Rating Friends: the Effect of Personal Connections on Credit Ratings

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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 about one notch. The results are robust to several alternative tests including additional controls for managerial traits, placebo tests and propensity score matching. Moreover, our tests on default rates and bond yields do not appear to reflect a favorable treatment by the rating agency. Rather, they suggest 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, L14

1. Introduction

In this paper we investigate a very important issue that has not received any attention in the literature: are credit ratings affected by the presence of personal connections between directors of issuing companies and the rating agencies?

Credit rating agencies (CRAs) are expected to provide impartial independent ratings. 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* [...]". For instance, Section 2 of Moody's Code of Professional Conduct assures investors of the "Independence and Avoidance and/or Management of Conflicts of Interest". Consequently, the rating they provide should not be affected by the presence of connections between directors.

However, directors play an active role in the rating process. 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.*"[1] Therefore, personal connections between directors of CRAs and those of issuing firms may affect the quality of the ratings in at least two ways. On the one hand, personal connections may work like an information channel. CRAs are characterized by an asymmetric loss function which implies that the costs of overvaluation are higher than those of undervaluation (Beaver, et al., 2006). As a consequence, CRAs have the incentives to issue more conservative ratings to those firms with stronger asymmetric information (Bannier, et al., 2010). 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), enabling them to legally make use of private information (Jorion, et al., 2005;

[1] [1] http://www.moodys.com/sites/products/ProductAttachments/Moody%27s%20Rating%20System.pdf

Mählmann, 2011 and Butler and Cornaggia, 2012). Personal connections could thus provide CRAs with access to those "private and soft information" that could reduce the asymmetric information between the two parties. This would reduce the innate strategic conservatism of CRAs (Bannier, et al., 2010) so they would assign higher ratings to, ceteris paribus, less informationally opaque issuers.

On the other hand, the need of CRAs to maintain market share may create an incentive for them to cater to the interests of the issuers. For instance, Bolton, et al. (2012) show that increased competition among CRAs increases the scope and incentive for companies to shop around for the best ratings. Mählmann (2011) reports that credit ratings by Standard and Poor's (S&P's) increase with the strength of the relationship between firms and CRAs. In his work, the strength of the relationship is proxied by the length of time firms and CRAs have been in business together. Jiang, et al. (2012) find that S&P's ratings of the same issues were lower than Moody's when S&P's was charging investors and not issuers for the rating service. After switching to an issuer-pay model in 1974, S&P's ratings increased and became virtually identical to Moody's. Therefore, we expect that personal connections may exacerbate this potential conflict of interest between CRAs and issuers.

To undertake our investigation, 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. An increasing number of studies use this database as a primary source of information on corporate social connections (e.g. Engelberg, et al., 2012, and Fracassi, 2014). This dataset gives us information regarding past education, employment history and army service for managers and directors. This allows us to establish whether, for example, a director from an issuing company has shared either education experience, or Army service or employment with a director of Moody's. Among the top three CRAs we choose Moody's since it is a standalone company, and so we are able to directly identify all its directors. Further, it has full coverage in BoardEx over the entire sample period.[2]

Our ordered-probit results confirm that the existence of personal connections between directors of the rating agency and those of the issuing company has indeed a significant positive impact on the credit ratings assigned to the company's issues. Issues by personally connected firms have a higher probability of having a higher rating. We also investigate whether the impact is affected by the nature of the connection (i.e. when managers worked together in the past, attended the same University or served in the Army together). We still find that the effect of connections remains statistically strong and positive irrespective of the type of connection in place. These results are robust to controlling for standard determinants of credit ratings.

We run a series of robustness tests where we control for numerous other possible confounding factors. First, we split the sample between solicited and unsolicited ratings since the solicitation status may exacerbate the possible conflict of interest inherent to the issuer-paid model. Second, we build proxies for the presence of business ties between issuers and CRAs similar to Mählmann (2011) to verify whether our connection status simply reflects the business ties effect documented in his study. Third,

[2] The other top CRA in the US market, S&P'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 S&P's division. Further, only two out 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 S&P's.

we collect information on managerial traits to control for the possibility that our results are driven by differences in managerial quality. To this end, we build proxies for the education of managers, and for the average number of directorships held by board members. We also collect information on the age of the directors and on their compensation package to control for their risk-taking incentives which CRAs may use in assigning their ratings. As a last step, we collect information on the governance of companies (proxied by the entrenchment index by Bebchuk, et al. (2009). The results from all these tests are largely unaffected: firms run by connected managers receive higher ratings than firms run by unconnected managers.

The relationship between connections and ratings is not only statistically significant but it is also economically important. Our OLS tests indicate that the average difference in rating between (issues by) connected and unconnected firms is about one full notch. Similarly, when we use the total number of connections, we find that the average difference in rating between a firm without connection and a firm with a median number of connections (three) is still near one full notch.

As in any empirical study, a potential problem with the interpretation of our results is the issue of endogeneity. We believe that this problem is less of a concern in our exercise. Similar to Engelberg, et al. (2012), our connections were always formed prior to the debt issues. This addresses the potential concern of reverse causality, where the rating of a debt issue may lead to the creation of a personal connection. Nonetheless, one may argue that, since ratings can be solicited by the issuing company, this may lead to a potential self-selection bias. We undertake three steps to control for this potential issue. First we include the solicitation status in all our models. Second, in our descriptive statistics we show virtually no difference in solicitation of ratings between the two groups. Finally, when we perform robustness tests splitting solicited and unsolicited ratings, as discussed above, we find the results do not change across the two sub-samples.

To reduce further potential concerns of endogeneity, we employ a propensity score matching procedure to identify identical subsamples of issues by connected and non-connected firms, based on various sets of both 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.

We also run placebo tests to investigate whether omitted firm-specific characteristics are driving the results. In these tests, 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. 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 issues. However, we fail to find a single instance where the randomly shuffled coefficient statistically dominates the estimated parameter from the true connection status which tends to provide support for the validity of our previous tests.

In the second part of the paper we investigate whether the (higher) credit ratings to connected companies represent a favorable treatment from the CRA to the issuing company or, rather, reflect a better flow of information. To attempt 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 issues based on credit rating, issue and firm 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.

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. Rather, our tests seem to suggest that everything else being equal, connected issuers receive on average higher ratings because the connection renders the issuer less informationally opaque.

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, et al. (2008) document that personal connections between mutual fund managers and corporate board members act as an information channel between firms and investors. Engelberg, et al. (2012) report strong evidence that connected borrowers obtain loans at significantly lower interest rates when their managers have personal connections with managers of the lender due to better flow of information. 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 (2014) reports that companies whose directors share a higher degree of personal connections tend to exhibit a greater similarity in their investment decisions.

Our paper also contributes to the growing literature on the determinants of the credit rating process. 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. He 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. Results by Mathis, et al. (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. Also, Bannier, et al. (2010), find strong evidence that solicited ratings tend to be higher than unsolicited ones because solicitation reduces asymmetric information between issuers and CRAs. Kraft (2014) 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 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. Section 2 describes the sample and the variables included in the analysis. Section 3 presents the methodologies we employ and all the results. Section 4 includes the discussion of our findings. Section 5 concludes.

2. Sample and Variables Description

To perform our analysis we construct a database from several different sources. First, 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 find the relevant S-3 forms on EDGAR, from which we identify the solicited ratings.[3] Second, data on solicitation come from the SEC's

[3] 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.

EDGAR (Electronic Data Gathering, Analysis and Retrieval) database. Third, 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. Further, 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. Finally, we gather information on personal connections and managerial traits from BoardEx which provides biographical data on board members and senior executives around the world.

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 9,593 issues from 890 companies with information available on solicitation from the S-3 forms. We exclude financial firms (SIC 6000-6999) and regulated utility companies (SIC 4909-4939) as these firms are subject to different rating standards. This leaves a sample of 4,304 bonds issued by 563 companies . After matching these data with BoardEx, we end up with a final sample of 1,719 issues from 327 companies with information on connections available between 1994 and 2011.[4] This sample size is comparable if not larger than those in the recent credit rating literature. For instance, Poon (2003) reports

[4] When we use the full set of control which includes several non-conventional determinants for credit ratings the sample is severely limited. Nonetheless,, we still remain with 435 issues from 150 unique firms.

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.

2.1. PERSONAL CONNECTIONS

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 indeed sit on the ratings committees and play an active role in the rating process as discussed above. 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.*[…]"[5] 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

[5] http://www.sec.gov/comments/s7-18-11/s71811-33.pdf

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;[6] 2) *Educational Connections* originate when two people have attended the same education institution (e.g., University) at the same time;[7] 3) *Army Connections* refer to cases where two people have served in the army together.[8]

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 and any different origin of connection as described above. For instance, for a company X issuing a bond in 1999, an educational connection

[6] The biographical information included in BoardEx allows us, for instance, to identify whether; 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.

[7] Educational relationships are of two kinds: those between two classmates (i.e. a non-executive director of an issuing company completed an MBA (or any other degree) with one of the top executives of Moody's), 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.

[8] We also identify *Social Connections* when two people know each other through their activities in a social organization such as a charity or a volunteer group. 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 similarly to Engelberg, et al. (2012).

between a top executive of X and a director of the CRA dating back to 1980s is categorized as past connection and for that bond the *Connection Dummy* will be equal to 1. Alternatively, for a company Y issuing a bond in 2000, the connection between two top executives sitting together on the board of a third company from 1994 to 2001 is considered as current and for that bond the *Connection Dummy* will be equal to 1.

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.

2.2. RATING OF DEBT ISSUES

We focus on public non-convertible debt issues, as their characteristics differ significantly from convertible bonds and other types of debt obligations. 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.

2.3. CONTROL VARIABLES

We include a number of control variables in each of regressions. We first control for several characteristics at issue level that previous studies show to affect debt rating.

Solicitation is a binary variable equal to one if the rating is solicited by the issuer and zero otherwise. 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 (e.g., Gan, 2004 and Butler and Cornaggia, 2012), 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.

Ln. Issue Amount is the natural logarithm of 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; while *Seniority* is a dummy equal to one for senior bonds and zero otherwise. Fenn (2000) and Butler and Cornaggia (2012) document the importance of these aspects in determining the credit spread and rating respectively.

We then control for several other firm's characteristics largely following Blume, et al. (1998) and Amato and Furfine (2004), among others. In particular, to control for the corporate financial risk we include: 1) *Interest Coverage Ratio*, as the three-year average of the sum of pre-tax income and interest expenses divided by interest expenses; 2) *Profit Margin*, as the three-year average of operating income before depreciation divided by sales; 3) *Return on Assets*, as the three-year average of income before extraordinary items divided by the sum of total assets, accumulated depreciation and amortization; and 4) *Leverage*, defined as the three-year average of total long-term debt to total assets. To capture the business risk we use: 1) *Book-to-Market Ratio*, as the three-year average of book value of equity divided by market value of equity; 2) *Ln.*

Total Assets, as the three-year average of the natural log of total assets; 3) *MM Beta*, estimated from the market model based on a 200-day period prior to issue; and 4) *Sigma*, calculated as the share price volatility over the 200-day period prior to issue.

Finally, 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, et al. (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 within the entire universe of Boardex, which is equal to the the natural log of one plus the number of connected individuals to each firm (*Ln. (1+No. of Connected Individuals))* . This is the sum of all personal connections that managers and directors of the issuing companies have with all other firms covered in BoardEx.

2.4. UNIVARIATE ANALYSIS

In Table I 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. About 79% of the issues in our sample are connected. Among them, *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 issues do not appear to be clustered into specific industries.

Table I about here

In Table II we provide summary statistics of issue (Panel A) and firm characteristics (Panel B) for the full sample and also for connected and non-connected issues 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, et al. (2012) report an average rating of 10 while Cornaggia and Cornaggia (2013) report an average of 11 (for industrial firms). Panel A reveals that connected issuers obtain significantly higher credit ratings. Connected issues have an average 11 (A3) while non-connected ones have an average of 8 (Baa3). 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. There is no remarkable difference in the maturity of the issues across the two groups.

Table II Panel A about here

We also include in Table II two other variables that we use in the second part of the paper (see Section 4): 1) *Default - 5Y (10Y)* which is a dummy equal to one if the company defaults in a five (ten) year period following each issue; and 2) *Bond Yield* is the issue yield to maturity. We note that both the percentage of defaults and the bond yields are significantly lower in the connected group.

Analysis of the firm characteristics reveals that 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 companies generally have more connections to other individuals or organizations than do non-connected issuers.

Table II Panel B about here

In Figure 1 we plot the average ratings of all issues in our sample 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 trend is reported by Hovakimian, et al. (2012) for S&P's ratings.[9] 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.

Figure 1 about here

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[9] Untabulated tests report the same results when we look at average ratings by S&P's rather than Moody's.

3. Personal Connections and Credit Ratings: 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:

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

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

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 at the time of the issue and zero otherwise; $\sum_{k=1}^{K} \gamma_k X_i$ is a vector of both issue and company characteristics described above; 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*. 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 III (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.

Table III Panel A about here

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.[10] With regards to the origination of the connection, all types of connection (professional, education and army) have a positive effect on ratings.

In Table III Panel B we replicate the above tests using 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

[10] In our tests, we also follow Engelberg, et al. (2012) in limiting connections to those initiated two (five) years prior to the event. Untabulated results are very similar to those reported here.

largely mirrors model IV Panel A, although educational connections are not significant. Results for most of the other control variables are in line with previous studies.

Table III Panel B about here

3.1. ROBUSTNESS TESTS

The above results appear to suggest that issues by connected firms tend to receive higher ratings than issues by non-connected firms. Our ordered-probit models are based on the most widely adopted set of determinants of credit ratings. However, a concern could be that there are further key determinants of ratings which have been omitted in the previous models. In this section, we introduce a number of possible confounding factors that may influence the rating of issues.

3.1.a The Role of Solicitation

One first concern is whether the connection status is a vehicle for access to soft information similarly to the solicitation status. Typically, CRAs have no access to "soft information" when assigning a rating to an unsolicited issue and therefore will have to base their assessment merely on "hard information" such as annual reports (Butler and Cornaggia, 2012). When companies pay for the rating however, there is usually a better flow of soft as well as hard information. Moreover, the presence of a connection to the CRA may give managers of issuing firms a much better sense of the optimal timing to issue a security. A number of papers find that paying for the rating has a very strong influence on the rating itself. For instance, in a recent paper Bannier, et al. (2010) find strong evidence that solicited ratings tend to be higher than unsolicited ones because solicitation acts as an information channel. Also, Jiang, et al. (2012) find that S&P's ratings of the same issues were lower than Moody's when S&P's was charging investors and not issuers for the rating service. After switching to an issuer-pay model in 1974, S&P's rating became virtually identical to Moody's.

Although we do control for solicitation status in our baseline models (Table III), here we split the sample between solicited and unsolicited ratings to disentangle the role of personal connections from that of solicitation. We expect our results to disappear if the connection effect is simply driven by the solicitation status. In Table IV both models I and II show that the connection dummy behaves as in previous tests being positive and statistically significant in both subsamples.

3.1.b The Role of Business Ties between Issuers and CRAs

A number of papers highlight the importance of the level of interaction between issuers and CRAs. For instance, Mählmann (2011) reports that the longer the length of time issuers and CRAs have been doing business together, the higher the rating. For instance, more frequent issuers may represent a higher fraction of the income of CRAs which may give issuers more leverage to get better ratings. This is what Mählmann (2011) refers to as the ‘‘adverse incentives’’ argument. To test whether this factor is driving our results we build two different proxies for the relationship between issuers and CRAs. The first one (*Relate*) is defined as the number of years elapsed between the first bond issue in the dataset and the current year similarly to Mählmann (2011). This should proxy the length of the business ties between the two parties. The second proxy we construct is the total number of issues by each firm (*Total Issues*). If our proxy for connection simply captures a relation effect, then the result should disappear as soon as we include one of the two variables above. Results in Table IV Models III and IV show that both these proxies are positive and statistically significant. More importantly, the coefficient for the personal connection dummy is unaffected by the inclusion of such proxies.

3.1.c The Role of Managerial Traits

A further possible concern with our tests so far is that differences in managerial traits may be driving our results. For instance, better quality managers are more likely to graduate from the best universities and end up working for the same subset of attractive employers (including Moody's). Moreover, better managers are more likely to work for companies less prone to default, and so, with a higher probability to have better ratings. To control whether our results are driven by differences in managerial quality we take a number of steps. First, we collect information on the education of directors from BoardEx, and in particular, on the degree and/or qualification possessed by a manager. We check whether they have an MBA, an MSc or a PhD degree. We also create a category (*Other*) that includes all the different professional titles that do not fall into the previous three (e.g. Certified Accountant, Certified Bank Auditor, Certified Management Consultant). Then for each title we construct the fraction of directors in the board with that title.

Second, we proxy the quality of managers by collecting information on the number of board seats they have in other firms. An underlying argument from previous studies (e.g., Ferris, et al., 2003) is that the more board seats a manager has the better the quality of that manager. This might be even stronger when managers sit in boards of other listed firms. Consequently, we build two proxies. The first *Total Boards* is the average number of boards seats held by the directors of the issuing firm. The second one *Quoted Boards* is the average number of other quoted firms where the directors of the issuing company sit.

We also collect information on the age of the directors. Prior psychology studies suggest that propensity to take risk declines with age (Taylor, 1975; Forbes, 2005; Kovalchik, et al., 2005). Also, it is mechanically more likely that more connected directors are older as they would have had more time in their careers to build up relationships with other managers. *Age* is defined as the average age of the directors of the issuing company.

We augment our baseline model with these proxies for managerial quality. Results are reported in Table IV models V and VI. The inclusion of these proxies does not alter our conclusion that personal connections between issuers and CRAs are associated with higher ratings.[11]

3.1.d The Role of Managerial Compensation

The compensation scheme adopted by different companies may give different incentives towards risk taking to their managers. This may be an element which CRAs use in deciding the rating to assign to firms (Kuang and Qin, 2013). In an attempt to control for this we collect *Delta* (average dollar change in wealth associated with a 1% change in the firm's stock price (in \$000s)) and *Vega* (average dollar change in wealth

[11] Interestingly, the variable MBA is the only proxy for education that is statistically significant and it displays a negative sign. This may be explained with the work by Bertrand and Schoar (2003) which indicates that managers with an MBA show a greater propensity to take on risk.

associated with a 0.01 change in the standard deviation of the firm's returns (in $000s)) estimates kindly made available by Coles, et al. (2014). While both *Delta* and *Vega* appear to have a negative association with rating, the association between connection and rating remains unaltered (Table IV model VII).

3.1.e The Role of Corporate Governance

Finally, we test whether differences in governance, omitted from the tests in Table III, may play a relevant role in explaining our result (Table IV model VIII). According to Ashbaugh-Skaife, et al. (2006), weak governance is one of the key predictors of corporate fraud. Indeed, they show that credit ratings are related to the corporate governance of the firm. We use the Entrenchment index by Bebchuk, et al. (2009) as a proxy for corporate governance. Since the *E-index* is available only for a subset of companies and years, this severely reduces the number of observations in the sample. Nonetheless, our results remain largely unaffected by its inclusion. If anything, the estimated coefficient of the connection dummy is now much larger (Table IV Model VIII).

As a last attempt to test the robustness of the documented association between personal connections and credit ratings we run one final model (Table IV Model IX) where we include all the above proxies. Still, our results do not appear to be driven by any of these further factors.

Table IV about here

3.2 ECONOMIC IMPORTANCE

For its own nature, ordered-probit tests do not lend themselves to an easy interpretation of the results. The impact (marginal effect) of the variable of interest is different for the different thresholds of the dependent variable. For instance, issues by connected firms are about 3% more likely to be rated A3 but they are about 15% more likely to be rated A2. So they are hard to summarize in a simple statistic. Therefore, we follow the approach common to many papers in the field and we replicate our baseline tests with OLS estimations. Table V Models I-III report results on dummy variables while Models IV-VI report results on the continuous variables. The economic significance of the connection variables is reported beneath the p-values (in bold). In Models I-III, the estimated coefficient on the connection dummy represents the numerical difference in average rating between issues by connected and unconnected firms. Across all three specifications this is near one full notch. For the variables in logarithm in Models IV-VI, we attempt to capture a representative average effect by calculating the change in rating between issues by firm with zero connections and issues by firm with median (three) connections. Again, the difference in rating between the two groups across all specifications is near one full notch. [12]

Therefore, the effect of personal connections is not only statistically significant but also economically meaningful. For comparison purposes, Mählmann (2011) reports

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[12] In an unreported test, we run a logit analysis on the probability of receiving an Upper Medium Rating of A3 or above (a more natural choice might have been the investment grade threshold; however, as we show in Table II issues by both connected and unconnected firms typically are rated Baa3 (8) or above). This analysis reveals that connected firms are about 30% more likely to be rated A3 or above.

that ten more years of relationship with the CRA are associated with a rating increase of 0.61 notches.

Table V about here

3.3. 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 that this problem is less of a concern in our exercise. Similar to Engelberg, et al. (2012), our connections were always formed prior to the debt issues. This addresses the potential concern of reverse causality, where the rating of a debt issue may lead to the creation of a personal connection. Nonetheless, one may argue that, since ratings can be solicited by the issuing company, this may lead to a potential self-selection bias. We undertake three steps to control for this potential issue. First, we include the solicitation status in all our models. Second, in our descriptive statistics we show virtually no difference in solicitation of ratings between the two groups. Finally, when we perform robustness tests splitting solicited and unsolicited ratings, as discussed above (Table IV Models I and II), we find the results do not change across the two sub-samples.

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 I partly corroborate this view although we do control for all these characteristics at both issue and firm level in all models. Nonetheless, we use some tests to minimize this potential concern.

3.3.a Propensity Score Matching

We first employ a propensity score matching procedure, as in Rosebaum 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.[13] 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 VI we present the propensity score matching results.[14] To limit the chance that omitted variable bias affects the matching results, we use all the most complete set of determinants of ratings presented in Table IV Model IX to perform the matching.[15] To ensure the issues in the control sample are sufficiently similar to the issues with connected 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 0.586 and 0.830, confirming that the two sets of issues are statistically indistinguishable.

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[13] See Rosenbaum and Rubin (1985), Rubin and Thomas (1992) for further discussion of propensity score matching.

[14] The propensity score matching method is implemented using the PSMATCH2 package in STATA by Leuven and Sianesi (2014). In unreported tests we replicate the matching analysis using the nearest neighbour matching method, by Abadie, et al. (2004). Results are very similar irrespective of which matching procedure is used.

[15] Results are qualitatively similar if we use the baseline specification used in Table III

Table VI Panel A shows the results for matching connected and non-connected issues. Connected issues still show significantly higher credit ratings (Difference in Means) than do matched non-connected issues. The difference is about half a notch (0.564). Results are even stronger when we isolate *Current* from *Past Connections:* the difference is about a notch across the two subsamples. In particular, we find a difference of 0.878 with *Current Connections* and 0.806 with *Past Connections*. These differences are statistically significant in all cases (Table V Panel B).[16]

Table VI about here

3.3.b Falsification Tests

To ensure that our results do not capture spurious correlation, we run a series of falsification tests. In particular, one concern with our previous tests could be that the results are driven by an unobservable firm-specific characteristic. The ordered probit specification does not allow us to control for firm fixed effects. Also, if an unobservable characteristic drives both the ratings and the ability of an issuer to attract connected managers this may not be captured by the propensity score matching. To try to confute this alternative interpretation of our results, we perform permutation tests for all the treatment (connection) variables. We 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

[16] 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.

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, we perform a full Monte Carlo with 100,000 permutations 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 VII. The true coefficients in the table refer to the estimated coefficient from the true connection variable. To run these tests, we use the same specification as in Table IV model IX. For instance, for 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. Similarly, when we perform this exercise on the other proxies for personal connection we find no cases where the placebo effect dominates the treatment effect.

We perform an additional unreported falsification test 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 or simply luck. 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

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Table VII about here

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4. Results Discussion

Credibility is the 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 S&P'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 VIII 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.

Table VIII about 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 IX 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.[17] 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 firms. If anything we find a slightly higher yield for unconnected issues, which suggests that their bond prices have decreased proportionally more in time.

Table IX about here

These results appear to rule out the favorable treatment hypothesis and provide further evidence in support of the flow of 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. This result is in line with recent evidence by

[17] 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.

Bannier, et al. (2010) who find that conservativism is a crucial determinant of credit ratings. In particular, they report evidence that the downward rating bias of CRAs is stronger, the more informationally opaque banks are.

In other words, our results should probably not be interpreted as connected firms always having "good news" to disclose to CRAs through the connection. Rather, the presence of connections renders the issuer less opaque and this reduces the natural conservativism of CRAs. Therefore, everything else being equal, connected issuers receive on average higher ratings.

5. 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) all have a positive impact on assigned credit ratings.

We perform a series of robustness tests to control for managerial traits, including education, experience and age, risk-taking incentives embedded in managerial compensation packages, and finally the governance of the firm. The documented positive association between personal connections and credit ratings remains substantially unaltered. On average, we find the difference between connected and unconnected issues to be around one notch.

Further, 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.

We finally 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.

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. In particular, concerns about potential conflict of interests between issuing firms and CRAs and, more generally, about a lack of understanding of the rating process, have been raised by regulators during the Enron scandal (SEC, 2003) and in the more recent financial crisis (SEC, 2008). A lot of the debate in the political arena has focused on the conflicts of interest innate in the issuer-paid model. Our results 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. 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. Therefore, although we find no evidence of "foul play", our tests still show another possible important aspect for regulators to consider: the full independence of the analyst team.

References

Abadie, A., Drukker, D., Herr, J.L. and Imbens, G.W. (2004) Implementing matching estimators for average treatment effects in Stata, *Stata journal*, 4, 290-311.

Amato, J.D. and Furfine, C.H. (2004) Are credit ratings procyclical?, *Journal of Banking & Finance*, 28, 2641-2677.

Ashbaugh-Skaife, H., Collins, D.W. and LaFond, R. (2006) The effects of corporate governance on firms' credit ratings, *Journal of Accounting and Economics*, 42, 203-243.

Bannier, C.E., Behr, P. and Guttler, A. (2009) Rating opaque borrowers: why are unsolicited ratings lower?, *Review of Finance*, 14, 263-294.

Bannier, C.E., Behr, P. and Güttler, A. (2010) Rating opaque borrowers: why are unsolicited ratings lower?*, *Review of Finance*, 14, 263-294.

Bebchuk, L., Cohen, A. and Ferrell, A. (2009) What Matters in Corporate Governance?, *Review of Financial Studies*, 22, 783-827.

Benmelech, E. and Dlugosz, J. (2009) The alchemy of CDO credit ratings, *Journal of Monetary Economics*, 56, 617-634.

Bertrand, M. and Schoar, A. (2003) Managing with Style: The Effect of Managers on Firm Policies, *The Quarterly Journal of Economics*, 118, 1169-1208.

Blume, M.E., Lim, F. and Mackinlay, A.C. (1998) The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality?, *The Journal of Finance*, 53, 1389-1413.

Bolton, P., Freixas, X. and Shapiro, J. (2012) The Credit Ratings Game, *The Journal of Finance*, 67, 85-111.

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

Cohen, L., Frazzini, A. and Malloy, C. (2008) The Small World of Investing: Board Connections and Mutual Fund Returns, *Journal of Political Economy*, 116, 951-979.

Coles, J.L., Daniel, N.D. and Naveen, L. (2014) Co-opted Boards, *Review of Financial Studies*, 27, 1751-1796.

Cornaggia, J. and Cornaggia, K.J. (2013) Estimating the Costs of Issuer-Paid Credit Ratings, *Review of Financial Studies*, 26, 2229-2269.

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

Engelberg, J., Gao, P. and Parsons, C.A. (2012) Friends with money, *Journal of Financial Economics*, 103, 169-188.

Fenn, G.W. (2000) Speed of issuance and the adequacy of disclosure in the 144A high-yield debt market, *Journal of Financial Economics*, 56, 383-405.

Fracassi, C. (2014) Corporate finance policies and social networks, *SSRN Working Paper Series 1121503*.

Fracassi, C. and Tate, G. (2012) External Networking and Internal Firm Governance, *The Journal of Finance*, 67, 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. and Tang, D.Y. (2012) Did Subjectivity Play a Role in CDO Credit Ratings?, *The Journal of Finance*, 67, 1293-1328.

Hovakimian, A., Kayhan, A. and Titman, S. (2012) Are Corporate Default Probabilities Consistent with the Static Trade-off Theory?, *Review of Financial Studies*, 25, 315-340.

Jiang, J., Harris Stanford, M. and Xie, Y. (2012) Does it matter who pays for bond ratings? Historical evidence, *Journal of Financial Economics*, 105, 607-621.

Kraft, P. (2014) Rating agency adjustments to GAAP financial statements and their effect on ratings and credit spreads, *SSRN Working Paper Series 1266381*.

Leuven, E. and Sianesi, B. (2014) PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing, *Statistical Software Components*.

Mählmann, T. (2011) Is There a Relationship Benefit in Credit Ratings?, *Review of Finance*, 15, 475-510.

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

Pittman, M. (2008) Moody's, S&P's defer cuts on AAA subprime, hiding loss, *Bloomberg*, March 11, 2008.

Poon, W.P.H. (2003) Are unsolicited credit ratings biased downward?, *Journal of Banking & Finance*, 27, 593-614.

Rosebaum, P.R. and Rubin, D.B. (1983) The central role of the propensity score in observational studies for causal effects, *Biometrika*, 70, 41-55.

Rosenbaum, P.R. and Rubin, D.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. and Thomas, N. (1992) Characterizing the effect of matching using linear propensity score methods with normal distributions, *Biometrika*, 79, 797-809.

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.

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 I. 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 II. 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. *Bond Yield* is the yield to maturity.

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	0.000
Solicitation	0.596	367	0.599	1352	0.595	0.889
Issue Amount ($m)	1550.332	367	773.000	1352	1760.000	0.000
Maturity	12.049	367	12.422	1352	11.948	0.475
Seniority	0.970	367	0.921	1352	0.984	0.000
Default – 5Y (%)	1.264%	335	5.373%	1247	0.160%	0.000
Default – 10Y (%)	2.449%	324	9.568%	1187	0.505%	0.000
Bond Yield	5.446	75	6.189	354	5.288	0.000

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 personal 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	0.000
Leverage	0.252	367	0.306	1352	0.237	0.000
Book-to-Market Ratio	0.404	367	0.477	1352	0.385	0.000
Total Assets ($m)	16025	367	5380	1352	18900	0.000
MM Beta	0.829	367	0.022	1352	0.020	0.000
Sigma	0.020	367	6.879	1352	8.231	0.000
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).

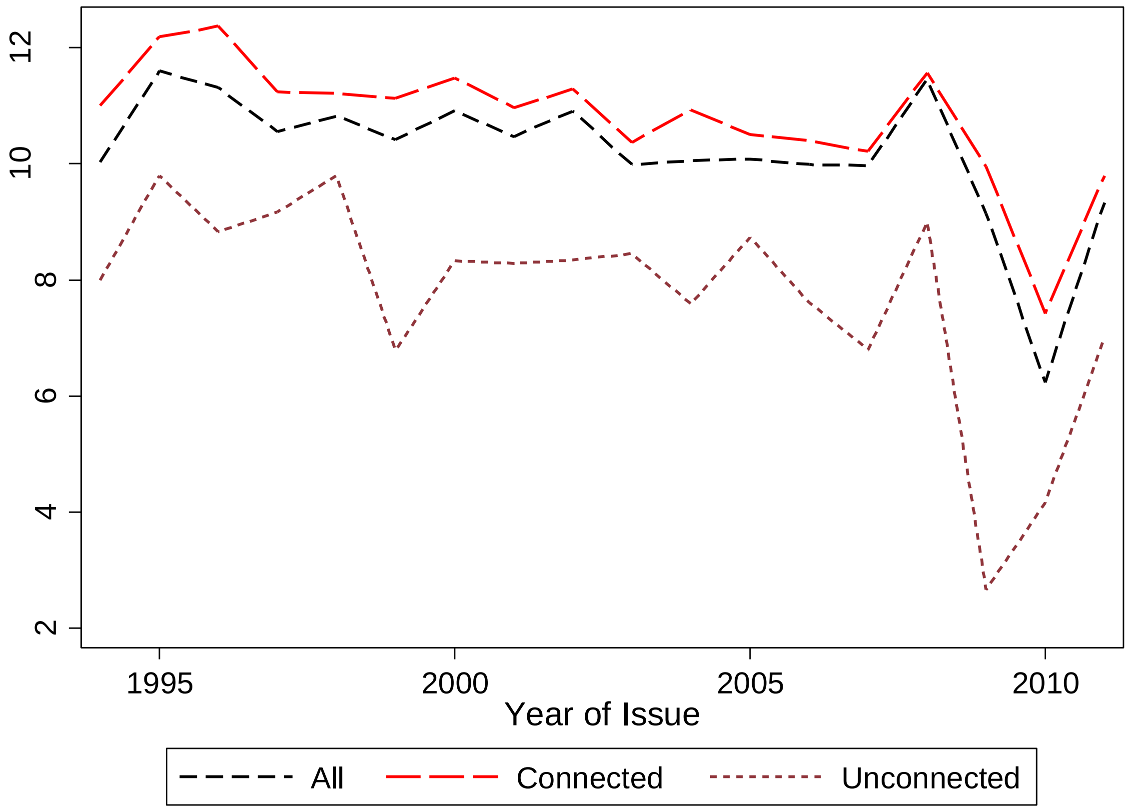

Table III. Ordered-probit regressions

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 credit 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 and they are clustered at the firm level. *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 IV. Ordered-probit robustness tests

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). *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. *Relate* is the number of years elapsed between the first bond issue in the dataset and the current year. *Total Issues* is the sum of all the debt issues made by a company. *MBA* (*MSc*, *PhD*) measures the fraction of board members that have an MBA (MSc, PhD) qualification. *Other* measures the fraction of board members that have professional qualifications. *Quoted Boards* measures average number of board seats on public (quoted) companies held by directors of the issuing firm. *Age* measures the average age of directors of issuing firms. *Delta* is the average dollar change in wealth associated with a 1% change in the firm's stock price (in $000s). *Vega* measures average dollar change in wealth associated with a 0.01 change in the standard deviation of the firm's returns (in $000s). *E-index* represents the value of the entrenchment index as a measure of the quality of the governance in the firm. *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 and they are clustered at the firm level. *P*-values are reported in brackets. *, **, and *** report the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Solicited	**Unsolicited**	**Business ties**		**Education**	**Experience**	**Compensation**	**Governance**	**All**
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
Connection Dummy	0.274***	0.316**	0.301***	0.295***	0.330***	0.332***	0.287***	0.557***	0.681***
	[0.002]	[0.035]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Relate			0.026***						0.027
			[0.005]						[0.379]
Total Issues				0.005**					0.006

				[0.047]					[0.336]
MBA					-0.916***				-1.419***
					[0.000]				[0.005]
MSc					0.196				-0.311
					[0.487]				[0.632]
PhD					-0.299				-0.35
					[0.249]				[0.538]
Other					-1.187***				-1.138
					[0.002]				[0.176]
Total Boards						-0.011**			0.006
						[0.030]			[0.501]
Quoted Boards						0.021***			0.028*
						[0.005]			[0.067]
Age						-0.024**			-0.01
						[0.010]			[0.665]
Delta							-.00004**		-0.00016*
							[0.050]		[0.093]
Vega							-0.0006***		0.00033
							[0.001]		[0.545]
E-index								0.032	-0.056
								[0.399]	[0.219]
Solicitation Dummy			0.005	0.011	0.048	0.017	-0.137**	0.351***	0.312**
			[0.923]	[0.839]	[0.401]	[0.776]	[0.024]	[0.001]	[0.024]
Ln. Issue Amount	-0.035	-0.072***	-0.049**	-0.055***	-0.050**	-0.048**	-0.040*	-0.008	-0.035
	[0.243]	[0.006]	[0.016]	[0.007]	[0.013]	[0.017]	[0.068]	[0.870]	[0.524]
Maturity	0.009***	0.012***	0.011***	0.011***	0.012***	0.009***	0.010***	0.011***	0.004
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.007]	[0.468]
Seniority	1.629***	1.384***	1.604***	1.593***	1.567***	1.428***	1.748***	1.868***	2.042***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Interest Coverage Rati	-0.007***	-0.003	-0.004**	-0.004**	-0.004***	-0.003*	-0.004**	-0.005	0.001
	[0.005]	[0.273]	[0.011]	[0.013]	[0.007]	[0.056]	[0.033]	[0.278]	[0.867]
Profit Margin	1.335***	-1.471***	-0.064	-0.054	-0.128	-0.495	0.301	-0.58	-0.917
	[0.003]	[0.002]	[0.838]	[0.866]	[0.682]	[0.147]	[0.395]	[0.317]	[0.207]
Return on Assets	6.381***	8.583***	7.560***	7.608***	7.925***	8.275***	8.310***	9.868***	11.978***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Leverage	-4.162***	-3.785***	-3.884***	-3.849***	-3.769***	-3.452***	-3.844***	-3.847***	-3.172***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Book-to-Market Ratio	-1.258***	-1.227***	-1.121***	-1.138***	-1.082***	-0.945***	-1.224***	-1.493***	-0.926**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.030]
Ln. Total Assets	0.586***	0.577***	0.532***	0.525***	0.525***	0.587***	0.590***	0.827***	0.886***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
MM Beta	0.213*	-0.208	0.071	0.085	0.123	-0.074	0.038	0.101	0.062
	[0.097]	[0.228]	[0.495]	[0.415]	[0.240]	[0.539]	[0.727]	[0.502]	[0.748]
Sigma	-28.320**	-26.540***	-31.054***	-31.433***	-35.807***	-22.566***	-30.358***	-30.408***	-30.434**
	[0.031]	[0.001]	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]	[0.010]	[0.035]
Ln.(1+ No. of Connected Individuals)	-0.085	-0.039	-0.065	-0.066	-0.02	-0.156**	-0.107*	-0.328***	-0.262
	[0.269]	[0.650]	[0.198]	[0.203]	[0.735]	[0.012]	[0.055]	[0.002]	[0.130]
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.216	0.267	0.228	0.227	0.231	0.222	0.224	0.279	0.288
N	1,025	694	1,719	1,719	1,715	1,502	1,499	541	435

Table V. Economic Importance

The table presents the OLS results of the determinants of Moody's credit ratings for easiness of interpretation of the economic significance of our results. *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). *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*). *Ln.(1+No. of Connections)* is the natural log of one plus the total number of connections. *Ln.(1+No. of Current Connections)* is the natural log of one plus the total number of current connections. *Ln.(1+No. of Past Connections)* is the natural log of one plus the total number of past connections. The economic significance of the connection variables is reported beneath the p-values (in bold); this number is the numerical change in the dependent variable (in absolute terms) in response to a change in the connection variables. For Dummy Variables, this is the same as the estimated coefficient. For the variables in logarithm, we report the change in rating between issues by firm with zero connections and issues by firm with median (three) connections. For brevity we omit to report all the control variables but we use all firm, managerial and issue characteristics included in our regression analyses, as well as year and industry dummies (Table IV model IX). Standard errors are robust to heteroskedasticity and they are clustered at the firm level. *P*-values are reported in brackets. *, **, and *** report the statistical significance at the 10%, 5%, and 1% levels, respectively.

	I	**II**	**III**	**IV**	**V**	**VI**
Connection Dummy	0.903***					
	[0.002]					
	0.903					
Current Connection Dummy		0.765***				
		[0.000]				
		0.765				
Past Connection Dummy			0.838***			
			[0.005]			
			0.838			
Ln.(1+No. of Connections)				0.662***		
				[0.000]		
				0.918		
Ln. (1+No. of Current Connections)					0.689***	
					[0.000]	
					0.956	
Ln. (1+No. of Past Connections)						0.666***
						[0.000]
						0.923
Issue and Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	435	435	435	435	435	435

Table VI. 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 issue, firm, and managerial characteristics included in our regression analyses, as well as year and industry dummies (Table IV model IX). 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 Issues	**Credit Rating Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
Connected	124	9.895	0.564	0.0492	0.830
Non-Connected	124	9.330			

Panel B. Current Connections

	Matched Issues	**Credit Rating Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (p-value)**
Connected	41	10.390	0.878	0.077	0.586
Non-Connected	41	9.512			

Panel C. Past Connections

	Matched Issues	**Credit Rating Mean**	**Diff. in Means (Connected-Non-Connected)**	**Diff. (*p*-value)**	***P*-Score (*p*-value)**
Connected	119	9.916	0.806	0.011	0.795
Non-Connected	119	9.109			

Table VII. Falsification tests - Monte Carlo permutations

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 on Table IV Model IX. 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 true coefficients reported in the first column, then we would fail to reject the null hypothesis. The connection status variable is reshuffled across issues of treated firms only.

	True Coefficient	**Random Shuffle Coefficient> True Coefficient**	**No. of Trials**	**Implied *p*-value**
Connection Dummy	0.681	0	100,000	0.000
Current Connection Dummy	0.561	0	100,000	0.000
Past Connection Dummy	0.626	0	100,000	0.000
Ln.(1+No. of Connections)	0.523	0	100,000	0.000
Ln. (1+No. of Current Connections)	0.536	0	100,000	0.000
Ln. (1+No. of Past Connections)	0.524	0	100,000	0.000
N	435			

Table VIII. Default rate 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, 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 Issues	**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 Issues	**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 IX. 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. *Bond Yield* is the yield to maturity. 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			