Rating friends: the effect of personal connections on credit ratings

Rating friends: the effect of personal connections on credit ratings

Seyed Hossein Khatami
Manchester Business School
University of Manchester
Crawford House, Booth Street East
Manchester, M13 9PL, United Kingdom
e-mail: seyedhossein.khatami@mbs.ac.uk

Maria-Teresa Marchica
Manchester Business School
University of Manchester
Crawford House, Booth Street East
Manchester, M13 9PL, United Kingdom
e-mail: maria.marchica@mbs.ac.uk

Roberto Mura*
Manchester Business School
University of Manchester
Crawford House, Booth Street East
Manchester, M13 9PL, United Kingdom
e-mail: roberto.mura@mbs.ac.uk

First Version January1st 2013

Current Version: August 9th 2013

Acknowledgments: We thank Bernard Black, Marie Dutordoir, Mara Faccio, Andrea Fracasso, Massimo Guidolin, Evgeny Lyandres, Roni Michaely, Stefano Puddu, Konstantinos Stathopoulos and Norman Strong for helpful comments. We also gratefully acknowledge research funding from the European Community's Seventh Framework Program FP7-PEOPLE-ITN-2008 under grant agreement number PITN-GA-2009-237984. The usual disclaimers apply.

* Corresponding author.

Rating friends: the effect of personal connections on credit Ratings

Abstract

Using a large sample of US public debt issues we show that personal connections between directors of issuing companies and rating agencies result in higher credit ratings. We estimate the average effect to be between half a notch and one full notch. We also follow companies after their public debt issues. Our tests indicate that the higher rating connected companies receive is not due to a favorable treatment by the rating agency. Rather, our evidence indicates that personal connections act as a mechanism to reduce asymmetric information between the rating agency and the issuer.

Key words: executive and director networks, credit rating, asymmetric information

JEL Classification: D82, G24

1. Introduction

Our paper aims at answering two important questions: 1) are credit ratings affected by the presence of personal connections between directors of issuing companies and the rating agencies? and, 2) if so, do these connections exacerbate the conflict of interests or do they act as a better information channel between issuers and rating agencies?

Credit rating agencies (CRAs) play a crucial role in financial markets. The Credit Rating Agency Reform Act of 2006 explicitly states that "Congress finds that credit rating agencies are of national importance …". The recent lawsuit by the US government against Standard and Poor's offers further testimony to the increasingly pivotal role CRAs play in financial markets.[1] Yet, despite their importance, little is known about how CRAs set their ratings. Our results therefore have potential important implications, as they shed more light on the factors that influence credit ratings.

CRAs operate under a constant dilemma. On the one hand, they are expected to provide impartial independent ratings. In fact, as noted by the Securities and Exchange Commission (SEC) in 2003, CRAs strongly take the position that "[...] their reputation for issuing objective and credible ratings is of paramount importance [...]". Section 2 of Moody's Code of Professional Conduct assures investors of the "Independence and Avoidance and/or Management of Conflicts of Interest". The existence of personal connections with issuers should therefore play no role in determining the ratings.

On the other hand, personal connections may hinder the impartiality of CRAs and ultimately affect the quality of their ratings. Specifically, this could affect ratings in two ways. Firstly, the need of CRAs to maintain market share may create an incentive

[1] U.S. sues S&P over ratings, Wall Street Journal, 5 February 2013; U.S., S&P settle in for bitter combat, Wall Street Journal, 6 February 2013.

for them to cater to the interests of the issuers. For instance, Bolton, Freixas, and Shapiro (2012) show that increased competition among CRAs increases the scope and incentive for companies to shop around for the best ratings. In an internal presentation "Ratings Erosion by Persuasion" to the board of directors, Mr Fons (ex Managing Director of Moody's) stated: "Analysts and managing directors are continually pitched by bankers, issuers, investors, all with reasonable arguments whose use can color credit judgment [...]".[2] Moreover, managers are known to get involved in the rating process, which can further undermine the independence of the analyst team. In his comment on the SEC proposed rules for Nationally Recognized Statistical Rating Organizations (2011), William Harrington, a former senior president at Moody's, declared how the organization's senior management interferes with analysts' independent assessments to "form desired public opinion". The presence of personal connections could therefore exacerbate the conflict of interests between the issuing firm and the CRA, which in turn could result in higher and less reliable ratings.

An alternative is that personal connections work like an informal information channel. Prior to the Dodd-Frank Wall Street Reform and Consumer Protection Act (2010), CRAs did not have to abide by Regulation Fair Disclosure (Reg FD), essentially enabling them to legally make use of private information [Jorion, Liu, and Shi, 2005; Butler and Cornaggia, 2012]. Personal connections could thus provide CRAs with access to 'soft information' that could reduce asymmetric information between the two parties. Further, as noted by Beaver, Shakespeare, and Soliman (2006), CRAs have an asymmetric loss function, that is, the costs from losses due to overvaluation are weighted more than the forgone gains from an undervaluation. This could provide the

[2] Credit Rating Agencies and the Financial Crisis, House Hearing, 110 Congress 2008.

incentive for CRAs to issue more conservative ratings to those firms with more asymmetric information. Conversely, everything else being equal, rating agencies might assign higher credit ratings to connected firms that can provide CRAs with soft information that reduces the level of asymmetric information.

To test our hypothesis, we examine a sample of 1,719 non-convertible public debt issues by 327 US industrial companies from 1994 to 2011. BoardEx is the source of data for connections among directors of a very large sample of US companies. To use a more precise measure of social ties, we collect information on connections between top executives and directors of the issuing companies and one of the top two CRAs in the US markets, Moody's. Moody's is a standalone company so we are able to directly identify all its directors. Further, it has full coverage in BoardEx over the entire sample period.

The other top CRA in the US market, Standard and Poor's, is a division of McGraw-Hill. From the annual reports we are able to identify only McGraw-Hill’s principal operations executives and, in particular, only the President of Standard and Poor's division. Further, only two of four identified presidents are available in BoardEx in the most recent years of our sample period. Consequently, our analysis does not consider connections between issuing firms and Standard and Poor's.

Our ordered-probit results indicate that the existence of personal connections between the rating agency and the issuing company has indeed a significant impact on the credit ratings assigned to the company's issues. In particular, we find that being personally connected increases the probability of having a better rating. This result is robust to alternative definitions of connections.

A potential issue in the interpretation of our results, as in any empirical study, is the issue of endogeneity. One potential cause of endogeneity in our study is the presence of cross-causality. This would happen, for instance, if the personal link between directors of the issuing firm and the CRA takes place after the rating. To rule out this possibility, we only include connections that are initiated before the security issue. Further, when we separate connections initiated in the past and lasting to the time of the issue (current connections) from connections initiated and terminated in the past (past connections), results are largely unchanged.

A further source of endogeneity could be that companies able to attract better-connected managers are systematically different from those that cannot. If not properly controlled for, this factor could lead to an omitted variable bias. To address this potential concern, we take several steps. First, across all tests we include a proxy for the total connectivity of the firm. This represents the total number of connections that the directors of a certain firm have at any point in time with any other firm in the BoardEx universe. Also, we employ a propensity score matching procedure to identify identical subsamples of issues by connected and non-connected firms, based on various sets of observable company and issue characteristics. Our results still show that issues by connected firms obtain higher credit ratings than issues by (virtually indistinguishable) matched non-connected firms.

Furthermore, to stress-test the causal effect of the treatment, we perform a number of permutation tests. In the first instance, we run placebo tests to try to investigate whether firm-specific characteristics are driving the results. The treated/untreated (connected/unconnected) status is reassigned randomly across issues of treated firms. The idea is that randomly shuffling the treatment should destroy any association between the connection status and credit ratings. For robustness purposes, for each of our connection variables we implement a full Monte Carlo permutation test with 100,000 repetitions of this random shuffle. The distribution of the coefficients obtained from this repeated random shuffling approximates the distribution under the null hypothesis that there is no difference between connected and non-connected issuers. If the random coefficients are larger than the coefficients observed from our previous regressions, then we would not be able to reject the null hypothesis. Instead, our tests show that the coefficient on the randomly shuffled connection dummy exceeds the observed coefficient only in 170 cases out of 100,000 (0.17%). As a final attempt to confute our results, we perform a parallel set of permutation tests in which the treatment is randomly reassigned to issues of all firms. In this case we fail to find a single instance where the randomly shuffled coefficient is higher than the estimated parameter from the true connection status. Taken all together, these falsification tests strongly indicate that spurious correlation does not drive our previous results and, more importantly, that personal connections do indeed play an important role in determining a CRA rating.

Having established that there is a significant relation between connections and ratings, we investigate whether the (higher) credit ratings to connected companies represent a favorable treatment from the issuing company to the CRA or, rather, reflect a better flow of information. To discriminate between these two alternatives we study default rates and bond yields. First, we isolate identically rated bond issues by connected and non-connected companies. On this subset, we perform a stringent matching exercise in which we match companies based on several firm and issue characteristics and then follow these through time. The underpinning idea behind this test is that if connected firms receive ratings that are higher than they deserve (due to favorable treatment), over time these firms should exhibit higher default rates than a matched sample of non-connected firms whose rating is not affected by favoritism. The same reasoning applies to yields as we would expect the prices of these bonds to fall in time as the market receives information, through trading, on these initially ‘overrated’ bonds. On the other hand, if the higher rating is the result of reduced asymmetric information between the CRA and the firm due to personal connections, then we would not expect connected firms to fare any worse in the bond market. Results from these further tests consistently show that, at the time of the issue, connected firms have equal estimated default probability (we use Altman's Z-Score) and equal bond yields to those of the non-connected companies with similar ratings in the matched sample. However, five (or ten) years after the public debt issues, we observe that connected firms display lower default rates. Further, three years after the issue connected firms have bond yields that are comparable to those of the non-connected matching sample. These tests therefore do not support the view that CRAs treat connected companies favorably.

Our results contribute to the literature in several ways. First, we contribute to the growing body of studies that show the importance of executive and directors' networks on corporate policies and decisions. Cohen, Frazzini, and Malloy (2008) study the role of personal connections between mutual fund managers and corporate board members. They report compelling evidence that these personal connections act as an information channel between firms and investors. Engelberg, Gao, and Parson's (2012) tests strongly indicate that connected borrowers obtain loans at significantly lower interest rates when their managers have personal connections with managers of the lender. Fracassi and Tate (2012) show that the existence of personal connections between CEOs and board members significantly weakens corporate governance and negatively affects firm value.

Fracassi (2012) reports that companies whose directors share a higher degree of personal connections tend to exhibit a greater similarity in their investment decisions. We show that personal connections between executives and directors of issuing firms and CRAs result in higher ratings. This novel evidence is robust to a number of alternative tests that control for potential endogeneity and spurious correlation that could hamper the interpretation of our results.

Our paper also contributes to the growing literature that studies the determinants of the credit rating process. On one hand, Benmelech and Dlugosz (2009) refer to this process as the "alchemy" of credit ratings. Griffin and Tang (2012) provide evidence that during the financial crisis CRAs used a high degree of subjectivity in assigning ratings to collateralized debt obligations (CDOs). Mählmann (2011) shows that the longer the relationship between the issuing firm and the rating agency, the higher the rating. Mählmann appears to rule out the hypothesis that a higher rating reflects better credit quality. Rather, the longer the relationship the stronger the incentives for the CRA to cater to client interest, leading to less accurate ratings. The results of Mathis, McAndrews, and Rochet (2009) suggest that reputation concerns are not sufficient to discipline CRAs, in particular when they rate complex products such as mortgage-backed securities and CDOs.

On the other hand, Covitz and Harrison (2003) look at the anticipation of credit rating downgrades by the bond market and find that rating changes are not driven by a favorable treatment of issuing companies; rather, they are consistent with CRAs protecting their own reputation as delegated monitors, in particular in those instances that have generated substantial publicity. Further, Gan (2004) and Butler and Cornaggia (2012) show that rating fees measure the effort CRAs exert to acquire soft information from the issuing companies and efficiently incorporate it in their (solicited) ratings. Kraft (2012) provides evidence that CRAs' adjustments for off-balance sheet debt capture relevant aspects of the credit risk of the issuing company, consistent with the argument that CRAs are indeed efficient processors of accounting information.

Our results also add to the intense debate of the last decade over the role of CRAs as efficient delegated monitors and information providers. Our study does suggest that personal connections between issuing firms and CRAs play a role in shaping their ratings. However, our tests also indicate that these connections appear to be used as a vehicle for a better flow of information and we find no evidence consistent with the presence of any kind of favorable treatment for connected issuers.

The rest of this paper is structured as follows. In section 2, we discuss some of the key procedures in extracting the required information from various datasets and describe our sample. In section 3 we present and discuss the paper's analyses and results in detail, and explain the methodologies and statistical tools we employed. In Section 4 we summarize our main findings and conclusions.

2. Data and sample description

2.1. Personal connections

We gather information on personal connections from BoardEx which provides biographical information on board members and senior executives around the world. We focus on connections between board members and senior executives of Moody's and those of public debt issuers. Directors and top executives of CRAs sit on the ratings committees. For instance, in their description of the rating process, Moody's states: "At minimum, the committee includes a managing director or other designated individual and the lead analyst."[3] Further, in his comment on the SEC proposed rules for Nationally Recognized Statistical Rating Organizations (2011), the former senior president William Harrington at Moody's, declared: "From the Managing Directors of the Derivatives Group upward to the CEO of Moody’s Corporation Ray McDaniel and for every intervening management level, Moody’s management undercut analyst attempts to produce informed Moody’s opinions regarding CDOs.” Therefore we expect the personal connection between directors and top executives of the CRA and those of US issuing companies to be relevant in the rating process.

BoardEx starts its coverage in 2000. However, since it tracks the individuals' employment histories back to earlier years, we can use this information to identify connections between senior managers and directors of Moody’s and several of the issuing firms before 2000. We include this information in our analysis. Results are qualitatively unchanged when we use a sub-sample starting from 2000 only.

To build our main variable, *Connection Dummy*, we focus on information relating to the personal connections between directors and top executives of the CRA and those of US issuing companies. We identify personal connections through time, by defining *Current Connections* and *Past Connections*. We require all connections to have been originated before the issue date. This allows us to make more robust causal inferences about the effect of connections on ratings. In contrast to *Current Connections*, we require *Past Connections* to terminate before the issue dates.

We also pinpoint different origins of the personal connections: 1) *Professional Connections* are formed when two people have previously worked (or are still working) together in an organization; 2) *Educational Connections* originate when two people

[3] http://www.moodys.com/sites/products/ProductAttachments/Moody%27s%20Rating%20System.pdf

have attended the same education institution (e.g., University) at the same time;[4] 3) *Army Connections* refer to cases where two people have served in the army together; 4) *Social Connections* are identified when two people know each other through their activities in a social organization such as a charity or a volunteer group.[5] Since in our sample there are a very few instances of *Social Connections* with complete start and end date information, we exclude them from the analysis [similar to Engelberg, Gao, and Parsons, 2012]. In our analysis we set the *Connection Dummy* equal to one if the issuing company has at least one individual (either director or top executive) personally connected to another individual (either director or top executive) in the CRA at the same time of the debt issue. When we define the *Connection Dummy* we take into account both current and past connections as described above. For instance, for a company that issues a bond in 1999, an educational connection between a top executive of the company and a director of the rating agency dating back to 1980s is categorized as past; whereas the connection between two top executives sitting together on the board of a third company from 1994 to 2001 is considered as current.

As an alternative, we also use the natural logarithm of the total number of connections between issuing firms and Moody's. Further, we construct a measure of the total connectivity of the issuing company as the total number of connections between the individuals (managers or directors) of the issuing firm and all other individuals covered in BoardEx (*Ln 1+No. of Connected Individuals*). This captures the overall degree of connectivity of the issuing firm.

---

[4] Educational relationships are of two kinds: those between two classmates, and those between a professor and a student. We consider them together. Results when we distinguish between these two types are not qualitatively different from those included in this paper.

[5] The biographical information included in BoardEx allows us, for instance, to identify whether a non-executive director of an issuing company completed an MBA with one of the top executives of Moody's; or if the CEO of an issuing company and the president of Moody's have served on the board of a third company together for several years.

2.2. Debt issues

We use the Securities Data Company (SDC) Platinum Database to gather information on securities issuances, including credit rating, issue date, maturity, and seniority, among others. SDC also provides information on the S-3 form filing date and SEC filing number that we use to identify the solicited ratings. [6]

We focus on public non-convertible debt issues, as their characteristics differ significantly from convertible bonds and other types of debt obligations. Financial firms (SIC 6000-6999) and regulated utility companies (SIC 4909-4939) are also excluded from the analysis as these firms are subject to different rating standards. Our tests include only rated issues. We convert the ratings into numerical values in descending order in line with the literature, with number 17 representing the highest rating and number 1 representing the lowest rating category.

Data on solicitation come from the SEC's EDGAR (Electronic Data Gathering, Analysis and Retrieval) database. Prior to September 2007 rating agencies were not required to report whether (domestic) ratings were solicited or not. Therefore we use the registration statements available online. Many of these registration statements are filed using the S-3 form, which contains information on the rating agency fees. We follow the procedure of several previous studies including Butler and Cornaggia (2012) and Gan (2004), to distinguish solicited from unsolicited ratings. Companies report estimated rating agency fees based on the total issue amount and the number of paid (solicited) ratings. We define an issue as “unsolicited” if the rating agency fees are zero or not reported and as “solicited” if the estimated rating agency fees are sufficient to cover the fees for all the agencies involved.

[6] A comparative advantage of using SDC as a source of rating information is that it is the only dataset (to the best of our knowledge) that also provides information on S-3 forms.

We use Compustat and Center for Research in Security Prices (CRSP) to collect financial and accounting variables. Information about defaults is extracted from Compustat Ratings, where 'D' and 'SD' represent default and selective default events on obligations respectively. Finally, we obtain bond yields from TRACE (Trade Reporting and Compliance Engine). We collect data starting from 2003, as TRACE's coverage is very limited before 2003.

We begin by collecting information on 58,162 straight bond issues (from 8,045 companies) from 1994 to 2011, using S-3 forms and SEC file numbers from SDC. We obtain the required information from Compustat and CRSP for 1,200 of these companies (with 14,412 issues). Of this sample, we are able to identify from the S-3 forms 9,593 issues (from 890 companies) with information available on solicitation. Excluding financial and utility companies from the sample leaves 563 companies issuing 4,304 bonds. After matching these data with BoardEx, we end up with a final sample of 327 companies with 1,719 issues with information available on connections. This sample size is comparable to those in the recent credit rating literature. For instance, Poon (2003) reports 595 issues by 265 firms, Gan (2004) studies 1,410 issues by 303 firms, and Butler and Cornaggia (2012) study 360 issues by 153 firms.

2.3. Univariate analysis

In Table 1 we present descriptive statistics of the connection variables. The first set of variables are dummies that take a value of one if there exists a connection of a specific kind between the rating agency and the issuer, and zero otherwise; the second set of variables represents the number of existing connections. Among connected firms, *Past Connections* are more common than *Current Connections* (about 77% of connections come from a past link between directors of the issuing firm and Moody's). As expected, *Professional Connections* are the most common source of connections, followed by *Educational Connections*. Unreported tests show that connected companies do not appear to be clustered into specific industries.

Please insert Table 1 here

In Table 2 we provide summary statistics of issue (Panel A) and firm characteristics (Panel B) for the full sample and also for connected and non-connected firms separately. Average rating is about 10 (this corresponds to a Baa1 in Moody's scale), which is in line with previous studies. For instance, Hovakimian, Kayhan, and Titman (2012) report an average rating of 10. Panel A reveals that connected issuers obtain significantly higher credit ratings. We find no sizeable difference in solicitation of ratings between connected and non-connected issuers. Both groups appear to pay for their ratings about 60% of the time. The percentage of defaults is also significantly lower in the connected group. Non-connected issuers (Panel B) have higher book-to-market ratios and operating margins, but are generally smaller and riskier (e.g. higher interest coverage ratio) and have lower profitability than connected issuers. Also, connected issuers generally have more connections to other individuals or organizations than do non-connected issuers.

Please insert Table 2 here

Last, in Figure 1 we plot the average ratings over time. The plot shows how there seems to be a persistent difference in average ratings between connected and non-connected issuers in each year of our sample period. We also observe a general decline in the quality of credit ratings. Similar figures are reported by Hovakimian, Kayhan, and Titman (2012) for Standard and Poor's.[7] We complement their evidence by showing that the decrease in ratings is particularly severe in the post financial crisis period. More importantly, while the decreasing trend applies to all firms, non-connected issuers appear to be much more severely hit than connected ones.

3. Personal connections and credit ratings: regression results

In line with the literature in this field, we employ ordered-probit models to estimate the determinants of credit ratings. The ratings are ordered partitions of an unobservable continuous variable, which is a linear function of the explanatory variables. The model can be expressed as follows:

$$R_i^* = \beta Connection_i + \sum_{k=1}^{K} \gamma_k X_i + Industry\ FE + Year\ FE + \varepsilon_i$$

$$R_i = \begin{cases} 17 & if\ R_i^* \in [\mu_{16}, \infty), \\ 16 & if\ R_i^* \in [\mu_{15}, \mu_{16}), \\ & \dots\dots\dots\dots \\ 2 & if\ R_i^* \in [\ \mu_1, \mu_2), \\ 1 & if\ R_i^* \in (-\infty,, \mu_1), \end{cases} \qquad (1)$$

where R_i^* is the unobserved linking variable; $Connection_i$ is the variable of interest, which is a dummy equal to one if the debt issue *i* is of a company with at least one director personally connected with a director of the credit agency and zero otherwise;

[7] Untabulated tests report the same results when we look at average ratings by Standard and Poor's rather than Moody's.

$\sum_{k=1}^{K} \gamma_k X_{ki}$ is a vector of both issue and company characteristics; ε_i is a mean-zero normal random error representing the unobservable factors affecting the rating; $\mu_1 to\ \mu_{16}$ are the threshold parameters and R_i is the observed rating category assigned to issue i. To reduce the possibility of spurious correlation, in our regression tests we include several issue and firm characteristics. In addition, we control for the solicitation status of the issues, and the overall connectivity of the firm. Also included are dummy variables indicating the year of the issue and the industry the company operates in, to control for systematic differences in credit rating standards across years and industries.

The estimated coefficients from the ordered-probit tests are presented in Table 3 (Panels A and B). The results across all specifications suggest that personal connections do indeed play an important role in determining the credit ratings: connected issues are more likely to obtain higher credit ratings than non-connected ones.

Please insert Table 3 here

As we discussed above, one possible concern is that the CRA–issuer connection effect might be affected by the overall connectivity of the firm. In other words, the rating agency might assign higher ratings to issues of better-connected companies as these companies could exploit their connections to other companies (e.g., bank officials) in turbulent times, to avoid default. For instance, Engelberg, Gao, and Parsons (2012) find that borrowers whose directors are connected to directors of the lender obtain loans at lower interest rates. To alleviate this concern, we always include a proxy for the overall connectivity of the issuing firm. (Controlling for this factor does not seem to affect our main results.) The coefficient of *Connection Dummy* in model I is positive and statistically significant but we fail to detect a statistically significant effect of the overall connectivity of the firm on its credit rating across all models. In models II and III we split current and past connections while in model IV we split connections according to their origination (professional, educational or army). The results show that both current and past connections play a significant role in determining the credit ratings, although past connections show a slightly stronger effect.[8] With regards to the origination of the connection, all types of connection (professional, education and army) have a positive effect on ratings.

In Table 3 Panel B we replicate the above tests on the natural logarithm of the total number of existing connections (plus one) rather than the connection dummies (*Ln 1+ Connections)*. Results are similar to those in Panel A, further corroborating the strong role that CRA–issuer connections play on credit ratings. For instance, model V shows a positive and statistically significant association between the proxy for the total number of connections (*Ln 1+ Connections)* and credit ratings. Similar results emerge from models VI and VII where we split current and past connections. Model VIII also largely mirrors model IV Panel A, although educational connections are not significant.

3.1. Endogeneity concerns

As with any empirical study in our field, a caveat in the interpretation of our results is the issue of endogeneity. We believe this problem is less of a concern in our exercise for two reasons. First, similar to Engelberg, Gao, and Parsons (2012), our connections pre-date the debt issues. Second, for unsolicited ratings it is the CRA's

[8] In our tests, we also follow Engelberg Gao and Parsons. (2012) in limiting connections to those initiated two (five) years prior to the event. Results are very similar to those reported here.

decision to rate firms, not a firm's decision. When the company solicits the rating, we control for this in our tests. This leaves little room for self-selection problems. Furthermore, our descriptive statistics show virtually no difference in solicitation of ratings between the two groups.

Nonetheless, a potential reason for concern could be that companies with connected managers are systematically different from companies with non-connected managers. Our descriptive statistics in Table 1 partly corroborate this view although we do control for all these issue and firm characteristics in all models. Nonetheless, we use several tests to minimize this potential concern.

3.1.1. Propensity score matching

We first employ a propensity score matching procedure, as in Rosenbaum and Rubin (1983), to identify a control sample of issues by non-connected firms that exhibit no observable differences in characteristics relative to issues by firms run by connected managers. Thus, the control and treated firms are restricted to a set of peers that are virtually indistinguishable except for one key characteristic: the connection between managers and directors of the issuing firm and Moody's.[9] This procedure provides a more reliable test of the impact of the treatment (i.e. the connection to the CRA) on the outcome variable, credit ratings.

In Table 4 we present the propensity score matching results.[10] To ensure the issues in the control sample are sufficiently similar to the issues with connected

[9] See Rosenbaum and Rubin (1985), Rubin and Thomas (1997) for further discussion of propensity score matching.

[10] The propensity score matching method is implemented using the PSMATCH2 package in STATA [Leuven and Sianesi, 2003]. In unreported tests we replicate the matching analysis using the nearest neighbour matching method, by Abadie, Drukker, Leber Herr, and Imbens (2009). Results are very similar irrespective of which matching procedure is used.

directors, we require that the maximum difference between the propensity score of the treated and control issues (*caliper*) does not exceed 1% in absolute value. The reported *p*-value of the difference in mean *P*-Scores ranges between 0.796 and 0.957, confirming that the two sets of issues are statistically indistinguishable.

Table 4 Panel A shows the results for matching connected and non-connected issues based on all characteristics as in the previous regression tests. Connected issues obtain significantly higher credit ratings (Difference in Means) than do matched non-connected issues. The difference is about half a notch (0.53). In line with our ordered-probit results, both current and past connections have significant impacts on credit rating, with current connections showing a much stronger effect. The difference in credit rating, on average, varies between 0.52 (*Past Connections*) to 1.27 notches (*Current Connections*), and is statistically significant in all cases.[11]

Please insert Table 4 here

3.1.2. Falsification tests

To ensure that our results do not capture spurious correlation and to further strengthen our causal interpretation of the treatment, we run two different types of falsification tests. One first concern with our previous tests could be that the results are driven by an unobservable firm-specific characteristic. For instance, there could be an unobservable characteristic that drives both the ratings and the ability of an issuer to attract connected managers. To try to confute this alternative interpretation of our results, we perform permutation tests for all the treatment (connection) variables. We

[11] We also run ordered-probit regressions on the matched samples (here and in later tests) and observe qualitatively similar results for the effect of personal connections on credit ratings.

randomly shuffle the treatment variable (connection status) across the subsample of firms that have at least one treated issue. If our results are mainly driven by firm-specific unobservable characteristics, then we should still find a positive and significant association between this placebo treatment and ratings. On the other hand, if the higher rating is due to the presence of a real connection, then the reshuffling effectively discards any possible association between the connection status and the credit rating. The distribution of the coefficients obtained from this repeated random shuffling approximates the distribution under the null hypothesis that there is no difference between connected and non-connected issuers, or, in other words, there is no link between treatment (connection) and outcome (credit rating). Then we would expect to find no association between this placebo treatment and credit ratings.

To draw statistically robust conclusions on this type of analysis, we perform a full Monte Carlo permutation test. That is, we perform 100,000 repetitions of the above exercise where the connection status is randomly reassigned across issues of connected firms. We then compare the coefficient from the true connection variable with this distribution of randomly shuffled coefficients obtained under the null hypothesis. If the coefficients from the shuffled variable are larger than the estimated coefficient from our previous regressions, then we would not be able to reject the null hypothesis. We report the results from these tests in Table 5, panel A. The true coefficients in the table refer to the estimated coefficient from Table 3, models I–VIII. For instance, looking at the *Connection Dummy*, we find no instance, out of 100,000 draws, where the estimated placebo coefficient is larger than the estimated coefficient from the treatment. This corresponds to an implied *p*-value of 0.000, which allows us to comfortably reject the null hypothesis of no association between personal connection and credit rating. When we run the same test on the *Current Connection Dummy*, we find only 170 instances (out of 100,000) where the placebo effect is estimated to be stronger than the true treatment effect. Again, we can comfortably reject the null, this time with an implied *p*-value of 0.001. Figures for the *Past Connection Dummy* are similar. When we turn to the tests where we use the *Ln.(1+No. of Connections)*, we find no cases where the placebo effect dominates the treatment effect.

Please insert Table 5 here

We perform an additional falsification test (Table 5 Panel B) in which we allow the treatment to be randomly reassigned to any issue of any company in the dataset. In this way we can more broadly test whether our results are driven by some sort of spurious correlation. Similarly to the previous exercise, we find no case where the effect of the placebo appears to be stronger than the effect of the treatment, except with the *Current Connection Dummy* (110 cases; implied *p*-value 0.001). Altogether the falsification tests indicate that the (causal) effect we find between the existence of personal connections and credit ratings is not spurious and is not driven by other unobservable firm characteristics, since randomly assigning connections to the same set of companies does not yield significant results. This further corroborates our previous evidence that personal connections between CRA directors and executives and issuing company directors and executives is an important determinant of credit rating.

3.2. Results discussion

Credibility is a credit rating agency's most valuable asset, and it is hard to believe that credit rating agencies are willing to put this at risk. During an investor conference, Raymond McDaniel, CEO of Moody's, was reported as stating: "We are in a business where reputational capital is more important" (Pittman, 2008). Further, the reputation argument played a central role in Standard and Poor’s President Deven Sharma’s response during the Congressional hearing in 2008 after the SEC investigations into the subprime scandal. Therefore, we take a number of steps to investigate whether higher ratings are the result of a better flow of information from the issuing company and the CRA or the result of more favorable treatment of connected firms.

First, we study post-issue default rates. We match issues on the basis of credit rating, Z-Scores, overall connectivity, solicitation, maturity, issue amount, issue years and industry using the propensity score technique. The basic intuition is that if the connected issue had received an "artificially high" rating due to favorable treatment by Moody’s, this would be more likely to default than an identical non-connected issue that did not receive any favorable treatment (and which was rated equally). If, however, the higher rating is driven by availability of and reliance on soft information, the connected issues' default rates should not be higher than those of non-connected issues. The results presented in Table 6 strongly suggest that connected issues display significantly lower default rates within a five- or ten-year horizon than a set of virtually identical non-connected ones. This evidence is strongly at odds with the notion that the CRA assigns, at the expense of their own reputation, artificially higher ratings to issues by companies with which its directors have personal connections.

Please insert Table 6 here

To further distinguish between the favorable treatment and flow of information hypotheses, we analyze bond yields as a market-based measure of company (bond) performance. If market efficiency holds, and connected issuers receive artificially higher ratings due to favorable treatment, we expect bond prices, and hence yields, to adjust over time as more information becomes available to the market. In particular, we should observe higher bond yields (lower prices) for connected issuers than non-connected issuers with identical ratings several years after the issue. In contrast, if connections act as an informal information channel between issuers and the CRA, we should not observe such a stronger increase in yield across the connected group.

In Table 7 we present the differences between bond yields for connected and non-connected subsamples of companies rated by Moody's, both at the time of issue and three years after issue.[12] The issues are matched using propensity score matching based on credit rating, overall connectivity, solicitation, maturity, issue amount, issue years and industries. Bonds issued by connected and non-connected companies have very similar yields at the time of issue. When we compare the yields three years after the issue, we fail to detect any significant difference between connected and non-connected firms. If the rating assigned to the connected firm had been driven by a favorable treatment of the issuer, in time the negative information "disguised" in the artificially higher rating would be revealed to the market and would be incorporated into the price of the bond. This, in turn, would result in significantly higher yields for connected

[12] As most bonds are not traded daily, we compute the yield in three years as the average yield in a [−45,+45] day window three years after the issue date (and similarly for other intervals in untabulated tests). Altering the window period does not affect the results significantly.

firms. If anything we find a slightly higher yield for unconnected issues, which suggests that their bond prices have decreased proportionally more in time.

Please insert Table 7 here

These results appear to rule out the favorable treatment hypothesis and provide further strong evidence in support of the better information hypothesis. In other words, they indicate that credit rating agencies assign higher ratings to issuers that are connected to them through personal relationships, not as a favor but because they face lower asymmetric information. These connections appear to provide better access to soft information, and allow CRAs to better rely on this information when assessing the creditworthiness of the obligations.

4. Conclusions

We study whether connections between credit rating agencies and issuing companies at director or top executive level play any role in the determination of ratings. Our tests indicate that personal connections between issuers and rating agencies have a positive effect on credit ratings. Our results also indicate that connections with different time frames (current and past) as well as connections with different origins (professional and army mostly) have a positive impact on assigned credit ratings.

We control for possible endogeneity using propensity score tests and placebo falsification tests. All the results corroborate our previous findings on the effect of each class of connections on credit ratings. Connected issues on average obtain higher credit ratings of about half a notch for past connections and more than one notch when the connection is still ongoing.

We also test whether these connections act as informal information channels that allow CRAs to better assess the rating of firms or whether connections are an alternative mechanism for CRAs to favor connected issuers. Our tests on default rates and bond yields all suggest that the higher ratings of connected companies are due to lower degrees of asymmetric information and uncertainty, availability of better and more information through the information channels, and stronger reliance on soft rather than hard information.

Our findings have potentially important implications both for academics and practitioners. In particular, these results have important consequences given the current political climate where the role and the *modus operandi* of CRAs are under increasing scrutiny. Section 2 of Moody's Code of Professional Conduct assures investors of the "Independence and Avoidance and/or Management of Conflicts of Interest." For instance, Item 2.4 states that: "The Credit Rating MIS [Moody’s Investors Service] assigns to an Issuer or obligation will not be affected by the existence of, or potential for, a business relationship between MIS (or its affiliates) and the Issuer (or its affiliates), or any other party, or the non-existence of any such relationship." Standard and Poor’s President Deven Sharma’s response during the Congressional hearing in 2008 further enforces the same idea: “We have been in this business for over one hundred years and studies on rating trends and performance […] have repeatedly confirmed that S&P’s ratings – whether of corporate debt, municipal bonds, structured finance, or the like – have been highly effective in informing the markets about both deterioration and improvement in credit quality. […] There is no evidence of any misconduct by our analysts or that the fundamental integrity of our ratings process has been compromised. Indeed, the SEC itself concluded that it found no evidence during its examination that S&P had compromised its standards to please issuers. It is also worth repeating that no single analyst, including the authors of these emails, has the ability to determine ratings on his or her own as all of our ratings are determined by committee. […]"

Concerns about potential conflict of interests between issuing firms and CRAs and, more generally, about a lack of understanding of the rating process CRAs employ, have been raised by regulators during the Enron scandal (SEC, 2003) and in the more recent financial crisis (SEC, 2008). Our results showing that connected issuers receive, on average, higher ratings may cast doubt over the quality of these ratings. Nonetheless, we find no evidence that the higher rating of connected firms is undeserved. On the contrary, our tests indicate that personal connections appear to act as an informal information channel through which asymmetric information between the issuing firm and the CRA can be reduced.

References

Abadie A., Drukker, D., Leber Herr, J., Imbens, G., 2009. Implementing matching estimators for average treatment effects in Stata. The Stata Journal 4, 3, 290–311.

Beaver, W.H., Shakespeare, C., Soliman, M.T., 2006. Differential properties in the ratings of certified versus non-certified bond rating agencies. Journal of Accounting and Economics 42, 303–334.

Benmelech, E., Dlugosz, J., 2009. The alchemy of CDO credit ratings. Journal of Monetary Economics 56, 617–34.

Bolton, P., Freixas, X., Shapiro, J., 2012. The credit ratings game. Journal of Finance 67, 85–112.

Butler, A., Cornaggia, K., 2012. Rating through the relationship: Soft information and credit ratings. SSRN working paper 345860.

Cohen, L., Frazzini, A., Malloy, C., 2008. The small world of investing: board connections and mutual fund returns. Journal of Political Economy 116 (5), 951–979.

Covitz, D.M., Harrison, P., 2003. Testing conflicts of interest at bond ratings agencies with market anticipation: evidence that reputation incentives dominate. Working Paper Federal Reserve Board.

Engelberg, J., Gao, P., Parsons, C., 2012. Friends with money. Journal of Financial Economics 103, 169–188.

Fracassi, C., 2012. Corporate finance policies and social networks. SSRN working paper 1121503.

Fracassi, C., Tate, G., 2012. External networking and internal firm governance. The Journal of Finance 67 Issue 1 (February), 153–194.

Gan, Y.H., 2004. Why do firms pay for bond ratings when they can get them for free? Working paper, The Wharton School, University of Pennsylvania.

Griffin, J. M., Tang, D.Y., 2012. Did subjectivity play a role in CDO credit ratings? Journal of Finance 67 (4), 1293–1328.

Hovakimian, A., Kayhan, A., Titman, S., 2012. Are corporate default probabilities consistent with the static tradeoff theory? Review of Financial Studies 25, 2, 315–340.

Jorion, P., Liu, Z., Shi, C., 2005. Informational effects of regulation FD: evidence from rating agencies. Journal of Financial Economics 76, 309–330.

Kraft, P. 2012. Rating agency adjustments to GAAP financial statements and their effect on ratings and credit spreads. SSRN working paper 1266381.

Leuven, E., Sianesi, B., 2003. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing.

Mahlmann, T., 2011. Is there a relationship benefit in credit ratings? Review of Finance 15, 475–510.

Mathis, J, McAndrews, J., Rochet, J-C., 2009. Rating the raters: are reputation concerns powerful enough to discipline rating agencies? Journal of Monetary Economics 56(5), 657–674.

Pittman M., 2008. Moody's, S&P defer cuts on AAA subprime, hiding loss. Bloomberg

Poon, W.P.H., 2003. Are unsolicited credit ratings biased downward? Journal of Banking and Finance 27, 593–614.

Rosenbaum, Paul R., Rubin, Donald B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.

Rosenbaum, Paul R., Rubin, Donald B., 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician 39, 33–38.

Rubin, D.B., Thomas, N., 1997. Characterizing the effect of matching using linear propensity score methods with normal distributions, Biometrika 79, 797–809.

Securities and Exchange Commission (SEC), 2003. Report on the role and function of credit rating agencies in the operation of the securities markets. Mimeo, US Securities and Exchange Commission.

Securities and Exchange Commission (SEC), 2008. Summary report of issues identified in the commission staff's examinations of select credit rating agencies. Mimeo, US Securities and Exchange Commission.

Table 1. Summary statistics of personal connection variables

This table presents descriptive statistics for the personal connection variables used in assessing the effect of personal connections between Moody's and issuing firms. Our sample contains all US non-convertible debt issues by industrial companies between 1994 and 2011 that meet the data requirements explained in Section 2. The first set of variables contains binary variables equal to one if there exists at least one instance of a specific type of connection between the issuer and the rating agency. *Total Connections* is the sum of all the instances where directors or executives from the issuing firm are reported to have some personal relationship with directors or executives from Moody's. These connections are always initiated before the issue and are either still ongoing (*Current Connections*) or ended before the issue (*Past Connections*). These connections take place because directors or executives from the issuing firm and directors or executives from Moody's either: worked (work) at the same place (*Professional Connections*), went to the same school (*Educational Connections*) or served time in the military together (*Army Connection*).

	Mean	**S.D.**	**Min**	**Max**
Connection Dummy	0.786	0.409	0	1
Current Connection Dummy	0.272	0.445	0	1
Past Connection Dummy	0.770	0.420	0	1
Professional Connection Dummy	0.618	0.485	0	1
Educational Connection Dummy	0.544	0.498	0	1
Army Connection Dummy	0.161	0.367	0	1
Total Connections	5.153	11.668	0	104
Current Connections	1.488	6.458	0	71
Past Connections	3.665	7.639	0	61
Professional Connections	4.068	11.505	0	101
Educational Connections	0.905	1.056	0	6
Army Connections	0.179	0.440	0	3
Number of Issues	1,719			
Number of Firms	327			

Table 2. Summary statistics of issue and company characteristics

The table presents the descriptive statistics for non-connected and connected issues separately over a set of issue (Panel A) and company (Panel B) characteristics that are likely to affect credit ratings. The sample contains all US non-convertible debt issues by industrial companies between 1994 and 2011 that meet the data requirements explained in section 2. Tests of difference in the means are also reported. *Moody's Rating* is the numerical conversion of the rating assigned by Moody's in descending order, with number 17 representing the highest rating (Aaa) and number 1 representing the lowest rating category (Caa, Caa1 & Caa2). *Solicitation* is a binary variable equal to one if the rating is solicited by the issuer and zero otherwise. *Issue Amount* is the value of the issue (in millions of US dollars) filed with the SEC (from the S-3 form). *Maturity* is the total number of years to maturity. *Seniority* is a dummy equal to one for senior bonds and zero otherwise. *Default - 5Y (10Y)* is a dummy equal to one if the company defaults in a five (ten) year period following each issue.

Panel A. Issue Characteristics

	All Sample	**Non-Connected Issues**		**Connected Issues**		**Diff. in Means (*p*-value)**
	Mean	N	Mean	N	Mean	
Moody's Rating	10.442	367	8.376	1352	11.003	0
Solicitation	0.596	367	0.599	1352	0.595	0.889
Issue Amount ($m)	1550.332	367	773.000	1352	1760.000	0
Maturity	12.049	367	12.422	1352	11.948	0.475
Seniority	0.970	367	0.921	1352	0.984	0
Default – 5Y (%)	1.264%	335	5.373%	1247	0.160%	0
Default – 10Y (%)	2.449%	324	9.568%	1187	0.505%	0

Panel B. Company Characteristics

Interest Coverage Ratio is the three-year average of the sum of pre-tax income and interest expenses divided by interest expenses. *Profit Margin* is the three-year average of operating income before depreciation divided by sales. *Return on Assets* is the three-year average of income before extraordinary items divided by the sum of total assets, accumulated depreciation and amortization. *Leverage* is the three-year average of total long-term debt to total assets. *Book-to-Market Ratio* is the three-year average of book value of equity divided by market value of equity. *Ln. Total Assets* is the three-year average of the natural log of total assets. *MM Beta* is the Market Model Beta based on a 200-day period prior to issue. *Sigma* is the share price volatility over the 200-day period prior to issue. *Ln. (1+No. of Connected Individuals)* is the natural log of one plus the number of connected individuals to each firm. This is the sum of all connections that managers and directors of the issuing companies have with all other firms covered in BoardEx.

	All Sample	**Non-Connected Issues**		**Connected Issues**		**Diff. in Means (*p*-value)**
	Mean	N	Mean	N	Mean	
Interest Coverage Ratio	9.957	367	7.252	1352	10.691	0.006
Profit Margin	0.192	367	0.205	1352	0.190	0.024
Return on Assets	0.166	367	0.150	1352	0.171	0
Leverage	0.252	367	0.306	1352	0.237	0
Book-to-Market Ratio	0.404	367	0.477	1352	0.385	0
Total Assets ($m)	16025	367	5380	1352	18900	0
MM Beta	0.829	367	0.022	1352	0.020	0
Sigma	0.020	367	6.879	1352	8.231	0
Ln. (1+No. of Connected Individuals)	7.942	367	7.252	1352	10.691	0.006

Figure 1

This figure shows the averages of Moody's Rating calculated each year for the entire issues sample, and for connected and non-connected issues separately. *Moody's Rating* is the numerical conversion of the rating assigned by Moody's in descending order, with number 17 representing the highest rating (Aaa) and number representing the lowest rating category (Caa, Caa1 & Caa2).

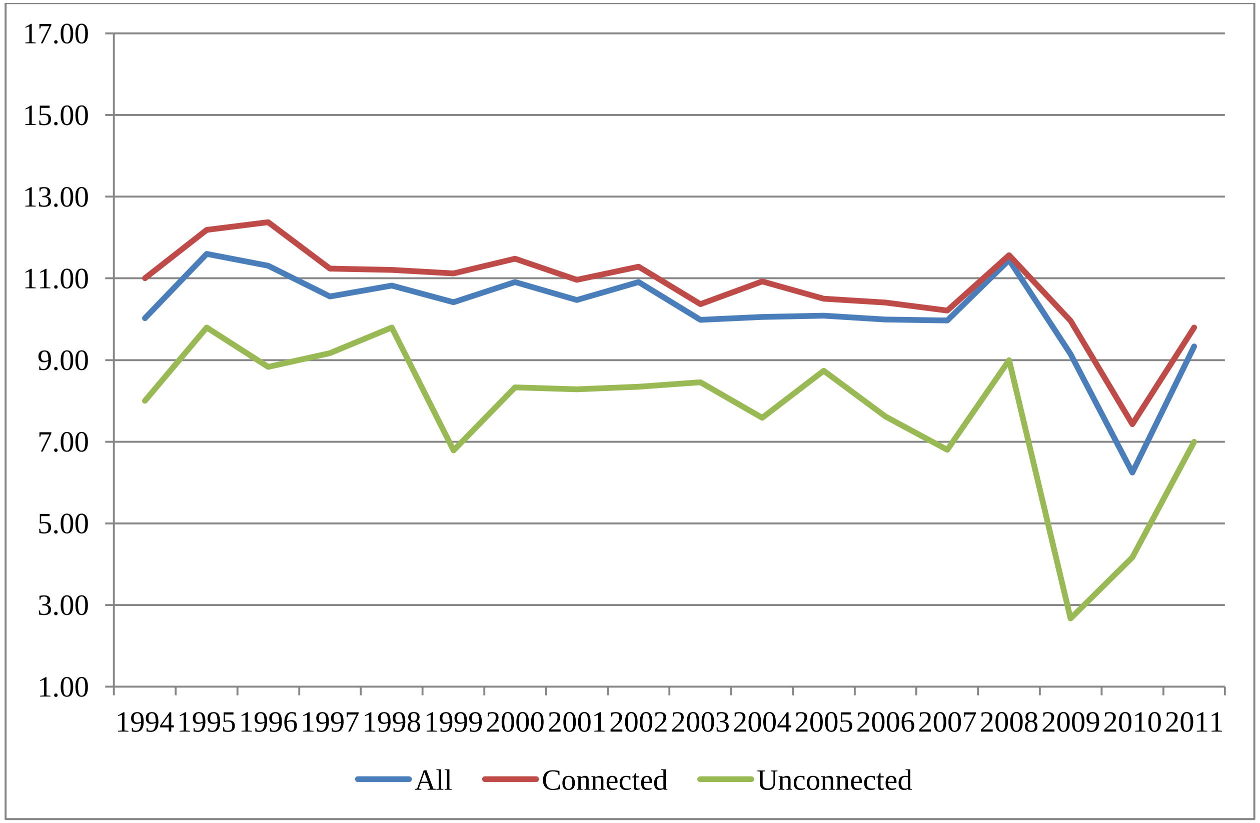

Table 3. Ordered-probit regressions

The table presents the ordered-probit results of the determinants of Moody's credit ratings. *Moody's Rating* is the numerical conversion of the rating assigned by Moody's in descending order, with number 17 representing the highest rating (Aaa) and number 1 representing the lowest rating category (Caa, Caa1 & Caa2). In Panel A the agency–issuer personal connections are proxied by binary variables. *Connection Dummy* takes the value of one when at least one instance is reported in *Boardex* where directors or executives from the issuing firm have personal relationship with directors or executives from Moody's. These connections are always initiated before the issue and they are either still ongoing (*Current Connections*) or ended before the issue (*Past Connections*). These connections take place because directors or executives from the issuing firm and from Moody's either: worked (work) at the same place (*Professional Connections*), went to the same school (*Educational Connections*) or served time in the military together (*Army Connection*). In Panel B the agency-issuer personal connections are measured by the natural log of one plus the total number of connections, according to the type of connection. *Solicitation* is a binary variable equal to one if the rating is solicited by the issuer and zero otherwise. *Issue Amount* is the value of the issue (in millions of US dollars) filed with the SEC (from the S-3 form). *Maturity* is the total number of years to maturity. *Seniority* is a dummy equal to one for senior bonds and zero otherwise. *Interest Coverage Ratio* is the three-year average of the sum of pre-tax income and interest expenses divided by interest expenses. *Profit Margin* is the three-year average of the operating income before depreciation divided by sales. *Return on Assets* is the three-year average of income before extraordinary items divided by sum of total assets and accumulated depreciation and amortization. *Leverage* is the three-year average of total long-term debt to total assets. *Book-to-Market Ratio* is the three-year average of book value of equity divided by market value of equity. *Ln. Total Assets* is the three year average of the natural log of total assets. *MM Beta* is the Market Model Beta based on 200-day period prior to issue. *Sigma* is the Stock's Sigma over the 200-day period prior to issue. *Ln. (1+No. of Connected Individuals)* is the natural log of one plus the number of connected individuals to each firm. The number of connected individuals to each firm is the total number of all individuals included in BoardEx who are connected to the directors and/or senior managers of the issuer at the time of each issue. All tests include year dummies and industry dummies. Standard errors are robust to heteroskedasticity. *P*-values are reported in brackets. *, **, and *** report the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Connection (Dummy Variables)

	I	II	III	IV
Connection Dummy	0.308***			
	[0.000]			
Current Connection Dummy		0.184***		
		[0.003]		
Past Connection Dummy			0.251***	
			[0.001]	
Professional Connection Dummy				0.150**
				[0.032]
Education Connection Dummy				0.148**
				[0.021]
Army Connection Dummy				0.164**
				[0.030]
Solicitation	0.02	-0.006	0.019	0.013

	[0.718]	[0.918]	[0.725]	[0.814]
Ln. Issue Amount	-0.004***	-0.005***	-0.004***	-0.004***
	[0.008]	[0.003]	[0.010]	[0.010]
Maturity	-0.103	-0.133	-0.128	-0.125
	[0.741]	[0.665]	[0.679]	[0.685]
Seniority	7.740***	7.710***	7.753***	7.891***
	[0.000]	[0.000]	[0.000]	[0.000]
Interest Coverage Ratio	-3.757***	-3.945***	-3.784***	-3.814***
	[0.000]	[0.000]	[0.000]	[0.000]
Profit Margin	-1.116***	-1.115***	-1.118***	-1.106***
	[0.000]	[0.000]	[0.000]	[0.000]
Return on Assets	0.535***	0.521***	0.530***	0.526***
	[0.000]	[0.000]	[0.000]	[0.000]
Leverage	0.068	0.056	0.065	0.084
	[0.515]	[0.589]	[0.535]	[0.423]
Book-to-Market Ratio	-31.673***	-31.361***	-31.674***	-32.636***
	[0.000]	[0.000]	[0.000]	[0.000]
Ln. Total Assets	-0.052***	-0.051**	-0.052***	-0.055***
	[0.009]	[0.010]	[0.009]	[0.006]
MM Beta	0.011***	0.011***	0.011***	0.011***
	[0.000]	[0.000]	[0.000]	[0.000]
Sigma	1.602***	1.594***	1.602***	1.612***
	[0.000]	[0.000]	[0.000]	[0.000]
Ln (1+No.of Connected Individuals)	-0.044	0	-0.031	-0.057
	[0.374]	[0.996]	[0.521]	[0.288]
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R2	0.227	0.226	0.226	0.227
N	1,719	1,719	1,719	1,719

Panel B. Connection (Continuous Variables)

	V	VI	VII	VIII
Ln.(1+No. of Connections)	0.303***			
	[0.000]			
Ln. (1+No. of Current Connections)		0.257***		
		[0.000]		
Ln. (1+No. of Past Connections)			0.329***	
			[0.000]	
Ln. (1+No. of Professional Connections)				0.247***
				[0.000]
Ln. (1+No. of Educational Connections)				0.058
				[0.380]
Ln. (1+No. of Army Connections)				0.278***
				[0.003]
Solicitation Dummy	-0.001	-0.023	0.009	0.009
	[0.993]	[0.675]	[0.875]	[0.879]
Ln. Issue Amount	-0.004**	-0.005***	-0.004**	-0.004**
	[0.011]	[0.002]	[0.025]	[0.015]
Maturity	-0.331	-0.317	-0.333	-0.297
	[0.282]	[0.300]	[0.278]	[0.332]
Seniority	7.979***	7.856***	8.011***	7.812***
	[0.000]	[0.000]	[0.000]	[0.000]
Interest Coverage Ratio	-3.802***	-4.006***	-3.746***	-3.804***
	[0.000]	[0.000]	[0.000]	[0.000]
Profit Margin	-1.073***	-1.123***	-1.063***	-1.096***
	[0.000]	[0.000]	[0.000]	[0.000]
Return on Assets	0.502***	0.516***	0.501***	0.505***
	[0.000]	[0.000]	[0.000]	[0.000]
Leverage	0.083	0.053	0.086	0.073
	[0.428]	[0.616]	[0.413]	[0.489]
Book-to-Market Ratio	-29.951***	-30.776***	-30.282***	-29.966***
	[0.000]	[0.000]	[0.000]	[0.000]
Ln. Total Assets	-0.046**	-0.045**	-0.048**	-0.049**
	[0.024]	[0.023]	[0.017]	[0.014]
MM Beta	0.012***	0.011***	0.012***	0.012***
	[0.000]	[0.000]	[0.000]	[0.000]
Sigma	1.637***	1.612***	1.639***	1.632***
	[0.000]	[0.000]	[0.000]	[0.000]
Ln.(1+ No. of Connected Individuals)	-0.130**	-0.016	-0.123**	-0.110**
	[0.019]	[0.726]	[0.024]	[0.046]
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R2	0.233	0.233	0.234	0.232
N	1,719	1,719	1,719	1,719

Table 4. Propensity score results

In this table, for each issue by a company connected to Moody's through its executives and/or directors, we identify a control issue by a company that is not connected to Moody's. We use a propensity score matching procedure. The propensity score is estimated using all firm and issue characteristics included in our regression analyses, as well as year and industry dummies. We require that the difference between the propensity score of the connected firm and its matching peer does not exceed 1% in absolute value. We then compare the average Moody's credit rating between connected and non-connected companies at the time of issue. *Moody's Rating* is the numerical conversion of the rating assigned by Moody's in descending order, with number 17 representing the highest rating (Aaa) and number 1 representing the lowest rating category (Caa, Caa1 & Caa2). We also report the difference in credit rating means across the two groups, as well as the *p*-value of the significance of the difference and the *p*-value of the propensity score. Panel A presents the results where the observations are grouped based on the existence of both current and past connections between the issuer and Moody's (*Connection Dummy*); while Panel B and Panel C show tests for current (*Current Connection Dummy*) and past connections (*Past Connection Dummy*) respectively.

Panel A. All Connections

	Matched Firms	**Credit Rating Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
Connected	211	9.583	0.526	0.051	0.796
Non-Connected	211	9.056			

Panel B. Current Connections

	Matched Firms	**Credit Rating Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (p-value)**
Connected	84	11.029	1.268	0.004	0.957
Non-Connected	84	9.761			

Panel C. Past Connections

	Matched Firms	**Credit Rating Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
Connected	217	9.661	0.522	0.062	0.803
Non-Connected	217	9.139			

Table 5. Falsification tests - Monte Carlo permutation

This table presents the results from a full Monte Carlo Permutation test with 100,000 trials. In each trial, a random shuffling of the treatment variable (*Connection Dummy, Current Connection Dummy, Past Connection Dummy, Ln. (1+No. of Connections), Ln. (1+No. of Current Connections), Ln. (1+No. of Past Connections)*) is performed and models I to VIII in Table 3 are estimated. The distribution of the estimated coefficients obtained from this repeated random shuffling approximates the distribution under the null hypothesis that there is no difference between connected and non-connected issuers. If the randomly shuffled coefficients are larger than the coefficients observed from models I or V, then we would fail to reject the null hypothesis. Estimated coefficients from Table 3 are reported below as "True Coefficient". In Panel A, the connection status variable is reshuffled across issues of treated firms only. In Panel B, the connection status variable is reshuffled across all issues of all firms.

Panel A

	True Coefficient	Random Shuffle Coefficient> True Coefficient	No. of Trials	Implied *p*-value
Connection Dummy	0.308	0	100,000	0.000
Current Connection Dummy	0.184	170	100,000	0.001
Past Connection Dummy	0.251	50	100,000	0.0005
Ln.(1+No. of Connections)	0.303	0	100,000	0.000
Ln. (1+No. of Current Connections)	0.257	0	100,000	0.000
Ln. (1+No. of Past Connections)	0.329	0	100,000	0.000
N	1,719			

Panel B

	True Coefficient	Random Shuffle Coefficient> True Coefficient	No. of Trials	Implied *p*-value
Connection Dummy	0.308	0	100,000	0.000
Current Connection Dummy	0.184	110	100,000	0.001
Past Connection Dummy	0.251	0	100,000	0.000
Ln.(1+No. of Connections)	0.303	0	100,000	0.000
Ln. (1+No. of Current Connections)	0.257	0	100,000	0.000
Ln. (1+No. of Past Connections)	0.329	0	100,000	0.000
N	1,719			

Table 6. Default rate analysis

In this table, for each issuing company connected to Moody's through its executives and/or directors, we identify a control firm that is not connected to Moody's. We use a propensity score matching procedure. The propensity score is estimated using Moody's credit rating, Z-Score, overall connectivity, and all issue characteristics included in our regression analyses (*Solicitation, Issue Amount*, *Maturity* and *Seniority*), as well as year and industry dummies. We require that the difference between the propensity score of the connected firm and its matching peer does not exceed 1% in absolute value. We then compare the average default rate of firms in five years (Panel A) and ten years (Panel B) after the issue respectively. We report also the difference in default rate means across the two groups, as well as the *p*-value of the significance of the difference and the p-value of the propensity score.

Panel A. Default in five years

	Matched Firms	**Default Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
Connected	157	0.000	-0.025**	0.044	0.838
Non-Connected	157	0.025			

Panel B. Default in ten years

	Matched Firms	**Default Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
Connected	145	0.000	-0.069**	0.001	0.847
Non-Connected	145	0.069			

Table 7. Bond yield analysis

In this table, for each issue by a company connected to Moody's through its executives and/or directors, we identify a control issue by a firm that is not connected to Moody's. We use a propensity score matching procedure. The propensity score is estimated using Moody's credit rating, overall connectivity, and all issue characteristics included in our regression analyses (*Solicitation, Issue Amount*, *Maturity* and *Seniority*), as well as year and industry dummies. We require that the difference between the propensity score of the connected firm and its matching peer does not exceed 1% in absolute value. We then compare the average bond yields of firms at the time of the issue and three years after the issue. We report also the difference in bond yield means across the two groups, as well as the *p*-value of the significance of the difference and the *p*-value of the propensity score. As most bonds are not traded on a daily basis, we compute the three-years-yield as the average yield in a [-45,+45] day window three years after the issue date.

	Matched Issues	**Bond Yield Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
At the time of the issue					
Connected	34	5.676	0.091	0.741	0.928
Non-Connected	34	5.585			
Three years after the issue					
Connected	34	7.234	-0.949	0.225	
Non-Connected	34	8.183			