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Research Paper

Debt, information asymmetry and bankers on board

‘on boards’ rather than ‘on board’ in paper title?

João Amaro de Matos[1] and João Mergulhão[2]

[1]Nova School of Business and Economics, Campus de Campolide,
1099-033 Lisbon, Portugal; email: amatos@novasbe.pt
[2]Moody’s Analytics, One Canada Square, London E14 5FA, UK;
email: joao.mergulhao@moodys.com

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ABSTRACT

This paper contributes to the financial networks literature by providing evidence that well-connected bankers on the boards of directors of nonfinancial firms reduce information asymmetry between credit markets and firms. Although it is well known that the presence of bankers on these boards likely facilitates firms’ capacity to increase their debt level, we clarify this statement in two different ways. First, we show that the impact of the presence of bankers on leverage is driven by firms with low levels of debt. For firms with high levels of debt this effect is not statistically significant. Second, the impact on the leverage ratio of the presence of bankers on the board is amplified the more connected these bankers are to the corporate world. In addition, the results are more pronounced for less transparent firms. Our findings suggest that the connectedness of bankers plays a key role in reducing information asymmetry.

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- Bankers on boards of nonfinancial firms are associated with higher leverage ratios.
- The more connected the banker, the higher the leverage ratio.
- The higher the information asymmetry, the greater the impact of the banker’s connectedness.

Corresponding author: J. Amaro de Matos

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- Bankers facilitate the increase of leverage ratio only for low-debt firms.
- The more connected the banker, the larger the impact on the leverage ratio.

Keywords: information asymmetry; debt level; social networks; corporate boards; bankers.

1 INTRODUCTION

There is evidence that the presence of bankers on a firm's board positively affects that firm's capacity to increase its debt level (see, for example, Engelberg *et al* 2012; Ferreira and Matos 2012). In this paper, we provide evidence that this leverage impact is essentially driven by low-debt firms. We also suggest that the role of bankers as debt facilitators can be better understood by exploring their connectedness. In fact, we provide further evidence that the impact of bankers is amplified the more connected they are to the corporate world, and that this amplification effect is greater for firms with lower levels of debt. Finally, we show that these results are stronger for less transparent firms, which is consistent with the idea that connected bankers reduce information asymmetry.

Using a sample of nonfinancial US firms (Standard & Poor's 1500 (S&P 1500) constituents), we find that the presence of a banker increases the leverage ratio by 22.6%. This positive average treatment effect is consistent with previous results in the literature.

We then test if the connectedness of bankers affects the debt level. We measure the connectedness of each of the board members using board membership data. In contrast to the board interlocks literature, this approach allows us to distinguish the connectedness of different directors, thus identifying the role of individual bankers in the information transmission mechanism. Our results indicate that the impact of bankers' connectedness on the debt level is also positive, on average, and robust to different measures of connectedness commonly used in the social networks literature.

In addition, we build an information asymmetry index for each firm, following Gomes and Phillips (2012), and determine how the previous result differs across various levels of transparency. Our findings indicate that the impact of bankers' connectedness on the debt level is reduced when information asymmetry problems are less severe. These results are consistent with the interpretation that connected bankers contribute more to the reduction of information asymmetry, and that this contribution is more important for opaque firms.

Finally, we use quantile regressions to distinguish both effects (the presence and the connectedness of bankers) for firms with different levels of leverage. We show that, for firms with relatively low levels of debt, both the presence and the connectedness of bankers will impact positively on the debt level. These effects are not present when analyzing firms with relatively high levels of debt. Our interpretation is that bankers contribute to the reduction of information asymmetry, transmitting to the market their perception of the debt capacity use. Again, these results are robust to the different measures of connectedness used.

We classify two individuals as connected if they sit on a given board in the same year. By construction, the number of directors in each board will automatically affect the connectedness measures. Also, the larger the board, the more likely it is that we will find a banker on it board. We thus address the endogeneity concerns using board size as an instrument, since board size does not affect the debt level of a firm per se. Change OK?

An extensive literature (see Berger and Udell 1995; Byrd and Mizruchi 2005; Ciamarra 2006; Engelberg *et al* 2012; Ferreira and Matos 2012; Petersen and Rajan 1994) provides evidence that the presence of bankers on companies' boards positively affects the capacity of these firms to increase their debt level. Among others, Engelberg *et al* (2012) and Ferreira and Matos (2012) argue that the effect of bankers' presence on the boards of borrower firms is the development of a special lending relationship that facilitates access to the credit market.

The relations between banks and corporations are known to reduce informational asymmetries and thus lower financing costs (Diamond 1984). In particular, banker–directors (bankers who sit on the boards of directors of banks and nonfinancial firms simultaneously) provide financial expertise (Lorsch and Maciver 1989; Mace 1971) and effectively monitor the management of firms, lowering the costs of funds (Berger and Udell 1995; James 1987; Kroszner and Strahan 2001; Williamson 1988). Booth and Deli (1999), Kroszner and Strahan (2001) and Byrd and Mizruchi (2005) show a positive correlation between firms' capital structures and the presence of unaffiliated banker–directors (who do not have direct conflicts of interest in capital structure decisions). Krakaw and Zenner (1998) show evidence of a negative price reaction to the announcement of loan renewals involving a bank represented on the firm's board, reflecting the fact that creditors on the board have an informational advantage over outside creditors. Using an international sample of firms with bankers on board, 'their boards'? Ferreira and Matos (2012) provide evidence that banks extract informational rents from firms by charging higher loan rates in favorable market conditions. Güner *et al* (2008) also shows that the presence of financial experts on a board affects corporate decisions, although this is not always in the best interest of shareholders.

Our methodology is based on network analysis. Many papers analyzing networks in the financial system have focused on the stability of the lending network among banks. Examples cover different geographies, such as the US and UK markets in Birch and Aste (2014), the US market in Battiston *et al* (2012b), the Italian market in Iori *et al* (2008) and De Masi and Gallegati (2012), and the Austrian market in Boss *et al* (2004). Other papers such as Tasca *et al* (2017) analyze how a proper diversification strategy may help to create more resilient networks, whereas others (for example, Leduc and Thurner 2017; Poledna and Thurner 2016) point out how this goal may be achieved by introducing suitable transaction taxes. Some other papers, however, which are more in line with our argument, have raised the point that organizational networks are an effective way of conveying information (Caldarelli and Catanzaro 2004; Dodds *et al* 2003), providing a more efficient interbank trading mechanism based on trust and memory (Iori *et al* 2015; Jan Simon *et al* 2016).

The role of networks connecting board members has been exploited in many different corporate finance contexts (for example, Bouwman 2011; Bouwman and Xuan 2010; Chiu *et al* 2013; Cohen *et al* 2008; Fracassi 2012; Goldman *et al* 2009; Stuart and Yim 2010). In addition, a simultaneous line of work uses network analysis to describe the network of corporate boards as connectors of influence in the decision-making process (Battiston *et al* 2003), emphasizing its small-world characteristics and the role of centrality (Barak and Kapah 2017; Battiston and Catanzaro 2004) as well as the role of connectedness in the flow of control (Glattfelder and Battiston 2009) and in risk sharing (Battiston *et al* 2012a). Regarding the relation of firms <u>to</u> Change OK? credit markets, Chuluun *et al* (2014) provides evidence that, on average, the connectedness of the firm (as measured by board interlocks) is negatively related to the cost of debt, and this effect is stronger in the presence of higher information asymmetry. By assuming that networks facilitate the information dissemination mechanism, as argued by Chuluun *et al* (2014), following Nohria (1992), Burt (1997) and Nahapiet and Ghoshal (1998), using board interlocks instead of individual connections will not allow us to understand the role of individual bankers in the process.

Our work contributes to this discussion by building on two critical aspects. First, the connectedness measures in our paper are based on the connectedness of each of the members of the board, allowing us to identify the role of individuals in the information transmission mechanism. Our technology allows us to further refine the results of Chuluun *et al* (2014) by focusing on the role of specific bankers who sit on the boards of firms, in the spirit of Byrd and Mizruchi (2005), Engelberg *et al* (2012) and Ferreira and Matos (2012). In addition, we are able to show that the reported impact of board connectedness on the leverage of firms is mostly driven by banker–directors' connectedness.

Second, and most importantly, we explain the average positive impact of bankers and financial experts on debt level, as reported by Güner *et al* (2008), Ferreira and Matos (2012) and Chuluun *et al* (2014). We distinguish this impact for firms with different levels of leverage. In particular, we provide robust evidence that this positive impact is significant only for firms with relatively low levels of debt. We further provide evidence to corroborate the interpretation that bankers sitting on the boards of firms help to reduce information asymmetries in the credit market.

This paper is organized as follows. In Section 2, we hypothesize how the presence (and the centrality) of a banker–director may affect capital structure decisions. In Section 3, we describe our methodology and data, addressing first the directors' network and the centrality measures used to classify the influential role of bankers, and second the estimation procedures used to correct for a possible endogeneity bias. We then describe our databases. In Section 4, we present the results. Our main conclusions are summarized in Section 5.

2 THE ROLE OF BANKERS

Podolny (1994) points out that social relationships between market agents may prevent market failure due to uncertainty and information asymmetry. In addition, networks of social relationships can be shown to allow information gathering from nondirectly connected sources, playing a crucial role in screening and selecting the relevant pieces of information (Burt 1997) and lowering information-gathering costs (Nahapiet and Ghoshal 1998).

In the same way, we should expect the social relationships of the directors of a firm to play a role in information transmission, reducing the information asymmetry between agents in the market. Shane and Cable (2002) show the importance of social ties in obtaining venture capital.

Our proposal is to use the network of boards and directors as a proxy for the real social network of market agents. This means that the network we construct only contains partial information regarding the professional relationships between agents, and excludes all other relationships, both professional (all nonboard-related connections) or private (family/friendship ties or common memberships of universities, clubs, etc). Also, we can only observe that two directors sit on the same board at a particular time and assume that they must know each other and are, therefore, directly connected.

Using social network analysis and suitable centrality measures, we infer the influence of each director. In particular, we are interested in the role of banker–directors in the information flow, their impact on the reduction of information asymmetries and, Change OK? as a consequence, how this affects a firm's access to the credit market. If the social network of directors is a good proxy for the real-life social network, we should then expect that the presence of a banker on the board of a firm may reduce the information asymmetry between that firm and its lenders, which, in turn, allows the firm to increase its leverage. Specifically, we test the following hypothesis:

Hypothesis 1. On average, the presence of a banker on the board increases the leverage of a firm.

Byrd and Mizruchi (2005) have already tested for Hypothesis 1, ie, they tested for the mere presence of bankers on boards. However, no study has evaluated the role of banker–directors in the information transmission mechanism. If it is true that bankers are important in reducing information asymmetry, then the more connected a banker is, the more effective they will be in that role. Note that we do not assume that the banker is sharing insider information or acting in any other illegal way. It suffices to interpret the banker's role in the information transmission mechanism as in Burt (1997), where the network is used as a filter for the relevant pieces of information: when the market analyzes all pieces of available information, it will give more weight to information coming from more influential sources. Again, assuming that a reduction in information asymmetry facilitates access to credit markets, we test for the following hypothesis:

Hypothesis 2. On average, the more connected a banker–director, the higher the leverage of a firm.

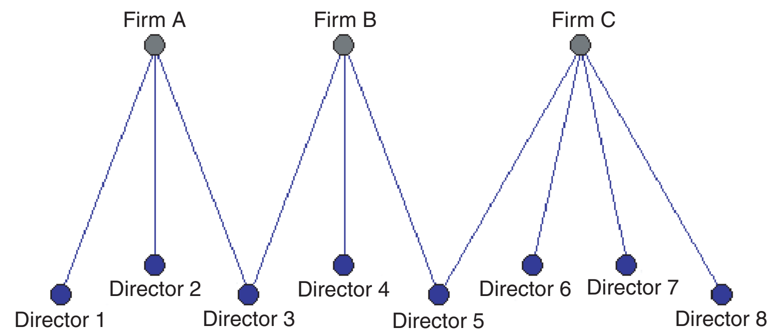
Factors other than connected bankers may contribute toward disseminating information and, hence, the level of information asymmetry (or opacity) does not depend solely on the presence of bankers. Bankers may be invited to sit on boards of more or less opaque firms. Our assumption is that the higher the information asymmetry, the more important the role of a connected banker regarding the information transmission mechanism. This same idea is corroborated in the financial literature in different contexts (for example, Butler 2007; Chuluun *et al* 2014; Engelberg *et al* 2012; Mansi *et al* 2010). If the effect of the presence of a banker–director on a firm's level of debt is in fact due to a reduction in information asymmetry, then one should expect this effect to be higher the more opaque the firm and the more connected the banker–director. We specify this hypothesis as follows:

Hypothesis 3. The higher the level of information asymmetry, the larger the average impact of the connectedness of a banker on the leverage of a firm.

It is also natural to assume that the way bankers reduce information asymmetry will differ strongly according to the debt levels of firms. A banker sitting on the board of a firm with a relatively low level of debt will perceive as very high the probability that such a firm is below its optimal debt capacity. In that case, the banker's role is to facilitate the dissemination of that message to the market, favoring both the firm and potential lenders. On the contrary, if a banker is sitting on the board of a firm with a relatively high level of debt, the probability of bankruptcy may be perceived as too high, and the banker's role should thus be to discourage further debt. We formalize our hypothesis as follows:

Hypothesis 4. For firms with relatively low levels of debt, bankers facilitate an increase in leverage level; for high-levered firms, this is not true.

FIGURE 1 Graphical representation of a two-mode network.



Example of a network with three firms and eight directors.

Finally, we combine the assumptions in Hypotheses 2 and 4 into a different observable assumption. Hypothesis 2 states that the more connected a banker–director is, the larger their impact on the debt level of a firm. Hypothesis 4 states that the likelihood of debt increase gets larger the lower the initial value of debt. We therefore assume that the effect described in the latter must be amplified by a banker's level of connectedness. Our final hypothesis reads as follows:

Hypothesis 5. For firms with relatively low (high) levels of debt, the more connected the bankers, the larger their capacity to facilitate (impede) debt increase.

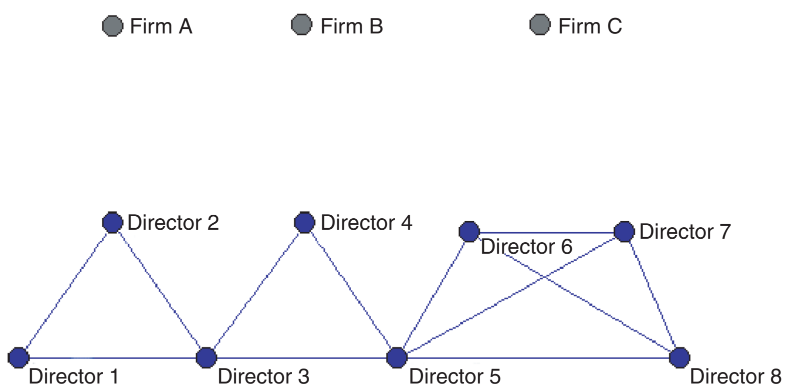
3 NETWORK CONSTRUCTION AND CENTRALITY MEASURES

Information does not flow between firms, but rather through the individuals placed in different firms. Therefore, we opt to construct a network of relationships between Change OK? directors instead of pure board interlocks, as exemplified below. In Figure 1, there are three firms and eight directors. Note that there are no connections between directors, who are linked only to firms where they sit on the board.[1]

Figure 2 is the result of projecting the network in Figure 1 onto the space of directors. Each individual is linked to all others with whom they share a board. However, a usual approach in the literature is to consider only the board interlocks. This dilutes the network characteristics relevant to information transmission. In the example above,

[1] This is a characteristic of affiliation networks, more generally referred to as two-mode networks. These networks have two types of vertexes and connections can only occur between vertexes of different types.

FIGURE 2 Graphical representation of a one-mode network.



Projection of the example network represented in Figure 1 onto the space of directors.

the complex network of Figure 2 would be reduced to a simple network in which firms A and C are connected to firm B.

Instead, using the network of directors, we are able to measure the role of each individual on the flow of information, by computing a connectedness measure for each individual on the network. We focus on three basic measures of connectedness commonly used in information flows/contagion analysis: degree, closeness and betweenness. These measures are also referred to as centrality measures.

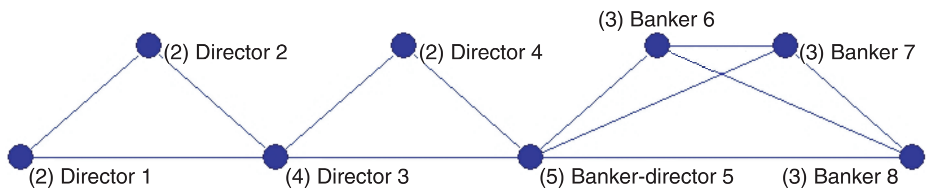
The degree of a vertex is the number of connections a vertex has with other vertexes in the network. Within the directors' network, it represents the number of directors to whom a particular individual is related. A director with a higher degree of centrality knows more directors inside the network.

Closeness centrality (Sabidussi 1966) is the inverse of the average distance between a particular vertex and every other vertex. Within the directors' network, it represents the average number of contacts that a director would have to make in order to reach any other director in the network.[2] A director with higher closeness centrality will need, on average, fewer intermediaries to reach any other director.

Betweenness centrality (Freeman 1977) may be interpreted as the probability that director i is a vehicle for information transfer between director k and director j, assuming that all the shortest paths are equally likely to be used.

[2] As there are directors who are isolated/separated from part of the network, the classical definition of closeness is not well defined. The solution in these cases is to use the influential range of each director, that is, to measure the centrality within the reachable component of the network (Lin 1976) as a ratio of the total number of vertexes.

FIGURE 3 Degree centrality example.



Going back to the firm dimension: example using degree centrality.

After computing the connectedness measures for each individual in the directors' network, we aggregate these at the firm level. As we are interested in the information role of banker–directors, we only use the connectedness of banker–directors in the aggregation process: for each firm, the corresponding connectedness measure is the maximum value of the banker–director on the board. If there is no banker–director, the centrality measure is 0. We proxy the informational role of the board through the maximum for two reasons. First, we assume that the determinant individual in the information distribution is the one who is most connected/influential. Second, the sum of centrality measures can be ambiguously interpreted. Figure 3 demonstrates this procedure using the previous three-firms example. Firm C now plays the role of a bank and, hence, director 5 is a banker–director. Each director's centrality degree is shown in parentheses. The three directors of firm 1 have degrees of 2, 2 and 4. However, the degree centrality of firm 1 will be 0, as it has no banker sitting on its board. Firm 2 has a one banker on the board with degree 4. Therefore, the degree centrality of firm 2 will be 4. Should this firm have boasted a second banker on its board with connections to fewer than four other directors, the degree centrality of firm 2 would still be 4.

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4 DATA

Our network data is based on the directors database provided by ISS (formerly Risk-Metrics). The sample includes board information for S&P 1500 firms from 1996 to 2013, with data on more than 11 000 directors per year. We consider that two directors are connected in a particular year if they sit on the same board during that year and compute the connectedness measures mentioned above for each individual/year.[3]

The remaining variables are compiled using Compustat/Center for Research in

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[3] We only consider contemporaneous connections, although it can be argued that the social network is built throughout the years, accumulating connections.

TABLE 1 Descriptive statistics: main variables.

	Count	Mean	SD	Minimum	Maximum
MDRplus1	15 426	0.2073	0.1974	0.0000	1.0000
EBIT/assets	15 426	0.0899	0.1114	−0.4305	0.3691
Log market-to-book	15 426	0.3357	0.5815	−0.8672	2.0415
Depreciation/assets	15 426	0.0446	0.0260	0.0063	0.1620
Log assets	15 426	21.2317	1.4912	18.1884	25.2040
Tangibles assets	15 426	0.2834	0.2167	0.0135	0.8872
R&D expenses	15 426	0.0300	0.0497	0.0000	0.2531
R&D not declared	15 426	0.3495	0.4768	0.0000	1.0000
SD returns	15 426	0.0266	0.1110	0.0000	0.8378
Industry median	15 426	0.1659	0.1206	0.0000	0.6948
Presence	15 426	0.2671	0.4424	0.0000	1.0000
Board size	15 426	5.9654	1.2923	1.0000	15.0000
Degree	15 426	9.6262	18.3179	0.0000	165.0000
Closeness	15 426	0.0480	0.0812	0.0000	0.2468
Betweenness	15 426	0.0009	0.0021	0.0000	0.0285
IAmm	12 005	2.7758	0.4608	1.5000	4.6000

"SD" denotes standard deviation. "MDRplus1" denotes market debt ratio (plus one).

Security Prices (CRSP) data. Our variable of debt level is the leverage ratio, computed as the ratio of total interest bearing debt to the sum itself with market capitalization [Compustat items: $(\text{dltt} + \text{dlc})/(\text{dltt} + \text{dlc} + (\text{prcc\_f} \times \text{csho}))$]. We also include the usual controls:[4] earnings before interest and taxes (EBIT) [Compustat item: ib + xint + txt] over total assets [Compustat item: at] as the profitability measure; the log of the market-to-book ratio as our growth opportunities measure [Compustat items: $\ln((\text{dltt} + \text{dlc} + \text{pstkl} + \text{prcc\_f} \times \text{csho})/\text{at})$]; the ratio of depreciation expenses [Compustat item: dp] to total assets, controlling for firms with less need for a debt-related tax shield; the logarithm of total assets as a measure of size; the ratio of fixed [Compustat item: ppegt] to total assets as a measure of asset tangibility; the ratio of research and development (R&D) expenditure [Compustat item: xrd] to total assets as a proxy for asset specificity;[5] and the standard deviation of abnormal returns as a proxy for firm volatility. We also control for industry median and year fixed effects.

After merging the two databases, our sample includes 15 426 firm–year observations. The descriptive statistics are presented in Table 1. Banker–directors are present in 26.7% of the firms.

[4] For a thorough review of the literature, see Frank and Goyal (2008).

[5] For firms not reporting R&D expenses, this ratio is set to zero. We add a dummy variable to identify these cases.

TABLE 2 Descriptive statistics: information asymmetry index and proxies used.

	Count	Mean	SD	Minimum	Maximum
Information asymmetry	12 005	2.7758	0.4608	1.5000	4.6000
Forecast error	12 005	220.3316	1026.2388	0.0000	5000.0000
Dispersion of opinion	12 005	5.2906	24.6292	0.0000	120.0000
Abnormal returns volatility	12 005	0.0237	0.0118	0.0053	0.2305
Firm age	12 005	25.9603	19.6885	0.0000	87.0000
Bid–ask spread	12 005	0.2478	4.3880	0.0100	330.0000
Effective spread	12 005	0.4766	0.4117	−4.7518	1.0000
Information-driven volume	12 005	0.4588	0.3999	−1.8368	2.0649
Proportional spread	12 005	0.9961	0.1242	−0.9217	6.6504
Amihud	12 005	0.0004	0.0064	−0.4050	0.2938
Amivest	12 005	665 743.1296	11 956 781.8291	4.1017	8.4887e+08

We build a proxy of firm opacity based on the method proposed by Gomes and Phillips (2012) (henceforth IAmm), which consists of averaging quintile rankings of individual information asymmetry proxies. As in Maskara and Mullineaux (2011), we include analysts' forecast errors and the dispersion of analysts' opinions from the Institutional Brokers' Estimate System (IBES) as well as the volatility of residual returns and firm age from CRSP.[6] Following the suggestion of Bharath *et al* (2009), we also rank the quintiles of the Amihud (2002) illiquidity measure, the Amivest illiquidity ratio (Amihud *et al* 1997; Kerry Cooper *et al* 1985), the fraction of proportional quoted and Roll's (1984) effective spread due to adverse selection for each stock. After merging this with our sample, we have 12 005 firm–year observations. Table 2 presents the descriptive statistics.

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We use board size as an instrument, where board size is the total number of directors on each board, measured by the number of directors listed in RiskMetrics. The larger the number of directors on the board, the higher the probability that one of the directors also sits on the board of a bank. We do not expect the board size itself to impact directly on the debt ratio of the firm; however, a positive relationship between firm size and board size is documented in the literature. Both Linck *et al* (2008) and Boone *et al* (2007) find evidence that the board size of firms increases along with the size and complexity of operations; the former study focuses on young firms (< 10 years since

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[6] We do not compute the volatility of abnormal returns around earnings announcements.

the initial public offering), while the latter explores the different characteristics of boards in small and large firms. This positive relationship between firm and board size is also present in our data. Nevertheless, when using centrality measures under the instrumental variables (IV) approach, board size seems to be a good instrument candidate, as the centrality measures of the directors are, by construction, dependent of the original board size.[7] Therefore, larger boards will automatically increase the number of connections between the directors seating on those boards, independently of any boards' interlocks.

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5 RESULTS

This section presents our results for the testing of the main hypothesis.

As for Hypotheses 1 and 2, the market debt ratio (MDR) of a firm, as defined in the former section should be directly related to the presence and the connectedness of the banker–director. We thus generate a variable $\text{Banker}_{i,t}$ that in the case of Hypothesis 1 is associated with the presence of a banker–director, and in the case of Hypothesis 2 is associated with their degree of connectedness. In that sense, the regression reads as follows:

Apart from in Table 1, this is the first mention of the market debt ratio, is it not? Please clarify.

$$\text{MDR}_{i,t+1} = \delta \text{Banker}_{i,t} + \boldsymbol{\beta}\text{Controls}_{i,t} + \varepsilon_{i,t}, \tag{5.1}$$

where the dependent variable is the market leverage ratio, as defined in the previous section; "Banker" may denote either the presence of a banker on the board (Hypothesis 1) or one of the three banker–director connectedness measures (Hypothesis 2); and "Controls" includes all control variables, such as year fixed effects, which are also defined in the previous section. The latter are winsorized at a 1% level. The ε term may include firm fixed effects.

We need to correct for possible endogeneity bias when testing our hypothesis that banker–directors (and their centrality in the network) affect the debt level of a firm. The choice of board composition, and hence the presence and connectedness of the banker, may not be independent of the choice of debt level. We use average treatment effects regression to estimate the average impact of the presence of a banker–director on debt level (Hypothesis 1) and IV regressions to correct for possible endogeneity biases (Hypothesis 2).[8]

Changes to footnote OK? There seemed to be a word missing after "endogenous".

In order to test Hypothesis 3, we add an extra term, interacting the presence and the connectedness of the banker–directors with the information asymmetry index

[7] We construct the network of directors by projecting the original (two-mode) network, with boards and directors, onto a network of only directors, where directors are connected if they share the same board in the same year.

[8] Using IV with binary endogenous regressors may lead to biased estimates of the parameters of interest (Angrist *et al* 1996; Imbens and Angrist 1994).

presented in the former section:

$$\mathrm{MDR}_{i,t+1} = \delta\mathrm{Banker}_{i,t} + \gamma_0\mathrm{IAmm}_{i,t} + \gamma_1\mathrm{Banker}_{i,t} \times \mathrm{IAmm}_{i,t} + \boldsymbol{\beta}\mathrm{Controls}_{i,t} + \varepsilon_{i,t}. \tag{5.2}$$

Hypotheses 4 and 5 require a quantile regression approach (Koenker and Basset 1978; Koenker and Machado 1999). We use the method proposed by Cattaneo (2010), which allows us to estimate treatment effects on different quantiles, dealing simultaneously with endogeneity and multidosage treatments.

5.1 Average effect of the presence of banker–directors

We test Hypothesis 1 by running the regression on (5.1). Table 3 presents the results for testing the average impact of the presence of banker–directors on the debt levels of firms.

Please check Table 3 notes have been copyedited appropriately.

The first column presents the results of the ordinary least squares (OLS) regressions; the second column is a panel regression including firm fixed effects; and the third column reports the result incorporating the average treatment effect that takes into account the endogeneity problem. As expected, this latter result reiterates what was found in Byrd and Mizruchi (2005) and Ciamarra (2006): the presence of banker–directors on boards increases, on average, the debt level of firms. Note that, although in the OLS and the panel regression the sign of the average impact of a banker–director is negative, when the endogeneity is taken into account the sign reverts, becoming positive and significant.

5.2 Average effect of the connectedness of banker–directors

We test Hypothesis 2 by running the regression on (5.1) again, this time using the variable “Banker” as different measures of connectedness of the bankers sitting on the board. Table 5 presents the results for testing the average impact of banker–directors’ connectedness on the debt levels of firms.

The first three columns of Table 5 present the results of IV regressions on the connectedness measures, with year fixed effects, whereas the last three columns also incorporate firm fixed effects. As can be easily observed, in both cases the three measures of connectedness (degree, closeness and betweenness) are positive and statistically significant.

In a similar vein to Chuluun *et al* (2010), who find that board connectedness negatively impacts the cost of debt (on average), our results indicate the connectedness of banker–directors positively impacts the debt level (on average). As a robustness test of our results, we compute the connectedness of boards excluding bankers and note

TABLE 3 Presence of banker–director.

	(1)	(2)	(3)
Main			
EBIT/assets	−0.277***	−0.165***	−0.252***
	(−15.32)	(−8.82)	(−14.11)
Log market-to-book	−0.122***	−0.0806***	−0.120***
	(−41.22)	(−16.44)	(−41.18)
Depreciation/assets	−0.432***	−0.346**	−0.464***
	(−6.34)	(−2.52)	(−6.99)
Log assets	0.0193***	0.0335***	0.0186***
	(21.10)	(5.88)	(20.55)
Tangibles assets	0.0851***	0.0777**	0.0868***
	(10.06)	(2.24)	(10.46)
R&D expenses	−0.261***	−0.189**	−0.236***
	(−8.00)	(−2.30)	(−7.36)
R&D not declared	0.0209***	−0.0100	0.0197***
	(6.71)	(−0.82)	(6.44)
SD returns	0.0399***	0.0502*	0.0309**
	(2.65)	(1.86)	(2.08)
Industry median	0.253***	0.168***	0.246***
	(17.51)	(4.60)	(17.46)
Presence	−0.00629**	−0.00253	0.226***
	(−2.16)	(−0.57)	(38.40)
Constant	−0.108***	−0.508***	−0.271***
	(−5.03)	(−4.22)	(−13.02)
Year FE	Yes	Yes	Yes
Firm FE	No	No	Yes
Observations	15 426	15 426	15 426

We test Hypothesis 1 by running the following regression on (5.1), where the dependent variable MDR_{t+1} is the debt level, measured as the ratio of total debt to the sum of market capitalization, and total debt is regressed on EBIT over total assets (EBIT/TA). "Depreciation/assets" is the log of total assets as a measure of size; "tangible assets" is the ratio of fixed to total assets as a measure of asset tangibility; the ratio of R&D expenditure to total assets is a proxy for asset specificity (missing R&D data is set to zero); and the standard deviation (SD) of total returns index is a proxy for firm volatility. We also control for year and industry median effects. "Presence" denotes the presence of a banker–director on the board. The first two columns are estimated with OLS, while the third presents the average treatment effects estimates, where board size is used as our instrument. All variables are winsorized at a 1% level. Robust standard errors. t statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. "FE" denotes fixed effect.

in Table 4 that its impact on debt level is statistically insignificant.[9] In this sense, our

[9] This result holds for all connectedness measures except degree. The reason this variable is less interesting for our purposes is that, while it captures only direct connections between individuals, both the closeness and betweenness variables integrate connectedness information from the whole network. Thus, these last two variables better capture the information flow within the network.

TABLE 4 Connectedness of banker–directors.

	(1)	(2)	(3)
Degree	0.00363	0.00419	0.0140
	(1.76)	(1.79)	(1.70)
Closeness	1.132	2.585	5.300
	(1.66)	(1.45)	(1.17)
Betweenness	36.40	46.88	608.1
	(1.65)	(1.54)	(0.30)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	15 229	15 229	11 079

We test Hypothesis 2 by running the following regression on (5.1), where the dependent variable MDR_{t+1} is the debt level, measured as the ratio of total debt to the sum of market capitalization, and total debt is regressed on different measures of connectedness: degree, closeness and betweenness. In the first column, the value for the firm is given by the value of the most connected banker on the board, where a firm with no banker is given a value of zero. In the second column, the value of board connectedness is measured as the maximum connectedness of the individual director (excluding bankers). In the third column, we repeat the latter variable but exclude firms that have banker–directors. All estimates include the controls used in the previous tables, board size as an instrument, and year and firm fixed effects (FE). We also control for year and industry median effects. All variables are winsorized at a 1% level. Robust standard errors. t statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

results suggest that the findings in Chuluun *et al* (2010) are driven by the presence of bankers on boards. Given the highly skewed distribution of connectedness, it is not enough to consider the mere presence of a banker–director on the board. We show that, on average, the higher the banker's connectedness, the stronger their impact on the debt level of the firm, ceteris paribus.

These effects are also economically significant. If we only consider the data with year effects and no fixed effects, an increase of one standard deviation in any of the connectedness measures (ie, degree, closeness or betweenness) is associated with an increase of 8.13, 9.72 and 11.13 percentage points for the MDR, respectively. By including fixed effects, these numbers change to 6.65, 9.19 and 7.64.

As explained previously, we use board size as our instrument in all regressions. Word added – OK? Unreported first-stage results confirm the positive relation between board size and connectedness of banker–directors. In addition, the coefficients of the control variables are significant and have the expected sign.

5.3 Information asymmetry and banker–directors

Our basic interpretation is that the presence of bankers on the board facilitates communication with the market, and the more connected the banker is, the more effective that communication is in reducing information asymmetry. We thus assume that the impact of bankers in defining the debt level is greater for firms facing higher levels

TABLE 5 Connectedness of banker–directors.

	(1)	(2)	(3)	(4)	(5)	(6)
EBIT/assets	−0.295*** (−13.68)	−0.300*** (−12.72)	−0.297*** (−12.87)	−0.166*** (−9.78)	−0.172*** (−9.30)	−0.171*** (−9.46)
Log market-to-book	−0.123*** (−36.85)	−0.123*** (−35.83)	−0.122*** (−34.12)	−0.0841*** (−21.91)	−0.0815*** (−17.96)	−0.0865*** (−20.96)
Depreciation/assets	−0.544*** (−5.78)	−0.534*** (−5.70)	−0.583*** (−5.07)	−0.414*** (−3.76)	−0.426*** (−3.61)	−0.433*** (−3.75)
Log assets	0.0000313 (0.00)	−0.00367 (−0.30)	−0.00274 (−0.23)	0.0237*** (3.75)	0.0230*** (3.27)	0.0281*** (6.13)
Tangibles assets	0.0999*** (8.42)	0.101*** (7.94)	0.106*** (6.99)	0.0832*** (3.59)	0.0735*** (2.87)	0.0987*** (3.89)
R&D expenses	−0.212*** (−5.00)	−0.198*** (−4.09)	−0.229*** (−5.62)	−0.302*** (−3.30)	−0.340*** (−3.00)	−0.278*** (−3.12)
R&D not declared	0.0257*** (6.09)	0.0287*** (5.23)	0.0232*** (5.85)	−0.0206** (−2.06)	−0.0166* (−1.82)	−0.0246** (−2.03)
SD returns	0.0158 (0.75)	0.0124 (0.54)	0.0137 (0.59)	0.0580*** (2.73)	0.0608*** (2.61)	0.0503** (2.37)
Industry median	0.217*** (8.84)	0.213*** (7.86)	0.210*** (7.16)			
Degree	0.00444* (1.90)			0.00363* (1.76)		
Closeness		1.197* (1.83)			1.132* (1.66)	
Betweenness			53.01* (1.77)			36.40* (1.65)
Constant	0.170 (0.82)	0.236 (0.94)	0.224 (0.89)			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Observations	15 426	15 426	15 426	15 229	15 229	15 229

We test Hypothesis 2 by running the following regression on (5.1), where the dependent variable MDR_{t+1} is the debt level, measured as the ratio of total debt to the sum of market capitalization, and total debt is regressed on EBIT over total assets (EBIT/TA). "Depreciation/assets" is the log of total assets as a measure of size; "tangible assets" is the ratio of fixed to total assets as a measure of asset tangibility; the ratio of R&D expenditure to total assets is a proxy for asset specificity (missing R&D data is set to zero); and the standard deviation (SD) of total returns index is a proxy for firm volatility. Degree, closeness and betweenness denote the respective connectedness measures of a banker–director on the board. All estimates include board size as an instrument and year fixed effects. The last three columns add firm fixed effects. We also control for year and industry median effects. All variables are winsorized at a 1% level. Robust standard errors. t statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

of information asymmetry, as in Hypothesis 3. We test that hypothesis by considering the interaction of an aggregate index of information asymmetry proxies (as in Bharath *et al* (2009), Maskara and Mullineaux (2011) and Gomes and Phillips (2012)) with (i) the presence of bankers on the board and (ii) several different measures of connectedness among these bankers.

From Table 6, we can see that the interaction with both the presence of bankers and with the different connectedness measures of these bankers are positive and significant, thus corroborating the hypothesis as stated.

5.4 Quantile regressions and bankers' presence

We assume that a banker–director in a firm with a relatively low level of debt will perceive the probability of bankruptcy as very low. Alternatively, if the level of debt is relatively high, the probability of bankruptcy is perceived to be high. Thus, the way bankers use their channels of communication to the market in order to reduce information asymmetry will differ according to the debt level of firms. For low debt levels, the presence of bankers on the board will facilitate the increase of debt, whereas for high debt levels the presence of bankers will make it harder to increase the debt level. This is the content of Hypothesis 4.

In order to test this hypothesis, we use quantile regressions, as it allows us to focus on effects on a specific quantile – where low (high) quantiles represent relatively low (high) debt-level firms – instead of on the average effect provided by the previous estimations. In particular, we compute the quantile treatment effects (Cattaneo 2010; Firpo 2007), taking into account the same endogeneity issue referred to in the previous sections. The results in Table 7 represent the average treatment effect of the presence of a banker per quantile. As we can see, for low quantiles including the median (ie, firms with low levels of debt) the effect is positive and statistically significant at a 90% level. For higher quantiles, although this effect is not statistically distinguishable from zero, the impact is negative; this suggests that the presence of bankers on the board tends to reduce firms' debt levels.

These results are coherent with those presented in Byrd and Mizruchi (2005). There, the authors split their sample into high- and low-distressed firms, analyzing for each subgroup its average behavior. Although their results pointed to a similar interpretation, our quantile approach allows us to analyze different impacts throughout the whole distribution of debt level.

5.5 Quantile regressions and bankers' connectedness

Following the argument raised above, we assume that more connected banker–directors are more effective in the dissemination of information, simply because they have more channels of information available to them in order to pass their messages on to the markets. In that sense, we would expect the connectedness of bankers to amplify the effect described above. This has been expressed as Hypothesis 5.

In order to test this hypothesis, we again run a quantile regression to measure the Changes to sentence OK?

TABLE 6 Interaction information opacity proxy and bankers' presence and connectedness.

	(1)	(2)	(3)	(4)	(5)
EBIT/assets	−0.152*** (−7.35)	−0.207*** (−4.69)	−0.171*** (−7.40)	−0.197*** (−5.37)	−0.171*** (−6.92)
Log market-to-book	−0.0924*** (−16.99)	−0.0880*** (−9.96)	−0.0953*** (−18.51)	−0.0910*** (−13.20)	−0.0954*** (−17.69)
Depreciation/assets	−0.352** (−2.06)	−0.541** (−2.40)	−0.522*** (−3.29)	−0.603*** (−2.76)	−0.432*** (−2.73)
Log assets	0.0341*** (5.54)	0.0215* (1.90)	0.0181* (1.90)	0.0140 (0.97)	0.0295*** (5.35)
Tangibles assets	0.0701* (1.77)	0.0444 (0.88)	0.0654** (2.00)	0.0499 (1.11)	0.0703** (2.06)
R&D expenses	−0.163 (−1.64)	−0.470* (−1.87)	−0.320** (−2.44)	−0.485* (−1.95)	−0.239** (−2.21)
R&D not declared	−0.00102 (−0.08)	−0.0369 (−1.36)	−0.0292* (−1.65)	−0.0332 (−1.40)	−0.0255 (−1.61)
SD returns	0.0438** (1.99)	0.0470 (1.21)	0.0428 (1.50)	0.0346 (0.96)	0.0674* (1.92)
Information asymmetry	0.0138*** (3.46)	−0.119* (−1.66)	−0.0682** (−2.18)	−0.0949* (−1.85)	−0.0642* (−1.92)
Presence		−0.732 (−1.26)			
Degree			−0.0149** (−2.40)		
Closeness				−3.108 (−1.52)	
Betweenness					−181.7** (−2.12)
Interaction		0.441* (1.81)	0.00768** (2.56)	2.008** (2.08)	84.44** (2.26)
Constant	−0.529*** (−4.06)				
Years	Yes	Yes	Yes	Yes	Yes
Observations	12 500	11 760	11 760	11 760	11 760

We test Hypothesis 3 by running the following regression on (5.2), where the dependent variable MDR_{t+1} is the debt level, measured as the ratio of total debt to the sum of market capitalization, and total debt is regressed on EBIT over total assets (EBIT/TA). "Depreciation/assets" is the log of total assets as a measure of size; "tangible assets" is the ratio of fixed to total assets as a measure of asset tangibility; the ratio of R&D expenditure to total assets is a proxy for asset specificity (missing R&D data is set to zero); and the standard deviation of total returns index is a proxy for firm volatility. "Information asymmetry" is a proxy for information asymmetry based on Maskara and Mullineaux (2011). Degree, closeness and betweenness denote the respective connectedness measures of a banker–director on the board. All estimates include board size as an instrument and year fixed effects. We also control for year and industry median effects. All variables are winsorized at a 1% level. Robust standard errors. t statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 7 Quantile treatment effects: effect of the presence of banker–director (1) versus no banker (0) on the debt level of firms.

	Coefficient	Standard error	90% confidence interval	
Q10				
(1 versus 0)	0.0043846	0.0022729	0.000646	0.0081232
Q25				
(1 versus 0)	0.0156265	0.0041548	0.0087925	0.0224606
Q50				
(1 versus 0)	0.01082	0.0045298	0.0033692	0.0182708
Q75				
(1 versus 0)	−0.0043977	0.0069998	−0.0159113	0.0071159
Q90				
(1 versus 0)	−0.0034469	0.0110712	−0.0216574	0.0147636

We test Hypothesis 4 by running a quantile treatment effects regression on (5.1) as in Cattaneo (2010). The dependent variable MDR_{t+1} is the debt level, measured as the ratio of total debt to the sum of market capitalization, and total debt is regressed on EBIT over total assets (EBIT/TA). "Depreciation/assets" is the log of total assets as a measure of size; "tangible assets" is the ratio of fixed to total assets as a measure of asset tangibility; the ratio of R&D expenditure to total assets is a proxy for asset specificity (missing R&D data is set to zero); and the standard deviation of total returns index is a proxy for firm volatility. All estimates include board size as an instrument and year fixed effects. We also control for year and industry median effects. All variables are winsorized at 1% level. Robust standard errors.

impact of highly connected bankers against that of not-so-well-connected bankers. We do so by estimating a multitreatment effect quantile regression with two levels of treatment. We split the bankers in two groups: group 1, composed of weakly connected bankers (with respect to the median degree); and group 2, composed of highly connected bankers. The results are shown in Table 8. These indicate that for low-levered firms the impact of well-connected bankers is approximately twice that of low-connected bankers. In the lowest quantile, the presence of a highly connected banker increases debt by 1.5%, whereas the presence of a low-connected banker increases debt by only 0.6%. In the next quantile, the ratio is 1.7% to 0.9%. In the median, the ratio drops from 1.0% to 0.5%, but these numbers are no longer Change OK? statistically significant, as is the case for higher quantiles (ie, for firms with relatively high levels of debt). Interestingly, although not significant, almost all the numbers for higher quantiles are negative; this suggests that the presence of highly connected bankers on the board tends to reduce firms' debt levels.[10]

[10] We repeated the analysis for the different measures of connectedness and the results are qualitatively equivalent.

TABLE 8 Quantile multivalued treatment effects: effect of the connectedness of a banker–director on the debt level of firms.

	Coefficient	Standard error	90% confidence interval	
Q15				
(1 versus 0)	0.0062865	0.0026585	0.0019135	0.0106594
(2 versus 0)	0.0146297	0.0074593	0.0023603	0.0268991
Q25				
(1 versus 0)	0.0093877	0.0042583	0.0023833	0.016392
(2 versus 0)	0.016726	0.0060698	0.0067421	0.0267099
Q50				
(1 versus 0)	0.0045433	0.0047509	−0.0032712	0.0123579
(2 versus 0)	0.0103283	0.0068571	−0.0009506	0.0216073
Q75				
(1 versus 0)	−0.0032754	0.0077939	−0.0160953	0.0095445
(2 versus 0)	−0.0047175	0.0092802	−0.0199821	0.0105471
Q90				
(1 versus 0)	0.0004884	0.0158953	−0.0256571	0.0266339
(2 versus 0)	−0.0047172	0.0199636	−0.0375544	0.0281201

Weakly connected banker–directors (1) versus no bankers (0); highly connected banker–directors (2) versus no bankers (0). We test Hypothesis 5 by running a quantile treatment effects regression on (5.1), as in Cattaneo (2010). The dependent variable MDR_{t+1} is the debt level, measured as the ratio of total debt to the sum of market capitalization, and total debt is regressed on EBIT over total assets (EBIT/TA). "Depreciation/assets" is the log of total assets as a measure of size; "tangible assets" is the ratio of fixed to total assets as a measure of asset tangibility; the ratio of R&D expenditure to total assets is a proxy for asset specificity (missing R&D data is set to zero); and the standard deviation of total returns index is a proxy for firm volatility. All estimates include board size as an instrument and year fixed effects. We also control for year and industry median effects. All variables are winsorized at a 1% level. Robust standard errors.

6 CONCLUSION

There are two different classes of well-known results regarding the role of boards in the debt capacity of firms. The first result is that the presence of bankers help firms to increase their debt levels. The second is that the leverage effect becomes more effective as boards become more connected. We contribute to the first result by showing that the presence of bankers has a greater impact the more connected those bankers are. We contribute to the second result by showing that the impact of boards' connectedness is driven by bankers' connectedness. Finally, we show that both effects are only relevant for firms with relatively low debt levels.

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Our findings suggest that firms can use connected bankers on their boards in order to reduce information asymmetry. The presence of connected bankers is shown to increase on average the debt level of the US firms included in our sample. After correcting for endogeneity and controlling for other firms' characteristics, this effect is shown to be statistically significant. Moreover, this result is stronger the greater the connectedness of the banker in the directorship network. Our results seem to be robust with respect to the various measures of connectedness used throughout the paper.

In particular, the last part of these results suggests that banker–directors play an essential role in the market dissemination of information. The more connected a banker is in the network, the more channels of communication they can use to transmit information, reducing information asymmetries between the firm and the credit market and, consequently, allowing for higher levels of debt. This effect on the debt level is reduced for less opaque firms, bolstering our interpretation of the role of banker–directors as information asymmetry reduction mechanisms.

We provide evidence that both the presence and the connectedness of bankers increase the debt of low-leverage firms, while decreasing the debt of high-leverage firms. These effects are shown to be statistically significant for the former but not for the latter. Once again, this justifies the mechanism of information asymmetry reduction described above.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper. The views expressed herein are solely those of the author and do not represent the views of his employer, Moody's Analytics, its parent company (Moody's Corporation), or its affiliates.

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