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Director Networks and Credit Ratings of Insurance Companies

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National Association of Insurance Commissioners

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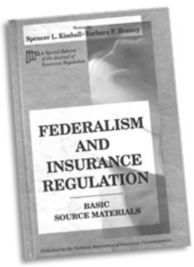

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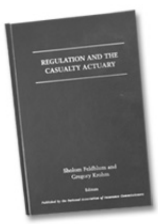

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Director Networks and Credit Ratings of Insurance Companies

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Abstract

Previous finance literature has found that a firm's credit rating is influenced by the connectedness of its board members. Due to the subjective nature of credit ratings, qualitative information like a board's connections can influence a rating agency's decision making. We investigate the impact of four dimensions of board connectedness on credit ratings in the highly-regulated insurance industry. We find mixed evidence regarding the relationship between board connectedness and credit ratings in the insurance industry. As is the case for non-financial companies, we find some evidence that board connectedness is positively related to credit ratings for property/casualty (P/C) insurers, in line with social capital theory. However, for life insurers, we find that board connectedness is negatively associated with credit ratings, which supports the "board-busyness" theory. We suggest that the differing relationships between board connectedness and credit ratings among insurers are due to the short-term and riskier nature of property insurers, and that the disconnect between life insurers and non-financial companies is explained by life insurers' greater size, lower liquidity and higher leverage.

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Introduction

The insurance industry's stability is increasingly vital to overall economic health (Das, Davies and Podpiera, 2003). Although traditionally stable, risk-taking within the sector has increased as insurance companies diversify into products traditionally offered by banks and wealth management firms. Investment losses within these products, along with miscalculations in underwriting, can befall an insurance company; and those risks can reverberate throughout the economy. As such, more stringent regulations, requiring increased financial reporting, have historically been required by state insurance regulators to strengthen insurers' solvency (Klein, 1995). BarNiv and Hershbarger (1990) highlight the concerns the NAIC has in avoiding insurance company failures.

Credit rating agencies (CRAs) assign scores based on the perceived likelihood of default and a firm's perceived solvency. In their assessments, CRAs appropriately consider financial information relevant to a firm's economic health. However, credit ratings are not assigned based on financial information alone. Acknowledging the presence of asymmetric information, CRAs attempt to close the information gap by relying on qualitative information (Frost, 2007). Recent research has shown that one mechanism that CRAs consider is director connections, both in the form of social capital (Benson, Iyer, Kemper and Zhao, 2018) and also the direct connections that boards have with a CRA (Khatami, Marchica and Mura, 2016). However, both of these papers exclude insurance companies from their sample, arguing that a tight regulatory environment in this sector might compromise their results.

We revisit Benson et al. (2018) to examine how a tighter regulatory environment affects the need for qualitative information. Benson et al. argue that CRAs rely on the trustworthiness of the members of a firm's board of directors to close the information gap and proxy for trustworthiness by examining the directors' social capital. Their results show that firms which employ a highly connected board receive higher credit ratings. Following the work of Belliveau, O'Reilly and Wade (1996) and Paldam (2000), the authors relate the social capital of the board to trust. This social capital is built by expanding one's personal network, which increases an individual's reputation. Once earned, an individual is likely to behave in a manner that preserves that reputation.

Due to regulatory agencies requiring insurance companies to disclose significant additional financial information, we argue that this sector warrants investigation to better understand the relationship between board connectedness and credit ratings. We are motivated to examine the role that stringent regulations play in CRA decision making in the presence of additional financial constraints. Using a global sample of 10,973 firm-year observations, including both insurers and non-insurers, we find mixed evidence regarding the relationship between board connectedness and credit ratings. Regarding P/C insurers, we find some evidence of results similar to Benson et al. (2018). Namely, we see a positive relationship between board connectedness and credit ratings in two of our four measures, suggesting that CRAs may value the social capital of highly connected board members. Given that property insurers face more claim volatility and a much higher potential for underwriting losses, this seems plausible. However, the same relationship does not exist regarding life insurers. In fact, when examining life insurers, we find evidence that board connectedness is associated with lower credit ratings. This result is consistent with the "board busyness" theory (Fich and Shivdasani, 2006). This theory posits that boards containing members with many commitments, which are more likely to be classified as highly-connected in our sample, actually result in weaker corporate governance. Taken in concert, our findings suggest that the impact of board connectedness is different for P/C firms and life insurance firms. Property insurers face more unpredictability, and thus risk, in their operations than life insurers, which could account for the opposite relationship between board connectedness and credit ratings seen in our results. In our sample, our results suggest that the connectedness of boards leads to lower credit rating for life insurers. One possible explanation for this result, which is the opposite found by Benson et al. (2018) for non-financial firms, is that the larger size, greater leverage and lower liquidity of life insurers (relative to both P/C firms and non-financial firms) explains why CRAs react differently to board connectedness for life insurers, because the detrimental effects of a "busy board" are greater at larger, more highly levered, and less liquid firms.

The first contribution of our paper is to analyze the impact of board connectedness on CRA's decision making in a highly regulated industry. State insurance regulators recognize the systemic importance of insurance companies and provide oversight. A natural question would be to examine whether the regulatory oversight of insurers negates the impact of board connectedness on CRAs found in prior studies. Specifically, if state insurance regulators trust the additional financial information required of insurers, they may not consider board connectedness. From our results, some evidence exists that CRAs appear to consider board connectedness at property insurers in a way similar to that of non-financial companies, meaning that higher board connectedness is positively associated with credit ratings. Our results suggest that CRAs consider highly connected boards negatively with respect to life insurers. This result stands in contrast to the work of Benson et al. (2018), while our results for P/C insurers tend to support it.

Our second contribution is to add to the literature that focuses on understanding the rating process. Graham and Harvey (2001) illustrate the importance that firms place on their ratings as chief financial officers (CFOs) list a firm's credit rating as a top priority. Dichev and Piotroski (2001) also show that credit ratings affect firm investment decisions. Additionally, both bond and equity markets react to changes in credit ratings (Hand, Holthausen and Leftwich, 1992). Because investment decisions are made with ratings in mind and stockholder wealth is affected by changes in ratings, the analysis of the rating process is valuable to managers and investors alike. However, the rating process is not fully transparent, nor does the rating process rely solely on firm financials (Frost, 2007). Therefore, this paper's focus is on revealing another qualitative measure that CRAs likely consider.

There also exists rating literature that is specific to insurers. Pottier and Sommer (1999) show the value that insurers place on their own ratings. Chen, Gaver and

Pottier (2018) highlight insurer stock return movements associated with changes in ratings. Halek and Eckles (2010) also highlight equity reactions to changes in insurance company ratings, confirming the effect that ratings have on stockholder wealth. Much research has hence been devoted to understanding the rating process. This paper adds to the evidence that the rating process is a function of the regulatory environment each industry faces.

Hypothesis Development and Methodology

CRAs create a numerical measure which attempts to quantify default probability. In the process, analysts rely on financial ratios and other quantitative information. However, financial information alone does not capture the entire process. Instead, the final credit rating reflects qualitative information (Odders-White and Ready, 2006). Benson et al. (2018) introduce social capital into the equation and show that, in non-financial companies, CRAs consider the connectivity of the boards of directors in their assessment. The authors argue that CRAs expect a board that is well-connected to take steps to maintain its reputation and do its duty. As such, the credit rating for firms with well-connected boards is higher than the financial models would suggest, ceteris paribus.

BarNiv and Hershbarger (1990) stress that the Insurance Regulatory Information System (IRIS), developed by the NAIC, will take immediate action when firm financials move outside preferred limits. Over time, the implementation of the NAIC's Financial Analysis Solvency Tools (FAST) ratios and risk-based capital standards further refined information provided to state insurance regulators. Because the insurance sector is highly regulated and remedial actions are swift, we consider a natural experiment in which firms that face more stringent financial reporting standards are evaluated. Eckles and Halek (2012) ask how the rating process affects information dissemination for these firms. If firms are more transparent in their financial situation, then the need of CRAs for qualitative information decreases. Therefore, we hypothesize that CRAs rely less on qualitative information in the evaluation of highly regulated firms.

H1: The credit rating process for firms in a highly regulated industry is different from the rating process of other industries.

To test this hypothesis, we examine the credit ratings of insurance companies. Skipper and Klein (2000) discuss the role insurance companies play in an advanced economy. They also validate the existence of stringent reporting standards. Grace, Harrington and Klein (1998) also highlight the regulatory environment that insurers face. To conduct our experiment and further understand the credit rating process, we follow the board connection methodology used in Benson et al. (2018) and apply it to insurance companies. This methodology uses four measures of board connectedness: degree centrality, betweenness centrality, closeness centrality and eigenvector centrality.

Degree centrality counts the number of direct relations a person has. The second measure is betweenness centrality, which examines if a person is between two powerful individuals and therefore acts as a bridge. Closeness centrality considers how close a person is to others in a network. The assumption is that a person closer to information obtains information more quickly and therefore has more power. Lastly, eigenvector centrality measures the importance of the person to which one is connected. For example, a person may have few connections. However, if that person is connected to another person who is highly connected, then eigenvector centrality would be high.

Data and Variables

Ratings of insurance companies have historically been dominated by A.M. Best, spanning a hundred-year history. In the 1980s, Standard & Poor's (S&P) entered this market and currently rates more than 80% of the insurance industry (Doherty, Kartasheva and Phillips, 2008). Our methodology involves examining the relation between board connectedness, using measures from BoardEx data, and credit ratings measured by the S&P Domestic Long-Term Issuer Credit Rating variable in the Compustat database. Benson et al. (2018) find a positive relation between board connectedness and credit ratings. Following their methodology, we construct models that include both insurers and non-insurers in a global regression, and then insert dummy variables for both life insurers and property insurers. We then examine the relation between board connectedness and credit ratings for: 1) non-insurers and life insurers; and 2) non-insurers and property insurers.[1] The coefficient on an interaction term of the dummy variable for the insurers and board connectedness will yield evidence about the relationship between board connectedness and credit ratings for the insurers in the sample. Using this methodology precludes the use of A.M. Best ratings, because they exist only for insurers. Based on the work of Doherty, Kartasheva and Phillips (2008), we are confident that the S&P rating is an appropriate measure of creditworthiness for insurance companies.

We gather ratings data from Compustat, excluding firms with a rating below C, as these firms are near default and could taint results (Behr, Kisgen and Taillard, 2015). To create our dependent variable *RATINGS*, we follow an inverse coding system in which an "AAA" rating takes on a value of 1 and a rating of "C" takes on a value of 21. All other financial information is also gathered from Compustat. We construct our connectivity measures using BoardEx and examine the years 1999 through 2011, focusing on professional relationships.

1. We identify life insurance companies (property insurance companies) as those companies with 63 (64) as their two-digit Standard Industrial Classification (SIC) code.

Board Connectedness Variables

We calculate betweenness centrality as the scaled value of the shortest number of connections that pass through a director. A director can be highly-central if she occupies pivotal bridge positions between other boards, making her a key proxy for information transfer. Let $d_{st}(i)$ denote the number of shortest paths between directors *s* and *t*, with director *i* being an intermediate connection; and let d_{st} (*i*) denote the total number of shortest links that connect directors *s* and *t* (including those that involve director *i*). *Betweenness centrality* for director *i* is measured as

$$C_B(i) = \sum_{s \neq t \neq i} \frac{d_{st}(i)}{d_{st}}$$

and the scaled measure is given as

$$C_B^*(i) = \frac{2}{(n-1)(n-2)} C_B(i)$$

Closeness centrality is defined as the measure of closeness to all other participants in the network. A highly connected director is closer to many other nodes. Let *d(i, j)* denote the shortest number of steps that connect director *i* to director *j* in the network. From director *i*'s perspective, the value

$$\sum_j d(i,j)$$

denotes the total number of (shortest) steps taken to connect with all other directors in the network. The measure of 'shortest' captures *closeness*. The inverse of this measure is denoted by

$$C_C(i) = \frac{1}{\sum_j d(i,j)}$$

and measures *closeness centrality*, where values indicate how closely tied director *i* is to other directors in the network. The scaled measure is

$$C_C^*(i,j) = (n-1) C_C(i)$$

We define degree centrality as the scaled number of connections possessed by a director. A director can be highly influential if she is a member of multiple boards delivering many relationships and channels of information transfer resulting in value enhancing opportunities and increased trustworthiness. In other words, *degree centrality* is the total number of connections possessed by a director. *Degree centrality* is measured as follows. Let A_{ij} denote a matrix containing a value of 1 if directors i and j are connected and 0 otherwise. Let $C_D(i)$ denote the number of nearest neighbors to director i,

$$C_D(i) = \sum_j A_{ij}$$

and scaled degree centrality is

$$C_D^*(i) = \frac{1}{n-1} C_D(i)$$

where n is the number of directors in the network.

Finally, we turn our attention to eigenvector centrality, which is derived from degree centrality. There may be instances when a director is closely connected with another director who might be highly influential within multiple clusters. Such a less-than well-connected director benefits from the connections possessed by their immediate connections, which can sometimes be construed as a parasitic effect. Let v_i denote the importance of director i. The value of v_i depends on the value of v_j for director j if director i is connected to director j. If we consider all directors in the network, v_i is determined by

$$\sum_j A_{ij} v_j$$

To compute v_i, suppose we assign a value of 1 to each director's importance and recursively determine v_i; by the following relation

$$v_i \leftarrow \sum_j A_{ij}(v_j)$$

the values increase in size without bound. To normalize this process, let

$$\lambda$$

be a normalizing constant such that

$$v_i = \frac{1}{\lambda} \sum_j A_{ij}(v_j)$$

In matrix notation, this is written as

$$Av = \lambda v$$

The constant

$$\lambda$$

is easily seen as an eigenvalue measure. The eigenvector associated with the largest eigenvalue indicates the measure of each director's importance in the network. In the next section, we describe the data and other variables.

Control Variables

We consider control variables used in Park, Xie and Rui, (2018); Behr, Kisgen and Taillard (2015); and Blume, Lin and Mackinlay (1998), and see that all of these emphasize measures of size, leverage and liquidity as control variables[2] when examining credit ratings and board connectedness. In this paper, we only use the control variables that are prevalent in the most recent highly cited papers in this area, alleviating concerns of multicollinearity among control variables. We define size as the natural log of total assets. Leverage is defined as the total liabilities to net worth (surplus). Net worth is defined as the difference between assets and liabilities. Liquidity is defined as the ratio of cash and equivalents to total assets. We expect size to be negatively related to our dependent variable, *RATINGS*, because larger firms tend to have higher credit ratings. We expect leverage to be positively related to our dependent variable due to the fact that more highly leveraged firms tend to have lower credit ratings. Finally, liquidity is expected to be negatively related to our dependent variable meaning that more liquid firms tend to be viewed more favorably by CRAs.

Summary Statistics

Table I presents our summary statistics. In our sample, we see that the average publicly-traded company has a rating of 10 (BBB-) and an average publicly-traded life insurance company has a rating of 8 (BBB+), while the average property

2. Recently, Benson et al. (2018) used size, leverage, interest coverage and operating margin as their controls.

publicly-traded insurance company has a rating of 10 (BBB-). The average firm in our sample has approximately $4 billion in assets, life insurance companies have $14 billion in assets, and average property insurance companies have $3.3 billion in assets. Firms have liabilities that are almost 2.83 times greater than surplus, whereas life insurance companies have liabilities that are six times greater than surplus, and property insurance companies have liabilities that are three times greater than surplus. Firms in the overall sample have a liquidity ratio of 30%, whereas life insurance companies maintain a liquidity ratio of 22%, and property insurance companies maintain a liquidity ratio of 28%.

Table I:
Summary Statistics

Panel A: All Companies

Variable	MEAN	MEDIAN	STD DEV	N
Rating code	10	10	3	10978
Size	8.2313	8.0765	1.5590	10978
Leverage	2.8333	1.7619	58.4746	10973
Liquidity	0.3015	0.3229	0.2420	10978

Panel B: Life Insurance Companies

Variable	MEAN	MEDIAN	STD DEV	N
Rating code	8	8	3	586
Size	9.5728	9.5490	1.5607	586
Leverage	5.7635	3.9753	5.7775	586
Liquidity	0.2221	0.1928	0.1475	586

Panel C: Property Insurance Companies

Variable	MEAN	MEDIAN	STD DEV	N
Rating code	10	12	3	36
Size	8.1313	7.2319	1.6411	36
Leverage	3.1253	2.5643	2.1449	36
Liquidity	0.2874	0.2775	0.1131	36

This table presents the summary statistics of the sample. Rating is provided by Compustat. An inverse coding system starting with an "AAA" rating, which is coded as 1, and a "C" rating, which is coded as 21. Firms with a "D" rating, an "SD" rating and no rating are dropped. Size is defined as the natural log of total assets. Leverage is defined as the total liabilities to surplus (net worth). Net worth is defined as the difference between assets and liabilities. Liquidity is defined as ratio of cash and equivalents to total assets.

Panel A of Table II (on page 11) presents the univariate statistics for our centrality variables for the entire sample. The centralities are normalized to the entire network, hence the values seem small. Normalization allows for the comparison of nodes of different sizes (Chuluun, Prevost and Puthenpurackal, 2014; El-Khatib, Fogel and Jandik, 2015). Board level centralities are combined from individual director level values. We use the interpretation in Fogel, Ma and Morck (2014) to explain our raw centrality variables. The mean (median) *betweenness centrality* is 0.00013 (0.00007), which means that the average director sits in about 7,700 paths (1/.00012 = 7,692.30). A director in the 75th percentile sits in about 7,140 paths. The mean (median) value for *closeness centrality* is 0.3135 (0.3147). A *closeness centrality* measure of 0.3135 indicates that a typical director is about (1/0.3135 = 3.18) degrees of separation from any other randomly chosen director in the network. The mean (median) value for *degree centrality* is 0.00133 (0.0010). A higher value means a larger number of connections. The mean (median) value for *eigenvector centrality* is 0.00160 (0.00080). *Eigenvector centrality* does not provide an intuitive interpretation beyond our description in Section 2, but a higher value certainly means that, on average, the directors are connected with other powerful directors in the network. Panel B presents the pairwise correlations between the centrality variables and ratings. The centrality variables are positively correlated with themselves, suggesting that they measure similar board member characteristics. The results in Table II support the findings in Chuluun, Prevost and Puthenpurackal (2014).

Panel C repeats the analysis for life insurance companies. The mean (median) *betweenness centrality* is 0.00012 (0.00007), which means that the average director sits in about 8,300 paths (1/.00012 = 8333.33). A director in the 75th percentile sits in about 7,140 paths. The mean (median) value for *closeness centrality* is 0.3154 (0.3173). A *closeness centrality* measure of 0.3154 indicates that a typical director is about (1/0.3153 = 3.17) degrees of separation from any other randomly chosen director in the network. The mean (median) value for *degree centrality* is 0.00139 (0.00117). The mean (median) value for *eigenvector centrality* is 0.00179 (0.00101). Panel D presents the pairwise correlations between the centrality variables and ratings, and they agree with the results in Panel B.

Panel E of Table II presents the univariate statistics for our centrality variables for the property insurance companies. The mean (median) *betweenness centrality* is 0.00023 (0.00025), which means that the average director sits in about 4,300 paths. A director in the 75th percentile sits in about 4,000 paths. The mean (median) value for *closeness centrality* is 0.3217 (0.3272). A *closeness centrality* measure of 0.3217 indicates that a typical director is about (1/0.3153 = 3.10) degrees of separation from any other randomly chosen director in the network. The mean (median) value for *degree centrality* is 0.00197 (0.00176). Directors in the property insurance companies seem to have higher connections than directors in the life insurance companies. The mean (median) value for *eigenvector centrality* is 0.00304 (0.00168). Overall, we see that directors in the property insurance companies are marginally better connected than directors in the life insurance companies. Panel F results are qualitatively similar to those in Panel B. Hence, we proceed to discuss the multivariate results.

Table II:
Board Network Centrality Measures

Panel A – Network Measures – All Companies

	Mean	SD	P25	Median	P75
Between	0.00013	0.00016	0.00004	0.00007	0.00014
Closeness	0.31358	0.01874	0.30235	0.31473	0.32630
Degree	0.00133	0.00100	0.00065	0.00106	0.00171
Eigen	0.00160	0.00274	0.00038	0.00080	0.00174

Panel B – Pairwise Correlation of Centralities for All Companies

	Rating	Between	Closeness	Degree
Between	-0.3287***			
Closeness	-0.2812***	0.5903***		
Degree	-0.3410***	0.8168***	0.8110***	
Eigen	-0.1450***	0.3425***	0.4325***	0.5488***

Panel C – Network Measures – Life Insurance Companies

	Mean	SD	P25	Median	P75
Between	0.00012	0.00017	0.00004	0.00007	0.00014
Closeness	0.31546	0.01900	0.30513	0.31734	0.32736
Degree	0.00139	0.00093	0.00069	0.00117	0.00180
Eigen	0.00179	0.00215	0.00046	0.00101	0.00225

Panel D – Pairwise Correlation of Centralities and Rating for Life Insurance Companies

	Rating	Between	Closeness	Degree
Between	-0.2998***			
Closeness	-0.1441***	0.5358***		
Degree	-0.2523***	0.7368***	0.8555***	
Eigen	-0.0095	0.2826***	0.5075***	0.5916***

Panel E – Network Measures – Property Insurance Companies

	Mean	SD	P25	Median	P75
Between	0.00023	0.00016	0.00005	0.00025	0.00034
Closeness	0.32172	0.01744	0.30589	0.32720	0.33799
Degree	0.00197	0.00103	0.00087	0.00176	0.00293
Eigen	0.00304	0.00531	0.00054	0.00168	0.00254

Panel F – Pairwise Correlation of Centralities and Rating for Property Insurance Companies

	Rating	Between	Closeness	Degree
Between	-0.6880***			
Closeness	-0.7525***	0.5730***		
Degree	-0.8058***	0.7763***	0.9116***	
Eigen	-0.0729	0.0763	0.3778***	0.4095***

This table provides the summary statistics for the centrality measures (non-standardized) for our sample. Panel A (Panel C) provides the summary statistics and Panel B (panel D) provides the pair-wise correlation tables of our centrality measures and ratings for life insurance companies (property insurance companies).

Results

Table III (on page 14) presents an ordered probit regression with credit ratings as the dependent variable and our board connections as independent variables. In our global regression, we use a dummy variable, *Insurance_Life (Insurance_Prop),* which takes on a value of 1 if the rated firm is a life insurance (property insurance) company. Employing a two-way fixed effects model controlling for year and industry, Panel A of Table III shows an inverse relation between our dependent variable and our life insurance dummy variable. This finding reveals that life insurance companies have higher credit ratings after controlling for each firms' financials. Panel A of Table III also supports the findings in Benson et al. (2018) and shows that board connections influence firm ratings for this sample, which includes both life insurers and non-insurers. A negative and significant relation between our dependent variable and each of the connectivity variables verifies that firms with connected boards enjoy a higher corporate rating. Panels A and B of Table III also show that larger, more liquid firms with slightly lower leverage have higher credit ratings.

In Table IV (on page 15), we introduce an interaction variable to examine if the connectivity of boards influence CRA decision making for insurers. This is the examination of our main hypothesis, which proposes that qualitative information, like board connectivity, will play a lesser role on the CRAs of firms in a highly regulated industry. Due to the regulatory obligation of providing additional financials, we hypothesize that CRAs would focus more on the available financial information. To study this hypothesis, we interact our insurance dummy variables with each of the connectivity variables. For P/C insurers, in Panel B of Table IV, we see that two of the four interaction variables are significant and negative, which, due to our inverse measure of credit rating, implies a positive relationship between board connectedness and credit rating. Consequently, we find some evidence that for P/C insurers, the impact of board connectedness on credit ratings is similar to that of non-financial firms; i.e., higher board connectedness appears to be associated with higher credit ratings for P/C firms, which aligns with Benson et al. (2018). The results for life insurers can be seen in Panel A of Table IV, where we see that three of the four interaction variables are significant and positive. In other words, when viewed in the isolation of the interaction variable, it appears that the connectedness of a life insurance company's board tends to be associated with lower credit ratings. We surmise that this may be due to life insurance companies' greater size, lower liquidity and higher leverage than other non-financial firms, and because of their greater predictability in operating results relative to property insurers. This finding should be of interest to state insurance regulators of life insurance companies, because it stands in contrast to the results of Benson et al. (2018), and instead supports the "board-busyness" theory of Fich and Shivdasani (2006) which found that boards composed of members with many commitments ultimately experienced weaker corporate governance. We posit that these contradictory findings among type of insurer are due to the nature of the risk to which these firms are exposed.

Specifically, life insurers' obligations are more predictable, and these firms hold asset portfolios that contain long-term bonds reflecting the nature of their obligations. The same cannot be said for property insurers. Underwriting losses can come in droves and are less predictable. Once again, the asset portfolio of a property insurer reflects this reality. Therefore, we posit that CRAs are more likely to rely on the social capital of the board and its sense of duty if losses mount to pay its obligations for P/C insurers, as is the case for non-financial companies. Because life insurers have more predictable outlays, they do not benefit as much from highly connected boards, and because they are larger and they have lower liquidity and higher leverage, overcommitted board directors represent a real risk to consider, which could also explain the contradictory result.

Sample Limitations

Our investigation seeks to extend and compare the findings of Benson et al. (2018) to examine if the same positive relationship between board connectedness and credit ratings exists for insurance companies. We rely on BoardEx data to construct measures of board connectedness and Compustat data for S&P ratings and other financial data. BoardEx data is limited to publicly traded companies. Our global regression methodology requires consistent data across examined companies. Consequently, though the great majority of insurance companies are not publicly traded, our investigation and results are limited to those that are.[3] This somewhat limits the generalizability of our results: unlike for other companies, there seems to be no relationship between board connectedness and credit ratings. This is an interesting finding for publicly traded insurers, but we cannot extend that finding to the broad category of insurers because most are not publicly traded. Future research in this area could serve to clarify the relationship between board connectedness and credit ratings for insurers by examining insurers that are not publicly traded.

3. For example, our entire sample, spanning 13 years, contains 586 (36) life insurer (P/C insurer) usable observations, while the Insurance Information Institute (I.I.I.) reports 1,730 (2,538) life-health (P/C) insurers operating in 2016.

Table III:
Ratings and Board Connectivity

Panel A (includes global sample and life insurers)

Variables	Rating	Rating	Rating	Rating
Insurance_Life	-0.3221**	-0.3094**	-0.3105**	-0.3113**
	(-2.4674)	(-2.3374)	(-2.3492)	(-2.3788)
Betweenness	-0.1260***			
	(-3.8138)			
Closeness		-0.0770***		
		(-2.7608)		
Degree			-0.1379***	
			(-5.3489)	
Eigen				-0.0523***
				(-2.5778)
Size	-0.8966***	-0.9162***	-0.8854***	-0.9436***
	(-21.4577)	(-22.4552)	(-21.6308)	(-23.9655)
Leverage	0.0544***	0.0533***	0.0524***	0.0574***
	(3.1329)	(3.0337)	(3.0158)	(3.2934)
Liquidity	-0.3876***	-0.3887***	-0.3886***	-0.3849***
	(-14.7482)	(-14.8495)	(-14.9064)	(-14.6129)
Observations	10,937	10,937	10,937	10,937
Industry Filing Exemption (FE)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.152	0.151	0.153	0.151

Panel B (includes global sample and property insurers)

Variables	Rating	Rating	Rating	Rating
Insurance_Prop	0.0468	-0.0025	0.0814	-0.0412
	(0.2349)	(-0.0135)	(0.4477)	(-0.2042)
Betweenness	-0.1262***			
	(-3.5989)			
Closeness		-0.0893***		
		(-3.1135)		
Degree			-0.1459***	
			(-5.5492)	
Eigen				-0.0581***
				(-2.8409)
Size	-0.9128***	-0.9278***	-0.8984***	-0.9596***
	(-20.8877)	(-21.8622)	(-21.0759)	(-23.3905)
Leverage	0.0488***	0.0459***	0.0460***	0.0507***
	(2.7697)	(2.5769)	(2.6134)	(2.8706)
Liquidity	-0.3826***	-0.3834***	-0.3839***	-0.3788***
	(-14.2769)	(-14.3779)	(-14.4388)	(-14.1076)
Observations	10,387	10,387	10,387	10,387
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.152	0.151	0.153	0.152

This table presents the ordered probit regression results of ratings against centralities and other control variables. The dependent variable is Ratings. Insurance_Life (Insurance_Prop) is a dummy variable that takes on a value of 1 if the firm is a life insurance firm (a property insurance firm). Size is defined as the natural log of total assets. Leverage is defined as the total liabilities to surplus (net worth). Net worth is defined as the difference between assets and liabilities. Liquidity is defined as the ratio of cash and equivalents to total assets. Two-way fixed effects with industry and year are employed with firm-level clustered standard errors. Control variables are winsorized at the 1% level and then standardized. T-statistics in parenthesis. Coefficients significant at the 1%, 5% and 10% level are marked by ***, ** and *, respectively.

Table IV:
Ratings and Board Connectivity – With Interactions

Panel A (includes global sample and life insurers)

Variables	Rating	Rating	Rating	Rating
Insurance_Life	-0.3214**	-0.3360***	-0.3225**	-0.3282**
	(-2.4786)	(-2.6234)	(-2.4755)	(-2.5175)
Betweenness	-0.1323***			
	(-3.6820)			
Insurance_Life*Betweenness	0.1038			
	(1.1279)			
Closeness		-0.0942***		
		(-3.2938)		
Insurance_Life*Closeness		0.3052***		
		(3.0948)		
Degree			-0.1503***	
			(-5.6930)	
Insurance_Life*Degree			0.2558***	
			(2.5804)	
Eigen				-0.0610***
				(-2.9776)
Insurance_Life*Eigen				0.2761***
				(2.6117)
Size	-0.8965***	-0.9201***	-0.8879***	-0.9478***
	(-21.3879)	(-22.5404)	(-21.6749)	(-24.1464)
Leverage	0.0545***	0.0512***	0.0516***	0.0573***
	(3.1408)	(2.9243)	(2.9800)	(3.2836)
Liquidity	-0.3875***	-0.3875***	-0.3882***	-0.3845***
	(-14.7464)	(-14.8211)	(-14.8902)	(-14.6066)
Observations	10,937	10,937	10,937	10,937
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.153	0.152	0.153	0.152

Panel B (includes global sample and property insurers)

Variables	Rating	Rating	Rating	Rating
Insurance_Prop	0.1095	0.0958	0.2159	-0.0620
	(0.6386)	(0.5943)	(1.2955)	(-0.2943)
Betweenness	-0.1260***			
	(-3.5917)			
Insurance_Prop*Betweenness	-0.1027			
	(-0.5784)			
Closeness		-0.0888***		
		(-3.0907)		
Insurance_ Prop *Closeness		-0.2237**		
		(-2.1687)		
Degree			-0.1453***	
			(-5.5165)	
Insurance_ Prop *Degree			-0.2096**	
			(-2.0572)	
Eigen				-0.0586***
				(-2.8293)
Insurance_ Prop *Eigen				0.0401
				(1.0533)
Size	-0.9127***	-0.9275***	-0.8981***	-0.9594***
	(-20.8820)	(-21.8505)	(-21.0667)	(-23.3781)
Leverage	0.0488***	0.0459***	0.0460***	0.0507***
	(2.7684)	(2.5767)	(2.6130)	(2.8706)
Liquidity	-0.3827***	-0.3835***	-0.3841***	-0.3788***
	(-14.2752)	(-14.3781)	(-14.4387)	(-14.1086)
Observations	10,387	10,387	10,387	10,387
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.152	0.151	0.153	0.152

This table presents the ordered probit regression results of ratings against centralities and other control variables. We interact the centralities and the insurance dummies. The dependent variable is Ratings. Insurance_Life (Insurance_Prop) is a dummy variable that takes on a value of 1 if the firms is a life insurance firm (property insurance firm). Size is defined as the natural log of total assets. Leverage is defined as the total liabilities to surplus (net worth). Net worth is defined as the difference between assets and liabilities. Liquidity is defined as the ratio of cash and equivalents to total assets. Two-way fixed effects with industry and year are employed with firm-level clustered standard errors. Control variables are winsorized at the 1% level and then standardized. T-statistics in parenthesis. Coefficients significant at the 1%, 5% and 10% level are marked by ***, ** and *, respectively.

Conclusion

The regulatory environment for insurance companies is tighter than it is in other industries. More financial information is required and is thus available for CRAs to use. As such, we are able to analyze whether the connectedness of members of boards of directors affects the credit rating that the firm receives in a highly regulated industry. This adds to existing literature on board connectedness and credit ratings as prior studies exclude financial companies, among which are insurance companies.

Benson et al. (2018) find that board connectedness is positively correlated to credit rating; i.e., better connected boards are associated with higher credit ratings, ceteris paribus. However, we find that, though CRAs traditionally rely on both qualitative and quantitative information in their final rating assessment, we find differing effects when examining our interaction terms for life and property insurers. Specifically, we find some evidence that board connectedness is positively related to credit ratings for property insurers. Two of our four examined interaction terms demonstrate this relationship, which is similar to that of non-financial companies found by Benson et al. (2018). In contrast, when viewing the interaction terms, three of our four measures exhibit a negative relationship between ratings and board connectedness for life insurers. We suggest that these contrary results can be explained by the difference between the predictability of the operations of property and life insurers. Further, the larger size, greater leverage and lower liquidity of life insurers relative to non-financial firms could also indicate the costs predicted by the "board-busyness" theory of Fich and Shivdasani (2006).

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Manders, John M., Therese M. Vaughan and Robert H. Myers, Jr., 1994. "Insurance Regulation in the Public Interest: Where Do We Go from Here?" *Journal of Insurance Regulation*, 12: 285.

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