Identifying Board of Director Network Properties for Firm Characteristics

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Abstract

We utilize network analysis to analyze the relationships between firms' characteristics and board of director networks. The 20 largest firms by their market values from the energy and utility industrials, 10 from each sector, are considered. We cluster the firms based on their firm-level characteristics and develop a multiplex network of firms' board members with two major layers, one for the direct and another for the indirect connections between board members. The 4 sub-layers of each major layer of the multiplex network represent corporate, non-profit organization, education and government/military connections between the board members. Each layer of the multiplex network is weighted so that their combined effect for the director network is depicted by a single layer. A firm's director network characteristics are related with the firm cluster characteristics in terms of the weights of the multiplex network. We observe that the director networks display high degree of connectivity at different multiplex layers and firms in the same cluster display similar director network characteristics, once specific layer of connections are appropriately weighted. The optimal values of network layer weights can be found guided by optimizing the cohesion of firms in a cluster and the director network multiplex layers.

Keywords: network analysis, multiplex network, board of director, firm characteristics

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1. Introduction

There is abundant evidence that people's behaviors are affected by their social interactions, including their impact on corporate decisions. Research has focused on how behavioral traits propagate among firms. Since the corporate scandals of Enron, it is recognized that company's performance can be deeply sabotaged by board of directors' negligence (Rebeiz, 2006). As a result, board of directors and their social networks are regarded as an important influential factor for firm behavior. Therefore, research on the significance of the precise properties of the directors' social networks for firm characteristics is an important analysis.

This paper focuses on investigating the relationships between board of director networks and firm's essential characteristics. More specifically, we analyze whether firms with similar characteristics have board of director networks with comparable network characteristics. Additionally, we identify the patterns in the nature or type of board of directors' connections, in order to develop a relative significance between different types of possible ties between board members and their relation with firm characteristics. The relative significance is used to jointly explain the structure in the board of director networks.

The relationship between board of director networks and firms' performance has been evaluated over past many years. By guiding corporate strategy and providing timely advice, board members can play a valuable and pivotal role in the corporate governance of a firm (Kim, 2005). Besides the essential duties of corporate management, research has analyzed board member network's influence, positive or negative, on firms' strategy and performance (Omer et al, 2014; Kim, 2005; Akbas et al, 2016), in issues such as new product launch (Srinivasan et al, 2018) and R&D strategy (Han et al, 2015; Ashwin et al, 2016). Srinivasan et al. show that board of directors' interlocks can enhance firms' access to market information and help firms better adapt to markets and launch new products. Due to network's transitivity, a board network is also able to spread information between firms widely and rapidly (Bizjak et al, 2009). Bizjak et al. provide evidence that board of directors' connection to firms engaging in options backdating can explain a one-third likelihood of other firms starting to backdate their option grants. Furthermore, firm's choice of activities for tax avoidance is also affected by board members' network, where having more board of directors connected to firms with high average tax rate lowers the probability of becoming a low-tax firm, while having board members with low-tax firms increases the likelihood of a firm becoming a lower taxed firm (Lismont et al, 2018; Brown, and Drake, 2014). Companies are more likely to engage in earnings management if their board of directors are connected to firms who pursue earnings management practices (Chiu, Teoh, and Han, 2013), as strategic decisions made by other firms is a confirming reference for firms considering their own decisions (Shaw et al, 2016; Noyes et al, 2014).

Market reactions and influence from leakage of non-public information can also be associated with board member network (Gove and Janney, 2017; Akbas et al, 2016). Firms prefer to have well-connected board of directors, as this can serve as a valuable channel for additional information from outside to support the firm's strategic decisions (Carpenter and Westphal, 2001; Stevenson and Radin, 2009; Aragon-Correa and Mandojana, 2015). Researcher also shed light on the nature of board of director network. Board member network can be considered to possess a cooperative mechanism if they are associated in the same industrial (Michele and Caiazza, 2012), and for-profit firms and non-profit organizations are likely to have common board members as the non-profit organization attempt to imitate for-profit firms' actions (Grant, 2012). Although research shows that board of director network and its characteristics play an important role in corporate financial management, the exploration is limited in the specific nature and property of the network with influence on the different aspects of financial management or firm performance. Therefore, building on the existing research on the impact of board of director networks on firms' performance and management, we aim to identify specific properties of the director networks that are important for firm characteristics.

Social network analysis (SNA), also known as "structure analysis" (Otte and Rousseau, 2002), is a broad set of techniques to analyze the social structure of interactions. SNA takes a network of individuals perspective and focuses on investigating the characteristics of connections (ties) between actors (nodes) (Wetherell et al, 1994). SNA constitutes two fields of study: ego and global network analysis. In the ego oriented social network analysis, an individual person's network is the target of study, while discovering and analyzing all networks between different individuals is the goal for global network analysis (Otte and Rousseau, 2002). In this paper, analyzing the characteristics of the global network, i.e. network of all board members of a set of firms, is the main objective, where the nodes are the individual board members. SNA defines relations underlying the links between different nodes in a network by four categories: *similarities*, *social relations, interactions*, and *flows* (Borgatti et al. 2009). *Similarity* defines nodes sharing common attributes, like location, industrials and attitudes. *Social relations* include three criteria: a commonly-defined social roles, such as teachers and students; cognitive awareness, knowing the other people; affective ties, capturing the feeling of one individual to the other one. *Interaction* represents the types of behavior-based links, such as helping, speaking and inviting. Lastly, *flows* are defined based on the exchanges between different nodes, like information and resources exchanges (Marin and Wellman, 2009).

More important than studying attributes, SNA studies the effects of common attributes, such as race, age and gender, for the information they can provide for explaining similar behaviors or phenomena. However, too much focus on individual’s attributes can result in overlooking the influence of some social factors that also cause similarity, as individuals with similar attributes often share similar social positions or structures (Marin and Wellman, 2009). Mixture of individuals’ attributes and social structures provides social scientists a macro-level explanation for people’s behavior. The goal of SNA is to explain behavioral patterns “as a large number of people acting *on one another* to shape one another's actions” that create particular outcomes (Marin and Wellman, 2009).

Outcomes of a social network analysis can be summarized as: *transmission, adaption, binding* and *exclusion* (Borgatti et al, 2009). *Transmission* means social networks can serve as a pipeline for flow and transfer of different information (Marin and Wellman, 2009). *Adaption* happens when the reasons for people’s choices are based on their similar social position defining their common constraints and opportunities (Marin and Wellman, 2009). *Binds* occurs when entire networks are linked (internally) to act as a unit, and *exclusion* results from a tie impeding another tie (Marin and Wellman, 2009). These outcomes together explain how people make choices based on their social structure, patterns, and relations they build. Therefore, analyzing such outcomes caused by social networks is an effective tool, combining with other statistical methods, to discover hidden causal factors that make people act similarly.

In this paper, we utilize concepts and techniques from SNA to analyze board of director networks and their impact on firms’ characteristics. We use a K-means clustering to differentiate between firms sharing common range of firm characteristics within energy and utility sectors. For the firms’ board of directors, we construct a multiplex network containing two major layers, consisting for board members’ direct and indirect connections, and 4 sublayers, consisting of connections arising due to a corporation, an association with a non-profit organization, sharing the educational institution, or being associated with a government entity or military. We collapse the multiplex network into a single-layer network with direct and indirect connections by assigning weight loadings to each layer of the multiplex network. These layer weight loadings allow analyzing the relationship between board networks and firm clusters. By changing the value of weight loadings, we assess how the directors’ network characteristics modify, and align with the firm characteristics. We find that firms in the same cluster display similar board of director network characteristics.

Moreover, different natures or types of connections in the multiplex board network layers possess varying capacity of influencing the firm characteristics.

The rest of the paper is organized as follows: we next continue with a discussion of the development of our methodology. A detailed description of data follows, including results of preliminary data analysis and network labeling schema used. In the results section, we present details of the implementation of the methodology, network property analysis, as well weight loading analysis for the multiplex network layers. Finally, we conclude the paper with a discussion of the contributions and future developments of the study.

2. Methodology

We construct the board of director networks as weighted multiplex network so that we can explicitly analyze the effects from different nature of connections between board members in the network. The network is divided into two subnetworks, namely network of direct and indirect connections, and further decomposed into 4 subnetwork layers based on the source of connection between board members. In order to reflect the relative strength of connections, different edge weights are assigned to the direct and indirect subnetwork layers. Thereafter, the set of firms are grouped based on their industrials and clustered based on key set of firm-level characteristics. Finally, we analyze the influence from the edge weights of board of director network layers by matching the network characteristics with the firm cluster characteristics. We next describe each step of the methodology in detail.

2.1 Multiplex Network Construction

We construct a two-layered network of the members of the board of directors' connections, which is further split into a multiplex network consisting of multiple sublayers. Analyzing the board of directors' social networks alone cannot provide meaningful information on how the board networks affect firms' performance. Therefore, the sublayers are defined to extract insight for the board network's influence on firms' performance. The board of director networks are divided into 2 sublayers: the direct connections network and the indirect connections network. The direct connections network describes how board members connect with one another based on their direct past associations. Indirect network contains information about how board members connect through other people they have associations with. The direct and indirect networks are further divided into 4 sublayers by the type of association between board members, namely through for-profit corporations (denoted as C), nonprofit organizations (denoted as NP), educational institutions (denoted as E) and government/military (denoted as G). We define these four sublayers based on the natures of relations that exist in the board members' links. As a result, the board of director networks are represented as a multiplex network as shown in Figure 1.

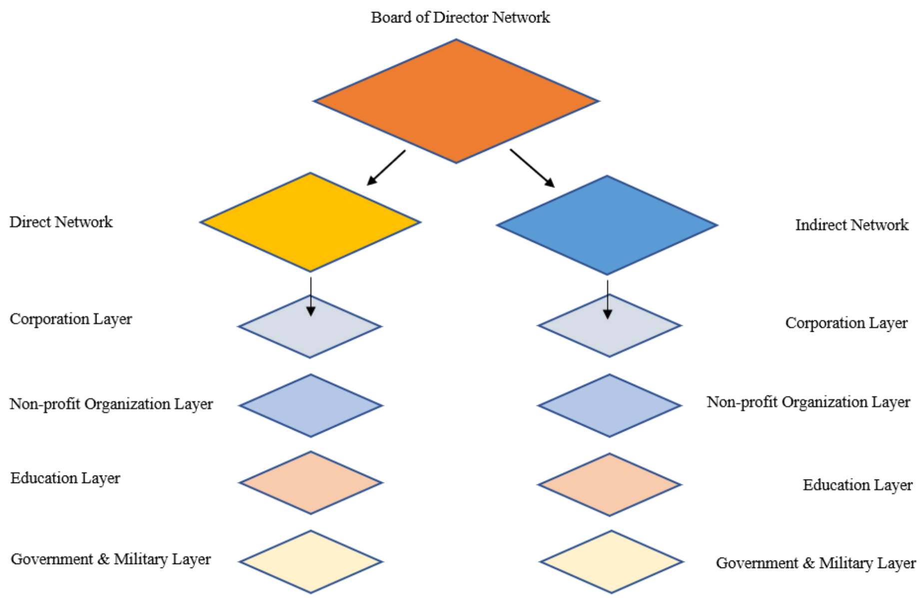


Figure 1: Network Construction

2.2 Network Characteristics

Edge weights are used to represent the link strength in each layer of the multiplex network. We use different methods to measure and assign the edge weights in the direct and the indirect network layers. The edge weights are thereafter transformed and aggregated to describe the impact of each layer of the multiplex network on the collapsed network's characteristics.

2.2.1 Direct Network

In the direct network, edge weights between two nodes in each layer are the total numbers of connections between the board member pair for the reason for connection for that layer. For example, two directors can be linked to each other by some firms in C layer, and by some other organizations in NP layer. Therefore, the weight of the edge between these two directors in the C layer is represented by the numbers of connections arising from their associations with firms in the C category. Similarly, the weight of the two directors' link in NP layer is the numbers of connections between them due to association with an entity in the NP category. Therefore, the intensity of an edge in a layer is simply represented by the number of connections that exist between the directors due to association of entities of that layer. We express the weights between node i and node j in layer m in the direct subnetwork as $w_{i,j}^{m}$, where m $\in [\mathrm{C}, \mathrm{NP}, \mathrm{G}, \mathrm{E}]$, representing the 4 sublayers of the direct networks.

2.2.2 Indirect Network

Weights for the indirect links in a sublayer are the mean number of all links between each pair of nodes and their common directly connected nodes (which could be out of sample nodes) in that layer. To further demonstrate the idea, assume node A and node B in Figure 2 do not have any direct connections, but they are indirectly connected by a single common node C. Suppose node A and C are linked by 2 different N firms, an NP firm and a G organization directly. Similarly, B and C are linked by 2 N firms, 2 G organizations and an E institution directly (shown in Figure 2). As a result, the indirect edge weight between A and B in N layer is the average of total N links A and B have with C, which give the weights of 2. Similarly, the weight of edge between A and B in the NP layer should be 0.5. Thus, we are able to represent the weights of indirect connections in each sublayer between A and B, represented by a dashed line.

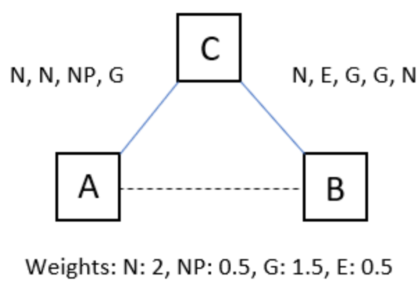


Figure 2: Indirect Edge Weights

Therefore, the weights of the indirect links between node i and j, $w_{i,j_{indirect}}^{m}$, can be expressed as:

$$w_{i,j_{indirect}}^{m} = \frac{1}{n_c^m} \sum_{c=1}^{n_c^m} n_{i,c}^{m} + n_{j,c}^{m}, \qquad \forall m \in \{\mathrm{C}, \mathrm{NP}, \mathrm{E}, \mathrm{G}\}, \tag{1}$$

where, m $\in \{\mathrm{C}, \mathrm{NP}, \mathrm{E}, \mathrm{G}\}$. In the above equation, $n_{i,c}^{m}$ *and* $n_{j,c}^{m}$ represent the numbers of direct links that node i and node j have with their common linked nodes c in layer m, respectively. n_c^m is the total number of common direct links node i and node j have in layer m.

2.2.3 Collapsed Network

We collapse the multiplex network into a single-layer network for both direct and indirect network layers by choosing the appropriate values of weight loadings. For any edge between i-th and j-th board members, $W_{i,j}$, in the direct and the indirect network is expressed as follows.

$$W(\alpha)_{i,j_{direct}} = \alpha_c w^C_{i,j_{direct}} + \alpha_{nc} w^{NP}_{i,j_{direct}} + \alpha_e w^E_{i,j_{direct}} + \alpha_g w^G_{i,j_{direct}}, \tag{2}$$

$$W(\beta)_{i,j_{indirect}} = \beta_c w^C_{i,j_{indirect}} + \beta_{nc} w^{NP}_{i,j_{indirect}} + \beta_e w^E_{i,j_{indirect}} + \beta_g w^G_{i,j_{indirect}}, \tag{3}$$

for $\alpha, \beta \in [0, \infty]$, and they represent edges' weight loadings in the direct and the indirect networks, respectively. In other words, the characteristics of collapsed networks are a linear combination of the 4 sublayers' edge weights.

2.3 Firm Clustering

K-means clustering is an unsupervised learning methodology, which does not require the input data to already have a target guiding variable for defining differences between categories or groups. The algorithm aims to define clusters so that the total within variation in each cluster is minimized. The algorithm first selects n objects (centroids) from data to obtain the initial centers for every cluster. Thereafter, all the remaining objects are assigned to their nearest centroid, where nearest is defined by the Euclidean distance between the objects and the centroids. Next, new centroids are calculated based on new clusters, and the algorithm reassigns the remaining objects to their new closest centroids and forming new clusters. The searching stops until the cluster assignments are optimal. Therefore, k-means clustering serves our purpose of grouping the set of firms based on their key characteristic features.

We first divide firms into two groups based on their industrials, namely energy and utility. Utilizing the significant firm features collected, we further cluster the firms within each group by applying k-means clustering to demonstrate how firms cluster based on these features differ by the groups identified.

Suppose we choose our set of firms to have feature vectors $x_1, x_2, \ldots, x_n$ with same size $S \in [0, \infty]$, and we want to group them into k clusters. Each group should have a total within-cluster variation and our objective would be to minimize the variation by (MacQueen,1967):

$$\min_C \sum_{j=1}^{k} \sum_{x_i^j \in C_j} ||x_i^j - c_j||, \tag{4}$$

where C_j represents the j-th group and $c_j$represents the centroid of C_j. Since there are 20 firms in our sample, with 10 firms in each industrial group, we set k to be no more than 3 for each group to avoid having meaningless clusters of one or two firms.

2.4 Relating Board of Director Networks to Firm Clusters

The collapsed direct and indirect networks maintain the information of which firm a board member serves on the board of, where one individual can possibly serve on multiple firms' boards. For the firms in the k-th cluster, we first define their board of director network characteristics or network indicator, which is defined by the average total loaded weights in each firm's director network, as follow:

$$F(\alpha)_{k,i}^{direct} = \frac{1}{n_i} \sum_{l<j,l=1}^{n_i} W(\alpha)_{l,j_{direct}}, \tag{5}$$

$$F(\beta)_{k,i}^{indirect} = \frac{1}{n_i} \sum_{l<j,l=1}^{n_i} W(\beta)_{l,j_{indirect}}, \tag{6}$$

where n_i represents the total number of edges in the i-th firm's director network. Additional to the average total loaded weights, we also consider the total loaded weights as an alternative network measure so that we can conduct a comparative analysis between these two network measures.

In order to relate the director network characteristics with the characteristics of the firm clusters, we also define the network characteristics for each cluster. Therefore, given a cluster, its network characteristics, C_k, is represented by the average values of firms' network characteristics (both direct and indirect) in that cluster:

$$C(\alpha)_{k}^{direct} = \frac{1}{n_k} \sum_{i=1}^{n_k} F(\alpha)_{k,i_{direct}}, \tag{7}$$

$$C(\beta)_{k}^{indirect} = \frac{1}{n_k} \sum_{i=1}^{n_k} F(\beta)_{k,i_{direct}}, \tag{8}$$

where n_k represents the total numbers of firms in the k-th cluster.

Thereafter, our goal to identify the appropriate network layer's load weight to match the board network characteristics with firm cluster characteristics will be achieved by minimizing the firm network distance within each cluster, while at the same time maximizing firm network distance between different clusters. The objective function is stated as follows:

$$\max_{\alpha,\beta}[\sum_{a<b,a=1}^{K}(||C(\alpha)_a^{direct} - C(\alpha)_b^{direct}|| + ||C(\beta)_a^{indirect} - C(\beta)_b^{indirect}||) - \sum_{a=1}^{K}\sum_{i<j,i=1}^{M_a}(||F(\alpha)_{a,i}^{direct} - F(\alpha)_{a,j}^{direct}|| + ||F(\beta)_{a,i}^{indirect} - F(\beta)_{a,j}^{indirect}||)], \quad (9)$$

where M_k is the numbers of firms in the k-th cluster and K represents the total numbers of clusters.

3. Data Description and Labeling

During the great oil crash of 2014, the firms in our set responded or were affected differently. Therefore, we choose the year 2014 as our main study year. Our data collection relies on 2 sources: *Compustat* NA and *BoardEx*. From *BoardEx*, we identified 384 members of the board of directors of the 20 firms, and extracted data for their networks for the year 2014. The distribution of the size of the each firm's board is shown in Figure 4. The market value of shareholder equity for the selected 10 firms from the energy sector and 10 firms from the utility sector (listed in the Appendix 1) is shown in Figure 3.

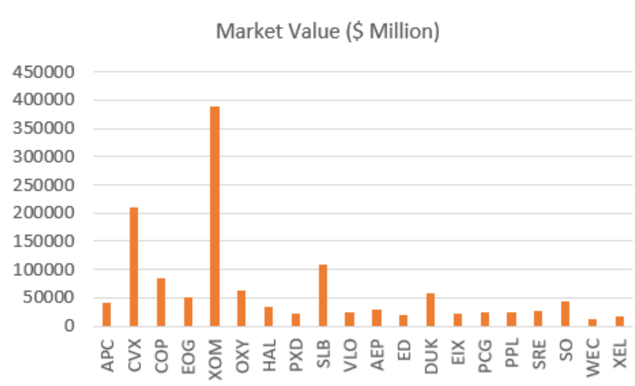


Figure 3: Firm Market Values in 2017

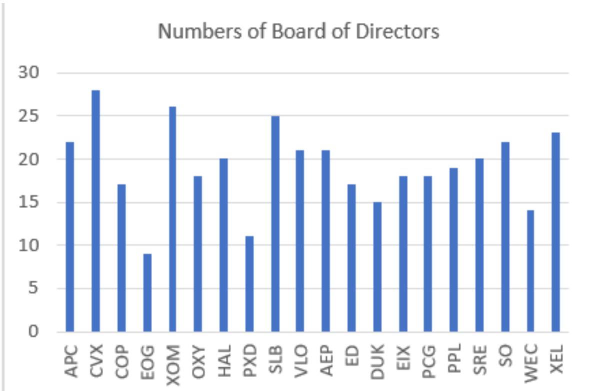


Figure 4: Board of Director Network Data Distribution

Figures 3 and 4 indicate that all energy firms (first 10 firms from the left in the figures) have on average a higher market values, with Exxon-Mobil (XOM) being significantly larger. However, the larger firms do not necessarily also have large board. XEL, for instance, is relatively small by market values, but it has a board size of 24, fourth largest among all firms. On the other hand, DUK, the largest utility firm by market value (10 right most firms in the figures), has a board size of only 15 members, which is the eighth largest board size among the utility firms. Therefore, even though we focus on the largest energy and utility firms, there is diversity in the firms by their firm size and size of the firms' boards. Moreover, besides the size of the board, board members' network may be instructive in the effectiveness of the board, which we explore in this paper.

We use *Compustat* to collect firm characteristic variables, such as, ROA, Debt-to-Equity ratio, volatility, beta, Tobin's Q ratio, P/E ratio. These set of variables represent firms' essential characteristics in terms of financial performance, leverage risk, market risk, management quality, market outlook of the firm. Figure 5 and Table 3 show the levels and summary statistics of the firm variables, respectively. For all variables, except for beta, the firm characteristics of energy firms are different from those of the utility firms, as seen in Figure 5. Beta across firms is not different for utility versus energy firms. Except for the P/E ratio and leverage, energy firms have on average higher values in all firm characteristic variables. Utility firms show less variation for these firm characteristic variables, while energy firms have high level of variation in these variables.

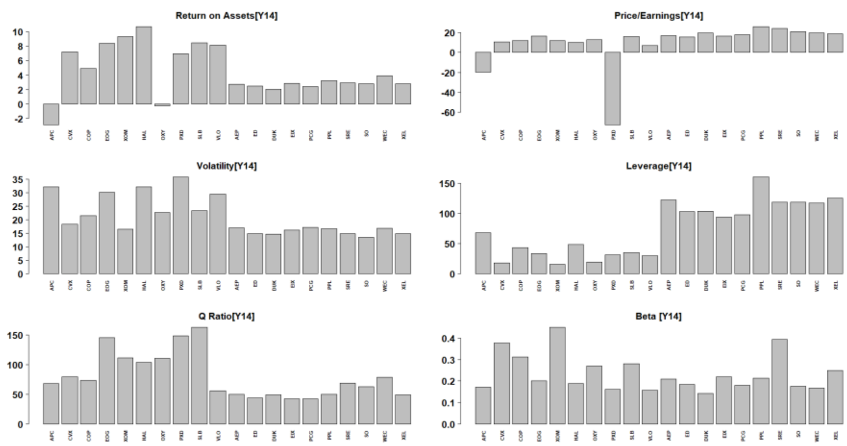


Figure 5: Firm Characteristics Plots

	Mean	Stdev	Median	Minimum	Maximum
ROA	4.448887	3.447162	3.080841	-2.83681	10.657568
P/E Ratio	9.904134	21.421907	16.082013	-72.257303	25.584524
Volatility	20.924635	7.116366	17.091779	13.434398	35.804843
Leverage	75.190657	45.341039	80.949619	16.083263	160.383035
Q Ratio	79.675915	37.956223	68.395727	42.14015	162.807004
Beta	0.235303	0.087391	0.205082	0.142678	0.451311

Table 3: Firm Characteristics Statistics

In Table 3, we observe that leverage has the highest standard deviation among all variables due to the high leverage rate of the utility firms. Some energy firms have a negative P/E ratio and ROA during the year of the oil price crash, which indicates that these firms suffered very significant losses during that year.

3.2 Data Labeling

The network data is collected from *BoardEx* database and it divides all board members' association as links into 12 categories: *private, quoted, medical, clubs, charities, sporting, universities, armed forces, government, navy, army*, and *air force*. As our first step, we label the data under our approach, where all observations in the *quoted* category are labeled as C (for Corporate), and observations with the *clubs*, *charities*, *sporting* categories are labeled as NP (for Non-Profit Organizations). Observations in the *universities* category are labeled as E and observations with *armed forces, army, air forces, government, navy* are labeled as G. The remaining labels of private and medical categories are classified as for-profit (C) or non-profit organizations (NP) by conducting a keyword filter. Using a set of keywords for for-profit organizations, such as "inc" and "corp", and for non-profit organizations, such as "association" and "forum", the remaining links are labeled.

Labeling Results				
	C	NP	G	E
Direct	6860	1407	272	466
Indirect	57502	40184	21542	41447

Table 4: Total Numbers of 4 Labels in each Layer

The labeling results are shown in Table 4. The sizes of the indirect networks are much larger (approximately 100 times) than the direct networks. Moreover, the C sublayer has the greatest number of links among all layers, which might suggest that the corporation network sublayer has a potential of playing a significant role in the board of director networks. In both direct and indirect networks, the G sublayer has the least number of board of director connections.

4. Results

This section presents the results for firm clustering, multiplex board of directors' network properties and relating the board of director network to the firm clusters. The results for dependence of the objective function defined in Section 2 for different levels of weight loadings are also presented.

4.1 Firm Clustering

We group the 20 firms by their industrials: energy and utility, and then cluster the firms in each industrial by their selected features: ROA, Leverage Ratio, Beta, volatility, Tobin's Q ratio, and P/E ratio. Our initial clustering of firms using all the above variables showed that ‘volatility’ doesn’t play a significant role in defining the clusters. Therefore, in the subsequent analysis, we eliminate volatility from the feature set for conducting the clustering. The clustering results are shown in Table 5.

	Cluster Size	ROA	P/E ratio	Leverage	Q ratio	Beta
Utility						
Centroid 1 (C1)	6	3.1	20.8	127.1	59.8	0.2
Centroid 2 (C2)	4	2.4	17.3	99.9	44.3	0.2
Mean (M)		2.8	19.4	116.2	53.6	0.2
(C1-M)/M		8.80%	7.40%	9.40%	11.60%	10.00%
(C2-M)/M		-13.20%	-11.10%	-14.00%	-17.40%	-15.00%
Centroid 1 (C1)	3	2.9	20.3	135.9	49.5	0.2
Centroid 2 (C2)	3	3.2	21.4	118.2	70.1	0.2
Centroid 3 (C3)	4	2.4	17.3	99.9	44.3	0.2
Mean (M)		2.8	19.4	116.2	53.6	0.2
(C1-M)/M		3.90%	4.50%	17.00%	-7.70%	4.90%
(C2-M)/M		13.70%	10.30%	1.70%	30.80%	15.20%
(C3-M)/M		-13.20%	-11.10%	-14.00%	-17.40%	-15.00%
Energy						
Centroid 1 (C1)	3	7.9	-13.3	33.1	152.2	0.2
Centroid 2 (C2)	7	5.3	6.3	34.6	85.8	0.3
Mean (M)		6.1	0.4	34.2	105.7	0.3
(C1-M)/M		30.20%	-3436.40%	-3.10%	43.90%	-16.70%
(C2-M)/M		-12.90%	1472.80%	1.30%	-18.80%	7.10%

Table 5: Clustering Statistical Summary

The 6-4 and 3-3-4 clustering results in Table 5 are for utility firms and the 3-7 cluster is for the energy firms. The 3 clusters case for energy firms is not included as it contains a cluster with only one firm. Each cluster’s centroid shown in Table 5 is significantly different from the population mean, which indicates the clusters are distinctive from the entire population of firms. The 3-7 clusters’ centroid deviate significantly for the P/E ratio dimension from the population mean (-3436.40% and 1427.80%, respectively) because 2 energy firms in the cluster possess negative values for their P/E ratio (as shown in Figure 5). The leverage centroid varies significantly between utility and energy firms, as was expected from observations in Section 3. The 3-3-4 clusters in 3-means clustering is split off from the 6 firms cluster in the 6-4 clusters of 2-means clustering, i.e. firms don’t redistribute in clusters, but only split off, when number of clusters is increased from 2 to 3. Figures 6 to 8 provide a visual display of the clusters, where projections of a 5-dimensional space into 2-dimensions are used. The smaller cluster in the 6-4 clusters is robust, as it doesn't further split into other or smaller clusters.

Figure 6: 6-4 Clusters

Figure 7: 3-3-4 Clusters

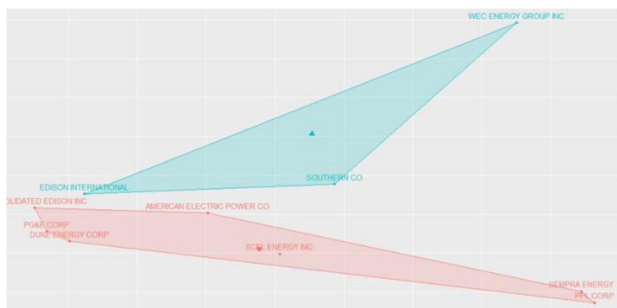


Figure 8: 3-7 Clusters

4.2 Multiplex Network Characteristics

We first calculate and assign edge weights to every link in each network sublayers. Table 6 shows the overview of final weights assigned in each network sublayer. We observe that the weights assigned to the indirect network layers are larger than those assigned to the direct network layers, as expected. In the direct network, the C layer has the highest maximum weight values, indicating that corporate connections are the major channel that make members of the board of directors to connect to one another. Similar results shown for the indirect networks reveal that the weights assigned to government/military (G) layer are quite large. In other words, unlike the direct network, education (E) and government/military (G) network layers have more weights arising through indirect connections. Therefore, this type of connections may play an important role through indirect connections. This shifting role of government/military (G) network layer gives some insights on the numbers of board members who have worked for government or served in the military.

	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Direct Network						
C	1	1	1	1.32	1	34
NP	1	1	1	1.097	1	4
E	1	1	1	1.013	1	2
G	1	1	1	1.022	1	2
Indirect Network						
C	0.5	1	2.5	11.24	6	1421.5
NP	0.5	0.5	2	8.631	4.5	1229
E	0.5	0.5	1.5	4.306	3	847
G	0.5	0.5	1	4.849	3	966.5

Table 6: Assigned Weights Summary

4.2.1 Direct Networks

The C layer of weighted direct network is shown in Figure 9 (top left), which is a fully connected network with all 384 directors being connected to each other through direct corporate associations. The graph illustrates that the board members of the 20 firms are linked to each other across firms and industrials just by their corporate connections, which in fact is a very dense network allowing strong potential for information flows.

The remaining three network graphs in Figure 9 allow comparing the C layer with the other 3 sublayers, which have a much smaller size. Only a subset of board members is connected in each of the other three network sublayers. The NP network layer has the greatest numbers of nodes connected and the E network layer has 48% of board members connected, whereas the G network layer has the smallest number of board members with connection, at only 23% of directors being connected through government/military connections. Although there are some isolated cliques appearing in all these three layers, the connected component of the network layer is still quite dense.

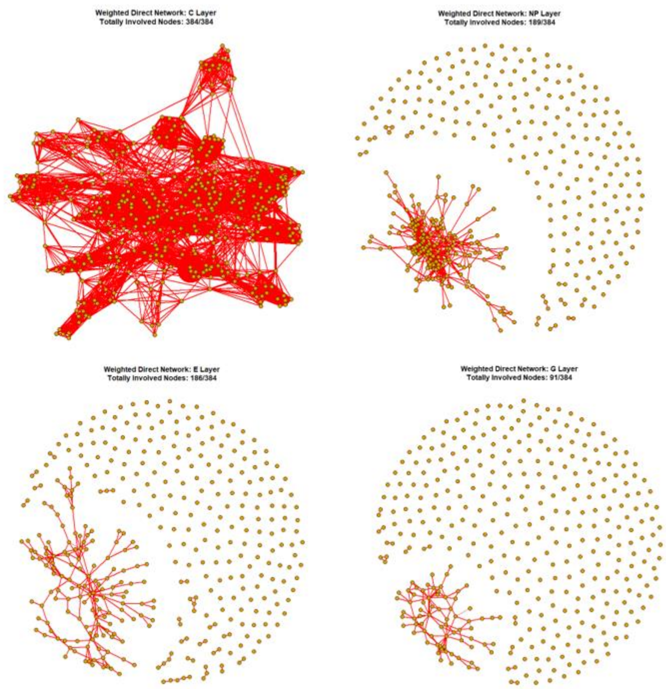


Figure 9: Direct Network

Within NP, E, and G layers, the percentage of connected nodes that come from energy firms are 54.5%, 50.0% and 53.8%, respectively, which means even though only a portion of all board members are directly connected in the NP, E and G layers, the cross-industrial board member links in these layers are still present. The reason for such cross-industrial network could be that the utility and the energy sectors work closely with each other and such close relationships between board members generates opportunities for connections. Table 7 and 8 show the network characteristics and network centrality summary for each network sublayer.

	Density	Diameter	Mean Distance
C Layer	0.093	5	2.958
NP Layer	0.079	8	3.354
G Layer	0.067	9	3.887
E Layer	0.027	12	5.065

Table 7: Network Summary

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum

C Layer:						
Degree (Normalized)	0.03	0.07	0.09	0.09	0.1	0.31
Closeness (Normalized)	0.26	0.32	0.34	0.34	0.37	0.46
Betweenness (Normalized)	0	0	0.003	0.005	0.007	0.069
NP Layer						
Degree (Normalized)	0.011	0.011	0.043	0.079	0.117	0.473
Betweenness (Normalized)	0	0	0	0.009	0.012	0.117
E Layer:						
Degree (Normalized)	0.011	0.011	0.022	0.027	0.032	0.146
Betweenness (Normalized)	0	0	0	0.012	0.008	0.268
G Layer:						
Degree (Normalized)	0.011	0.022	0.044	0.067	0.089	0.289
Betweenness (Normalized)	0	0	0	0.019	0.019	0.178

Table 8: Centrality Summary

Comparing all the 4 sublayers, the C layer is the densest network layer with lowest network diameter and mean distance, whereas the E layer is the least compact network. However, the E network has more connected nodes than the G network. This demonstrate that although the G layer less connected nodes, it is a denser network than the E network layer. The C layer has the highest maximum node degree and the lowest node betweenness. A low value of node betweenness indicates that nodes do not necessarily need to go through many other nodes to connect to various nodes in the network. G and E layers have similar node degree statistics, and as expected, similar node degree distribution.

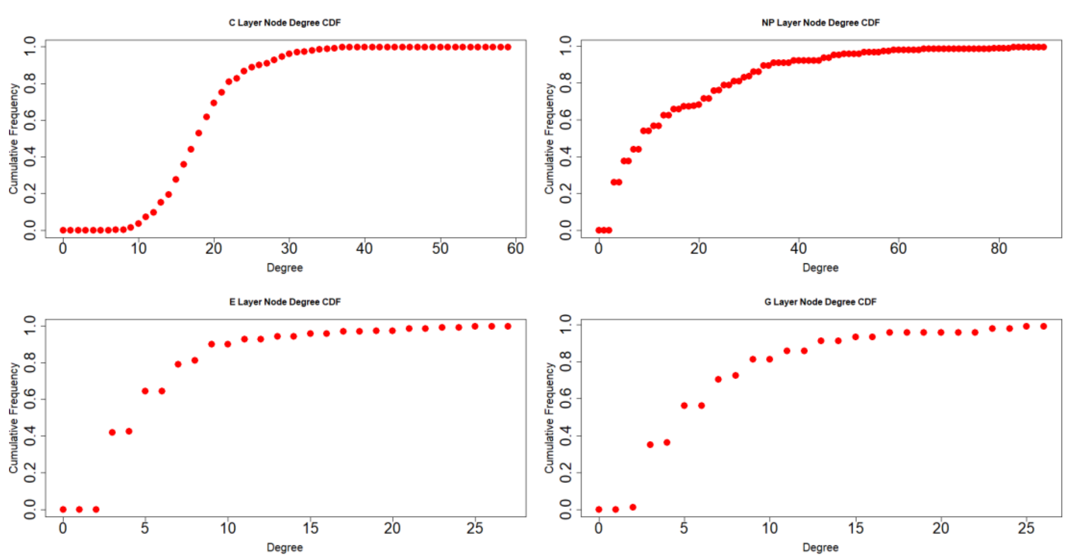


Figure 10: Direct Network Node Degree CDF

We also calculated and obtain the top 5 important directors measured by different centrality, and we find that directors with high degrees do not always have high betweenness or closeness at the same time. More specifically, different centrality measures give different set of candidates except for the first director in each layer. This demonstrates an important role for the first node in each layer and implies that these directors have access to nearly all information flow in the network. On the other hand, except for the first director (node), there is no other node that can have such significant effect on each network layer, indicating the high density of each network.

Figure 11 shows the cumulative distribution of node degrees in each sublayer of the direct network. We observe that the C layer has node degree of approximately a normal distribution, as C layer contains a great number of observations. This essentially results in a normal distribution for node degree. Unlike C layer, NP layer has node degrees following approximately exponential distribution. Because the G and E layers have smaller sizes, their CDF is not of an obvious standard model, but they can still be approximated by an exponential distribution.

4.2.2 Indirect Network

Layer of the indirect network is shown in Figure 11 for only the C layer, where only half of the nodes are included to aid visualization of an otherwise very dense network. Even with half of the C layer node, the network is already quite dense, and the edge weights are very high. The other 3 indirect network sublayers are similar to the C layer, with all nodes being connected and links possess high edge weights. This indicates that any two directors in our sample are connected (albeit with a path) due to third party associations even when the direct connections do not exist. This observation highlights the importance and power of the indirect network of board of directors. It also gives credence to the hypothesis that the nature of connections in a network can translate to the role the network plays.

Table 9 shows an overview of the indirect network layers, where the network density for the indirect network layers is seen to be much higher than that of the corresponding direct network layers, roughly over 10 times. Unlike for the direct network, in the indirect network, the NP layer is a denser network. It indicates that participation in non-profit organizations can end up connecting board of directors with more directors in different industrials. Also, surprisingly, the education (E) layer in the indirect network is the densest network layer. Therefore, indirectly educational links can make a significant impact on information flow on directors' network. Moreover, in comparison with the direct networks, the indirect network layers have a lower value of network diameter, indicating that path of indirect connections between board members are short.

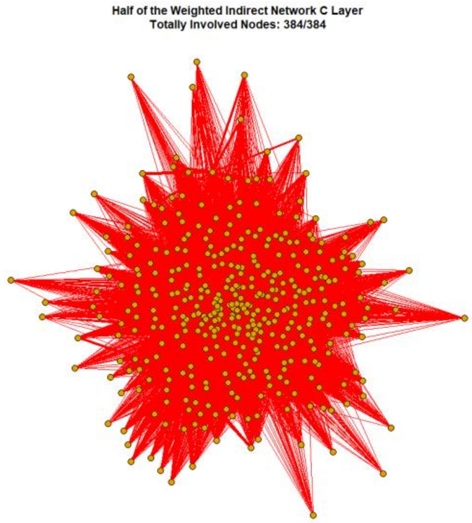


Figure 11: Indirect Network C Layer

	Density	Diameter	Mean Distance
C Layer	0.391	0.3	1.61
NP Layer	0.546	0.15	1.454
G Layer	0.293	0.2	1.707
E Layer	0.564	0.15	1.437

Table 9: Indirect Network Overview

Table 10 shows the centrality measures for the indirect network layers. Since the indirect layers are fully connected, we include closeness measures for indirect network layers. The maximum of node degree and closeness for each layer is close to 1 after normalization, which implies that some nodes are connected to all the other nodes in the network layer. Therefore, firms for which these directors serve as a board member could have indirect access to information from all board members of all other firms in our sample. Low values of betweenness reinforces the low network diameters. However, G layer has a relatively higher value of betweenness, implying that even for indirect connections, government/military associations are not as prevalent. Moreover, NP and E layers have similar node degree statistics.

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
C Layer:						
Degree (Normalized)	0.081	0.219	0.245	0.391	0.617	0.989
Closeness (Normalized)	0.521	0.561	0.57	0.648	0.723	0.99
Betweenness (Normalized)	0	0	0	0.002	0.003	0.009
NP Layer						
Degree (Normalized)	0.069	0.35	0.516	0.546	0.764	0.995
Closeness (Normalized)	0.518	0.606	0.674	0.709	0.809	0.995
Betweenness (Normalized)	0	0	0	0.001	0.002	0.006
E Layer:						
Degree (Normalized)	0.063	0.403	0.604	0.564	0.742	0.987
Closeness (Normalized)	0.516	0.626	0.717	0.713	0.795	0.987
Betweenness (Normalized)	0	0	0.001	0.001	0.002	0.007
G Layer:						
Degree (Normalized)	0.018	0.136	0.189	0.293	0.367	0.984
Closeness (Normalized)	0.5	0.536	0.552	0.601	0.612	0.985
Betweenness (Normalized)	0	0	0	0.002	0	0.022

Table 10: Indirect Network Centrality Summary

We identify the most important directors measured by their different centrality measures in the indirect network. We find that unlike in the direct network layers, in each indirect network layer the 3 centrality measures are consistent, implying that directors with the highest node degree also have the highest closeness and betweenness. Therefore, in the indirect network, the functionality or importance of a single director is amplified. However, the same director does not dominate in terms of centrality in multiple sublayers of the indirect network. Therefore, the role of dominant board members is amplified by different nature of associations.

In the histogram of node degrees for the indirect network in Figure 12, the C layer is clearly divided into two parts at a threshold of 100. Specifically, a third of the board members have node degree greater than 100 in the C layer. Of those one-third directors, 75% are board members of energy firms. This indicates that energy firms' board members are more likely to have more connections through corporate associations than the utility firms. Node degrees for NP layer spread out evenly, while E layer nodes degrees have a heavy left tail and G layer shows many outliers. Among the outliers in the G layer, approximately 57% of the directors are on the board of energy firms, once again demonstrating that energy firm boards have more indirect connections. In conclusion, the indirect network layers have many different characteristics compared to the direct network layers, which holds the potential of modifying the influence of the direct network.

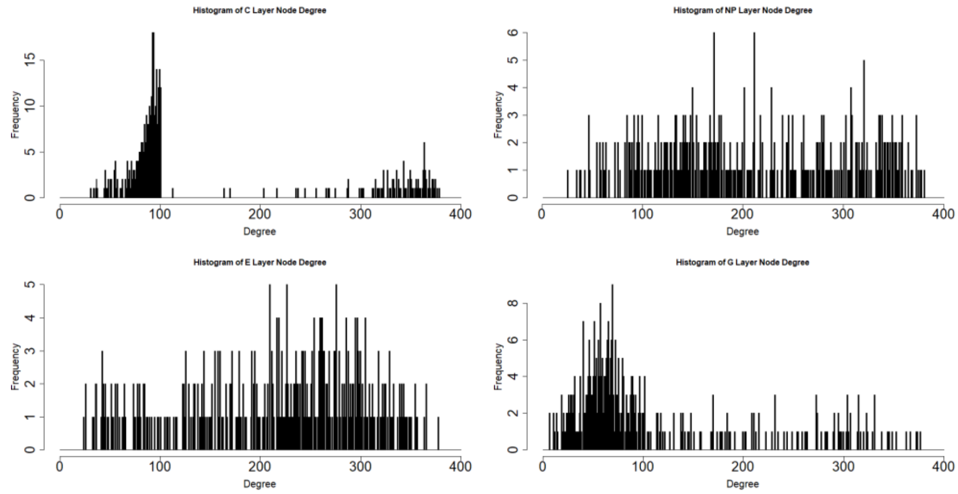


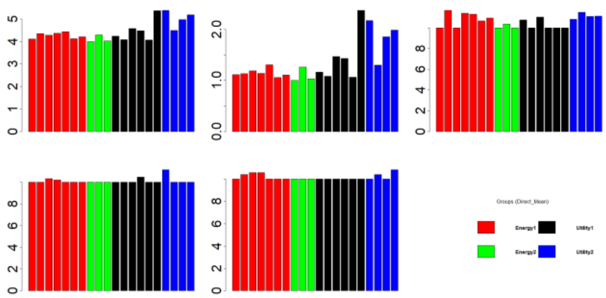
Figure 12: Histogram of Indirect Network Node Degree

4.3 Connecting Board of Director Network to Firm Clusters

The director network measures for the direct and the indirect network layers are obtained by taking a mean (or total) of the collapsed board of director networks using layer weight loadings for all the board members of each firm. In this section, we evaluate the change in the firm's director network measure within each firm cluster due to changes in the values of network layer weight loadings. More specifically, we choose a baseline of equal weight loadings of 1 for all layers and then change the weight loadings with different configuration to evaluate the impact on the objective function stated in Equation (9).

The firms' director network measure by mean for direct layers is shown in Figures 12 and 13 for the 4 and 5 clusters cases. Each bar represents a firm's network measure and each color represents firms in a cluster, where red and green clusters are energy firms. Five configurations are shown in each graph, which include a baseline and 4 other combination of network layer weight loadings that set exactly 1 of the 4 network layers weight to be nonzero. Figure 12 shows that firms' network measure within each cluster are similar, except in the second configuration where only C layer weight loading is nonzero. Firms' network measures are different between clusters.

The 5 clusters case shown in Figure 13 possesses a better distinguishing ability between cluster network measures compared to the 4 clusters case. The black colored cluster of Figure 12 splits into the yellow and black clusters, with the two clusters showing dissimilar network measures. Additionally, when only C layer's weight loading is nonzero, the in-cluster network measure differences are amplified and more fluctuating, whereas for the other 3 network layer dimensions, especially the E and the G layers, the in-cluster differences are "pulled" closer together. This review of firm clusters' network measures indicates that similar firms also possess similar board of director network characteristics. We explore this similarity further by enhancing network layer weight loadings.



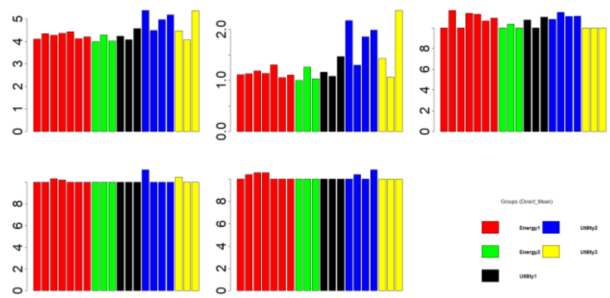


Figure 12: The 5 cases of weight loadings are applied to the direct firm network mean characteristics with 4 clusters. Top Left: The baseline case which sets weight loadings from all sublayers to be 10. Top Middle: The second case which only sets C layer's weight loading to be 1 and others be 0. Top Right: The third case which only set NP layer's weight loading to be 10. Bottom Left: The fourth case which only set E layer's weight loading to be 10. Bottom Middle: The last case which only sets G layer's weight loading to be 10.

Figure 13: The 5 cases of weight loadings are applied to the direct firm network mean characteristics with 5 clusters. Top Left: The baseline case which sets weight loadings from all sublayers to be 10. Top Middle: The second case which only sets C layer's weight loading to be 1 and others be 0. Top Right: The third case which only set NP layer's weight loading to be 10. Bottom Left: The fourth case which only set E layer's weight loading to be 10. Bottom Middle: The last case which only sets G layer's weight loading to be 10.

By fixing the direct network layer weight loadings at a baseline, we obtain the firms' indirect network mean network measure for 4 and 5 cluster cases, shown in Figures 14 and 15. Since the absolute value of indirect network measures is much larger than that of the direct network, we scale the level of weight loadings by a tenth for an equivalent comparison with the direct network layers. In Figure 14, we can clearly see the differences between the black and the blue cluster firms from utility industrial. This difference is most amplified when only NP layer has a nonzero weight loading. Therefore, unlike the direct network, the NP layer of the indirect network most differentiates firms in different clusters.

The 5 clusters case provides better differentiating firm characteristics between clusters. In Figure 15, the green energy firms cluster overall has a higher average network measure than the red cluster does. However, unlike in the direct network where G layer weakens the network differences, in the indirect network when only G layer has a nonzero weight loading, the red cluster outperforms, and such a switch indicates that among energy firms, government /military network structure also has changed. In the utility group, the blue cluster has a higher average network measure in all cases, which is also different our observations for the direct network.

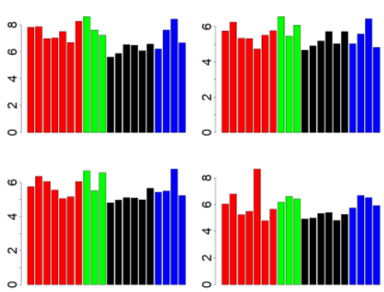


Figure 14: The 5 cases of weight loadings are applied to the direct and indirect firm network mean characteristics with 4 clusters. Top Left: The baseline case which sets weight loadings from all sublayers to be 0.1. Top Middle: The second case which only sets C layer's weight loading to be 0.1 and others be 0. Top Right: The third case which only set NP layer's weight loading to be 0.3. Bottom Left: The fourth case which only set E layer's weight loading to be 0.3. Bottom Middle: The last case which only sets G layer's weight loading to be 0.3.

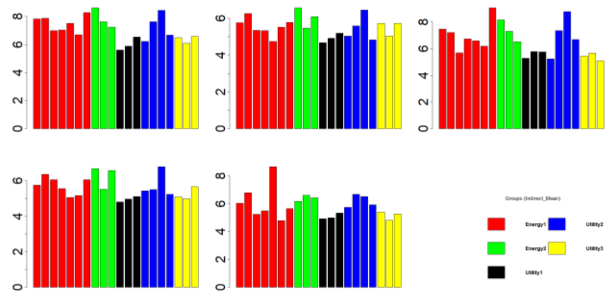


Figure 15: The 5 cases of weight loadings are applied to the direct and indirect firm network mean characteristics with 5 clusters. Top Left: The baseline case which sets weight loadings from all sublayers to be 0.1. Top Middle: The second case which only sets C layer's weight loading to be and others be 0.1. Top Right: The third case which only set NP layer's weight loading to be 0.3. Bottom Left: The fourth case which only set E layer's weight loading to be 0.3. Bottom Middle: The last case which only sets G layer's weight loading to be 0.3.

In order to further demonstrate how changes in the network layer weight loadings can result in different firm network measures for each cluster, we construct 6 additional configurations for the weight loadings, where we set two dimensions of weight loadings to be non-zero and hold the other two at zero. Figure 16 shows bar charts for the 6 new configurations for the direct network. The C sublayer generates similar results, confirming that the C layer of the direct network is a dominating layer among the 4 layers, making all firms differentiate from each other. On the other hand, the other 3 layers make firms in a cluster resemble each other. It further confirms that the direct network combining different dimensions generates distinct effects. If we want the firms' network measures to be disparate across firms, we would give a higher weight loading to the C sublayer. However, if we want to make the differences more moderate, we would give a lower weight to the C sublayer, and to increase the difference between clusters, give a higher weight loading to the other 3 sublayers.

Figure 17 shows 6 additional configurations for the indirect networks, where we observe that the C layer does not have a dominating effect. Configurations including the NP sublayer have similar results. Because NP, E and G sublayers in the indirect network have much larger sizes than in the direct network, the three network layers affect the firms' network measures more. As a result, not only different types of network layers have different characteristics, but direct and indirect networks produce distinguishable network structures.

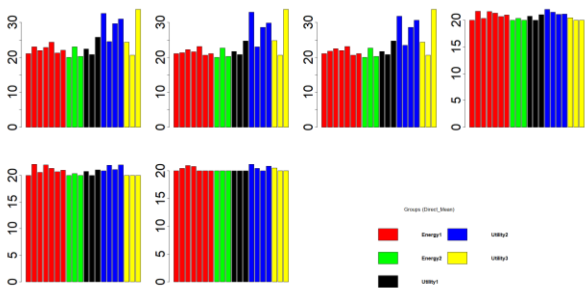


Figure 16: The 6 new cases of weight loadings are applied to the direct firm network mean characteristics with 5 clusters. Top Left: The first case which sets weight loadings of C and NP layers to be 10. Top Middle Left: The second case which only sets C and E layers' weight loading to be 10 and others be 0. Top Middle Right: The third case which only set C and G layers' weight loading to be 10. Top Right: The fourth case which sets NP and E layers' weight loadings to be 10. Bottom Left: The fifth case setting NP and G layers' weight loadings to be 10. Bottom Middle: The last case setting E and G layers' weight loadings to be 10.

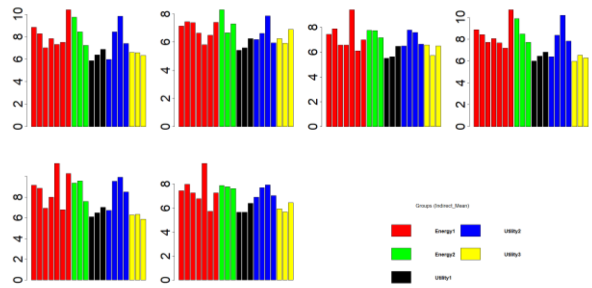


Figure 17: The 6 new cases of weight loadings are applied to the direct and indirect firm network mean characteristics with 5 clusters. Top Left: The first case which sets weight loadings of C and NP layers to be 0.1 and 0.3. Top Middle Left: The second case which only sets C and E layers' weight loading to be 0.1 and 0.3 and others be 0. Top Middle Right: The third case which only set C and G layers' weight loading to be 0.1 and 0.3. Top Right: The fourth case which sets NP and E layers' weight loadings to be 0.3. Bottom Left: The fifth case setting NP and G layers' weight loadings to be 0.3. Bottom Middle: The last case setting E and G layers' weight loadings to be 0.3.

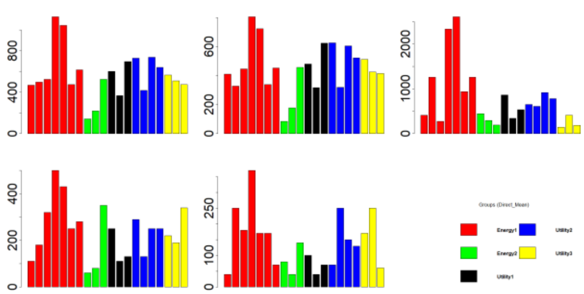


Figure 18: The 5 cases of weight loadings are applied to the direct firm network total characteristics with 5 clusters. Top Left: The baseline case which sets weight loadings from all sublayers to be 1. Top Middle: The second case which only sets C layer's weight loading to be and others be 1. Top Right: The third case which only set NP layer's weight loading to be 10. Bottom Left: The fourth case which only set E layer's weight loading to be 10. Bottom Middle: The last case which only sets G layer's weight loading to be 10.

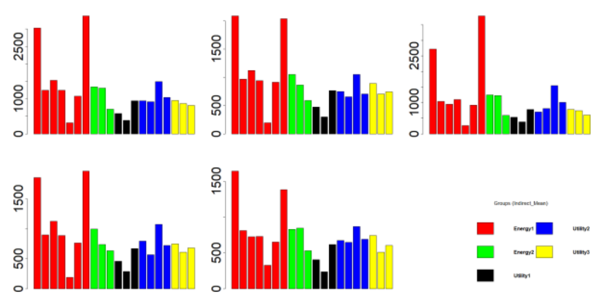


Figure 19: The 5 cases of weight loadings are applied to the direct and indirect firm network total characteristics with 5 clusters. Top Left: The baseline case which sets weight loadings from all sublayers to be 0.1. Top Middle: The second case which only sets C layer's weight loading to be and others be 0.1. Top Right: The third case which only set NP layer's weight loading to be 0.3. Bottom Left: The fourth case which only set E layer's weight loading to be 0.3. Bottom Middle: The last case which only sets G layer's weight loading to be 0.3.

Figures 18 and 19 use the firm network measure to be the total edge weight measure, and this changes the results. The in-cluster network differences are much larger than in the mean network measure case, with the red cluster showing higher network measure in all cases. This implies a higher variation in the board of director networks for the energy firms. However, similar to the mean network measure, differences between direct and indirect networks persist. The dominating effects of the C sublayer exist in both the direct and the indirect networks. While C and NP sublayers make firms' networks distinct, E and G sublayers still possess weakening the differences between firms in a cluster. Overall, the total network measure supports the results from the mean network measure.

By adjusting the values of each network layer's weight loadings, we are able to change the firms' network measure for both the direct and the indirect network. From the configurations considered, different sublayers enhance or weaken firm's network measures, so the near optimal choices of weight loadings can be found that helps minimize the differences in the firm network measures within a cluster, while maximizing the differences between clusters.

4.4 Results for the Objective Function

Table 11 shows the objective function values for a selected set of values for the direct network weight loadings (i.e. β′s are set to 0) to demonstrate the impact of different network sublayers.

Objective Function Results for 5 Clusters' Mean Characteristics

α1	**α2**	**α3**	**α4**	**β1**	**β2**	**β3**	**β4**	**Objective**
1	1	1	1	0	0	0	0	48.43
10	0	0	0	0	0	0	0	106.53
1	10	1	1	0	0	0	0	155.98
1	1	10	1	0	0	0	0	224.73
1	1	1	10	0	0	0	0	284.00
10	10	1	1	0	0	0	0	-39.79
10	1	10	1	0	0	0	0	20.21
10	1	1	10	0	0	0	0	78.28
1	10	10	1	0	0	0	0	206.09
1	10	1	10	0	0	0	0	270.46
1	1	10	10	0	0	0	0	338.69

Table 11: Objective Function Results

In the absence of indirect networks, the objective function has small baseline value. By keeping all sublayers' weight loadings as constant and solely increasing the government/military network layer's weight loadings gives a higher level of objective function value. This implies that the government/military network layer has similar firms' network measure across firms in each cluster. Only including the C layer's weight loading, the objective function takes on a small value. Despite all directors being connected in the direct network C layer, the average network measure shows high variation across firms, so that the in-cluster distance between firms' network measure is large. Additionally, any configuration that enhances C layer's role generates a relatively lower objective function value. This demonstrates that the C layer is not a distinguishing aspect of firm director networks that aligns with firm's cluster membership. On the other hand, pairing any sublayer with the G layer efficiently increases the objective function value, and thus shrinking the distance between firms' network measure within clusters. Therefore, the G sublayer in the direct director networks is a distinguishing board of director feature for firms.

5. Conclusion

After the fall of Enron, more attention is paid to the important roles board of directors plays in the corporate governance and financial management of firms. Board of director networks have long been considered as channels for firms to exchange information and eventually affect board members' decisions. In this paper, we provide an innovative angle to analyze the effects from different natures of connections between board of director networks on firms' characteristics. We study 20 largest firms by market values from the energy and the utility sectors, and analyze their performance and board of director networks during the 2014, the year of oil price crash. Firms are divided into two groups based on industrials, and then further clustered by 5 key firm characteristics, namely ROA, Beta, Tobin's Q ratio, P/E ratio and debt to equity ratio. The firms in the energy sector are clustered into a 7-3 cluster, whereas the firms in the utility sector are clustered into a 3-3-4 clusters.

We construct a multiplex network for board of directors in each firm. We separate the networks into 2 layers, namely direct and indirect layers, and further decompose both layers to 4 sublayers by the natures of association between board members, namely by for-profit corporation, non-profit organization, education institution and government/military. We define different network measures, edge weights, and layer weight loadings to collapse all sublayers into a single layer. We define firms' network measure as average or total of network's edge weights. By changing the values of weight loadings, we assess how distinguishable firm's network measure is across firms in a cluster and cluster's network measure is across clusters. We find that firms in the same cluster have similar board of director network characteristics, and that by changing the weight loadings we are able to find the optimal values of weight loadings which match firms' network measure to the firms' cluster.

The main contribution of this paper is to develop a multiplex network for board of director associations, and a way to assess if there these connections can be matched with the firm characteristics. We further demonstrate that natures of network connection can change the network characteristics significantly and different types of networks cannot be treated equally when analyzing the board members' network effects on firms' characteristics. We have so far shown implication of changing network layer weight loading. Finding the optimal results for the weight loadings remains to be accomplished in our future investigations, where we would also increase the number of firms included in the study for developing greater confidence in the conclusions.

Appendix

Company Name	Ticker
EXXON MOBIL CORP	XOM
CHEVRON CORP	CVX
SCHLUMBERGER LTD	SLB
CONOCOPHILLIPS	COP
EOG RESOURCES INC	EOG
OCCIDENTAL PETROLEUM CORP	OXY
HALLIBURTON CO	HAL
VALERO ENERGY CORP	VLO
PIONEER NATURAL RESOURCES CO	PXD
ANADARKO PETROLEUM CORP	APC
DUKE ENERGY CORP	DUK
SOUTHERN CO	SO
AMERICAN ELECTRIC POWER CO	AEP
SEMPRA ENERGY	SRE
CONSOLIDATED EDISON INC	ED
XCEL ENERGY INC	XEL
PG&E CORP	PCG
PPL CORP	PPL
WEC ENERGY GROUP INC	WEC
EDISON INTERNATIONAL	EIX

Table 1: Selected Sample Firms

Firm Clustering Results						
Energy (2 Clusters)		Utility (2 Clusters)		Utility (3 Clusters)		
Cluster 1	Cluster 2	Cluster 1	Cluster 2	Cluster 1	Cluster 2	Cluster 3
APC	EOG	AEP	ED	AEP	ED	SRE
COP	PXD	PPL	DUK	PPL	DUK	SO
VLO	SLB	SRE	EIX	XEL	EIX	WEC
CVX		SO	PCG		PCG	
XOM		WEC				
OXY		XEL				
HAL						

Table 2: Firm Clustering Results

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