Better borrowers, fewer banks?♣

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Abstract

We investigate the relationship between borrower quality and the structure of the pool of banks. First, we develop a theoretical model where the size of the banking pool is a credible signal of firm quality. We argue that better borrowers seek to disclose their quality in a credible way through the structure of the banking pool involving fewer banks. Second, we test our prediction using a sample of more than 3,000 loans from 19 European countries. We perform regressions of the number of bank lenders on various proxies of borrower quality. Our empirical tests corroborate the theoretical predictions. The size of the banking pool is a signal of borrower quality. Hence, good quality firms have fewer lenders in their banking pools.

Key words: bank lending, borrower quality, multiple banking, number of lenders, signaling, Europe.

JEL Classification: D82, G21, G32.

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1. Introduction

A typical European firm has more than five bank relationships (Ongena and Smith 2000, Hernandez-Canovas and Koëter-Kant, 2009) and multiple bank relationships are a common and significant economic phenomenon in all developed countries. Nevertheless, an important question still remains: why borrowing firms have multiple bank relationships?

In this article, we propose a novel explanation of multiple banking based on signaling. In a first step, we develop a theoretical model where we shot that the size of the banking pool is a signal of borrower quality. In a second step, we empirically test this result on a sample of more than 3,000 bank loans to European firms. Hence, we contribute to the literature on multiple banking by offering an alternative theoretical explanation for the existence of multiple lenders, along with an empirical test on a cross-country basis.

Numerous and various arguments for the existence of multiple banking can be found in both theoretical and empirical literature. From the borrower perspective[2], the usual explanation is the mitigation of the hold-up problem of long-term relationship lending and thus the diversification of financing sources (Rajan 1992). Furthermore, multiple banking is also relevant for firms to diversify their financial stakeholders and to limit bank liquidity risk (Detragiache et al. 2000). Indeed, the recent subprime crisis has put into light the necessity for all types of borrowing firms – SMEs and large firms – to diversify bank financing sources in order to limit consequences of sudden and exogenous credit shocks. However, theoretical foundations for the existence of multiple bank relationships are still weak. Furthermore, empirical evidence remains limited to single country studies. Moreover, to our knowledge, there is no combined theoretical and empirical evidence on the relationship between the number of banks and borrower risk or borrower quality.

Foglia et al. (1998) empirically investigate the relationship between the number of lenders and borrower quality using Italian data. They find that better quality firms are more prone to work with a small number of banks. The authors explain this result stating that diversified bank relationships implies less monitoring of the firm which, in consequence, becomes more fragile. However, such behavior should be anticipated by banks who would charge higher interest rates to firms with multiple lenders. Foglia et al. (1998) do not find any significant effect of the number of bank lenders on the interest rate. Furthermore, in a recent article Bonfim et al. (2009) show that firms can reduce their marginal cost of

[2] Banks can also benefit from multiple banking to tackle limited lending capacities (Carletti et al. 2007) and to diversify loans portfolio risk, especially in the case of small and opaque borrowers.

bank debt by increasing the size of their current pool of lenders. This result follows previous observations made by Petersen and Rajan (1995). Thus, the explanations provided by Foglia et al. (1998) appear to be incomplete.

The contribution of this article is in touch with intuitions developed by Foglia et al. but provides significant new findings. First, we provide a theoretical framework by developing a signaling model where the size of the banking pool is a credible signal of firm quality. In that framework, better firms seek to disclose their quality in a credible way through the structure of the bank lending pool. Our starting point is to consider a framework with information asymmetry between firm manager and investors. Following real option theory, firm value increases with business risk, especially if the firm faces severe default risk. As a result, we develop a signaling equilibrium where better quality firms will voluntary limit asset substitution (moral hazard) through an adapted structure of the banking pool which implies stronger monitoring, with a lower number of lenders. The cost of this decision is larger if the firm is risky and wants to choose a high level of business risk in order to gain in value. A signaling equilibrium emerges in which good firms borrow from a low number of lenders.

Second, we test our theoretical predictions using a cross-country analysis on a sample of more than 3,000 loans granted to firms from 19 countries between 1999 and 2006. We perform regressions of the number of bank lenders on borrower quality. In a first step, the latter is measured using Altman (2000) Z score. We perform various estimations using Z score computed on the same year as the loan, on the first semester of each year only, and on the next fiscal year with respect to the time of the loan. We also investigate the influence of the organization of the banking pool, the borrower size, and the size of the loan on the relationship between firm's quality and the size of the lending pool. In a second step, as a robustness check we employ a European version of the Altman Z score with same variables but with coefficients recomputed on a large sample of more than 365,000 European firms. The empirical analysis confirms the theoretical predictions. Our main finding is that the number of lenders is significantly reduced when the borrower quality increases. Hence, the size of the banking pool is effectively a signal of borrower quality.

The rest of the article is organized as follows. A survey of the existing theoretical and empirical literature is provided in section 2. The theoretical model is presented in section 3. Section 4 provides empirical evidence. Section 5 contains our main conclusions.

2. Literature on the optimal number of banks

The optimal number of bank relationships has been first analyzed with respect to the benefits and costs of a single bank relationship. As a sole lender usually provides efficient monitoring of a borrower, multiple bank relationships would only lead to duplication of transaction costs and moral hazard problem related to free riding of lenders in their monitoring duties (Diamond 1984). Furthermore, a multibank firm bears the risk of disseminating its strategic information to competitors. A concentrated pool of banks can protect the firm against such adverse consequences of multiple bank relationships as the success of any investment plan is strongly related to keeping strategic information private (Yosha 1995). Indeed, Bhattacharya and Chiesa (1995) and von Rheinbaben and Ruckes (2004) show that the choice between multiple and single bank relationships is driven by an arbitrage between the benefit of information sharing and the cost of free riding on one hand, and the benefit of interbank competition and the cost of private information dissemination on the other hand. Finally, an exclusive single bank relationship allows for greater flexibility in loan rate setting thus allowing firms to overcome potentially adverse economic conditions (Dewatripont and Maskin 1995).

Single bank relationship seems to provide numerous benefits for the borrower, but it may also generate bank's opportunistic behavior. Indeed, a sole lender acquires through time private valuable information on the firm, leading to an informational advantage that gives the bank important negotiation power permitting to extract private benefits. The latter can become larger than the borrower benefits from an exclusive bank relationship thus pushing the firm to increase the number of lenders (Sharpe 1990; Rajan 1992). This "hold-up" hypothesis is empirically validated by Petersen and Rajan (1995) for the US and by Farinha and Santos (2002) for the Portugal, while von Thadden (1992) shows that a pool of two banks allows to restore sufficient interbank competition and to limit their monopoly power. However, numerous other authors find much more mitigated results regarding this issue (Elsas and Krahnen 1998; Foglia et al. 1998; Harhoff and Korting 1998; Bonfim et al. 2009).

The choice of multiple bank relationships can also be related to bank liquidity risk. The greater the likelihood of bank liquidity shortage, the greater the incentives of the borrower to diversify the sources of loan funding, and thus a larger pool of lenders (Detragiache et al. 2000). This argument is empirically validated by Tirri (2007) using a large sample of Italian firms. She finds that borrowers which are more likely to become rationed increase the number of bank relationships. However, banks can also decide to engage into multiple relationships in order to diversify firm's default risk (Farinha and Santos 2002; Carletti et al. 2007).

The information produced by a firm is an important characteristic driving the choice of a bank relationship. Soft information should be more valued by a bank with decentralized and less hierarchical organization (Stein 2002). Hence, the number of bank relationships should be related to the structure of the banking pool, which can be more or less homogenous depending on the relative power of some members of the pool among the others. The choice of that structure is driven by information asymmetry between the lenders and the borrower (Bannier 2007), the quality of the firm's project (Elsas et al. 2004) and by the specificity and heterogeneity of firm's assets (Guiso and Minetti 2004). Indeed, Elsas (2005) shows that the banking pool structure is more important than just its size, and that more "relational" pools are composed of fewer banks.

However, banking pools imply specific problems, such as coordination because monitoring by multiple lenders can be weak, and because early project liquidation risk increases with the number of lenders (Bolton and Scharfstein 1996). Hence, managers of firms with profitable projects and capable of extracting private benefits will have more incentives to apply for funding from a larger number of banks (Carletti 2004). This problem remains even in the presence of heterogeneous banking pools. The presence of a bank strongly involved in borrower monitoring can discipline the other lenders of the pool (Elsas et al. 2004) but such bank can extract private benefits from its private information which can lead other banks of the pool to trigger early liquidation of the project (Guiso and Minetti 2004). Brunner and Krahnen (2008) show that a smaller pool implies better monitoring of the banks, and that more structured pools are negatively related to the presence of important lead banks. The coordination and moral hazard problems within the banking pool can be mitigated through the set up of a bank syndicate, which is a hybrid form of bank lending, mixing relationship and transaction lending (Dennis and Mullineaux 2000). Indeed, Lee and Mullineaux (2004), Jones et al. (2005), and Sufi (2007) find a negative relationship between the size of the syndicate and borrower quality. Furthermore, they show that syndicates are more concentrated when information asymmetry is important.

Banking sector concentration has also an influence on the number of bank lenders. In a less concentrated sector, bank competition can reduce the value of transaction lending, while relationship lending should be more valuable for borrowers (Boot and Thakor 2000). Empirical evidence tends to support this hypothesis (Bonfim et al. 2009). Also, as a strong legal environment limits the benefit of strategic default, duplicating bank relationships is less useful (Bolton and Scharfstein 1996). This result is empirically validated by Ongena and Smith (2000) on a cross-country basis.

Following this literature survey describing relevant theoretical and empirical literature dealing with the optimal number of banks, we set up our theoretical model in the next section.

3. The information content of the number of banks

We model the decision related to the size of the banking pool as a signal of firm's quality. We first describe agents and their decisions. We then specify the information context of the economy and preferences of the agents. Finally, after briefly solving the problem in the perfect information case, we derive the equilibrium decision under imperfect information.

3.1 Agents and decisions

The economy is composed of three types of agents, all risk neutral: managers of firms, banks and investors.

- **Managers**

Managers undertake risky investment projects financed with bank debt. Project size is normalized to 1 and generates a cash flow of *k* with probability *x*, and 0 otherwise. Each firm's risk is represented by the project's probability of success *x*. In order to finance their investment projects, managers choose the number of banks composing the pool of lenders of the firm.

- **Banks**

We assume there are *N* identical banks in our economy and firms may apply for funding from *n* banks. Negotiation between firms and banks is costless[3]. Each bank of the pool is supposed to monitor borrowing firms according to the portion of debt it funds and to the total number of bank lenders in the pool. The bank monitoring function is modelled by $\mu(n)$ $(\mu^{'} < 0, \mu^{''} > 0)$, where *n*, modelled as a continuous variable, is the number of banks in the pool for a given firm. Hence, the capacity of the manager to divert for himself firm's assets is limited when the size of the banking pool is small and the coordination of lenders is strong.

- **Investors**

Investors value the firm on the financial market which is supposed to be efficient.

[3] Introducing a cost doesn't change the results.

3.2 Information and preferences

- **Information**

On the initial date (*t=0*), managers and banks know perfectly the probability of success *x*. As the firm is managing a single economic activity, we assimilate the firm and the probability of success of its activity. Firms are distributed within a range $[c, d]$ (with $0 \leq c < d \leq 1$) according to the cumulative density function F (with a corresponding probability density function f). Investors are unaware of firms' risk, but they can freely observe the number of lenders. Hence, they can infer some information about firm's quality from the size of the banking pool. They will use this information to evaluate the firm.

On an intermediate date (*t=1*), the manager of the firm receives a signal *s* which is perfectly informative as for the foreseeable exit of the investment project. A signal *s=S* means that the project will be maintained and succeed with certainty. A signal *s=D* means that the activity will fail, thus no investment cash-flow will be generated. According to his signal, the manager decides or not to disengage from the investment project undertaken one period before. In the case of disengagement (signal *s=D*), the capacity of the manager to divert assets depends closely on the control exerted by the banking pool. The portion of firm assets that the manager can divert in that case equals $\left(1-\mu(n)\right) < 1$. The smaller the size of the banking pool, the more intense is the monitoring which induces lower capacity of the manager to divert assets. This re-employment of funds released by the investment withdrawal can take all the forms studied by Jensen and Meckling in their seminal paper (Jensen and Meckling 1976): extra-salaries, discretionary consumption, gratifications, and more generally abuse overheads of the manager. On the contrary, we suppose that in case of a positive signal (*s=S*), the manager continues the investment project undertaken.

On a final date (*t=2*), investment project's cash-flow is realized if the project was maintained on the intermediary date and the firm can reimburse the banks. In the case of disinvestment in *t=1*, the manager uses the diverted assets for himself.

- **Preferences**

Manager's utility function depends on two elements. The first is related to the firm's market value *V(x)* while the second comes from what the manager can extract from the firm in the case of investment withdrawal in *t=1*. Thus, the utility function of a manager funding his investment project from *n* banks is:

$$U\big(n(x)\big) = aV(x) + b(1-x)\big(1-\mu(n)\big) \qquad \textbf{(1)}$$

In equation (1), *a* captures the manager's preference towards market value maximisation while *b* is the weight which the manager grants to the profit that he can obtain from an investment withdrawal. This last case occurs with probability *(1-x).*Through this function, we model the intuition that the manager is sensitive to the market value of his firm. It also integrates the fact that the manager will divert assets in the case of an unfavourable signal in *t=1*. In the latter case, we note that the firm value is unaffected by the decision of the manager to divert assets or not, and that from the manager's perspective, the decision to divert assets in date 1 in case of signal *s=D* is optimal.

As banks are in perfect information, their budget constraint is:

$$xR(x) = r + \pi \qquad \textbf{(2)}$$

with the refinancing rate *r* and π a factor relative to the monopoly power of the bank. Because π is private information, the rate *R(x)* priced by banks in date 0 is uninformative for the investors who value the firm.

3.3 Equilibrium analysis

- **Perfect information case**

First, we suppose that the information on firm's quality is known by all economic agents. Hence, manager's utility function takes the following form:

$$U\big(n(x)\big) = ax(k - R(x)) + b(1-x)\big(1-\mu(n)\big)$$

Combining equations (1) and (2), we obtain:

$$U\big(n(x)\big) = a(kx - r - \pi) + b(1-x)\big(1-\mu(n)\big) \qquad \textbf{(3)}$$

The optimal number of banks *n** verifies the following condition:

$$\frac{\partial U(x)}{\partial n} = 0$$

$$\Leftrightarrow -\mu^{'}(n)b(1-x) = 0$$

$$\mu^{'}(n^*) = 0$$

Consequently, in the perfect information case, all firms choose *N* (the largest number of banks *n)*. This result is intuitive since the larger the number of banks, the more the manager can freely divert assets when he receives signal *s=D* in date 1.

- **Signaling equilibrium**

We consider now the case where investors do not know the quality of firms. However, they can observe the structure of the banking pool of firms in order to infer some information about their quality.

Let's take the case of a manager whose firm's probability of success is *y*. Let also suppose that this manager chooses to make his firm be considered by investors as a less risky firm, i.e. having a probability of success $x > y$. For this purpose, he chooses to replicate the structure of the banking pool of a good quality firm. Hence, his utility is given by:

$$U(x,y) = ax(k - R(y)) + b(1-y)\big(1 - \mu(n(x))\big)$$

The best level of risk to be signalled is the number of bank lenders *n(x)* which maximizes manager's expected utility. This leads to the following first order condition:

$$\frac{\partial U(x,y)}{\partial x} = 0$$

$$a\big(k - R(y)\big) - b(1-y)n'(x)\mu'\big(n(x)\big) = 0$$

$$n'(x)\left(b(1-y)\mu'\big(n(x)\big)\right) = a(k - R(y))$$

A signalling equilibrium is obtained when the former relation is satisfied at $x = y$, whatever the value of *y*, and for a level of risk *x* that can be left unspecified. We can deduce the signaling constraint

$$n'(x)\left(b(1-x)\mu'\big(n(x)\big)\right) = a(k - R(x)) \qquad \textbf{(4)}$$

Hence, we can infer the following proposition from equation (4):

Proposition 1: The number of banks in the pool is a credible signal of the quality of firms. Signalling equilibrium is such that the size of the banking pool is decreasing with the quality of the firm.

Proof: Since the NPV of the project is positive, the right-hand side of equation (4) is positive. Moreover, function $\mu()$ is decreasing, hence the sign of *n'(x)* must be negative.

The monitoring function $\mu()$ must be specified in order to obtain a precise solution for equation (4) regarding the optimal number of banks. Suppose that $\mu(n) = 1/n$. The optimal number of banks in the pool is (see appendix for a proof):

$$n(x) = \frac{\mathrm{a}}{\mathrm{b}}\left\{(r+\pi)\ln\left[\frac{(1-x)c}{x(1-c)}\right] - k\ln\left[\frac{1-x}{1-c}\right]\right\} + \mathrm{N} \qquad \textbf{(5)}$$

Equation (5) allows stating the following proposition:

Proposition 2: The optimal number of banks is:

1. A decreasing function of the manager's incentives to maximize firm value,

2. An increasing function of the manager's incentives to divert assets for himself.

This result is quite intuitive. A manager with a utility function close to the firm's shareholders utility function will have more incentives to signal the value of the firm that he is managing. Furthermore, if the manager puts less value on the assets diversion effect, he will be less willing to apply for funding from a concentrated pool of banks. Hence, the signaling role of the number of banks in the pool will be more important for firms which corporate governance allows for discretionary behavior of the manager.

4. Empirical evidence

The theoretical model shows that the number of banks is a credible signal of borrower quality, i.e. better quality firms are funded by smaller banking pools. We now bring empirical evidence to bear on that issue. We first describe data, methodology and variables. We then develop the empirical results.

4.1 Data, methodology and variables

The sample of bank loans is obtained from the Dealscan database which is supplied by the Loan Pricing Corporation (LPC), Reuters. This database is commonly used in empirical studies on bank loans (Bharath et al. 2007; Bharath et al. 2009) and contains a large number of syndicated loans. This database is well suited for empirical tests of our theoretical predictions as we investigate a banking pool in the model. A non syndicated loan is funded by a standard pool of bank lenders. A syndicated loan is funded by an organized, coordinated and hierarchical banking pool – the syndicate of banks. The theoretical model encompasses both cases as the banking pool can be considered as more or less coordinated and organized. Balance sheet data used to measure firm's quality comes from Amadeus (Bureau Van Dijk). Country-level data comes from Beck et al. (2000) and Djankov et al. (2007).

We proceed to regressions of the size of the banking pool, measured with the number of banks for a given loan (*Number of lenders*), on a set of variables including borrower's quality measure and a range of control variables. According to the theoretical model, we build an empirical proxy for the borrower quality which is not observable by investors when the loan is set up. This is challenging as signaling only makes sense if the information is private while, as most of external analysts, we only have access to external public information. To solve this problem, we adopt the following empirical strategy[4].

Our starting point is the use of the Altman (2000) Z score[5] for each firm. The Z score has been extensively used in the financial community (by financial intermediaries, among others) as an indicator of bankruptcy or business risk[6]. As such, it allows us to capture the firm quality as perceived by professionals. The Z score is defined as:

$$Z\ score = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$

with

X_1 = working capital/total assets,

X_2 = retained earnings/total assets,

X_3 = earnings before interest and taxes/total assets,

X_4 = book value equity/book value of total liabilities,

X_5 = sales/total assets.

The correlation coefficient between the company's rating (provided by Amadeus[7]) and the Altman Z score is significant (at the 1% confidence level) and positive, equal to 0.42. Furthermore, we also remark that the average score by rating grade is increasing with rating's quality (see table A.1 in appendix) meaning that firms with a better rating have also a larger Z score and thus a lower risk. These

[4] Our empirical strategy can be viewed as an extension of De Bodt et al. (2008).

[5] Amadeus provides company's equity market value for the last year only (2006 in our case), thus we cannot use the Altman (1968) Z score for public companies.

[6] For instance, Bloomberg provides Altman Z score for most of the companies in their database.

[7] The Multi Objective Rating Evaluation (MORE) model is essentially used to assess the level of distress of companies by using data included in financial statements. The rating grades are AAA, AA, A, BBB, BB, B, CCC, CC, C, and D. Companies rated AAA to BBB are considered as investment grade, while companies rated CC to D are considered as distressed.

elements make us confident regarding the relationship between the Altman Z score and the quality of the firms in our sample.

As financial statements are published several months after the end of the fiscal year, the Z score is, at the moment the loan is granted, still private information. Consequently, it can be considered as an ex post signal of the firm quality. Hence, our first measure of borrower quality is a Z score computed using accounting ratios of the same fiscal year as the year of the bank loan (variable *Z score (t)*). However, to tackle problems related to using a proxy for private knowledge using external public information, we also compute several additional proxies of firm quality. Our second measure is a Z score computed using loans made only in the first semester for each year (variable *Z score (t, S1)*). We also adopt a more forward-looking approach which alleviates any problem of using public information only as a proxy for private information. Our third measure of borrower quality is a Z score computed using accounting ratios of the t+1 fiscal year with respect to the year of the bank loan (variable *Z score (t+1)*)[8].

We use four control variables to take major loan characteristics into account, which have an impact on the size of the banking pool (Detragiache et al. 2000; Ongena and Smith 2000; Lee and Mullineaux 2004; Elsas 2005; Sufi 2007). These variables include the logarithm of loan facility amount in USD (*Loan size*) and the maturity of the bank loan in months (*Loan maturity*). We expect the former to have a positive influence on the size of the banking pool due to bank risk diversification and regulatory constraints purpose, while the latter can increase or decrease the number of lenders, depending on the riskiness of longer maturity loans. Loan type (*Term loan*), measured with a dummy equal to one if the loan is a term loan, is also taken into account. To control for the type of lending as well as the level of coordination and organization of the banking pool, we include a dummy variable (*Syndication*) equal to one if the loan is syndicated.

We also control for borrower cash flow through the *Ebit margin* variable, equal to the firm's EBIT to operating revenue ratio. Indeed, firms with larger cash flows should rely less on external debt financing thus influencing the size of the banking pool. We also take creditor rights protection and banking market concentration into account through the *Credit rights* index from Djankov et al. (2007) and the *Bank concentration* variable from Beck et al. (2000). These country characteristics are expected to have an impact on the number of lenders, as the quality and level of creditors protection influence

[8] This is, however, at the cost of obtaining a noisier estimator of the firm's quality at the end of fiscal year t, as it involves exogenous shocks between the end of fiscal year t and the end of fiscal year t+1.

their willingness to fund a loan (Ongena and Smith 2000; Hernández-Cánovas and Koëter-Kant 2009) and as the banking market structure has an impact on bank lending. Indeed, firm-level and country-level bank concentration are complementary, i.e. in countries where the banking sector is highly concentrated, we observe smaller pools of bank lenders (Ongena and Smith 2000). Finally, dummy variables for each industry (2 digits SIC codes) and each year are also included in the estimations to control for industry and time effects.

We use loan and borrower data for the period from January 1999 to June 2006. This time period provides the best coverage for bank loans in Dealscan. We carefully hand match Dealscan and Amadeus databases by borrower name and SIC code and we drop observations where the main variables of interest are missing (number of bank lenders and accounting ratios needed to compute the Z score). These criteria produce a sample of 616 borrowers from 19 European countries for a total of 3,303 bank loans over a period of 7.5 years. A list of countries is displayed in table 1 as well as descriptive statistics for main variables of interest in table 2.

We remark that most of the loans are granted to borrowers from France, Germany and Spain. On average, banking pools are smaller in Eastern Europe countries. The major industry sector is manufacturing (43% of sample) while year distribution is relatively homogenous, although the number of loans increases over time (259 loans in 1999 and 586 loans for the first two quarters of 2006).

We employ OLS regressions with standard errors clustered at the borrower level as the Z score is computed at the borrower level[9]. Using other estimation techniques such as Tobit, Zero Truncated Poisson and Zero Truncated Negative Binomial regressions gives similar results. However, OLS regressions provide the best information criteria values (Akayke and Schwarz criterions). Furthermore, this estimation technique is more suited with respect to the relatively large range of values for the explained variable (*Number of lenders* has a mean above 8 with a standard deviation of 8.5).

4.2 Main results: borrower quality and banking pool size

Table 3 contains main regression results where we test the central implication of our theoretical model: the relationship between borrower quality and the size of the banking pool. Models 1 to 3 correspond to different measures of borrower quality. In model 1 the Z score is computed on the same fiscal year as

[9] Results remain similar when clustering by loan rather than borrower.

the bank loan while we drop the last semester for each year in model 2. Model 3 employs the Z score computed on the year after the bank loan year[10].

We remark a good fit of the models with R^2 above 30% and significant Fisher statistics, above 5. We observe a significant and negative coefficient for borrower quality for most of the specifications[11]. Thus, our theoretical result regarding the relationship between borrower quality and the size of the banking pool is empirically validated. The number of lenders is significantly reduced when the borrower quality increases. Hence, the size of the banking pool is effectively a signal of borrower quality as the latter is negatively related to the number of lenders. The magnitude of this effect on the size of the banking pool increases in model 2 when the proxy for quality becomes even more private information, i.e. when the Z score is computed with a lead of one semester (model 2).

We also notice that among control variables, larger loan amounts and syndicated loans are associated with a larger number of lenders. These results are consistent with risk diversification motives and regulatory constraints. *Ebit margin* is significant and negative in model 2 only, while the creditors' rights protection index is significant and negative in model 3 only. Other control variables exhibit no statistically significant coefficients.

4.3 Additional results: the influence of syndication, firm, and loan size

In table 4 we investigate further the influence of lending type and the coordination of the banking pool on the relationship between the number of lenders and borrower quality[12]. Indeed, banks' syndicates can be considered as coordinated, hierarchical and organized banking pools. In such a setting, the presence of mandated arrangers, often reputable and well known banks retaining large shares of the loan[13], organize the banking pool and induce more efficient coordination among the other members of the syndicate (Lee and Mullineaux 2004; Sufi 2007; Panyagometh and Roberts 2008; Ivashina 2009). Thus, the size of the banking pool should be less informative regarding borrower quality in case of syndication.

[10] The sample size is reduced for models 2 to 3 due to sample restriction (first semester per year for model 2) and to information unavailability when using *Z score (t+1)* variable for model 3.

[11] However, the coefficient for the *Z score (t+1)* is not significant in model 3. This may be attributed to the use of a noisier estimator of firm's quality.

[12] On average, syndicated loans are funded by larger bank pools (10 lenders vs. 5) for better quality borrowers (*Z score (t)* equals to 1.94 vs. 1.87).

[13] A bank listed on a League Table is usually considered as a signal of reputation on the syndicated lending market (Rhodes 2004). In our sample, 13% of an average syndicate is composed of lenders listed on the Reuters League Table.

In order to identify the effect of lending type and lenders' coordination on the relationship between the number of lenders and the signal on borrower quality, we include an interaction term equal to the product of the measure of borrower quality (*Z score (t), Z score (t, S1),* and *Z score (t+1)* respectively) and the *Syndication* dummy. We expect a significant and positive coefficient for this interaction term.

The results confirm our predictions as every coefficient for the interaction term is positive and significant in models 1a to 3a, and exhibit important economic value as the coefficient is larger than 1 for the last two specifications. The largest value is obtained in model 2a where the interaction variable has a coefficient close to 1.5. Hence, the borrower quality signal is effectively weaker, but still significant, in presence of a specific lending organization such as bank loan syndication. In such framework, the size of the banking pool is less sensitive to the borrower quality. However, the negative relationship between firm quality and the number of lenders remains stronger, as the sum of the borrower quality and interaction variable coefficients is always negative.

The influence of banking pool organization, borrower and loan size on the relationship between firm quality and the number of banks is analyzed in table 5. We expect the information asymmetry problem (between the firm and investors) to be less important for large firms and large loans, for which there should be less need for signaling firm's quality. On the opposite, small firms funded with smaller loans should have more incentives to signal themselves. In other words, the structure of the banking pool should be less informative regarding borrower quality in case of large and less opaque firms funded by larger loans. Hence, we expect that the number of banks becomes a weaker signal of borrower quality for larger and better firms having larger loans. Regarding the influence of the banking pool influence, as previously stated, we also expect the organization of the banking pool in a syndicate to be less sensitive to borrower quality for large firms funded by large loans.

We use the medians of the borrower total assets and of the loan size to classify the firm and the loans as small or large. The results confirm our predictions. The coefficient for the firm quality remains negative but becomes less significant for large firms and loans in model 2b. Furthermore, the coefficient for the interaction term between syndication and firm quality is never significant for large firms and loans, while it is positive and significant for small firms and loans. For these types of firms and loans, we remark that the joint coefficient of the firm quality and the interaction term remains negative.

4.4 Robustness checks with European Z score

We now turn to the robustness checks of the main results obtained with the Z score. The latter is implemented using the same coefficients for the relevant financial ratios as in Altman (2000). Although financial data provider such as Bloomberg provides the same Altman Z score for every company listed in their database, not only for US firms, it is possible that the relevant coefficients of the Z score are different for European companies. To tackle this issue and provide a robustness check of our results, we compute a European version of the Altman (2000) Z score. We use the same financial ratios as Altman (2000) but we re-estimate the coefficients on a large dataset of European companies extracted from Amadeus. We provide a detailed description of the implemented procedure in the appendix.

We compute two score functions, each based on a different definition of default (one based on company's rating distress grade and one based on company's default probability, both measures provided by Amadeus) allowing computing two Z scores: *Z score Eur. D.R.* (based on rating) and *Z score Eur. D.P.* (based on default probability). Both are significantly and strongly correlated to the Altman Z score in our sample (coefficients close to 0.75). We then check the robustness of our main results (displayed in table 3) by performing the same regressions but using the two European Z scores, computed on the same year as the loan, on the first semester of the year of the loan and on the next year after the year of the loan. The results are provided in table 6. When compared to the results in table 3, we remark that they are virtually the same regarding the statistical quality of the regressions (R^2 between 0.38 and 0.46 and F statistic between 5 and 13), the level of significance and coefficient sign of the Z score, as well as control variables. Again, our conclusions are validated even when using a Z score function computed on a European dataset: the size of the banking pool is effectively a signal of borrower quality as the latter is negatively related to the number of lenders. Hence, our empirical results validate our theoretical model and survive this additional robustness check.

5. Conclusion

We have investigated how informative is the number of bank lenders regarding firm's quality. This is a timely question because theoretical foundations of multiple bank relationships remain weak although they are a common and significant economic reality in most of countries. Next to currently established and classical arguments related to mitigate hold-up problems or firm strategic default incentives, we propose alternative and original theoretical foundations for firm's multiple bank relationships.

We develop a signaling equilibrium model where better quality firms voluntary limit asset substitution through an adapted structure of the banking pool, with fewer lenders, which implies stronger monitoring. The main testable prediction of the model is that good firms borrow from a low number of banks.

In order to test this theoretical prediction, we perform an empirical European cross-country analysis based on the regression of the number of lenders on various proxies of borrower quality. We use a large sample of more than 3,000 loans to borrowers from 19 countries. Firm quality is measured using Altman (2000) Z score which is an indicator of firm's risk. We also use a European version of the Altman (2000) Z score where the coefficients have been re-estimated on a large European dataset. Furthermore, we also investigate the influence of the coordination and organization of the pool of lenders, as well as of the firm and loan size, on the relationship between the number of lenders and firm quality.

The empirical analysis confirms the theoretical predictions. The number of lenders is significantly reduced when the borrower quality increases. Hence, the size of the banking pool is effectively a signal of borrower quality as the latter is negatively related to the number of lenders. The size of the banking pool is less sensitive to the quality of the firm when the pool is more coordinated and organized as with a banks' syndicate. Furthermore, this sensitivity vanishes away for large firms and loans which need less to signal their quality. Finally, these results are robust to different measures of firm quality using various specifications for the Altman (2000) Z score as well as a European version of the Z score.

Hence, we offer new theoretical evidence validated by empirical tests on the informative role of the size of a firm's banking pool. The latter can be considered as a signal of borrower quality. These foundations support empirical findings by Foglia et al. (1998) on a sample of Italian firms, where better borrowers have fewer bank relationships. We also empirically test our theoretical model, but on a large and cross-country sample of borrowers from 19 European countries. Both theoretical and empirical results lead to same economic conclusions. The size of a firm's banking pool is informative regarding borrower quality: the better the firms, the smaller the number of banks.

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Table 1 Descriptive statistics by country

Means are displayed for the Number of lenders and Z score (t) variables.

Country	Number of loans	Percent of sample	Number of lenders	Z score (t)
France	1079	32.67	9.3438	1.9754
Germany	493	14.93	10.8227	2.2155
Greece	196	5.93	6.5073	1.5112
Hungary	13	0.39	9.1538	1.2768
Iceland	5	0.15	3.7142	1.2298
Italy	326	9.87	8.3737	1.6670
Latvia	7	0.21	3.3333	1.3278
Lithuania	16	0.48	4.4375	2.8818
Luxembourg	11	0.33	16.6666	1.7479
Netherlands	321	9.72	6.8975	2.2773
Poland	38	1.15	6.0000	1.9685
Portugal	34	1.03	13.0000	0.7743
Romania	36	1.09	5.4285	1.8051
Serbia	16	0.48	2.8750	1.4722
Slovakia	44	1.33	6.2666	2.4652
Slovenia	15	0.45	4.1333	0.8171
Spain	448	13.56	9.5887	1.4599
Sweden	150	4.54	7.5668	2.1170
Switzerland	55	1.67	7.8333	2.1608
Total	3303	100		

Table 2 Variables description and summary statistics

Number of lenders, Loan size, Loan maturity, Term loan, and Eastern Europe come from Dealscan (LPC, Reuters). X1 – X5 variables and Z score (t), Z score(t+1), Z score(t, S1), Z score Eur. D.R. (t), Z score Eur. D.R. (t, S1), Z score Eur. D.R. (t+1), Z score Eur. D.P. (t), Z score Eur. D.P. (t, S1), Z score Eur. D.P. (t+1), Ebit margin come from Amadeus (Bureau Van Dijk). Bank concentration comes from (Beck et al. 2000). Creditor rights come from (Djankov et al. 2007).

Variable	Description	Mean	Std. Dev.
Number of lenders	Number of bank lenders in the banking pool	8.7986	8.5245
Z score (t)	Altman (2000) Z score computed on the same fiscal year as the bank loan	1.9061	1.4641
Z score (t, S1)	Altman (2000) Z score computed on the same fiscal year as the bank loan including loans granted on the first semester of the year only	1.9067	1.4767
Z score (t+1)	Altman (2000) Z score computed on t+1 fiscal year with respect to the bank loan	2.0886	1.5866
Z score Eur. D.R. (t)	Z score computed on the same fiscal year as the bank loan using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's rating provided by Amadeus)	1.2437	1.8226
Z score Eur. D.R. (t, S1)	Z score computed on the first semester of the same fiscal year as the bank loan using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's rating provided by Amadeus)	1.2582	1.8555
Z score Eur. D.R. (t+1)	Z score computed on t+1 fiscal year with respect to the bank loan using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's rating provided by Amadeus)	1.4300	2.2553
Z score Eur. D.P. (t)	Z score computed on the same fiscal year as the bank loan using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's default probability provided by Amadeus)	1.2002	1.7453
Z score Eur. D.P. (t, S1)	Z score computed on the first semester of the same fiscal year as the bank loan using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's default probability provided by Amadeus)	1.2104	1.7734
Z score Eur. D.P. (t+1)	Z score computed on t+1 fiscal year with respect to the bank loan using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's default probability provided by Amadeus)	1.3722	2.1306
X1	Working capital / Total assets	0.1077	0.2248
X2	Retained earnings / Total assets	0.2425	0.1707
X3	EBIT / Total assets	0.0650	0.0920
X4	Book value of equity / Book value of total liabilities	0.8885	2.3839
X5	Sales / Total assets	1.0501	0.9882
Loan size	Logarithm of the loan facility amount in USD	19.150	1.5371
Loan maturity	Logarithm of the loan maturity in months	4.0208	0.7134
Syndication	=1 if loan is syndicated	0.8652	0.3414
Term loan	=1 if loan is a term loan	0.4361	0.4959
Ebit margin	EBIT / Operating revenue	0.0838	0.1648
Bank concentration	Share of 3 largest banks in total banking assets	0.61791	0.1498
Creditor rights	Index aggregating creditor rights (0:poor creditor rights to 4)	1.4264	1.1377

Table 3 Influence of borrower quality on the banking pool size

This table reports main OLS regressions results with standard errors clustered at the borrower level (in brackets). The explained variable is the number of bank lenders. In Model 1 Z score (t) is the Altman (2000) Z score computed on the same fiscal year as the bank loan while in Model 2 Z score (t, S1) is the Altman (2000) Z score computed on the same fiscal year as the bank loan including loans granted during the first and second semester of the year only. In Model 3 Z score (t+1) is the Altman (2000) Z score computed on the t+1 fiscal year with respect to the year of the bank loan. All variables are described in table 2. Dummies for industry sectors and years included but not displayed. ***, ** and * correspond to coefficient statistically different from 0 at 1%, 5% and 10% level.

Variables	**Model 1**	**Model 2**	**Model 3**
Z score (t)	-0.2824**		
	(0.1286)		
Z score (t, S1)		-0.4691***	
		(0.1444)	
Z score (t+1)			-0.2708
			(0.4023)
Loan size	3.6726***	3.8522***	3.4030***
	(0.3113)	(0.4237)	(0.6674)
Loan maturity	-0.0433	0.4840	-0.5440
	(0.4457)	(0.5933)	(0.8755)
Term loan	1.1446**	0.6291	1.3444
	(0.5774)	(0.7191)	(1.1444)
Syndication	2.7136***	4.4037***	4.9706***
	(0.8409)	(0.9799)	(1.7151)
Ebit margin	-0.0254	-0.0587***	-0.0294
	(0.0159)	(0.0186)	(0.0451)
Bank concentration	-1.7031	-4.9730	7.1009
	(2.3383)	(3.6691)	(4.5311)
Creditor rights	-0.1948	-0.4556	-1.6733***
	(0.2719)	(0.3758)	(0.5718)
Intercept	-58.2040***	-61.8407***	-56.2271***
	(6.4153)	(8.2458)	(14.0910)
N	2474	1184	603
R^2	0.3843	0.4313	0.4599
F	12.99***	9.91***	4.86***

Table 4 Influence of lending type on the relationship between banking pool size and borrower quality

This table reports main OLS regressions results with standard errors clustered at the borrower level (in brackets). The explained variable is the number of bank lenders. Borrower signal quality variables are interacted with the Syndication dummy. In Model 1 Z score (t) is the Altman (2000) Z score computed on the same fiscal year as the bank loan while in Model 2 Z score (t, S1) is the Altman (2000) Z score computed on the same fiscal year as the bank loan including loans granted during the first and second semester of the year only. In Model 3 Z score (t+1) is the Altman (2000) Z score computed on the t+1 fiscal year with respect to the year of the bank loan. All variables are described in table 2. Dummies for industry sectors and years included but not displayed. ***, ** and * correspond to coefficient statistically different from 0 at 1%, 5% and 10% level.

Variables	Model 1a	Model 2a	Model 3a
Z score (t)	-0.9887***		
	(0.2938)		
Z score (t, S1)		-1.7015***	
		(0.4500)	
Z score (t+1)			-1.3409**
			(0.5920)
Z score (t) x Syndication	0.7737**		
	(0.3024)		
Z score (t, S1) x Syndication		1.3564***	
		(0.4242)	
Z score (t+1) x Syndication			1.2649**
			(0.5462)
Loan size	3.7148***	3.8970***	3.5691***
	(0.3072)	(0.4274)	(0.6677)
Loan maturity	0.0465	0.6343	-0.3000
	(0.4425)	(0.5922)	(0.8542)
Term loan	1.1294**	0.6251	1.5885
	(0.5743)	(0.7233)	(1.1687)
Ebit margin	-0.0239	-0.0541***	-0.0344
	(0.0160)	(0.0192)	(0.0453)
Bank concentration	-1.6959	-4.9098	6.5586
	(2.3371)	(3.6319)	(4.4909)
Creditor rights	-0.2180	-0.4840	-1.6622***
	(0.2736)	(0.3771)	(0.5771)
Intercept	-56.7731***	-59.2656***	-55.2549***
	(6.3885)	(8.3360)	(14.5343)
N	2474	1184	603
R^2	0.3787	0.4192	0.4539
F	12.08***	8.80***	3.95***

Table 5 Influence of lending type on the relationship between banking pool size and borrower quality by firm and loan size

This table reports main OLS regressions results with standard errors clustered at the borrower level (in brackets). The explained variable is the number of bank lenders. A firm is considered as small (large) when its total asset is below (above) the sample median equal to 205 MLN USD, while a loan is considered as small (large) when its amount is below (above) the sample median equal to 205 MLN USD. In Model 1 Z score (t) is the Altman (2000) Z score computed on the same fiscal year as the bank loan while in Model 2 Z score (t, S1) is the Altman (2000) Z score computed on the same fiscal year as the bank loan including loans granted during the first and second semester of the year only. In Model 3 Z score (t+1) is the Altman (2000) Z score computed on the t+1 fiscal year with respect to the year of the bank loan. All variables are described in table 2. Dummies for industry sectors and years included but not displayed. ***, ** and * correspond to coefficient statistically different from 0 at 1%, 5% and 10% level.

Variables	Model 1b		Model 2b		Model 3b	
	Small firm / small loan	*Large firm / large loan*	*Small firm / small loan*	*Large firm / large loan*	*Small firm / small loan*	*Large firm / large loan*
Z score (t)	-0.5688***	-0.8985**				
	(0.1726)	(0.4152)				
Z score (t, S1)			-0.5559**	-1.3363*		
			(0.2205)	(0.7516)		
Z score (t+1)					-0.5826	-1.0131
					(0.3666)	(0.7507)
Z score (t) x Syndication	0.5055***	0.6357				
	(0.1681)	(0.4146)				
Z score (t, S1) x Syndication			0.4268**	0.7147		
			(0.2151)	(0.7493)		
Z score (t+1) x Syndication					0.2785	0.9563
					(0.3424)	(0.7215)
Loan size	1.7325***	5.5682***	1.5516***	5.8255***	0.9370**	3.9800***
	(0.2283)	(0.5391)	(0.3291)	(0.8002)	(0.3703)	(1.0555)
Loan maturity	0.2956	0.4107	1.1561***	0.6058	-0.3199	0.2279
	(0.3791)	(0.5568)	(0.3749)	(0.7710)	(0.8449)	(1.0275)
Term loan	1.0375**	1.5601*	0.7152	1.9128	0.1339	1.3783
	(0.4627)	(0.8465)	(0.4745)	(1.2078)	(1.3159)	(1.5610)
Ebit margin	-0.0202*	-0.0351	-0.0377**	-0.0741**	-0.0374**	-0.0170
	(0.0120)	(0.0253)	(0.0164)	(0.0289)	(0.0151)	(0.1048)
Bank concentration	-1.8033	0.5651	-0.4863	-1.3280	-4.6585	8.0394*
	(2.1095)	(3.1099)	(1.7222)	(5.3536)	(4.7680)	(4.6900)
Creditor rights	-0.2692	0.2634	-0.8640***	-0.0098	0.2959	-1.6063**
	(0.2391)	(0.3651)	(0.2974)	(0.6107)	(0.4181)	(0.6820)
Intercept	-24.3609***	-95.4737***	-25.2916***	-99.3727***	-2.3052	-67.0643***
	(4.4478)	(11.7474)	(6.4888)	(17.2081)	(7.9908)	(24.3160)
N	1183	1291	613	571	280	323
R^2	0.2348	0.3925	0.2757	0.4388	0.3708	0.4607
F	8.0674	10.0316	5.9108	5.4961	4.2594	4.0407

Table 6 Influence of borrower quality on the banking pool size

Robustness checks with alternative European Z scores

This table reports main OLS regressions results with standard errors clustered at the borrower level (in brackets). The explained variable is the number of bank lenders. In Models 1c, 2c and 3c, Z score Eur. D.R. (t), Z score Eur. D.R. (t, S1) and Z score Eur. D.R. (t+1) are Z scores (computed on same fiscal year as the bank loan, on the first semester of the same fiscal year as the bank loan and on the t+1 fiscal year with respect to the bank loan respectively) using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's rating provided by Amadeus). In Models 1d, 2d and 3d, Z score Eur. D.P. (t), Z score Eur. D.P. (t, S1) and Z score Eur. D.P. (t+1) are Z scores (computed on same fiscal year as the bank loan, on the first semester of the same fiscal year as the bank loan and on the t+1 fiscal year with respect to the bank loan respectively) using Altman (2000) variables but with coefficients re-estimated on a European firms' sample (default based on firm's default probability provided by Amadeus). All variables are described in table 2. Dummies for industry sectors and years included but not displayed. ***, ** and * correspond to coefficient statistically different from 0 at 1%, 5% and 10% level.

Variables	Model 1c	Model 2c	Model 3c	Model 1d	Model 2d	Model 3d
Z score Eur. D.R. (t)	-0.3082**					
	(0.1380)					
Z score Eur. D.R. (t, S1)		-0.3893**				
		(0.1679)				
Z score Eur. D.R. (t+1)			-0.0613			
			(0.2761)			
Z score Eur. D.P. (t)				-0.3302**		
				(0.1462)		
Z score Eur. D.P. (t, S1)					-0.4204**	
					(0.1796)	
Z score Eur. D.P. (t+1)						-0.0604
						(0.2933)
Loan size	3.6727***	3.8602***	3.4303***	3.6728***	3.8582***	3.4314***
	(0.3071)	(0.4192)	(0.6632)	(0.3070)	(0.4191)	(0.6624)
Loan maturity	-0.0351	0.5227	-0.5089	-0.0401	0.5117	-0.5096
	(0.4454)	(0.6002)	(0.8716)	(0.4453)	(0.6009)	(0.8720)
Term loan	1.1384**	0.6666	1.3290	1.1384**	0.6618	1.3287
	(0.5761)	(0.7195)	(1.1474)	(0.5760)	(0.7197)	(1.1485)
Syndication	2.7100***	4.3332***	5.0342***	2.6990***	4.3256***	5.0334***
	(0.8399)	(0.9880)	(1.6973)	(0.8404)	(0.9875)	(1.6992)
Ebit margin	-0.0237	-0.0551***	-0.0324	-0.0248	-0.0565***	-0.0328
	(0.0159)	(0.0183)	(0.0468)	(0.0158)	(0.0184)	(0.0461)
Bank concentration	-1.5645	-4.5823	7.2712	-1.5319	-4.5475	7.2701
	(2.3439)	(3.6764)	(4.5863)	(2.3437)	(3.6753)	(4.5996)
Creditor rights	-0.1840	-0.4293	-1.6884***	-0.1851	-0.4282	-1.6901***
	(0.2705)	(0.3778)	(0.5709)	(0.2705)	(0.3778)	(0.5703)
Intercept	-58.6642***	-62.9734***	-57.5735***	-58.6324***	-62.8744***	-57.5875***
	(6.3324)	(8.1585)	(13.9766)	(6.3290)	(8.1589)	(13.9886)
N	2474	1184	603	2474	1184	603
R^2	0.3857	0.4310	0.4584	0.3859	0.4313	0.4584
F	13.07***	9.52***	4.75***	13.09***	9.54***	4.74***

Appendix

Proof of proposition 2

We have to solve the following equation:

$$n^{'}(x)\left(b(1-x)\mu^{'}\left(n(x)\right)\right)=a(k-R(x)) \qquad \textbf{(4)}$$

with $\mu\left(n(x)\right)=\frac{1}{n(x)}$ and $R(x)=\frac{r+\pi}{x}$

Thus, the preceding equation becomes:

$$-\frac{n^{'}(x)}{n(x)^{2}}b(1-x)=a\left(k-\frac{r+\pi}{x}\right)$$

After algebraic manipulations, we find:

$$-\frac{n^{'}(x)}{n(x)^{2}}=\frac{a}{b}\frac{kx-r-\pi}{x(1-x)}$$

Using partial fraction decomposition, we can write:

$$-\frac{n^{'}(x)}{n(x)^{2}}=\frac{a}{b}\left[\frac{k}{1-x}-(r+\pi)\left(\frac{1}{x}+\frac{1}{1-x}\right)\right]$$

Hence, the function *n(x)* verifies:

$$n(x)=\frac{\mathrm{a}}{\mathrm{b}}\left\{(\mathrm{r}+\pi)\ln\left(\frac{1-\mathrm{x}}{\mathrm{x}}\right)-\mathrm{k}\ln(1-\mathrm{x})\right\}+Cte$$

where *Cte* is a constant which is determined following the fact that the quality of firms belongs to the interval *[c, d]*.

Since *n(x)* is a decreasing function, the application of the boundary conditions implies that the firm of the highest risk will opt for the most diversified financing, which is given by the relation: *n(c) = N*. By including this condition into the last equation, the value of the constant becomes:

$$Cte=N-\frac{\mathrm{a}}{\mathrm{b}}\left\{(\mathrm{r}+\pi)\ln\left(\frac{1-\mathrm{c}}{\mathrm{c}}\right)-\mathrm{k}\ln(1-\mathrm{c})\right\}$$

Finally, the solution is:

$$n(x)=\frac{\mathrm{a}}{\mathrm{b}}\left\{(r+\pi)\ln\left[\frac{(1-x)c}{x(1-c)}\right]-k\ln\left[\frac{1-x}{1-c}\right]\right\}+\mathrm{N} \qquad \textbf{(5)}$$

Remark: the term in bracket is always negative.

Table A.1 Univariate statistics for Z score (t) by Amadeus rating grade (MORE ratings)

Rating	Obs.	Mean	Std. Dev.
AA	67	3.6479	1.7689
A	270	3.1765	1.8677
BBB	728	2.4315	1.8477
BB	1294	1.8297	1.1148
B	665	1.3271	0.9987
CCC	244	0.9680	0.8771
CC	43	0.7201	0.6438
C	2	0.4081	0.5355

European Z score computation

We have extracted from Amadeus a sample of 365 140 European firms from the same countries, the same industry sectors and over the same time period as for our main sample used in the article.

We use the same five variables as Altman (2000) Z score but we re-estimate the coefficients of the score function for European firms. We build the default binary variable using two alternative definitions. The first one is based on the firm's rating provided by Amadeus (the Multi Objective Rating Evaluation (MORE) model is essentially used to assess the level of distress of industrial companies by using data included in financial statements; the rating's scales goes from AAA to D with 10 rating grades). We consider as default the last three rating grades (CC, C and D) corresponding to the distress category according to Amadeus, which amounts for 6.11% of the sample. The second one is based on the firm's default probability provided by Amadeus. We consider as default a firm which default probability is strictly greater than 10%, which amounts for 7.69% of the sample.

Pearson's correlation coefficients between the original Altman (2000) Z score computed on the European sample, the firm's rating (the ordinal scale has been converted to numerical values; the higher the numerical value the worst the rating) and the firm's default probability are shown in the table below. We observe significant coefficients at the 1% level. All are coherent with our expectations. The Z score is negatively related to the firm's rating and the firm's default probability.

	Z score Altman	Firm rating	Firm default probability
Z score Altman	1.00		
Firm rating	-0.42***	1.00	
Firm default probability	-0.15***	0.35***	1.00

For each definition of default, we have performed a stepwise discriminant analysis to confirm the use of the five Altman (2000) variables. Then, we have applied a linear discriminant analysis (with proportional priors) to estimate the coefficients for the five variables. The posterior probability error rate estimates equal 4.58 % and 7.37 % for the default based on ratings and on default probability respectively. We have also performed logistic regressions using the Altman (2000) five variables. The area under the ROC curve equals 96.8 % and 77.9 % for the default based on ratings and on default probability respectively. Hence, we can conclude that Altman (2000) variables give statistically better results when using default based on firm's rating. Nevertheless, we keep both default measures in order to build two alternative Z scores for European firms[14].

The coefficients for the *Z score Eur. D.R.* (Z score Europe, default based on rating) and for the *Z score Eur. D.P.* (Z score Europe, default based on default probability) are:

$$Z\ score\ Eur.D.R. = -2.0970 + 0.6324 \times X_1 + 7.1212 \times X_2 + 4.8744 \times X_3 + 0.0433 \times X_4 + 1.1326 \times X_5$$

$$Z\ score\ Eur.D.P. = -2.0334 + 0.4985 \times X_1 + 7.1820 \times X_2 + 3.3337 \times X_3 + 0.0372 \times X_4 + 1.1309 \times X_5$$

Main univariate statistics and correlation analysis computed on the European sample for these Z scores and for the Altman (2000) Z score are provided below.

Variable	Mean	Std. Dev.	Min.	Max.
Z score Eur. D.R.	1.8451	2.0725	-1.9999	29.9483
Z score Eur. D.P.	1.7775	1.9974	-1.9576	29.8034
Z score Altman	2.4385	1.4533	-0.9135	29.9090

	Z score Eur. D.R.	Z score Eur. D.P.	Z score Altman	Firm default probability	Firm rating
Z score Eur. D.R.	1.00				
Z score Eur. D.P.	0.99***	1.00			
Z score Altman	0.87***	0.87***	1.00		
Firm default probability	-0.21***	-0.21***	-0.14***	1.00	
Firm rating	-0.60***	-0.58***	-0.42***	0.34***	1.00

We observe that the European Z scores are on average smaller than the Altman Z score, but all remain within a similar range of values regarding the minimum and the maximum. All correlation coefficients are significant at the 1% level. We remark that the correlation between the Altman Z score

[14] All detailed calculations and results are available from the authors upon request.

and its two European alternatives are very large: 87.24% and 87.11% for the Z score Eur. D.R. and Z score Eur. D.P. respectively.

We then use these two alternative score functions (each based on an alternative definition of default) to compute the *Z score Eur. D.R. (t), Z score Eur. D.R. (t, S1) and Z score Eur. D.R. (t+1)*, as well as the *Z score Eur. D.P. (t), Z score Eur. D.P. (t, S1) and Z score Eur. D.P. (t+1)* (computed on same fiscal year as the bank loan, on the first semester of the same fiscal year as the bank loan and on the t+1 fiscal year with respect to the bank loan respectively) for our main sample to provide the robustness check results displayed in table 6.