		(0.022)
rating		0.010^{***}		0.002^{*}
		(0.002)		(0.001)
log(total_asset)		-0.019^{***}		-0.020^{**}
		(0.004)		(0.008)
tangprop		0.088^{***}		-0.023
		(0.033)		(0.039)
cashratio		0.076		-0.053
		(0.060)		(0.044)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	245,927	245,927	245,927	245,927
R^2	0.050	0.057	0.657	0.657
Adjusted R^2	0.050	0.057	0.651	0.651
Residual Std. Error	0.387 (df = 245925)	0.386 (df = 245920)	0.235 (df = 241819)	0.235 (df = 241814)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table presents the OLS regression coefficients, where the dependent variable is the share of total bank loans owned by relationship banks as part of the total amount of bank loans at firm level and the explanatory variable is the number of months before default, i.e. *TTD*. The variable *TTD* takes value between −60, which indicates 60 months before default, and 0 that is the time of default. Columns 3 and 4 show results including both year and firm fixed effects.

Table 7: Bank pools and firms' credit rating as firms approach default

	Dependent variable:			
	nbbank		relshare	
	(1)	(2)	(3)	(4)
TTD	0.0004	−0.002	−0.005***	−0.005***
	(0.001)	(0.002)	(0.0002)	(0.0004)
highrating	0.745***	0.340***	−0.061***	−0.040***
	(0.084)	(0.070)	(0.011)	(0.011)
leverage		0.995**		0.020
		(0.459)		(0.018)
rating		−0.017		0.009***
		(0.014)		(0.002)
log(total_asset)		1.192***		−0.018***
		(0.042)		(0.004)
tangprop		−0.450*		0.088**
		(0.247)		(0.037)
cashratio		−1.592**		0.085
		(0.649)		(0.062)
TTD×highrating	0.015***	0.012***	−0.001***	−0.001***
	(0.001)	(0.001)	(0.0003)	(0.0003)
Controls	No	Yes	No	Yes
Fixed Effects	No	Yes	No	Yes
Observations	245,927	245,927	245,927	245,927
R^2	0.009	0.362	0.052	0.073
Adjusted R^2	0.009	0.362	0.052	0.073
Residual Std. Error	2.470 (df = 245923)	1.982 (df = 245842)	0.387 (df = 245923)	0.383 (df = 245842)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table presents the OLS regression coefficients of a model where the dependent variable is the number of banks (columns (1) and (2)) and the relationship share of loans (columns (3) and (4)) and the main explanatory variable is the interaction term between the number of months before default, , i.e. *TTD*, and the variable *highrating*. *highrating* is a dummy variable that takes value 1 if the average level of firms' rating between 5 and 1 year before default is above the sample mean and 0 otherwise. For presentation purposes, we only included one month per year but Figure 5 and Figure 6 display graphically the coefficients of the regression month by month. Columns 2 and 4 include all the control variables and year fixed effect.

Table 8: Bank pools and firms' asset tangibility as firms approach default

	Dependent variable:			
	nbbank		relshare	
	(1)	(2)	(3)	(4)
TTD	0.006***	0.004***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.0002)	(0.0002)
tangibles	0.241***	0.216***	−0.021*	−0.024**
	(0.069)	(0.046)	(0.011)	(0.010)
leverage	0.534**	1.434***	0.040***	−0.041*
	(0.237)	(0.133)	(0.014)	(0.022)
rating	−0.029*	−0.010*	0.010***	0.003*
	(0.015)	(0.006)	(0.002)	(0.001)
log(total_asset)	1.128***	0.943***	−0.017***	−0.020**
	(0.044)	(0.047)	(0.004)	(0.008)
cashratio	−2.176***	0.521**	0.080	−0.058
	(0.425)	(0.208)	(0.060)	(0.045)
TTD×tangibles	0.001	0.003**	−0.001***	−0.001***
	(0.001)	(0.001)	(0.0003)	(0.0002)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	No	Yes	No	Yes
Observations	245,927	245,927	245,927	245,927
R^2	0.274	0.869	0.057	0.658
Adjusted R^2	0.274	0.867	0.057	0.652
Residual Std. Error	2.114 (df = 245919)	0.905 (df = 241813)	0.386 (df = 245919)	0.234 (df = 241813)

Note: *p<0.1; **p<0.05; ***p<0.01

This table presents the OLS regression coefficients of a model where the dependent variables is the number of banks (columns (1) and (2)) and the share of relationship banks (columns (3) and (4)) and the main explanatory variable is the interaction term between the number of months before default, , i.e. *TTD*, and the firms' share of tangible assets, i.e. variable *tangibles*, taking the value 1 if the firm's ratio of fixed assets to total assets is above the sample's median and 0 else. The variable *TTD* takes value between −60, which indicates 60 months before default, and 0 that is the time of default. Columns 2 and 4 show results including all control variables and both year and firm fixed effects.

Table 9: Share of main banks (continuous TTD)

	Dependent variable:			
	mainshare			
	(1)	(2)	(3)	(4)
TTD	−0.005***	−0.005***	−0.005***	−0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
leverage		0.089**		−0.104***
		(0.044)		(0.021)
rating		0.011***		−0.002
		(0.002)		(0.001)
log(total_asset)		−0.062***		−0.052***
		(0.004)		(0.008)
tangprop		0.085***		−0.106***
		(0.031)		(0.036)
cashratio		0.262***		−0.046
		(0.077)		(0.044)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	238,131	238,131	238,131	238,131
R^2	0.060	0.111	0.721	0.723
Adjusted R^2	0.060	0.111	0.716	0.718
Residual Std. Error	0.344 (df = 238129)	0.335 (df = 238124)	0.189 (df = 234029)	0.189 (df = 234024)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table presents the OLS regression coefficients, where the dependent variable is the share of total bank loans owned by the bank with the highest share of loans 5 years before default as part of the total amount of bank loans at firm level and the explanatory variable is the number of months before default, i.e. *TTD*. The variable *TTD* takes value between −60, which indicates 60 months before default, and 0 that is the time of default. Columns (3) and (4) show results including both year and firm fixed effects.

Table 10: Propensity score matching estimations

	2013		2014		2015		2016	
	nbbank	main_share	nbbank	main_share	nbbank	main_share	nbbank	main_share
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
TTD	−0.013**	−0.004***	−0.006	−0.005***	0.017***	−0.006***	−0.001	−0.004***
	(0.006)	(0.001)	(0.006)	(0.001)	(0.005)	(0.001)	(0.007)	(0.001)
default	0.552***	−0.100***	0.630***	−0.119***	0.511***	−0.068***	0.393***	−0.068***
	(0.123)	(0.022)	(0.114)	(0.021)	(0.111)	(0.020)	(0.139)	(0.022)
TTD:default	0.010***	−0.002***	0.009***	−0.002***	0.006***	−0.001***	0.004**	−0.001***
	(0.002)	(0.0004)	(0.002)	(0.0004)	(0.002)	(0.0003)	(0.002)	(0.0004)
Observations	93,461	91,528	106,672	104,439	112,255	110,670	89,850	88,038
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.387	0.183	0.390	0.192	0.349	0.175	0.397	0.199
Adjusted R^2	0.386	0.183	0.389	0.191	0.348	0.174	0.397	0.198

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports the evolution of the number of banks (models (1)) and the share of firms' loans held by the relationship bank (model (2)) in the five years preceding firms' distress, estimated using a propensity score matching methodology. We implement the analysis per year and we compare firms that experience a default (treated firms) with similar firms that did not (control firms). We compute the propensity score based on firms' credit rating, leverage, total assets, industry, share of tangible assets, number of banks and share of the main bank 60 months before the firms' default. The table displays the coefficient of the variable TTD –time to default –, the dummy default that indicates whether the firm experienced a default and their interaction. All models include control variables.

9 Appendix

9.1 Proof of Proposition 1

We will first shown that the inside bank is indifferent between bids on its support and earns lower profits outside the support.

i) Inconclusive signal: If the inside bank has received an inconclusive signal, it is supposed to bid with the distribution function H_i defined in equation (5) on the support $\left(\hat{b}, X\right]$. The profits can be calculated by plugging the competitors bid distribution H_o,into equation 3:

$$\begin{aligned}
\pi_i^0(b) &= +(\lambda b - 1)\left[1 - \left[1 - \frac{(1-\lambda)\, q_i}{(b\lambda - 1)}\right]\right] && (9)\\
&= (\lambda b - 1)\left[\frac{(1-\lambda)\, q_i}{(b\lambda - 1)}\right] && (10)\\
&= (1-\lambda)\, q_i. && (11)
\end{aligned}$$

As required, this does not depend any more on b.

The above calculation holds for all b. This means that if the outside bank would bid for $b < \hat{b}$ with the same distribution as on $\left(\hat{b}, X\right]$ the inside bank would continue to be indifferent on $\left(1/\lambda, \hat{b}\right]$. However for $b \in \left(1/\lambda, \hat{b}\right]$ the actual bid distribution H_o is higher than the functional form of H_o on $\left(\hat{b}, X\right]$. Therefore the probability that the outsider is winning is higher on $\left(1/\lambda, \hat{b}\right]$, hence the inside bank's profit is lower than on $\left(\hat{b}, X\right]$. It is easy to see that bids $b < 1/\lambda$ are still less profitable, and clearly bids $b > X$, will not be profitable. Hence the inside bank will be able to randomly choose bids on $\left(\hat{b}, X\right]$.

ii) Good signal: On $\left(1/\lambda, \hat{b}\right]$, the profit of on inside bank competing with an outsider is

$$\pi_i^g(b) = (b-1)\left[\left[1 - \frac{b}{(b-1)} + \frac{1}{(b-1)\lambda}\right]\right] \tag{12}$$

$$= \frac{1-\lambda}{\lambda}. \tag{13}$$

For bids in $\left(\hat{b}, X\right]$, the same argument as above can be applied. The prolongation of the functional form of H_o on $\left(1/\lambda, \hat{b}\right]$ into $\left(\hat{b}, X\right]$ is smaller than the actual bidding density H_o of the outsider on $\left(\hat{b}, X\right]$. The insider would be indifferent for the functional form from $(b_1, b_2]$, hence it makes lower profits with the actual definition of H_o on $(b_2, X]$.

Similarly in can be shown that that the outside bank earns a profit of zero on all bids within its bidding support $(1/\lambda, X]$.

9.2 Tables (discrete TTD)

Table 11: Number of banks (discrete TTD)

	Dependent variable:			
	nbbank			
	(1)	(2)	(3)	(4)
TTD_{-59}	0.021***	0.015*	0.017**	0.012
	(0.008)	(0.008)	(0.008)	(0.008)
TTD_{-49}	0.157***	0.096***	0.111***	0.074***
	(0.019)	(0.018)	(0.020)	(0.020)
TTD_{-37}	0.338***	0.238***	0.241***	0.186***
	(0.025)	(0.025)	(0.029)	(0.029)
TTD_{-25}	0.462***	0.347***	0.344***	0.285***
	(0.028)	(0.029)	(0.034)	(0.033)
TTD_{-13}	0.512***	0.398***	0.390***	0.330***
	(0.031)	(0.035)	(0.037)	(0.036)
TTD_{-1}	0.351***	0.329***	0.245***	0.232***
	(0.033)	(0.046)	(0.040)	(0.042)
leverage		0.592**		1.440***
		(0.276)		(0.137)
rating		−0.027*		−0.002
		(0.016)		(0.006)
log(total_asset)		1.134***		0.916***
		(0.043)		(0.047)
tangprop		−0.146		0.338
		(0.228)		(0.212)
cashratio		−2.142***		0.539***
		(0.461)		(0.209)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	245,927	245,927	245,927	245,927
R^2	0.004	0.273	0.861	0.869
Adjusted R^2	0.004	0.273	0.859	0.867
Residual Std. Error	2.477 (df = 245866)	2.116 (df = 245861)	0.933 (df = 241760)	0.905 (df = 241755)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table shows the evolution of the number of banks before firms' default. We present the estimates of a regression where the dependent variable is the firms' number of lenders and the explanatory variables are time dummy variables that capture the months (t) before default. Precisely, t goes from −59 to 0 and. For brevity, we include in the tables the results of the coefficient of only one time dummy (one month) per year but Figure 2 displays graphically the coefficients of the all the time dummy variables month by month. In column 1 we show results without control variables and fixed effects. We progressively include from column 2 to 4 control variables, year fixed effect and firm fixed fixed. Column 4 thus represents model 7 and include all control variables.

Table 12: HHI (discrete TTD)

	Dependent variable:			
	HHI			
	(1)	(2)	(3)	(4)
TTD_{-59}	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.002)
TTD_{-49}	-0.024^{***}	-0.018^{***}	-0.013^{***}	-0.009^{**}
	(0.003)	(0.003)	(0.004)	(0.004)
TTD_{-37}	-0.046^{***}	-0.039^{***}	-0.028^{***}	-0.022^{***}
	(0.004)	(0.004)	(0.005)	(0.005)
TTD_{-25}	-0.057^{***}	-0.047^{***}	-0.035^{***}	-0.027^{***}
	(0.004)	(0.005)	(0.005)	(0.005)
TTD_{-13}	-0.058^{***}	-0.048^{***}	-0.035^{***}	-0.025^{***}
	(0.005)	(0.005)	(0.006)	(0.006)
TTD_{-1}	-0.037^{***}	-0.036^{***}	-0.010	-0.002
	(0.005)	(0.006)	(0.007)	(0.007)
leverage		-0.049		-0.211^{***}
		(0.032)		(0.020)
rating		0.006^{***}		-0.001
		(0.002)		(0.001)
log(total_asset)		-0.079^{***}		-0.088^{***}
		(0.004)		(0.006)
tangprop		-0.014		-0.057^{**}
		(0.027)		(0.029)
cashratio		0.443^{***}		-0.042
		(0.056)		(0.033)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	238,131	238,131	238,131	238,131
R^2	0.004	0.123	0.729	0.737
Adjusted R^2	0.003	0.123	0.724	0.733
Residual Std. Error	0.283 (df = 238070)	0.266 (df = 238065)	0.149 (df = 233970)	0.147 (df = 233965)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table shows the evolution of the the concentration of firms' borrowing before default. We present the estimates of a regression where the dependent variable is the Herfindahl Index computed as the sum of squared shared of the loans borrowed by the firm from each lender, and the explanatory variables are time dummy variables that capture the month (t) before default. Precisely, t goes from -59 to 0, where 0 is time of default. For brevity, we include in the table the results of the coefficient of only one time dummy (one month) per year. However, Figure 3 displays graphically the coefficients of the time dummy variables month by month. In column 1 we show results without control variables and fixed effects. We progressively include from column 2 to 4 control variables, year fixed effect and firm fixed fixed.

Table 13: Propensity score matching: Summary statistics

		Before Matching		After Matching	
	Defaulted firms	Control firms	Δ	Control firms	Δ
	2013		p−value		p−value
Rating	5.16	4.45	0.00***	5.15	0.91
Leverage	0.10	0.11	0.18	0.10	0.91
TotalAssets	3491	28028	0.00***	3781	0.51
Tangprop	0.15	0.23	0.00***	0.14	0.65
Nbbanks	3.09	2.59	0.00***	3.06	0.78
Mainshare	0.70	0.76	0.00***	0.70	0.83
	Defaulted firms	Control firms	Δ	Control firms	Δ
	2014		p−value		p−value
Rating	5.31	4.38	0.00***	5.29	0.72
Leverage	0.10	0.11	0.14	0.10	0.95
TotalAssets	9260	30804	0.00***	8863	0.94
Tangprop	0.15	0.23	0.00***	0.15	0.55
Nbbanks	3.08	2.69	0.00***	3.00	0.90
Mainshare	0.71	0.76	0.00***	0.71	0.82
	Defaulted firms	Control firms	Δ	Control firms	Δ
	2015		p−value		p−value
Rating	5.31	4.41	0.00***	5.29	0.75
Leverage	0.10	0.08	0.06*	0.10	0.85
TotalAssets	4104	31541	0.00***	4610	0.38
Tangprop	0.15	0.22	0.00***	0.15	0.59
Nbbanks	3.16	2.74	0.00***	3.19	0.76
Mainshare	0.68	0.75	0.00***	0.68	0.85
	Defaulted firms	Control firms	Δ	Control firms	Δ
	2016		p−value		p−value
Rating	5.52	4.47	0.00***	5.49	0.50
Leverage	0.12	0.08	0.00***	0.12	0.89
TotalAssets	4593	31705	0.00***	4598	0.99
Tangprop	0.17	0.22	0.00***	0.16	0.67
Nbbanks	3.35	2.75	0.00***	3.38	0.75
Mainshare	0.69	0.75	0.00***	0.68	0.65

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports summary statistics for defaulted firms and non-defaulted firms per year. Δ p−value indicates the p−value for a t-test that checks whether the average for the non-defaultes firms is equal to the average value for the defaulted firms, before matching (column 3) and after matching (column 5).