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Identifying influential directors in the United States corporate governance network

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The influence of directors has been one of the most engaging topics recently, but surprisingly little research has been done to quantitatively evaluate the influence and power of directors. We analyze the structure of the US corporate governance network for the 11-year period 1996–2006 based on director data from the Investor Responsibility Research Center director database, and we develop a centrality measure named the *influence factor* to estimate the influence of directors quantitatively. The US corporate governance network is a network of directors with nodes representing directors and links between two directors representing their service on common company boards. We assume that information flows in the network through information-sharing processes among linked directors. The influence factor assigned to a director is based on the level of information that a director obtains from the entire network. We find that, contrary to commonly accepted belief that directors of large companies, measured by market capitalization, are the most powerful, in some instances, the directors who are influential do not necessarily serve on boards of large companies. By applying our influence factor method to identify the influential people contained in the lists created by popular magazines such as *Fortune*, *Networking World*, and *Treasury and Risk Management*, we find that the influence factor method is consistently either the best or one of the two best methods in identifying powerful people compared to other general centrality measures that are used to denote the significance of a node in complex network theory.

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I. INTRODUCTION

Corporate governance is important for developing company policies and assuring business growth and innovation. For successful industry positioning and competitiveness, companies tend to elect directors who are influential and well known in the business world as well as in the community. We assume that the influence of a director is reflected by the impact that a director can have on the whole industry. Usually an influential director functions as a model in the industry and can impose his or her philosophy on a wide range of companies. Many rankings of powerful and influential people have been created by business magazines based on interviews and public opinion. However, to the best of our knowledge, there are no quantitative studies conducted on the influence of corporate directors.

The influential directors, according to research done by economists, are usually those who serve on many company boards, because they are more likely to be active in various policy planning organizations and form a leading edge of the "capitalist class" [1]. These directors also often constitute a vanguard of the corporate elite; typically they are often in the forefront of innovation and well integrated in the community [2,3]. In addition, directors of large companies are considered to be more important than those who serve on small company boards, which is emphasized by magazines that create lists of the "most powerful people."

We define the total capitalization of all the companies (TCC) with which a director is affiliated as a quantity that contains both the number and the size of the companies on whose boards a director serves. We argue that the number and the size of the companies with which a director is affiliated do not entirely reflect the influence of a director. To illustrate this point, we show in Fig. 1 an example of Martha Stewart in the year 2001 when she was named the third most powerful woman in America by *Ladies Home Journal*. As illustrated in this figure, Martha Stewart was director of only two companies, Revlon Corp. and Martha Stewart Living Omnimedia. If we rank the directors by TCC, Martha Stewart would only be ranked in the bottom 16th percentile in the Investor Responsibility Research Center (IRRC) directors database. Figure 1 shows that the directors who serve on the same boards as Martha Stewart are also affiliated with many large companies. We argue that Martha Stewart's influence comes from her proximity to directors who serve on the boards of these large companies. This indicates that the relative position of a director (node) in the network contributes to this director's influence, i.e., the influence of a director depends not only on his or her own characteristics but also on the characteristics of the other directors surrounding a specific director.

In this paper, we develop a systematic measure which we call the *influence factor* (I) that incorporates both the topological and nontopological characteristics of directors in the network, to quantitatively study the influence of directors. In our approach, the influence of a director is based on the amount of information a director obtains from the other directors due to his or her position in the network. In the director network, nodes represent directors and links between directors represent their service on common corporate boards. In such a network, we assume that directors acquire information from the companies with which they are affiliated and spread this information to other directors through information sharing between connected directors [4]. The influence factor measure is affected by common centrality measures taken from complex network theory such as degree [5], betweenness [6], closeness [7], and the capitalization of companies. According to the influence factor method, Martha Stewart is ranked in the 84th

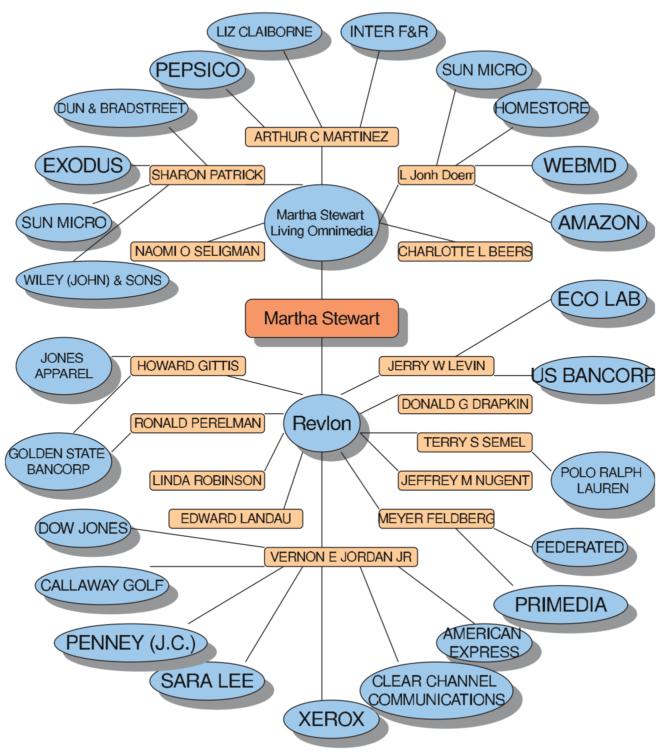

FIG. 1. (Color online) Illustration of a subnetwork of the company-director bipartite network. Nodes shown as rectangles represent directors, while nodes shown as ovals depict companies. If a director serves on the board of a company, a link exists between them. This subnetwork includes Martha Stewart, the corporate boards on which she serves, and the other directors who serve on common boards with Martha Stewart, including the additional companies on whose boards these directors serve.

percentile in 2001, in contrast to only the 16th percentile when ranked by the TCC. We also find that Douglas Leone, who was named as one of the top ten venture capitalists in the United States by *Forbes*, is only in the 30th percentile when ranked by the TCC. However, based on the influence factor method, he is ranked in the 90th percentile in 2001. We then statistically compare the influence factor method with the TCC and common centrality measures, such as degree, betweenness, closeness, K-shell [8–10], and Bonacich centrality [11,12], which are usually assumed to be equivalent to influence [13–15]. We apply all these methods to identify the influential directors who are selected as powerful people by popular business opinion, such as "powerful women in business" from *Fortune* magazine, "powerful people in networking" from *Networking World* magazine, and "100 most influential people in finance" from *Treasury and Risk Management* magazine. We find that for all three cases the influence factor method is consistently among the most efficient methods to identify the most influential directors.

II. DATA

We build a network of directors based on the IRRC director database [16] which contains information about approximately 1600 US corporations and 10 000 directors per year from 1996 to 2006.

We compare our results with popular rankings from magazines including the following:

(1) The ranking of "50 most powerful women in business" from *Fortune* for nine years from 1998 to 2006. Each year, *Fortune* interviews industry experts, Wall Street analysts, and executive recruiters to identify powerful women. The importance of these business women is broadly valued by revenues and profits controlled, their influence inside the company, the importance of the business in the global economy, and its impact on American culture. Each year the rankings include 50 female directors. We regard the same person in different years as a different entity. Thus, there are 450 entities for nine years, of which 193 entities are included in the IRRC director database.

(2) The list of "most powerful people in networking" from *Network World* for nine years from 1997 to 2006 except 2001 (due to a magazine policy change in 2001). From 1997 to 2000, the lists include 25 people and from 2002 to 2006, they include 50 people each year. Thus there are 350 entities, of which 112 entities are included in the IRRC director database.

(3) The list of "100 most influential people in finance" from *Treasury and Risk Management* for four years from 2003 to 2006. The lists include 400 entities, of which 47 are included in the IRRC director database.

Fewer than half of the influential people listed in these business magazines are included in the IRRC director database, since many influential people selected by the magazines are not directors. In this paper, we focus only on the power of influential directors.

III. NETWORK AND ITS PROPERTIES

For each year, we create a bipartite network of companies and directors [17] based on the IRRC database. As shown in Fig. 2, a node in this network represents alternatively a director or a company. A link between a director and a company represents the fact that the director serves on the board of the company. The largest connected cluster of the bipartite

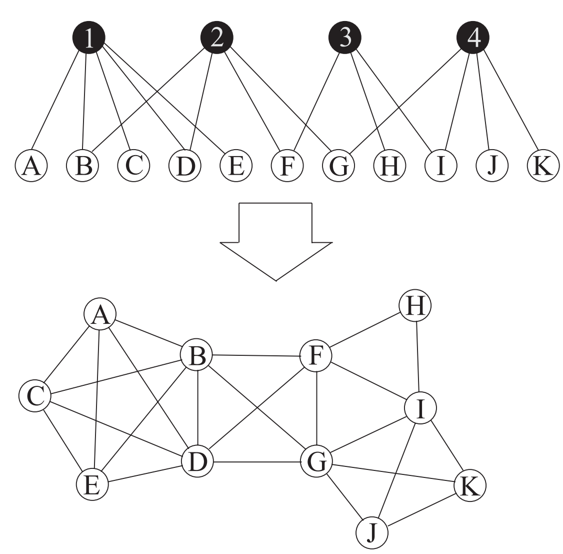

FIG. 2. Illustration of a bipartite network and its "one-mode" projection [18]. Nodes labeled by numbers correspond to boards, nodes labeled by letters correspond to directors.

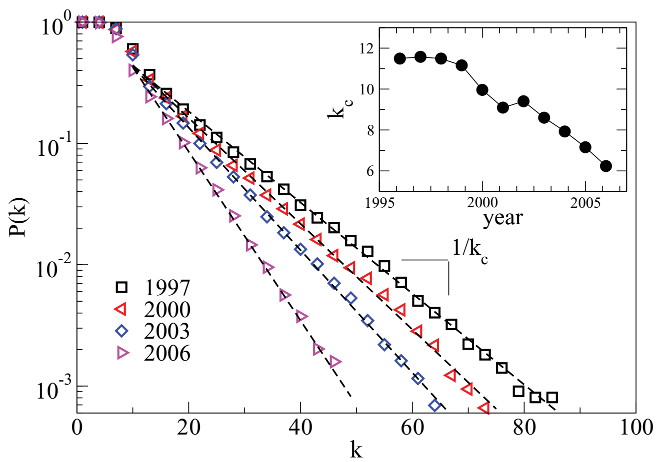

FIG. 3. (Color online) Demonstration that the cumulative degree distribution function [$P(k)$] of the network of directors for four typical years 1997, 2000, 2003, and 2006 follows an exponential distribution $P(k) \propto \exp(-k/k_c)$. Note that k_c decreases as time evolves (inset graph) which means that directors tend to sit on fewer boards in more recent compared to earlier years. The CDF displays a plateau up to a degree of 8 as a consequence of the fact that 8 is the characteristic size of a board for all years studied.

network includes over 80% of the companies and directors in the database, while the second largest cluster only contains fewer than 3% of companies and directors. Given this topology, we study only the largest cluster of the network. In a typical year, e.g., 1999, the largest cluster contains 1528 companies and 11 116 directors. By projecting the bipartite network into one mode [18], we create a director network (Fig. 2). The existence of a link between two directors means that they serve on at least one common board. Note that in this network, directors within one company's board form a fully connected cluster. The overall network is constructed by attaching these fully connected clusters to each other.

Previous studies [17] analyze statistical properties of similar director networks, such as degree distribution. Consistently, Fig. 3 shows that the tail of the cumulative distribution function cumulative distribution function (CDF) of degree in our director network is exponential, $\exp(-k/k_c)$, where k is the node degree of a director and k_c is the exponential decay parameter. Up to a degree of 8, all the CDFs for different years display a plateau as a consequence of the fact that 8 is the characteristic degree of directors for every year. This means that a large number of directors have degree around 8. Because 80% of directors serve on only one corporate board, the characteristic degree of directors is also the characteristic size of the boards. Directors who serve on many corporate boards usually have large degree and their degree distribution is described by k_c. We find that k_c decreases over time from 1997 to 2006. Since the characteristic size of the boards is stable, this indicates a tendency for directors to serve on fewer boards [19].

IV. INFLUENCE FACTOR MEASURE

We introduce a model to analyze the influence of directors by defining the influence factor for each director based on the level of information that the director can obtain from the entire network. The rationale for using the amount of information to value the influence of directors is that (i) information is a valuable commodity in corporate governance, and the more information the director has, the more valuable as a director she or he is; (ii) a director who has access to company information tends to be able to impose his or her influence on those companies, which indicates that the amount of information a director obtains reflects the level of the influence he or she has. These two points coincide with our view of the influence of a director. The first point enables directors to impose their influence well and strongly. The second point enables directors to impact a wide range of the whole industry.

The influence factor model is defined as follows:

(i) Each company is considered a source of information, which can be obtained by the directors who serve on the company's board. The amount of information embedded in the company is valued by the market capitalization of the company, based on the fact that directors who can obtain information from and impose influence on large companies should be more influential than directors who are affiliated with a marginal company.

(ii) After information is obtained by directors, it flows in the director network by information sharing between directors who are connected.

In Fig. 4, we demonstrate, as an example, how the influence factor of director **u** is calculated:

(i) We determine the amount of information w_j for each company by its market capitalization. If we choose to study the influence of directors within the technology industry, we set w_j for the companies from other industries to 0, e.g., $w_A = 0$, $w_D = 0$, because **A** and **D** are financial companies.

(ii) Distances between each director and director **u** are calculated in the director network as shown in Fig. 4 and we define d_j as the shortest distance between director **u** and those directors who serve on the board of company **j**.

(iii) We reduce the information of each company by r_j until it reaches director **u**. r_j is the information reduction rate per unit distance. Since this reduction rate differs from one

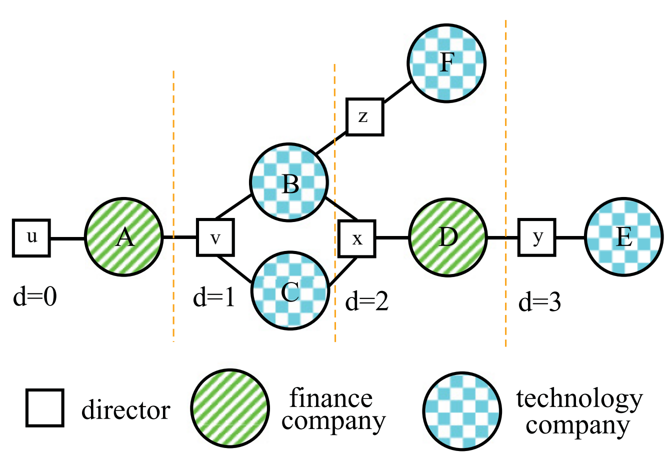

FIG. 4. (Color online) Illustration of the distance between directors used when calculating influence factor (I) of a director. The distance between two directors is defined as the number of intermediate companies on the shortest path between these two directors. Thus with respect to director **u**, director **v** has a distance 1, director x has a distance 2, etc.

pair of directors to another pair depending on people's nature and relationships, we assume r_j to be some random number following a certain probability distribution. Without further knowledge of how people share information with each other, we assume for simplicity a uniform distribution and choose r_j to be a random number between 0 and 1. All information relevant to company **E** can be accessed by director **y** (who sits on the board of **E**), but only a fraction ($w_E r_{E1}$) is passed to director **x** (who sits with **y** on another board), and so on. Thus, the amount of information about company **E** that director **u** can access is $S_{uE} \equiv w_E r_{E1} r_{E2} r_{E3}$.

(iv) By adding the information of all the companies we find that the total information that passes through director **u** is $S_u = S_{uA} + S_{uB} + S_{uC} + S_{uD} + S_{uE} + S_{uF}$.

(v) Then the influence factor (I) is calculated as the percentage of the total amount of information that flows through director **u** by $I_u \equiv S_u / \sum_j w_j$.

In general, the influence factor I of a director **i** is defined as

$$I_i \equiv \frac{\sum_j w_j r_{j1} r_{j2} \cdots r_{jd_j}}{\sum_j w_j}, \tag{1}$$

where w_j is the amount of information embedded in company **j** based on market capitalization, d_j is the shortest distance between director **i** and the directors in company **j**, which represents the number of intermediaries the information of company **j** has passed before it reaches director **i**, and r_j is the random information reduction rate. We obtain the *influence factor* of director **i** as the average of 50 random realizations of I_i calculated by Eq. (1).

The *normalized influence factor* (NIFs) of each director is then defined as

$$\tilde{I}_i \equiv \frac{I_i - \langle I \rangle}{\sigma(I)}, \tag{2}$$

where $\langle I \rangle \equiv \sum_{i=1}^{n} I_i/n$ is the annual average of the influence factor of all directors and $\sigma(I)$ is the standard deviation of influence factors of directors for one year. A negative value of the NIF does not mean that a director has negative influence. Only the relative rank is meaningful, e.g., a director with NIF -0.5 is more influential than a director who has NIF -1.1.

V. PROPERTIES OF THE INFLUENCE FACTOR

For different years, as shown in Fig. 5(a), the influence factor I of directors for all the companies follows different cumulative distribution functions because the sizes of the networks are different from year to year. Hence, the influence factors of directors are not comparable over the years. However, we find that the CDFs of the NIF $\tilde{I}$ for different years collapse to a single curve, which means that there is a scaling mechanism for $\tilde{I}$ for different years. As shown in Fig. 5(b), the scaled curve fits the complement cumulative function of the Gaussian function. This scaling property enables us to compare NIFs of directors for different years.

As described in the previous section, the information reduction rate is a random parameter. However, we find that the rankings of directors given by different realizations are consistent with each other, as shown in Fig. 6. For each realization, we calculate the influence factors of directors and choose the top 100 and 1000 directors out of around 10 000 directors each year. We then find the overlapping percentage of these top directors for every pair of realizations and plot the average overlapping ratio and error bar in the graph. Out of 10 000 directors each year, there is about 60% overlap for the top 100 directors and more than 80% overlap for the top 1000 directors. This result justifies our approach since it shows that the microscopic detail of how much information is shared by a certain pair of directors is not critical for the process of finding the most influential directors; instead the network property plays an important role.

The influence factor of a director is calculated based on a progressively reduced information exchange process, which is relevant to the director network topological properties. We

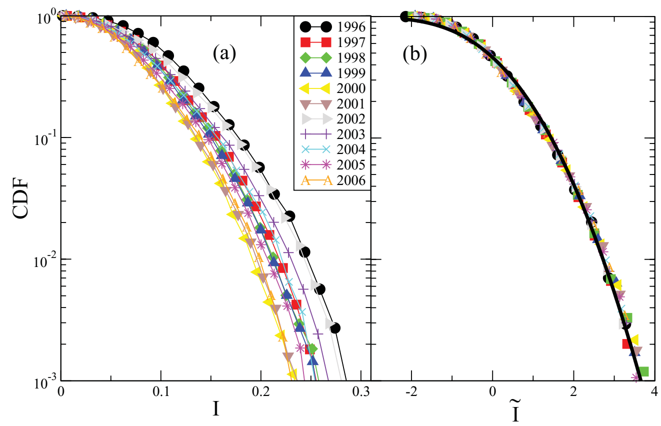

FIG. 5. (Color online) Demonstration of cumulative distribution of director's influence factor I and NIF $\tilde{I}$ in different years. (a) Cumulative distributions of influence factor I in different years show dissimilar behavior. (b) Cumulative distributions of the normalized influence factor $\tilde{I}$ collapse onto a single curve, which indicates a scaling relation for $\tilde{I}$. The solid curve corresponds to the complement cumulative function of the Gaussian function with a mean -0.12 and a standard deviation of 1.22. The scaling relation makes $\tilde{I}$ of directors in different years comparable.

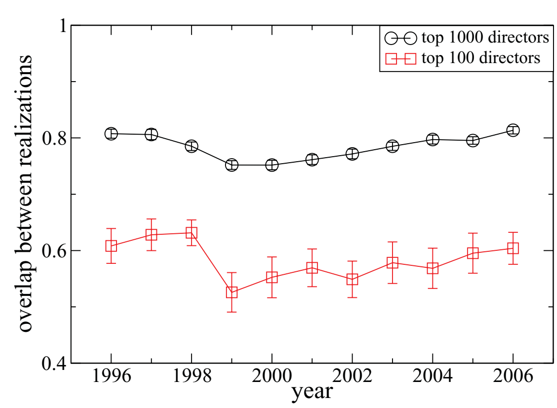

FIG. 6. (Color online) Percentage of overlap of top directors according to influence factor between different realizaitons vs years. For each realization, we calculate the influence factor for each director and choose the top 100 and 1000 directors out of around 10 000 directors each year. We find the overlapping percentage of these top directors between each pair of realizations and then the average and error bar of these overlapping percentages.

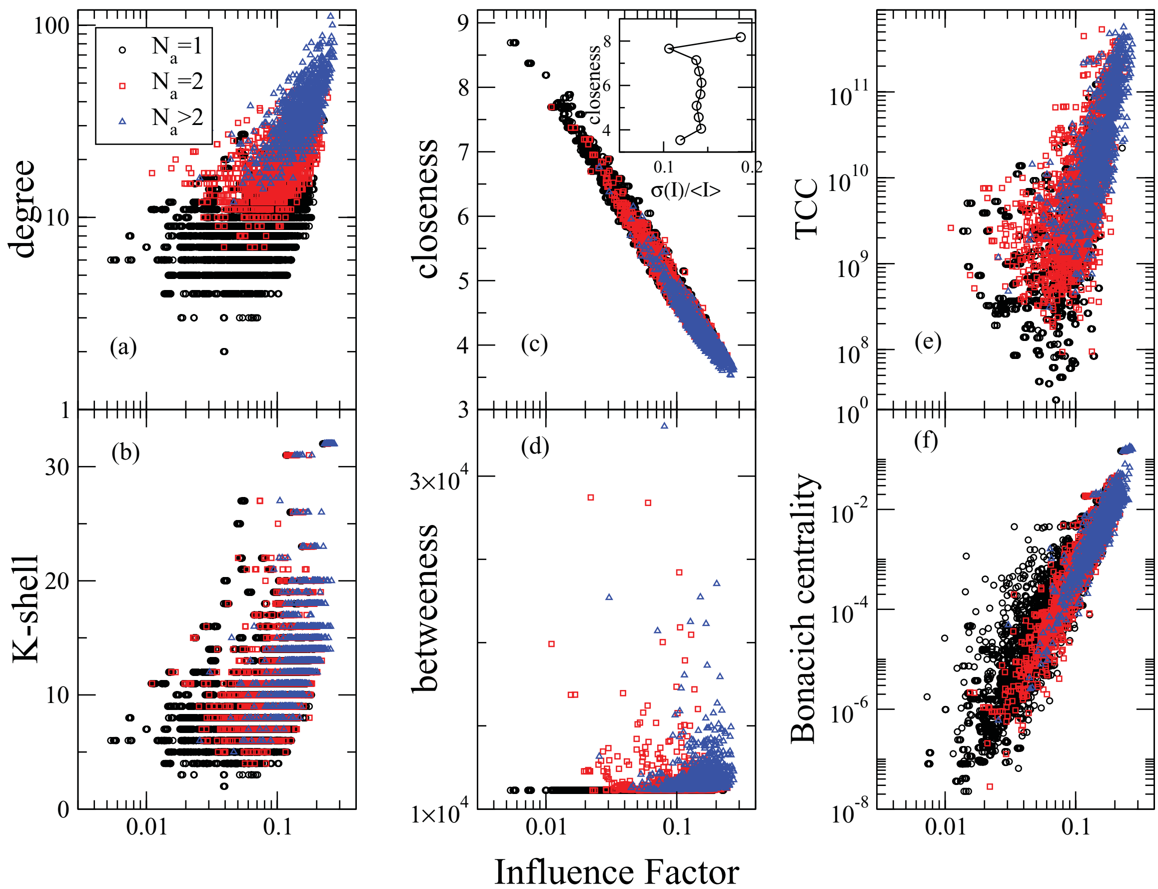

FIG. 7. (Color online) Comparison between the influence factor I, TCC, and the existing centrality measures for a typical year 1999. N_a is the number of companies with which a director is affiliated. We can see that directors with larger N_a tend to be more powerful by all measures. However, there is always a large overlap between directors with different N_a, which supports our argument that directors who serve on more corporate boards are not necessarily more powerful than those who serve on fewer boards. Moreover, we find (i) significant correlation between closeness and influence factor, (ii) some positive correlation between TCC, Bonacich centrality, and influence factor, and (iii) a low correlation between influence factor and degree, K-shell, and betweenness measures. Inset: The relative variance of the influence factor $[\sigma(I)/\langle I\rangle]$ with respect to closeness. Directors are divided into ten bins according to their closeness, and variance $\sigma(I)$ and average $\langle I\rangle$ for each bin are calculated to plot this relative rariance versus closeness graph. Typically, the relative variance is around 14%.

now compare the influence factor to the TCC and to the other centrality measures such as degree, K-shell, closeness, betweenness, and Bonacich centrality. Figure 7 shows that the influence factor is not significantly correlated with the centrality measures except closeness. The correlation between influence factor and closeness is not surprising because the information obtained for calculating the influence factor depends strongly on the distance between directors, and the closeness measures the average distance from one director to all the other directors in the network. However, in addition to distance, the influence factor also depends on the capitalization of companies, which differentiates the influence factor from closeness. This difference is reflected in the relative variance of the influence factor with respect to closeness, which is consistently larger than 10%, as shown in the inset of Fig. 7(c). Indeed, when we test the methods empirically in Sec. VI, we find that this variance causes a big difference between influence factor and closeness measures in identifying powerful people.

In addition, in Fig. 7, we show the effect of N_a, the number of companies with which a director is affiliated. The graphs show that directors with larger N_a tend to be more powerful by all measures. However, there is always a large overlap between directors with different N_a, which supports our argument that directors who serve on more corporate boards are not necessarily more powerful than those who serve on fewer boards.

As discussed in Sec. III, the director network is comprised of many fully connected clusters. Because of this specific topology, we argue that degree, K shell, and betweenness cannot entirely reflect the influence of a director. The degree and K shell of the directors depend largely on the size of the boards. If a board consists of a large number of directors, all the members of that particular board will have high degrees and will be present in the nucleus of the network by the K-shell measure, even if, as an extreme example, that board is isolated from the rest of the network. The betweenness centrality of a node is defined as the times that a node is on the shortest paths between all pairs of vertices. Because all directors who serve only on one board will not occur on the shortest paths between other directors and have zero betweenness, betweenness centrality does not distinguish the importance of people who are affiliated with only one company's board.

The influence factor is a measure affected by both nontopological properties, such as the capitalization of the companies, and the topological properties of a director, such as degree, closeness, etc. Moreover, the influence factor method is useful when applied to a network consisting of many fully connected clusters. Below we test the efficiency of our influence factor measure in identifying influential people compared to the TCC and existing centrality measures.

VI. EMPIRICAL TESTS OF METHODS

In order to study the efficiency of a method in identifying the most influential directors from the IRRC database, we first define an efficiency coefficient ϵ for each method as follows:

(1) Rank the directors according to the method that we want to test.

(2) Use the influential people lists made by popular business magazines as a benchmark.

(3) Examine the percentage (p) of people in the magazine lists who are included in the top q percent of people from the database ranking, i.e., select 10% ($q = 10\%$) of people who are ranked at the top of the database list and find that 30% ($p = 30\%$) of the people in the magazine lists appear in the top 10% of people from the database.

(4) Define the efficiency coefficient $\epsilon \equiv p/q$. The larger the ϵ, the better the performance of the particular method is in identifying influential directors.

A. Test: Power and influence of female directors in the US corporate governance network

The ranking of "50 most powerful women in business" selects the 50 most powerful and influential businesswomen in the United States every year according to the criteria of *Fortune*. Every year, about 20 out of these 50 powerful women are included in our database. To improve the statistics, we increase the sample size by mixing the executive women of all years from 1998 to 2006, which is validated by the scaling relation for $\tilde{I}$, indicating that the influence factors of directors in different years are comparable (see Sec. V). This means that the same executives in different years are treated as different entities. We find that between 1998 and 2006, 193 entities out of 450 are included in our database.

We apply the NIF, TCC, and common centrality measures to identify the influential female directors selected by these rankings. We plot the values of the efficiency coefficient ϵ versus q in Fig. 8(a) and p versus q in Fig. 8(b); the figures show that the NIF is more efficient in identifying powerful female directors in the network compared to the other centrality measures. Only the performance of the TCC is comparable with that of the NIF. The top 10% powerful female directors identified by the NIF from our database contain 40% of the directors who appear in the "50 most powerful women in business" list from *Fortune*.

B. Test: Power and influence of directors in the US corporate governance network for specific industries

In addition to studying the influence of directors in the overall US corporate governance network, we also analyze the influence of directors over a certain group of companies by assigning zero weight to those companies that we do not want to consider, as described in Sec. IV. Here we examine influential directors for the financial industry and the networking industry.

Treasury and Risk Management compiles annual rankings of the "100 most influential people in finance," selecting powerful people from the financial industry. In our database, companies are categorized into different economic groups, which allows us to identify the companies that belong to the financial industry. We assign zero weight to the companies that are not in the financial economic groups to calculate the influence factor and NIF of directors for the financial industry by Eqs. (1) and (2). We then calculate the efficiency coefficient ϵ for each method and plot our results in Figs. 8(c) and 8(d). We see that in the financial industry, only closeness provides similar performance to the NIF, while the other centrality measures provide inferior performance to the NIF. In addition, capitalization of companies, measured by the TCC, is found not to be a determining factor for influential directors in the financial industry.

Network World publishes annual rankings of the "most powerful people in networking." These lists include powerful people in networking- and communication-technology-related industries. In the IRRC database, these industries correspond to technology and communication economic groups. To calculate the influence factor and NIF of each director for the networking industry, we assign zero weight to the companies outside of the technology and communication economic groups. We then calculate the efficiency coefficient ϵ for each method and plot Figs. 8(e) and 8(f), showing that in the networking industry, lists made according to the TCC match the magazine lists better than lists made according to the NIF. However, the NIF is superior in identifying the powerful directors in networking industry compared to the centrality measures, such as closeness, betweenness, K shell, degree, and Bonacich centrality.

In summary, the influence factor measure is superior to degree, betweenness, K-shell, and Bonacich centrality in identifying powerful directors for all cases. Closeness shows similar efficiency as the influence factor measure in identifying influential directors in the financial industry. The TCC is as efficient as the influence factor measure when studying female directors, while it is more efficient when the power of directors in the networking industry is analyzed. When considering the criteria for creating the most powerful people lists, the above results can be explained as follows: The "100 most powerful people in finance" list is made by interviewing executives, bankers, economists, technology vendors, and consultants, so a director who has a shorter distance to all the other directors in the network is more likely to be known by the other directors in the network. The "50 most powerful women in business" list and the "most powerful people in networking" list emphasize the revenues and profits controlled by the directors and the importance of their businesses in the global economy. Thus a director who is affiliated with large companies would be considered to be more important. Nevertheless, our results show that, regardless of the approach used by magazines to create powerful people lists, our influence factor measure is always among the most efficient methods in identifying powerful people from these lists.

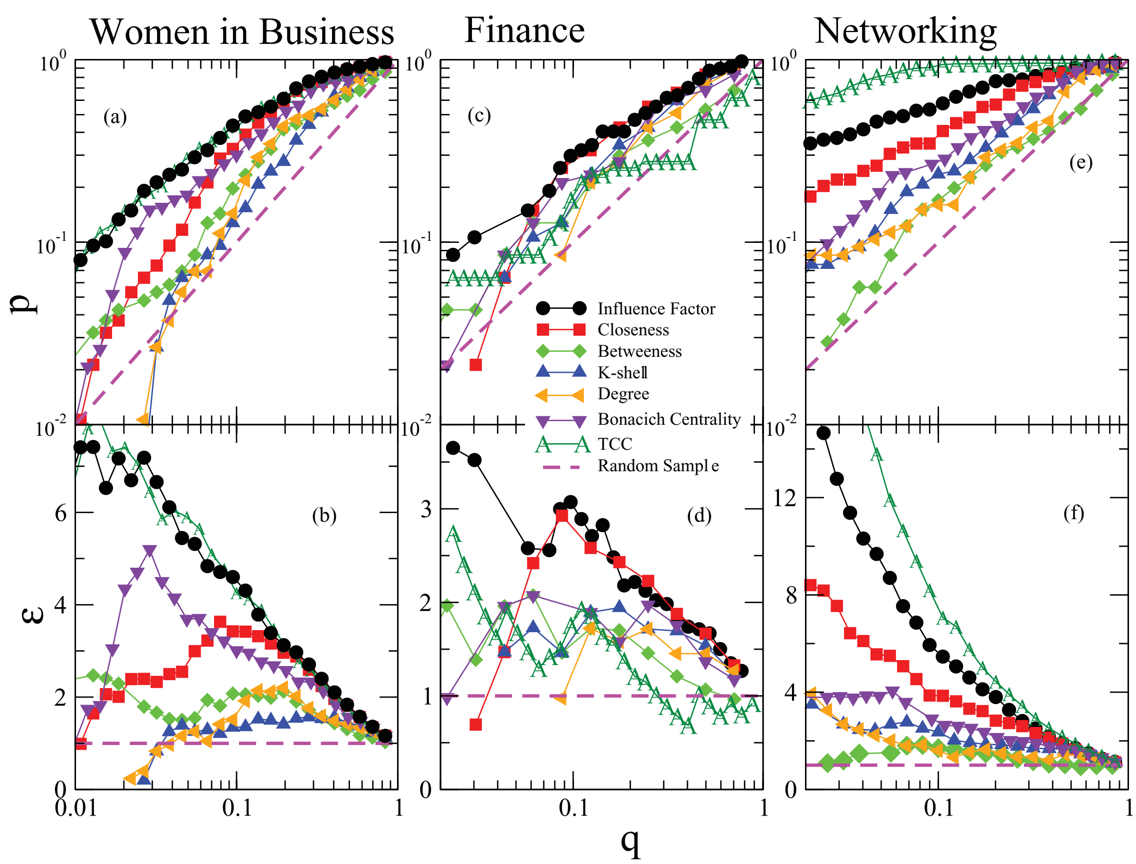

FIG. 8. (Color online) Comparison between the efficiency ϵ of the influence factor measure and other measures in identifying the most influential directors. We apply the NIF, TCC, closeness, betweenness, K-shell, degree, and Bonacich centrality to identify the influential people listed by magazines. The threshold q is the top fraction of directors after they have been sorted by descending importance, e.g., $q = 0.1$ for the influence factor means selection of 10% of the directors with the highest $\tilde{I}$ in our database; p is the fraction of directors in the magazines' powerful people lists who are included in the directors' set selected from the IRRC database by threshold q. The dashed line ($p = q$, $\epsilon = 1$) is obtained when directors are randomly selected from the database instead of being ranked. The ratio $\epsilon \equiv p/q$ represents the efficiency of a measure in identifying powerful people listed by magazines from the IRRC director database. Here we show three cases, "powerful women in business" from *Fortune*, "influential people in finance" from *Treasury and Risk Management*, and "powerful people in networking" from *Network World*. In the case of powerful women in business, the TCC is as efficient as the influence factor measure, in the financial industry closeness shows similar efficiency as the influence factor measure, while in the case of powerful people in networking the TCC is more efficient than the influence factor measure.

VII. CONCLUSION

In this paper we have analyzed the power of directors in the US corporate governance network. To measure the influence of directors, we develop a measure, the influence factor, that offers an objective and quantitative way of determining the power of directors. In our network, nodes represent directors and the links between two directors exist if the two directors serve on at least one common corporate board. We build this network of directors based on the Investor Responsibility Research Center director database for the 11-year period between 1996 and 2006, and find that the director network is comprised of many fully connected clusters. This network topology presents a challenge for the existing centrality measures to properly reflect the importance of a director. The influence factor method is based on an information-sharing process that propagates through the network, where the amount of information obtained by a director from other directors depends on the distance between the directors. The longer the distance between two directors is, the more intermediaries they have between them, and hence the higher the information reduction rate is. In addition, the influence factor is also affected by the market capitalization of the companies with which directors are affiliated. Thus, the influence factor combines the topological and nontopological properties of directors in the network. This combination makes the influence factor more suitable for identifying influential people in the overall corporate governance network or specific industries compared to other centrality measures or the TCC.

In addition to determining the influence factor, we also evaluate the normalized influence factor (NIF) of directors for different years and find a scaling relation between the NIF values which allows us to compare the influence of directors across the years. We then compare the efficiency ϵ of the influence factor in identifying powerful people with the efficiencies of other centrality measures and the TCC, using popular magazine lists as benchmarks. Powerful people lists created by magazines reflect public opinions of directors. Hence they are appropriate to use as benchmarks when testing how well different measures reflect the influence of a director.

We find that, contrary to commonly accepted belief that directors of large companies are most powerful, in some instances, influential directors do not serve on boards of large companies. We also find that the influence factor measure is consistently either the best or one of the two best methods in identifying the influential people listed in the "50 most powerful women in business" from *Fortune*, "powerful people in networking" from *Networking World*, and "100 most influential people in finance" from *Treasury and Risk Management*. In some cases, closeness and the TCC are in competition with the influential factor method when the criteria for creating the most powerful people lists emphasize TCC or closeness. However the influential factor method is still a better choice to identify the influential directors overall because of its consistency of performance in all three cases regardless of the criteria used to create the powerful people lists.

Even though the amount of information that a director can access through the network may not be the single aspect when determining the influence of the director, the influence factor measure developed here properly reflects the influence of directors in the US corporate governance network, and can be a good quantitative and objective measure to identify influential directors in corporate networks.

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