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Security Analyst Networks, Performance and Career Outcomes

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Abstract

Using a sample of 42,376 board directors and 10,508 security analysts we construct a social network, mapping the connections between analysts and directors, between directors, and between analysts. We use social capital theory and techniques developed in social network analysis to measure the analyst's level of connectedness and investigate whether these connections provide any information advantage to the analyst. We find that better-connected (better-networked) analysts make more accurate, timely, and bold forecasts. Moreover, analysts with better network positions are less likely to lose their job, suggesting that these analysts are more valuable to their brokerage houses. We do not find evidence that analyst innate forecasting ability predicts an analyst's future network position. In contrast, past forecast optimism has a positive association with building a better network of connections.

Security analysts are among the most important information intermediaries in capital markets. They produce reports that contain earnings forecasts, investment recommendations and target prices, through which they reveal important information to other market participants. Because of their significance for the efficient functioning of markets, prior studies have identified various factors that explain differences in analyst performance and affect their implicit or explicit incentives.

In this paper we investigate the importance of an analyst's network position on forecast accuracy, timeliness and boldness. Although it has been advocated that economic agents may

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gain information advantages through their network connections and their network position (Coleman 1988; Burt 1992; Cohen, Frazinni and Malloy 2009) it is not clear that such advantages would exist among security analysts. First, regulation Fair Disclosure (FD) in the US prohibits selective disclosure of information from companies. Therefore, information from board members to analysts should flow only through public announcements and conference calls that are open to the public. Second, information flows from one analyst to another competing analyst only if complementarities exist in the information structure (Stein 2008). Whether such complementarities, which allow information exchange through networks, exist is an empirical question. Third, studies have shown that analysts covering more firms and/or more industries have worse performance (Clement 1999; Jacob, Lys and Neale 1999). This result is counter intuitive from a network perspective, because if connections do provide information advantages to the analysts then analysts who cover relatively more firms over more industries are more likely also to be better-connected.

The network we construct comprises 42,376 board directors from 4,444 firms and 10,508 analysts from 612 brokerage houses. Using social capital theory and techniques developed in social network analysis we measure different qualities of the analyst's network position and use these measures to proxy for the likelihood that the analysts will be able to obtain private information from her network connections. This proxy assumes that analyst's connections determine inter alia, the likelihood of them receiving private information. For example, an analyst position within the network (e.g. the type of connections she has) will determine the quality, amount and timeliness of the information she receives. The proxy does not rely on the presumption that an executive or non-executive director will provide an analyst with insider information via an explicit one-on-one conversation. The proxy merely captures the increased likelihood that an analyst with a relatively better network position will have more opportunities to be privy to more and better quality information. For example, the closer an analyst is to others in the network (e.g. the more direct connections they have relative to indirect ones) will determine how early she will receive information and the quality of such information. Similarly, following Stein's (2008) argument these different connections may also provide the analyst with better opportunities to receive complementary information. For example, take the following scenario: a well connected analyst attends a press release; due to her better network position she is likely to be privy, at some point in time, to the separate complementary conversations taking place in the room. Whereas, a less well connected analyst is less likely to be privy to the same level of chatter/gossip and thus new information. Social capital theory would suggest that individuals who hold a 'brokerage position' within a network (i.e. connects disparate unconnected groups of individuals in network) will receive different information sets, which enable them to create information arbitrage. We validate this proxy by investigating the association between an analyst's network position and the likelihood of them attending and participating in a conference call. We find that the better an analyst's network position the more likely they are to participate in and to ask more questions in a conference call. This suggests that our proxy does capture the analyst's relative information inflow opportunities.

We find that the closer an analyst is to others in the network (e.g. the centrality of the analyst) and the quality of their brokerage position (e.g. the betweenness of an analyst) is positively related to forecast accuracy. Moreover, when the analyst is not a member of a very tight knit (highly clustered, cliquey) network they have better forecast accuracy. All these relations are economically meaningful. An analyst with an excellent brokerage position and therefore in the 90^{th} percentile of betweenness has 4.65 percent lower forecast error compared to an analyst at the

10th percentile. For example, Meredith Whitney, one of the most influential banking analysts in Wall Street after predicting the collapse of the banking sector due to subprime losses, scores at the 90th percentile of betweenness.

Moreover, we find that these network measures have a significant association with the forecast horizon of the first forecast each analyst makes for a company each year. Therefore, suggesting that better-networked analysts are also leaders in terms of forecast timeliness. An analyst at the 90th percentile of betweenness makes her first forecast on average four days earlier than an analyst at the 10th percentile. In addition, these analysts make bolder forecasts. The absolute difference between their revised forecast and the consensus forecast just prior to the revision is greater for analysts with higher closeness or betweenness. These results hold after we control for other known determinants of forecast accuracy, timeliness and boldness.

Since an analyst's position in the network can explain variation in analyst performance, we also investigate whether it has implications for an analyst's career outcome. Specifically, we test whether better-networked analysts face a lower probability of losing their job. We find that analysts in the bottom ten percent of betweenness have 7.73 percentage points higher probability of turnover relative to analysts in the top ten percent. This result holds after controlling for experience, brokerage house, number of firms and industries covered by an analyst, relative accuracy and relative optimism effects.

Finally, we provide evidence on determinants of networks. We use as a proxy for innate ability to forecast earnings, excluding any network effects, the forecast accuracy at the first year of an analyst's career. We find that this measure has no relation to future network position. Therefore, the results that link analyst performance and network position are unlikely to suffer from an omitted variable bias because of unobserved heterogeneity in analyst ability. We also construct a more comprehensive model that explains most of the variation in how well networked is an analyst. We find that past accuracy earlier or later in an analyst's career has no influence on networks. In contrast, past optimism later in an analyst's career is positively associated with building a good network position in the future. Contemporaneous size of brokerage house, number of industries and firms covered by an analyst and experience are all associated with better network position. In addition, past size of brokerage house, number of industries and number of firms covered by an analyst are also incrementally associated with better network position.

Our paper contributes to the growing literature on social network effects in economics (Hong, Kubik and Stein 2005; Hochberg, Ljungqvist and Lu 2007; Cohen, Frazinni and Malloy 2008; Cohen, Frazinni and Malloy 2009; Stein 2008). Security analysts influence stock prices and are therefore important economic agents in the price discovery process (Gleason and Lee 2003; Kelly and Ljungqvist 2007). As a result, understanding factors that affect their performance and implicit incentives is important. This paper also contributes to the debate surrounding the differential performance of individual analysts (Clement 1999; Jacob, Lys and Neale 1999; Malloy 2005) by showing that an analyst's social network position is an additional dimension that affects their performance. Moreover, the results on past optimism and network position suggest an agency component to the relation between firms and analysts since analysts can strategically exhibit optimism later in their career to improve their connections with firms and ultimately their network position.

This study also has implications for regulations such as Fair Disclosure that was passed in October 23, 2000. This regulation aims to eliminate selective disclosure and therefore any sources of information advantage such as the one this study uncovers. Since all our data is postregulation we infer that social network effects are too strong for any regulation to eliminate fully. This is consistent with Mayew (2008) who also documents that the information playing field is not leveled after Regulation FD by providing evidence that management discriminates among analysts during conference calls.

The paper proceeds as follows. In Section I, we review the related literature and form the hypotheses of this study. Section II describes the data. Section III constructs the necessary measures and presents the research design. Section IV shows the results on the association between forecast characteristics and an analyst's position in the network and Section V shows the results on the relation between analyst turnover and network measures. We present the results on the determinants of network measures in section VI and we conclude in Section VII.

I. Literature Review and Hypotheses

A large literature examines whether analysts exhibit differential forecasting ability (Clement 1999; Jacob, Lys and Neale 1999; Bolliger 2004; Malloy 2005; Bradshaw and Brown 2008). These papers document that forecast horizon and the inverse of brokerage house size are positively associated with forecast error. Portfolio complexity, defined as number of companies and industries followed by the analyst, is positively related to forecast error in the US (Clement 1999; Jacob, Lys and Neale 1999) but not in Europe (Bolliger 2004). The effect of firm-specific or general experience is rather more hotly debated with little emerging consensus (Jacob, Lys and Neale 1999; Clement, Koonce and Lopez 2007).

These previous studies however have paid less attention to the role of social networks in capital markets and in particular analyst performance. Cohen, Frazinni and Malloy (2009) document that analysts outperform on their stock recommendations when they have an educational link with a board member from the company. Similarly, Cohen, Frazinni and Malloy (2008) show that mutual fund managers gain information advantage through their educational ties with board members. Hong, Kubik and Stein (2005) explore the word-of-mouth effect between mutual fund managers by showing that trades of mutual funds, which are located in the same city, are correlated. Hochberg, Ljungqvist and Lu (2007) apply social network analysis to derive measures of centrality, as in this study, and find that better-networked venture capitalists have better performance.

There are several advantages to focusing on security analysts in testing whether social network position delivers an information advantage. The availability of analyst data provides us with the opportunity to construct a large network where each actor can be connected to a large number of people. Therefore, we are able to include almost the universe of sell side analysts in the US to construct a relatively comprehensive network. Also, since analysts' performance depends crucially on gaining an information advantage, this industry is an ideal testing ground to determine whether social networks facilitate information flow.

In contrast to prior studies and similar to Hochberg, Ljungqvist and Lu (2007), we do not consider a particular characteristic, such as education or geographical proximity, through which social interactions might take place but rather we construct a network to extract measures of social capital. Prior research documents that agents at the core of the social network have more valuable information (Freeman 1977). More importantly, being an information broker or spanning structural holes is an even better indicator of social capital than just network centrality (Cook and Emerson 1978; Burt 1992). People who act as information brokers in the network connect other people or groups of people indirectly through them and therefore if they were absent such an indirect link would not exist. These actors have access to a wider diversity of information, early access to that information and control over information diffusion (Burt 1982, 1992; Schumpeter 1934; Merton 1949; Granovetter 1973; March 1991). These three advantages together give an opportunity for information arbitrage (Burt 2005). Other studies have found a link between social capital and performance in other settings. For example, Mizruchi and Stearns (2001) show that loan officers in a large commercial bank with more social capital are more probable to close a successful deal. Apart from examining forecast accuracy and timeliness, we consider forecast boldness since Clement and Tse (2003) find that bold forecasts are more accurate than herding and incorporate analysts' private information more completely. Therefore, our first hypothesis is:

Hypothesis 1: An analyst with higher social capital will make more accurate, timely and bold forecasts.

Past research has also examined analysts' career outcomes (Michail, Walther and Willis 1999; Hong, Salomon and Kubik 2000; Hong and Kubik 2003). In general, these studies find that forecast accuracy and optimism are associated with promotion or a decrease in the probability of job loss. If analysts can gain an information advantage because of their position in the network then we expect that this leads to favorable career outcomes since analysts can use their network as a bargaining tool against their employers. Bolliger (2004) argues that brokerage houses consider the network an analyst has built during her tenure in hiring decisions. There is also evidence in other settings that information brokerage is rewarded. Podolny and Barron (1997) show that senior managers in an electronics firm with more social capital are more likely to get promoted early. Gabbay and Zuckerman (1998) find that expectations of promotion are higher for research and development scientists with higher social capital. Horton, Millo and Serafeim

(2009) show that in a broad cross-section of UK firms more central directors earn higher compensation. Therefore, our second hypothesis is:

Hypothesis 2: An analyst with higher social capital is less likely to face unfavorable career outcomes.

II. Data

A. Network Sample

We use two data sets to construct our network of analysts and directors. The data for directorships is obtained from The Corporate Library. This database provides data covering 2001-2007 for 136,615 directorships, 42,376 unique directors and 4,444 unique US firms (Table I). The analyst data is obtained from I/B/E/S. There are 10,508 unique analysts in the database working for 612 unique brokers. These analysts cover 10,231 unique companies. More data is available for the later years than for the earlier. For example, the network has 15,434 individuals in 2001 whereas there are 37,098 individuals in 2007.

For each year we construct the network by connecting analyst to analyst, analyst to director and director to director. A director is directly linked to another director if they sit on the same board and is directly linked to an analyst if the analyst covers their company. An analyst is linked to another analyst if they work for the same brokerage house or if they analyze the same firm (see Appendix). We assume that it is more probable that analysts and directors interact with each other under these conditions.[1] For example, analyst A is more likely to talk to analyst B if they participate in the same conference call compared to analyst C that neither works at the same

[1] Conversations with sell side analysts confirm that this is a reasonable assumption. Analysts are more likely to interact socially and professionally with directors that sit on the boards of firms they cover and analysts that either work on the same brokerage house or cover the same firms. The main reasons behind this phenomenon are common interests and physical presence in the same places during investment days or other professional and social events.

brokerage house nor covers any stocks in analyst A's portfolio. Similarly, if analyst A covers company E then she is more likely to talk to director D who sits on the board of company E than to director F who sits on the board of company G, which analyst A does not cover.

B. Analysis Sample

To test the hypotheses we obtain analysts' 1-year forecasts from I/B/E/S. However the data coverage of I/B/E/S does not provide a perfect match to the Corporate Library sample and therefore we were only able to obtain data for a sub-sample of our network sample. [2] On average this provides us with approximately 80% of the companies and 70% of the individual analysts in the network matching with I/B/E/S. The subsample does however provide us with a broad cross-section of the largest US firms.

We exclude all firms that are covered by fewer than three analysts in a year since we perform within firm-year analysis and all analysts that are teams or that have a code which appears unrealistically often in the database. For example, we exclude codes that cover more than one hundred firms in a year or codes that are associated with more than three brokerage houses in a year. Moreover, we exclude codes that make fewer than three forecasts during 2001-2007. We consider those codes more likely to be data errors than representing persons, or junior analysts with very limited experience who exit the profession quickly. This sample selection yields 3,502 unique companies and 7,736 unique analysts (Table I). The sample includes 160,460 unique analyst-firm-year forecasts.

[2] Extending the analysis to all companies with data available in IBES does not change the results of this study. The increase in the sample for years 2001-2005 is moderate and for years 2006 and 2007 is very small. This happens because the companies that Corporate Library does not have board membership data for are smaller and therefore it is more probable that they are going to be followed by fewer than three analysts from our sample.

III. Measurement of Variables and Research Design

A. Social Network Measures

Closeness centrality is calculated as the inverse of the mean geodesic distance (i.e. the shortest path) between an individual (node v), in our case an analyst, and all other individuals (nodes) reachable from it (see Appendix A). The higher this measure is, the more central the analyst is within the network. This centrality provides the analyst with the opportunity to have a relatively better access to the information in the whole network i.e. information has to travel through less mediators to reach a person with high closeness centrality compared to an individual with low closeness centrality (Stephenson and Zelen 1989). The measure is normalized and ranges from zero to one.

Betweenness centrality is the ratio between paths connecting two actors that pass through a particular actor and between all other paths that connect the two persons. Again, the measure is normalized and ranges from zero to one. Betweenness indicates how much information flows 'through' an analyst and, consequently, the degree to which that analyst can serve as a broker between pairs of other actors. Therefore, analysts with high betweeness have the opportunity to control the information flow within the network.

K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors (Seidman 1983). The higher the *k* of an actor, the better connected her neighbors are and, consequently, the less brokerage opportunities she will have, her information will be relatively less scarce and her actions will be more constrained (Moody and White 2003). We divide this measure by the analyst's degree[3] and therefore this measure also ranges from zero to one. The closer the measure is to one, the less relative advantage the analyst's information is likely to have.

[3] Degree is the count of the number of ties to other actors in the network.

To give a better feel of these measures Table II presents correlations between social network characteristics, analyst experience, size of the brokerage house and number of firms and industries covered by each analyst. Below the diagonal we present correlations for the raw variables and above the diagonal correlations for the variables after adjusting for firm-year effects. Ex ante we expect betweenness and closeness to have a positive association with all the variables. Whereas in contrast, the K-core should have a negative association. For example, the more experienced the analyst is to the more able they are to build a better network position over time. Also, by simply covering more firms and more industries provides relatively more opportunities for the analyst to control information flow in the network. In addition working for a larger brokerage house also increases the centrality of an analyst in the network.

Table II confirms the above predictions. Our discussion focuses only on the correlations between the variables after adjusting for firm-year effects, given the correlations for the raw variables are similar. We find the association between closeness and betweenness is positive association as expected (0.57). K-core has a strong negative association with betweenness (-0.35) and a weak negative relation with closeness (-0.05). More experienced analysts who work in larger brokerage houses and cover more firms and more industries appear to have a higher social capital. Although the brokerage house size is a more significant determinant of an analyst's closeness compared to other variables. In contrast, the number of firms and industries covered is a more significant determinant of betweenness and K-core. General and firm-specific experiences have a correlation of 0.63 exactly the same as in Clement (1999). Both experiences have a positive correlation with size of the brokerage house and number of firms and industries covered by each analyst as in Clement (1999). The number of firms and number of industries covered exhibit also a positive correlation consistent with Clement (1999). These statistics provides some assurance that the sample in this study is similar to other samples used in previous studies.

Table III shows the conference call analysis that attempts to validate our network measures. Specifically, we test whether better connected analysts are more likely to participate in a conference call and if they ask more questions during that conference call. We collect conference call transcripts from Thomson Street Events for all companies that are followed by ten or more analysts. We use the conference call for the annual earning results of 2007 to code two variables, one if the analyst participates in the conference call and one for the number of questions the analyst asks during the conference call. We restrict our analysis to just one year since the data needs to be hand-collected from the individual transcripts and we need to keep the process manageable. The first three columns in Table III present the estimates from the logit model, and the last three columns from an ordinal logit model. We control for firm, brokerage house and firm specific experience effects since we expect these to be systematically related to both network measures and conference call activity. We find that the better connected an analyst is the more likely she is to participate in an earnings conference call and the more questions she is able to ask. This result supports findings in Mayew (2008) that analysts have differential access to management even after Regulations FD and also supports our underlying assumption that an individual's connections increases the likelihood of receiving certain information sets.

B. Forecast Measures

Each analyst issues multiple forecasts for a firm during a year. Consistent with prior research (Clement 1999; Clement and Tse 2005) we exclude all forecasts with horizon less than 30 days and we keep the last forecast issued within a year for each firm-analyst pair.[4] We define forecast error of analyst *i* for firm *j* in year *t* (FE_{ijt}) as the absolute difference between the forecast and the actual earnings per share (EPS).

$$FE_{ijt} = \text{Absolute (Forecast EPS}_{ijt} - \text{Actual EPS}_{ijt}) \quad (1)$$

To construct a simple measure of forecast timeliness we calculate the forecast horizon of the first forecast made by an analyst for each firm-year. Forecast horizon (FH_{ijt}) is the number of days between the forecast date and the earnings announcement date.

$$FH_{ijt} = \text{First Forecast Date}_{ijt} - \text{Earnings Announcement Date}_{ijt} \quad (2)$$

We use a methodology similar to Clement (1999) by controlling for firm-year effects to test the hypotheses that analysts with higher social capital make more accurate and timely forecasts.[5] Therefore the demeaned versions of the above variables are:

$$DFE_{ijt} = \frac{\left[FE_{ijt} - Avg\left(FE_{jt}\right)\right]}{Avg\left(FE_{jt}\right)} \quad (3)$$

$$DFH_{ijt} = \frac{\left[First\,FH_{ijt} - Avg\left(First\,FH_{jt}\right)\right]}{Avg\left(First\,FH_{jt}\right)} \quad (4)$$

Since the social network measures are associated with known factors that affect accuracy and timeliness we need to be very careful that the research design appropriately controls for all other factors and thereby isolates the effect of social capital on forecast characteristics. We follow the methodology of Hong and Kubik (2003) and include control variables as fixed effects. Therefore, in all specifications we control for brokerage house, number of firms covered, number of industries covered, firms-specific experience and general experience effects. When the

[4] The results are not sensitive to this choice. Choosing the first forecast issued by each analyst for each firm-year pair yields similar results.

[5] We deflate the variables with the mean of forecast error or horizon for each firm-year since Clement (1998) proves that this procedure reduces heteroscedasticity.

dependent variable is forecast error we also include forecast horizon effects. To allow for the possibility that the relation between the dependent and independent variables is time varying we also interact all the above effects with year effects (*Y.E.*).[6]

$$DFE_{ijt} = f^{n}\begin{pmatrix} \alpha + \beta_1 Betweenness_{it} + \#\, firms\, xY.E. + \#industries\, xY.E. + General\, Experience\, xY.E. + \\ Firm\text{ - }Specific\, Experince\, xY.E. + Brokerage\, House\, xY.E. + Horizon\, xY.E. \end{pmatrix} \quad (5)$$

$$DFH_{ijt} = f^{n}\begin{pmatrix} \alpha + \gamma_1 Betweenness_{it} + \#\, firms\, xY.E. + \#industries\, xY.E. + General\, Experience\, xY.E. + \\ Firm\text{ - }Specific\, Experince\, xY.E. + Brokerage\, House\, xY.E. \end{pmatrix} \quad (6)$$

Although the specifications above include betweenness as the measure of social capital, we also re-estimate and run equations (5) and (6) by replacing betweeness with closeness or K-core. When we measure social capital using betweenness or closeness we expect $\beta_1<0$ and $\gamma_1>0$. When we use K-core we expect $\beta_1>0$ and $\gamma_1<0$.

We follow Clement and Tse (2005) to calculate forecast boldness. We define boldness as the absolute distance of analyst *i*'s revised forecast for firm *j* from the pre-revision consensus forecast in year *t* ($Distance_{ijt}$). We scale this variable to range from zero to one as in Clement and Tse (2005) to preserve the relative forecast boldness for firm *j* in year *t*.

$$Bold_{ijt} = \frac{\left(Distance_{ijt} - Min\, Distance_{ijt}\right)}{\left(Max\, Distance_{ijt} - Min\, Distance_{ijt}\right)} \quad (7)$$

When dependent variable is forecast boldness, apart from the effects discussed above, we also include an indicator variable for the number of days between the previous forecast and the revision.

[6] We test the sensitivity of our research design by running separate cross-sectional regressions and then computing the coefficients and t-statistics as in Fama and MacBeth (1973). However, this procedure yields similar results and is not reported.

$$Bold_{ijt} = f^{n}\begin{pmatrix} \alpha + \delta_1 Betweenness_{it} + \#\ firms\ xY.E. + \#industries\ xY.E. + General\ Experience\ xY.E. + \\ Firm\text{ - }Specific\ Experince\ xY.E. + Brokerage\ House\ xY.E. + Horizon\ xY.E. + \\ Days\ Elapsed\ xY.E. \end{pmatrix} \tag{8}$$

Although equation (8) includes betweenness as a measure of social capital we also re-estimate and run equations (8) by replacing betweeness with closeness or K-core. When we use betweenness or closeness we expect $\delta_1>0$. When we use K-core we expect $\delta_1<0$.

C. Analyst Turnover

We measure unfavorable career outcomes by identifying analysts who stop providing forecast in I/B/E/S. We classify an analyst as losing her job if she appears in the dataset in year *t* but not in year *t+1*.[7] We control for analyst experience, the number of firms and industries each analyst covers, and for the brokerage house the analyst is working for. We interact all indicator variables with year effects (*Y.E.*). Moreover, the model includes relative accuracy and optimism effects since Hong and Kubik (2003) find that more accurate and optimistic analysts face favorable job separations.[8] We estimate the probability of turnover as:

$$Pr\left(Turnover_{it+1}\right)_{ijt} = f^{n}\begin{pmatrix} \alpha + \delta_1 Betweenness_{it} + \#\ firms_{it}\ xY.E. + \#industries_{it}\ xY.E. + \\ General\ Experience_{it}\ xY.E. + Brokerage\ House_{it}\ xY.E. + \\ RelativeAccuracy\ Effects_{it} + Relative\ Optimism\ Effects_{it} \end{pmatrix} \tag{9}$$

We include indicator variables for various levels of the betweenness distribution similar to Hong and Kubik (2003), who also include indicator variables for accuracy and optimism to examine career outcomes. We expect that being in the right tail of the betweenness distribution

[7] This measure is a noisy indicator of career outcomes since analysts may stop providing forecasts because they voluntarily move to a buy-side firm. If these analysts are good performers with strong networks then we expect this to bias the results against finding the predicted negative relation between good network position and turnover.

[8] To construct the relative accuracy and optimism indicators we scale each signed and unsigned forecast error as in equation (8) to preserve the relative rankings of error and optimism within each firm-year. Then we calculate the mean of accuracy and optimism from these scaled variables for each analyst-year. We include in equation (9) twenty indicator variables for optimism and twenty indicator variables for accuracy, for increments of five percent.

lowers the probability of turnover and being in the left tail of the distribution increases the probability of turnover.

IV. Results on the Relation Between Network Position and Forecast Characteristics

Table IV presents estimates of equation (5) where dependent variable is the forecast error. The coefficients on the social network variables are all significant at one or five percent level. Higher betweenness or higher closeness is associated with lower forecast error. Moreover, analysts whose connections are clustered in one group, thereby having high K-core, are less accurate.[9] An analyst at the 90^{th} percentile of betweenness has 4.65 percent lower forecast error compared to an analyst at the 10^{th} percentile. Similarly, an analyst at the 90^{th} percentile of closeness has 3.11 percent lower forecast error compared to an analyst at the 10^{th} percentile. A similar move along the K-core distribution increases forecast error by ten percent. Clement (1999) reports that for a move from the 10^{th} to the 90^{th} percentile of firm specific experience, the number of firms covered or the number of industries covered the economic effects are 3.8, 1.5, and 2.9 percent respectively. Therefore, the network characteristics are of a similar significance as these variables in explaining forecast accuracy.

These results also provide support to the idea that social network position gives an information advantage to analysts potentially through word-of-mouth effects. We also test whether network position has an association with forecast optimism since better-networked analysts might be more accurate because they are less optimistic. In unreported results we substitute in equation (5) the unsigned forecast error with the signed forecast error. We find that the coefficients on the network variables are all insignificant. The analyst's network position therefore has no relation

[9] These results are robust to not including controls for all other variables. We find that forecast error decreases in betweenness, closeness and increases in K-core if we control only for firm x year effects. These relations are significant at one per cent level.

with their optimism after we include controls for other characteristics. We also include forecast optimism as an additional independent variable in equation (5) but the estimated coefficients for the network variables are unchanged to those reported in Table IV.

Table V shows estimates of equation (6) where the dependent variable is the first forecast's horizon for each analyst-firm-year. As expected, the coefficients on betweenness and closeness are positive, and are significant at one and five percent level respectively. Also the coefficient on K-core is negative and significant at one percent level. Analysts with higher social capital make their first forecast for each firm they cover earlier in the year. This suggests that these analysts exploit the early access to information, provided by their network position, to issue a forecast earlier. An analyst at the 90^{th} percentile of betweenness (closeness) makes her first forecast four (three) days earlier, than an analyst at the 10^{th} percentile. An analyst at the 90^{th} percentile of K-core makes her first forecast 11 days later than an analyst at the 10^{th} percentile.

We also construct a logit model to test whether better-networked analysts are the first to provide a forecast for a firm in a particular year. This model is different from the above analysis since it does not take into account the horizon of each forecast but separates forecasts between the first one made for each firm-year and all the rest. In unreported results we find that an increase in betweenness or closeness is associated with an increase in the probability of providing the first forecast. An analyst at the 90^{th} percentile of betweenness (closeness) is more likely to make the first forecast by 0.5 (1.9) per cent, than an analyst at the 10^{th} percentile. These effects are significant at ten and one per cent respectively. Since the unconditional probability that an analyst produces the first forecast is close to seven per cent, these marginal probabilities are economically interesting. An analyst at the 90^{th} percentile of K-core is also less likely to make the first forecast by 0.9 per cent compared to an analyst at the 10th percentile and this effect is significant at one per cent.

Table VI presents estimates of coefficients when the dependent variable is forecast boldness (equation (8)). We find the more central analysts and those analysts who act as information brokers in the network make bolder forecasts. Both coefficients are positive and significant at one percent level. The coefficient on K-core is also positive although not significant. This result suggests that the information advantage the analyst's receives from her ties, allows her communicate her private information rather than herd towards the forecast consensus. Collectively, the evidence suggests that an analyst's structural position in the social network and thereby her level of social capital is positive and significantly associated with forecast characteristics.

V. Results on the Association Between Network Position and Analyst Turnover

Table VII presents results from estimations of the logit model in equation (9) for analyst turnover. We use betweenness for this analysis since it has been found that it is better able to capture the information advantage an individual gains from their network (Freeman, 1977). Although the results reported below are qualitatively unchanged when we use replace betweeness with closeness. We control for the brokerage house, experience, number of firms and the number of industries covered. We also include controls for accuracy and optimism because we want to focus purely on the incremental effect that the networks have on career outcomes. For example, given that networks have a positive association with accuracy, and accuracy has a negative association with turnover, we might find a negative relation between networks and turnover if we do no control for accuracy.

We find that an analyst who is in the bottom ten percent of betweenness increases the probability that she loses her job by 3.26 percentage points, which is statistically different from zero at the one percent significance level (see Table VII, column one). Moreover being in the top ten percent of betweenness decreases the probability that the analyst loses her job by 4.34 percentage points, which is statistically different from zero at the one percent significance level (see Table VII, column two). In Table VII, column three we estimate more precisely the effect of social capital on analyst turnover by including dummy variables for various levels of betweenness except for the top ten percent. All the coefficients have a positive sign and the estimate is increasing monotonically as betweenness decreases. The marginal effect for being at the bottom ten percent of betweenness is an increase in the probability of turnover by 7.73 percentage points relative to the top ten percent. In contrast, being in the bottom 75-90 percent or 50-75 percent of betweenness increases the probability that an analyst loses her job by 6.26 or 4.13 percentage points respectively. These results provide support to the hypothesis that social networks influence career outcomes.

VI. Determinants of Analyst Network Position

A. Analyst Innate Ability and Network Position

The results so far suggest that better-networked analysts have performed relatively better and that they are less likely to lose their job. However, our analysis as yet has not examined how analysts actually become networked in the first place. It might be the case that higher ability analysts perform better and as a result build a better network over time. If this is the case and control variables, such as brokerage house or experience effects, are not good proxies for this superior ability then the association between performance and network position may suffer from an omitted variable bias. Although, we believe that these control variables adequately control for heterogeneity in ability (e.g. some level of human capital), we investigate formally whether analyst ability predicts strong network position.

To investigate this relation we need to proxy for an analyst's ability that is not influenced by her network position. We use each analyst's average accuracy during her first year in the profession. We expect that network effects are non-existent in the first year of employment since the analyst has not yet developed solid connections. To construct this variable we use a transformation of forecast errors as in equation (7) to preserve the relative rankings within each firm-year and then we average this measure to construct an analyst-year measure. To adequately separate the measurement of the network variable from the first year of employment we require that the latter is at least three years before the year that we measure an analyst's network position. We also control for the size of the brokerage house, number of firms and industries covered, average coverage by analysts[10] and general experience. We measure these variables both at the year of the network measure and at the first year of employment.

Table VIII presents estimates both including and excluding the contemporaneous control variables. The average distance between the years the network position is measured and forecast errors is measured is eight. Columns one and two present the estimates when the dependent variable is betweenness. The coefficient on first year's forecast error is not significant nor is the sign robust. The higher ability analysts do not become better networked. In column one the results indicate that analysts, who work for larger brokerage houses, cover more firms and industries and cover firms that are followed by fewer analysts in the first year of employment, built up a better network position. In column two, the analyst's experience also has positive and

[10] We expect that analysts who follow firms with higher analyst coverage will be more central in the network but will have fewer brokerage opportunities.

significant coefficient. Moreover, the variables measured in the first year of employment have incremental explanatory power even after we include contemporaneous variables. Both size of brokerage house and number of firms covered during the first year increase future social capital.

Columns three and four present the estimates when the dependent variable is closeness and columns five and six when the dependent variable is the K-core. Across all specifications the coefficient on lag forecast error is not significant. Analysts, who work for larger brokerage houses, cover more firms and industries and cover firms that are followed by more analysts in the first year of employment, become more central to the network. Overall, the results suggest that analysts' innate ability to forecast earnings is not related to their future network position. Therefore, the earlier association between performance and network position is unlikely to suffer from an omitted variable bias, such as human capital.

B. Determinants of Network Position

In this section we study factors that determine future network position. To do this we consider all analysts with at least five years of experience. To investigate how factors at different stages in an analyst's career can influence network position we separate each analyst's career to three parts. The first part spans from the first to the third year of her career, the second from the fourth year until one year before we measure the network position, and the third is contemporaneous with the measurement of the network. Forecast attributes in different stages of an analyst's career might have different effects on her network position. For example, Hong, Kubik and Salomon (2000) find that younger analysts are more likely to face an adverse job separation if they are inaccurate or bold.

If more accurate analysts build stronger reputation and are rewarded from their brokerage houses then we expect that past accuracy will be associated with better connections. From an agency perspective, we expect past optimism by the analyst will predict a better network position since more optimistic analysts have more favorable career outcomes (Hong and Kubik 2003). As in Table VIII we include as independent variables the size of the brokerage house, number of firms and industries covered, average number of analysts covering a firm and general experience.

All models in Table IX have high explanatory power. The adjusted R-squared in columns one, two, and three are 42, 80, and 67 per cent respectively. The most interesting results are with respect to forecast error and optimism. Accuracy in either the early or later years is not related to an analyst's network position. In contrast, the more optimistic the analyst is in their later years the more likely they are to be better networked. Apparently, it would appear optimistic analysts are rewarded with the ability to build a stronger network which then enables them to make better forecasts. The coefficient on early optimism is insignificant. This may be because younger analysts might be reluctant to exhibit optimism since being optimistic early in an analyst's career is not rewarded by building better network position.

Both contemporaneous and lags of brokerage house size have a positive association with all measures. The number of firms covered is positively associated with closeness and betweenness and negatively associated with K-core, both contemporaneously and later in their career. Contemporaneous and earlier in career the number of industries covered has a beneficial effect on an analyst's network position while later in career coverage of more industries has an adverse effect. The average number of analysts covering firms in an analyst's portfolio later in her career also has a beneficial effect on their network position.

VII. Conclusion

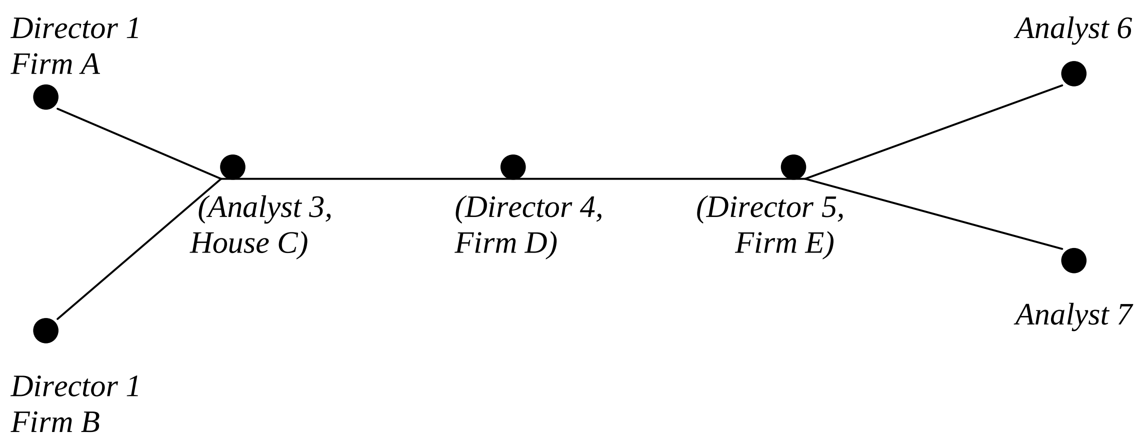
The paper is the first to connect a security analyst's structural position in a social network to her performance and career prospects. We find evidence in support of the hypothesis that analysts can gain an information advantage through their position in the network. Analysts with higher social capital make more accurate and bold forecasts. Also they issue on average earlier their first forecast for each firm in a year. These results collectively suggest that the social network position of an analyst affects their performance. Furthermore, we find that analysts with higher social capital are less likely to face an adverse career outcome i.e. lose their job. This result suggests that analysts building stronger networks are more valuable to their brokerage houses. We also document that analysts build their network position primarily by exhibiting forecast optimism and not accuracy.

The results support the conclusions of Stein (2008) who shows that word-of-mouth effects can take place even between competitors. However, these results are interesting not only from an academic perspective but also from a policy. The SEC has tried to eliminate information advantages received from selective disclosure. The results of this study suggest that such an advantage created by social network interactions still exists after the passage of Regulation FD. Given that social interactions surround economic life (Granovetter 1985) it is rather unlikely that any regulation will be able to fully eliminate such information advantages.

Appendix

Construction of the Network

Consider a network comprising of seven people. Each line represents a connection between the individuals (see the diagram below). In the context of this study we can consider for example actors 1 and 2 as directors of two different firms, firm A and firm B. These directors do not sit on any other boards and therefore there is no possibility that they are connected to each other. Actor 3 is an analyst who works for brokerage house C and covers firms A and B. Therefore she is connected both to Director 1 and Director 2. Actor 4 is a director in firm D that Analyst 3 also covers and therefore Analyst 3 is also connected to Director 4. Director 4 does not sit on the same board with either Director 1 or Director 2 and therefore is not connected to either of them. Actor 5 is a director in Firm E and also sits on the same board of directors as Director 4 in Firm F. Therefore, Director 4 and Director 5 are also connected to each other through sitting on the same board Firm F. Actors 6 and 7 are analysts working for different brokerage houses and both cover firm E. Thereby they are both connected to Director 5 but not Director 4. They are also directly connected to each other since they cover the same firm, Firm E.



Measures of network Positions

Closeness centrality is defined as the inverse of the mean geodesic distance (i.e. the shortest path) between a node v and all other nodes reachable from it. Closeness measures how close an actor is to all other actors or how central is the actor in the network, by taking into account the centrality of all other actors. Therefore, closeness is a measure of how long it will take for information to spread from a given node (i.e. an individual) to other reachable nodes.

$$X_v = \frac{N-1}{\sum_{w=1}^{N} u(v,w)}$$

X is the closeness centrality of a node v in a network where N is the number of nodes and u(v,w) is the distance between the given node (v) and another node (w). Director 4 has the highest closeness centrality 6/10=0.6 and therefore is better able to access the whole network quicker than anyone else. Director 1 and Director 2 have the lowest closeness measures 6/16=0.375. Analyst 6 and Analyst 7 have slightly higher closeness 6/15=0.4. Analyst 3 and Director 5 have even higher closeness 6/11=0.545.

Betweenness is a centrality measure of a node within a graph. Nodes that occur on many shortest paths between nodes have higher betweeness than those that do not. For graph G: = (V,E) with *n* nodes, the betweeness $X_B(v)$ for node *v* is:

$$X_B(v) = \Sigma_{w \neq v \neq k \in V} \frac{\mu(v)_{wk}}{\mu_{wk}}$$

Where μ_{wk} is the number of shortest geodesic paths from *w* to *k* and $\mu(v)_{wk}$ is the number of shortest geodesic paths from *w* to *k* that pass through a node *v*. This measure is normalized by dividing through the number of pairs of nodes not including *v*, which is (*n*-1) x (*n*-2). Betweenness takes into account that Analyst 6 and Analyst 7 communicate between themselves and therefore reduce the controllability of Director 5. Analyst 3 has the highest betweeness score 16/45 = 0.356. Director 4 and Director 5 have slightly lower betweeness 13/45 = 0.289. Director 1, Director 2, Analyst 6 and Analyst 7 have zero betweeness since they do not act as brokers in the network.

K-core in graph theory was introduced by Seidman (1983) as a method of simplifying graph topology to aid in analysis and visualization. Given a graph *G = {V,E}* with nodes set *V* and edges set *E*, the K-core is computed by pruning all the nodes (with their respective edges) with degree less than *k*. That means that if a node v has degree d_v, and it has n neighbors with degree less than *k*, then *v*'s degree becomes $d_v - n$, and it will be also pruned if $k > d_v - n$. K-core of a node is always less or equal that its degree. Therefore, K-core deflated by degree ranges always from zero to one. The higher this measure is for an analyst, the less scarce her information. Because graphical representation of K-cores is more complicated the reader is referred to de Nooy, Mrvar and Bategelj (2005) for further information.

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Table I

Number of Directors, Companies, Analysts and Brokerage Houses in the Network and the matched sample by year

For each year, this table presents the number of directors and analysts included in the network or the sample. Also the number of companies with data on board of directors, the number of companies with data on analyst coverage and the number of brokerage houses is tabulated.

	Network Sample					Matched Sample		
Year	**# Directors**	**# Companies with Directors**	**# Analysts Network**	**# Companies with Analysts**	**# Brokerage Network**	**# Companies Sample**	**# Analysts Sample**	**# Brokerage Sample**
2001	11,118	1,500	4,316	5,234	269	1,282	3,086	207
2002	16,243	1,797	4,454	4,951	244	1,371	3,339	209
2003	18,520	2,003	4,446	5,116	334	1,536	3,399	281
2004	14,170	2,002	4,338	5,682	384	1,673	3,155	287
2005	14,622	2,074	4,377	5,785	384	1,713	3,202	290
2006	29,437	3,034	4,466	6,060	353	2,455	3,495	293
2007	32,505	3,255	4,593	6,143	335	2,568	3,460	282
Total	136,615	15,665	30,990	38,971	2,303	12,598	23,136	1,849
Unique	42,376	4,444	10,508	10,231	612	3,502	7,736	485

Table II
Correlation Matrix for Social Network Measures and Analyst Characteristics

This table presents the correlations between the social network characteristics, analyst experience, size of the brokerage house and number of firms and industries covered by each analyst. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Closeness is the inverse of the mean geodesic distance between a vertex and all other vertices reachable from it. K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors. We divide this measure with the number of ties (degree) each analyst has. All three measures range from zero to one. Higher betweenness or closeness and lower K-core over degree characterize better-networked analysts. General experience is the number of years the analyst has been providing forecasts in IBES. Firm-specific experience is the analyst's years of experience forecasting a particular firm's earnings. # of analysts employed is the number of analysts in the analyst's brokerage in each year. # of firms covered is the number of firms the analyst follows in each year. # of industries covered is the number of two-digit SIC industries the analyst follows in each year. Below the diagonal we present correlations for the raw variables and above the diagonal correlations for the variables after adjusting for firm-year effects. All correlations are significant at 1 percent. N=160,460.

Variable	General Experience	Firm-specific Experience	# of Analysts Employed	# of Firms Covered	# of Industries Covered	Betweenness	Closeness	K-core
General Experience		0.63	0.06	0.39	0.22	0.22	0.18	-0.30
Firm-specific Experience	0.59		0.04	0.23	0.12	0.13	0.11	-0.18
# of Analysts Employed	0.06	0.06		0.03	-0.07	0.21	0.75	0.23
# of Firms Covered	0.27	0.17	-0.02		0.55	0.56	0.34	-0.76
# of Industries Covered	0.16	0.11	-0.04	0.43		0.46	0.26	-0.51
Betweenness	0.21	0.13	0.24	0.65	0.43		0.57	-0.35
Closeness	0.16	0.13	0.64	0.28	0.24	0.50		-0.05
K-core	-0.23	-0.15	0.42	-0.66	-0.33	-0.35	-0.05	

Table III
Association between Network Measures and Conference Call Participation

Logit and cumulative logit specification that examines whether an analyst's position in the network is associated with the probability of conference call participation and the number of questions asked in the conference call. An analyst is coded as participating in the conference call if his name appears on the transcript. Number of questions asked is the number of questions each analyst asks and ranges from zero to four. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Indicator variables for betweenness are included. Marginal probabilities appear below the coefficient estimates. For the cumulative logit the marginal probability is calculated for observations that the number of questions asked is four. The unconditional probability of participation is 38%. The unconditional probability that an analyst asks four questions is 5%. Standard errors are clustered at the analyst level. **Significant at 5 percent level. ***Significant at 1 percent level (one-sided).

		Participate in conference call			Number of questions asked		
Parameter	**Predicted Sign**	**Estimate (1)**	**Estimate (2)**	**Estimate (3)**	**Estimate (4)**	**Estimate (5)**	**Estimate (6)**
Betweenness	+	476.300***			454.800***		
		0.072			0.015		
Closeness	+		27.310***			27.650***	
			0.114			0.020	
K-core	-			-2.080**			-1.470**
				-0.056			-0.009
Firm effects		Yes	Yes	Yes	Yes	Yes	Yes
Broker effects		Yes	Yes	Yes	Yes	Yes	Yes
Firm Experience effects		Yes	Yes	Yes	Yes	Yes	Yes
N		3,555	3,555	3,555	3,555	3,555	3,555
Pseudo R-sq		29.01%	29.04%	28.92%	31.13%	31.18%	30.89%

Table IV
Association between Network Measures and Forecast Error

Ordinary least squares specification where the dependent variable is the forecast error for analyst *i* and firm *j* at time *t*. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Closeness is the inverse of the mean geodesic distance between a vertex and all other vertices reachable from it. K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors. We divide this measure with the number of ties (degree) each analyst has. All three measures range from zero to one. Higher betweenness or closeness and lower K-core over degree characterize better-networked analysts. The adjusted R-squared does not reflect firm x year effects. Standard errors are clustered at the brokerage house level and tabulated below the coefficients in parentheses. **Significant at 5 percent level. ***Significant at 1 percent level (one-sided).

		Forecast error		
Parameter	**Predicted Sign**	**Estimate (1)**	**Estimate (2)**	**Estimate (3)**
Betweenness	-	-25.33***		
		(6.48)		
Closeness	-		-0.64**	
			(0.31)	
K-core	+			0.36***
				(0.04)
Firm x Year effects		Yes	Yes	Yes
Broker x Year effects		Yes	Yes	Yes
# of Firms x Year effects		Yes	Yes	Yes
# of Industries x Year effects		Yes	Yes	Yes
Firm Experience x Year effects		Yes	Yes	Yes
General Experience x Year effects		Yes	Yes	Yes
Horizon x Year effects		Yes	Yes	Yes
N		160,460	160,460	160,460
Adj R-sq		15.18%	15.03%	15.72%

Table V
Association between Network Measures and Forecast Timeliness

Ordinary least squares specification where the dependent variable is the horizon of the first forecast made within year *t* by analyst *i*, for firm *j*. The forecast horizon is the number of days between the forecast and the earnings announcement date. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Closeness is the inverse of the mean geodesic distance between a vertex and all other vertices reachable from it. K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors. We divide this measure with the number of ties (degree) each analyst has. All three measures range from zero to one. Higher betweenness or closeness and lower K-core over degree characterize better-networked analysts. The adjusted R-squared does not reflect firm x year effects. Standard errors are clustered at the brokerage house level and tabulated below the coefficients in parentheses. **Significant at 5 percent level. ***Significant at 1 percent level (one-sided).

		Forecast horizon of first forecast		
Parameter	**Predicted Sign**	**Estimate (1)**	**Estimate (2)**	**Estimate (3)**
Betweenness	+	9.58***		
		(2.48)		
Closeness	+		0.26**	
			(0.12)	
K-core	-			-0.17***
				(0.02)
Firm x Year effects		Yes	Yes	Yes
Broker x Year effects		Yes	Yes	Yes
# of Firms x Year effects		Yes	Yes	Yes
# of Industries x Year effects		Yes	Yes	Yes
Firm Experience x Year effects		Yes	Yes	Yes
General Experience x Year effects		Yes	Yes	Yes
N		160,460	160,460	160,460
Adj R-sq		6.17%	6.09%	6.21%

Table VI
Association between Network Measures and Forecast Boldness

Ordinary least squares specification where the dependent variable is the forecast boldness for analyst *i* and firm *j* at time *t*. The boldness is the absolute distance of analyst *i*'s revised forecast for firm *j* from the pre-revision consensus forecast in year *t*. The dependent variable is transformed as in equation (7) to preserve the relative rankings for each firm-year and to range between zero and one. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Closeness is the inverse of the mean geodesic distance between a vertex and all other vertices reachable from it. K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors. We divide this measure with the number of ties (degree) each analyst has. All three measures range from zero to one. Higher betweenness or closeness and lower K-core over degree characterize better-networked analysts. Standard errors are clustered at the brokerage house level and tabulated below the coefficients in parentheses. **Significant at 5 percent level. ***Significant at 1 percent level (one-sided).

		Forecast boldness		
Parameter	**Predicted Sign**	**Estimate**	**Estimate**	**Estimate**
Betweenness	+	0.0181***		
		(0.0065)		
Closeness	+		0.0249***	
			(0.0090)	
K-core	-			0.0075
				(0.0071)
Broker x Year effects		Yes	Yes	Yes
# of Firms x Year effects		Yes	Yes	Yes
# of Industries x Year effects		Yes	Yes	Yes
Firm Experience x Year effects		Yes	Yes	Yes
General Experience x Year effects		Yes	Yes	Yes
Horizon x Year effects		Yes	Yes	Yes
Revision Days x Year effects		Yes	Yes	Yes
N		72,189	72,189	72,189
Adj R-sq		8.16%	8.16%	8.00%

Table VII

The Effect of Network Position on Analyst Turnover

A logit specification that examines whether an analyst's position in the network is associated with the probability of turnover. The dependent variable is one for year *t+1* if the analyst appears in the dataset in year *t* and not in year *t+1*. Otherwise it is zero. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Indicator variables for betweenness are included. Twenty dummies are included for relative accuracy and optimism scores respectively. Marginal probabilities appear below the coefficient estimates. Standard errors are clustered at the brokerage house level. ***Significant at 1 percent level (one-sided).

		Analyst Turnover		
Parameter	**Predicted Sign**	**Estimate**	**Estimate (1)**	**Estimate (2)**
Top 10% of Betweenness	-		-0.2847***	
			-0.0434	
10-25% of Betweenness	+			0.2273***
				0.0386
25-50% of Betweenness	+			0.2314***
				0.0393
50-75% of Betweenness	+			0.2426***
				0.0413
75-90% of Betweenness	+			0.3606***
				0.0626
Bottom 10% of Betweenness	+	0.1910***		0.4300***
		0.0326		0.0773
Broker x Year effects		Yes	Yes	Yes
# of Firms x Year effects		Yes	Yes	Yes
# of Industries x Year effects		Yes	Yes	Yes
General Experience x Year effects		Yes	Yes	Yes
Relative Accuracy Effects		Yes	Yes	Yes
Relative Optimism Effects		Yes	Yes	Yes
N		23,135	23,135	23,135
Pseudo R-sq		14.46%	14.53%	14.64%

Table VIII
Association between Network Measures and Analyst Ability

An ordinary least squares specification examining whether the forecast errors at the first year of an analyst's career are related to their future network position. An analyst is included only if her first year at the profession is at least three years before the measurement of the network variable. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Closeness is the inverse of the mean geodesic distance between a vertex and all other vertices reachable from it. K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors. We divide this measure with the number of ties (degree) each analyst has. All three measures range from zero to one. Higher betweenness or closeness and lower K-core over degree characterize better-networked analysts. Forecast error is measured as the average forecast error for each analyst-year of the as in equation (7) transformed forecast errors. General experience is the number of years the analyst has been providing forecasts in IBES. Brokerage house size is the number of analysts in the analyst's brokerage in each year. # of firms covered is the number of firms the analyst follows in each year. # of industries covered is the number of two-digit SIC industries the analyst follows in each year. Coverage is the average number of analysts following a firm from the portfolio of firms of each analyst. Subscript t=1 means that the variable is measured at the first year of the analyst's career. Subscript t means that the variable is measured at the same year as the network variable. Standard errors are clustered at the brokerage house level. *Significant at 10 percent level. **Significant at 5 percent level. ***Significant at 1 percent level (two-sided).

	Betweenness		**Closeness**		**K-core**	
Parameter	**Estimate (1)**	**Estimate (2)**	**Estimate (3)**	**Estimate (4)**	**Estimate (5)**	**Estimate (6)**
Intercept	0.00016***	-0.00045***	0.32210***	0.27721***	0.41504***	0.91845***
Forecast Error$_{t=1}$	-0.00002	0.00001	0.00039	-0.00026	0.01295	0.00307
General Experience$_t$		0.00001***		0.00014***		-0.00038
Brokerage House Size$_t$		0.00015***		0.01364***		0.02204***
Brokerage House Size$_{t=1}$	0.00013***	0.00003***	0.01128***	0.00257***	0.00452*	-0.00251
# of Firms$_t$		0.00041***		0.00460***		-0.16491***
# of Firms$_{t=1}$	0.00007***	0.00005***	-0.00084	-0.00026	-0.02868***	-0.01022***
# of Industries$_t$		0.00019***		0.00765***		-0.04375***
# of Industries$_{t=1}$	0.00007***	-0.00002	0.00299***	0.00091	0.00241	0.00984**
Coverage$_t$		-0.00035***		0.00407***		-0.05242***
Coverage$_{t=1}$	-0.00005***	0.00001	0.00374***	0.00189***	-0.02167***	-0.01362***
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
N	12,955	12,955	12,955	12,955	12,955	12,955
Adj R-sq	5.61%	38.60%	42.94%	78.41%	12.63%	64.72%

Table IX
Determinants of Network Measures

Ordinary least squares specification examining whether the forecast accuracy, optimism, brokerage and other analyst characteristics at various stages of an analyst's career are related to their future network position. An analyst is included only if at the year the network is measured the analyst has five years of experience. Betweenness is the number of shortest distance paths between two actors that pass by a certain actor divided by the number of shortest distance paths between these two actors. Closeness is the inverse of the mean geodesic distance between a vertex and all other vertices reachable from it. K-core is an area of the overall network (a sub-network) where each analyst has at least k immediate neighbors. We divide this measure with the number of ties (degree) each analyst has. All three measures range from zero to one. Higher betweenness or closeness and lower K-core over degree characterize better-networked analysts. Forecast error is measured as the average unsigned forecast error for each analyst-year of the as in equation (7) transformed forecast errors. Forecast optimism is measured as the average signed forecast error for each analyst-year of the as in equation (7) transformed forecast errors. General experience is the number of years the analyst has been providing forecasts in IBES. Brokerage house size is the number of analysts in the analyst's brokerage in each year. # of firms covered is the number of firms the analyst follows in each year. # of industries covered is the number of two-digit SIC industries the analyst follows in each year. Coverage is the average number of analysts following a firm from the portfolio of firms of each analyst. Subscript *early* means that the variable is measured as the average during the first three years of the analyst's career. Subscript *late* means that the variable is measured as the average from the fourth year of the analyst's career until one year before the measurement of the network variable (t-1). Subscript *t* means that the variable is measured at the same year as the network variable. Standard errors are clustered at the brokerage house level. **Significant at 5 percent level. ***Significant at 1 percent level (two-sided).

	Betweenness		**Closeness**		**K-core**	
Parameter	**Estimate (1)**		**Estimate (2)**		**Estimate (3)**	
Intercept	-0.00102	***	0.26541	***	0.97296	***
Forecast Error$_{Early}$	0.00011		0.00148		0.00057	
Forecast Error$_{Late}$	0.00026	***	0.00298		0.00676	
Forecast Optimism$_{Early}$	0.00007		0.00193		-0.01555	
Forecast Optimism$_{Late}$	0.00012	**	0.00456	***	-0.01622	**
General Experience$_t$	0.00001	***	0.00013	**	-0.00024	
Brokerage House Size$_t$	0.00014	***	0.01154	***	0.01741	***
Brokerage House Size$_{Early}$	0.00003	***	0.00147	***	-0.00446	
Brokerage House Size$_{Late}$	0.00002		0.00345	***	0.01599	***
# of Firms$_t$	0.00036	***	0.00454	***	-0.14599	***
# of Firms$_{Early}$	0.00001		-0.00129	**	0.00602	
# of Firms$_{Late}$	0.00029	***	0.00228	***	-0.05673	***
# of Industries$_t$	0.00026	***	0.00812	***	-0.05974	***
# of Industries$_{Early}$	0.00006	**	0.00306	***	-0.01521	**
# of Industries$_{Late}$	-0.00022	***	-0.00270	***	0.05388	***
Coverage$_t$	-0.00043	***	0.00040		-0.01169	**
Coverage$_{Early}$	-0.00003		0.00057		0.00796	
Coverage$_{Late}$	0.00010	***	0.00623	***	-0.07977	***
Year effects	Yes		Yes		Yes	
N	10,693		10,693		10,693	
Adj R-sq	41.86%		79.64%		66.62%	