**Network-based information synergy in analysts' coverage portfolios**

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**Abstract:**

Analysts dynamically adjust their coverage of firms in their coverage portfolios. We develop network topology-based measures of information synergy in analysts' coverage portfolios. In particular, we use customer-supplier trade flow data to construct a network of the inter-industry economic links and plot an analyst's research portfolio as a subgraph on this network. We utilize two properties of the subgraph, network density and network centrality, to measure information synergy in an analyst's coverage portfolio. We then find that analysts with higher information synergy in their research portfolio experience superior forecasting accuracy and better career outcomes.

**Keywords:** Analyst performance, Information synergy, Network properties

***JEL* classification:** D23, G14, G24, L14, M41

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## 1. Introduction

Sell-side financial analysts are important capital market intermediaries, and thus the ability to produce accurate and valuable information is critical for them. Analysts generate and integrate useful information from the limited sets of firms they cover, and thus their skills in information discovery are reflected in how they select and dynamically adjust their coverage portfolios. Literature find that analysts consider the characteristics of individual companies in determining coverage, such as firm size (Bhushan, 1989), liquidity (Alford and Berger, 1999; Roulstone, 2003), institutional ownership (O'Brien and Bhushan, 1990), and geographic distance between the analyst and the firm (O'Brien and Tan, 2015). However, few studies analyze analysts' information acquisition skills at the level of the entire coverage portfolios' information structure. Our paper fills this gap by constructing measures of analyst skills at the coverage portfolio level.

Analysts' overall portfolio allocation structure is determined by firms' information properties, thus, skilled analysts select firms to improve their portfolio information synergy (Kini et al., 2009; Sonney, 2009; Huang et al., 2019). For example, concentrating coverage in a single industry brings economies of scale to information production (Boni and Womack, 2006; Hilary and Shen, 2013; Engelberg et al., 2018), while extending cross-industries coverage also brings information complementarity (Luo and Nagarajan, 2014). This paper aims to use portfolio information synergy to measure an analyst's ability to construct a more information-efficient research portfolio.

The information flow of the entire coverage portfolio is hard to directly observable. In this study, we innovatively use graph theory to describe information synergy between the industries covered by analysts. We use nodes to represent industries and edges connecting two nodes to indicate the economic relationship between the two industries (Borgatti and Foster, 2003). Economic connections between industries constitute an information network that benefits analysts' information production by enabling them to follow connected industries (Guan et al., 2014; Huang et al., 2018). Our measure first uses Input-Output (IO) data from the Bureau of Economic Analysis (BEA) to construct a network of industries connected through customer and supplier trade flows. Literature shows that industry connections are an effective channel for information exchange and constitute a complete structure of market information.[1]

We then plot each analyst's research portfolio as a subgraph of this industry network. In this subgraph, we use industry nodes to represent the analyst's coverage and industry connections to identify economic connections between industries. We use two graph topology properties, network centrality and network density, as a metric of the information

[1] Ahern and Harford (2014) find that stronger industry product market connections lead to a greater incidence of cross-industry mergers. Aobdia et al. (2014) find that central industries better predict the stock returns and accounting performance of industries linked to them than noncentral industries. Anjos and Fracassi (2015) find that a conglomerate with a more diversified economic information structure has greater value and produces more and better patents. Herskovic (2018) examines asset pricing in a multisector model with sectors connected through an IO network, because changes in the network can reflect systematic risks in equilibrium.

connectedness of an analyst's research portfolio. Network centrality measures the information centrality of the analyst's subgraph in the entire economic network. More centralized nodes are better positioned for information access and to reach other individuals more efficiently, like the economic shocks to the central industry propagate more strongly and faster than shocks to other industries (Aobdia et al., 2014). Coverage of a central industry will furnish information complementary to other industries. The analyst's coverage portfolio has higher network centrality means that this analyst has a greater ability to obtain information. Network density measures the information closeness within the analyst's subgraph, closely linked industries provide complementary information. For example, the network density of the coverage portfolio network with the "Construction" industry and the "Wood products" industry is higher than the network density of the coverage portfolio with the "Construction" industry and the "Computer and electronic products" industry. A higher network density means that the economic connection between the industries studied by this analyst is stronger, so the industry information transfer is more efficient.

We first verify that our network properties capture the information synergy of analysts' coverage portfolios. We examine how the network centrality of industries affects the transferability and complementarity of information between industries by testing the relationship between a source industry's returns and the returns of industries to which it is linked. We find that when the source industry is the central industry, its return has a stronger relationship with its linked industries' returns and can predict its trading partners' future returns than these relatively noncentral industries. Moreover, to validate that our network density measure reflects the analyst's portfolio information synergy, we show that portfolio network density is significantly positively related to coverage portfolio return correlation. These results indicate that our portfolio network properties reflect information synergy across and within the analyst's coverage portfolio.

In our main tests, we find consistent empirical results that analysts with more information synergy in their coverage networks show a stronger ability to construct the optimal coverage portfolio. Analysts with higher network centrality and network density in their coverage portfolio experience superior forecasting accuracy and better career outcomes. Our findings hold after controlling for other analyst and portfolio characteristics found to affect forecast accuracy and career outcomes. Moreover, we identify a special structure in an analyst's subgraph based on the directed inter-industry graph. When at least one node in an analyst's graph network has both an out-edge and in-edge in the directed subgraph, we define this analyst as a supply chain analyst. A supply chain node can take in and transfer information both in the supplier's industry and the customer's industry, which leads to information complementarities between firms in the supply chain. We find that supply chain analysts have better forecast performance than non-supply chain analysts.

This study contributes to the literature in several areas. First, it contributes to the literature on measures of sell-side financial analysts' skills. We identify network properties to represent the analyst's overall coverage portfolio information synergy. Previous studies use isolated firm characteristics and discontinuous information indexes to measure the information features of analysts' research portfolios. For example, the supplier-customer relationship between firms (Guan et al., 2014), the prior work experience of certain industries of the analyst (Bradley et al., 2017), and the information sharing among colleagues in the brokerage house (Huang et al., 2019; Phua et al., 2020). These measures only capture part of the firms in the coverage portfolio and cannot describe the overall portfolio information environment. We use the network information synergy to provide a general measure of an analyst's ability to construct a more information-efficient research portfolio.

This paper highlights the literature on information transfer by documenting that analyst learns inter-industry information from the IO network. The economic trade flow network approach not only provides direct connections to the industry but also exploits connections between suppliers and customers. Although previous studies document that analysts facilitate the cross-industry diffusion of information through collaboration with their colleagues (Huang et al., 2019) and the transformation of information as it passes upstream and downstream (Ahern and Harford, 2014). Our study focuses on the role of IO connections within the analyst's cross-industry coverage portfolio and identifying the supply chain analysts.

Finally, our study provides further evidence of the applications of graph-based networks in financial analysis. Graph theory is widely applied in the finance literature to examine the impact of how managers' social networks impact investment decisions and corporate governance (Cohen et al., 2008; El-Khatib et al., 2015), how interbank market networks can inform risk management (Boss et al., 2004; Rogers and Veraart, 2013), and how sectoral network models assist in asset pricing (Herskovic, 2018). The effects of information sharing via networks on economic activity are significant and pervasive. Our study uses graph topology-based networks to visualize analysts' information acquisition and integration channels and quantify them as portfolio information synergy. We not only make use of industry information networks but also create analyst-year level subgraphs from inter-industry graphs. Our evidence suggests that network structure matters for financial analysts' information acquisition. To the best of our knowledge, we are the first to explore the analyst performance implications of a subgraph in the sectoral network model.

## 2. Measures of information synergy

### *2.1 Industry interdependence*

We measure the level of information complementarity between industries as industry-level economic interdependence, based on BEA IO Accounts Data. We do not construct the economic network at the firm level for three reasons. First, data on firms' supply chain relationships are voluntarily disclosed under SFAS No. 131. The rule only requires disclosing customers that contribute more than 10% of the firm's total revenues; therefore, firm-level economic networks may face data selection bias and do not have a sufficient sample to estimate firms' roles in the overall economy (Cohen and Frazzini, 2008; Ellis et al., 2012). Second, although Hoberg and Phillips (2016) provide a text-based network classification at the firm level, their measure finds pairwise peers are based on business descriptions from 10-K annual filings, it is hard to measure supply-chain trade flows in the entire economic system. Last, the large amount of data at the firm level will make the economic network more complex. Therefore, we use industry-level data to build a clearer and more comprehensive network of economic linkages.

The BEA reports industry trade in two tables—the Supply and Use tables. The Supply table reports the value of each commodity produced domestically by each industry. The Use table reports the value of commodities purchased by each industry as an intermediate input into the production process (Young et al., 2015). We follow Aobdia et al. (2014) by using a matrix to represent the inter-industry trade links and calculate the importance of trade between industries $k1$ and $k2$ as the element $W_{k1k2}$ in matrix $W$. The specific measure of $W_{k1k2}$ is shown in Equation (1):

$$W_{k1k2} = \frac{1}{4}\left(\frac{S_{k1k2}}{\sum_m S_{k1m}} + \frac{S_{k1k2}}{\sum_m S_{mk2}} + \frac{S_{k2k1}}{\sum_m S_{k2m}} + \frac{S_{k2k1}}{\sum_m S_{mk1}}\right), \tag{1}$$

where $S_{k1k2}$ equals to the supplies of commodities by industry $k1$ to industry $k2$, $\sum_m S_{k1m}$ ($\sum_m S_{mk2}$) is the total supply (use) of industry $k1$ ($k2$) for all commodities $m$. Therefore, the ratio $\frac{S_{k1k2}}{\sum_m S_{k1m}}$ ($\frac{S_{k1k2}}{\sum_m S_{mk2}}$) measures the supply (use) provided by industry $k1$ to industry $k2$ as a percentage of the total supply (use) of industry $k1$ ($k2$), i.e., the importance of industry $k2$ as a customer to industry $k1$. The last two ratios in the equation are defined in similar ways and measure the importance of industry $k1$ as a customer to industry $k2$. The range of $W_{k1k2}$ is from 0 to 1. A higher $W_{k1k2}$ indicates a more important relationship between industry $k2$ and industry $k1$. Formally, we calculate the 71*71 elements matrix $W_t$ each year. We represent an inter-industry importance network as a weighted undirected graph-based matrix.[2]

$$W_t \equiv \begin{pmatrix} w_{11,t} & \cdots & w_{1n,t} \\ \vdots & \ddots & \vdots \\ w_{n1,t} & \cdots & w_{nn,t} \end{pmatrix}.$$

Figure 1 shows the inter-industry importance links based on the BEA Input-Output matrix for 2015. A node represents an industry. An edge from industry *k1* to industry *k2* shows a direct economic link between them. The position of each industry node in the network is not random, and their positions imply information power when they are linked to more nodes and are closer to other nodes. Intuitively, the size of a node represents the number of edges connected to that node; bigger nodes have more direct economic links to other industries. The thickness of the edge indicates the importance of trade flow between industries; a thicker edge represents a more important economic tie between the industries. For example, in 2015, the industry nodes "Construction" (23) has economic trade relationships with 66 industries. The "Construction"

[2] To avoid the complexity of the graph structure and construct robust network measures, we use an undirected graph to ensure that there is only one clear single edge between every two industries in our baseline tests. Nonetheless, we also make use of a directed graph to capture supply chain relationships between industries.

industry node is the node with the most economic relations with other industries and therefore is in the most central position. The “Construction” industry is most closely connected to the “Mining, except oil and gas” industry, with an economic importance relationship value ($W_{k1k2}$) of 0.03. While industries with fewer economic connections, such as the “Housing” (HS) industry node, which is only connected with four industry nodes, are on the fringes of the graph. The highest important relationship value is 0.253, which is between the “Utilities” industry (22) and the “State and local government enterprises” industry (GSLE), thus the edge between them is the thickest in the graph.

[Insert Figure 1 here.]

### *2.2 Analyst coverage network*

After constructing a network of inter-industry economic links, we plot an analyst’s research portfolio as a subgraph of the industry economic network. Specifically, we first select nodes based on the industries of the companies are covered by an analyst. Next, we extract these nodes and preserve the edges between them to build the analyst subgraph. The structure of nodes and edges in the analyst subgraph is used to indicate the information connections of this coverage network. Due to the structure of their networks being diversified, we identify four types of analyst coverage networks in Figure 2. Panel A shows the case in which the analyst covers firms in a single industry. Panel B presents a disconnected network, in which the analyst covers multiple industries with no direct economic relationship. Panel C presents a partially connected network, in which some of the industry nodes have economic relationships. Panel D presents a fully connected network, in which all industries covered by the analyst have pairwise economic relationships.

[Insert Figure 2 here.]

Different types of analysts cover these types of networks, reflecting the connectivity of different subgraphs. For example, Panel A of Figure 3 presents an example of cross-section network information synergy difference for four different analysts. We find that analyst "163870" covers the most central industry "Construction" (23) and exhibits the highest network centrality in these four graphs. Moreover, Panel B of Figure 3 presents the coverage subgraphs of an analyst named Robert Drbul in four different years. We find that although Drbul only studied the apparel industry in the early stage, he expanded his coverage to four industries in 2003, including "Apparel and leather and allied products" (315AL), "Miscellaneous manufacturing" (339), "General merchandise stores" (452) and "Other retail" (4A0). According to the inter-industry relationship network between these industries in 2003, these industries can be connected to form a fully connected analyst coverage network. We also find that the edge between 4A0 and 339 is the thickest, which means that the trade flow between these two industries is the most important in this subgraph. When there is a connecting path between two industry nodes, relevant economic shocks can be transmitted, and information acquisition costs are reduced by information complementarity between connected industries.

We plot this analyst's pattern of changes in the analyst's network-based coverage portfolio information synergy with his forecast accuracy and career outcomes over his career in Figure 4. Panel A of Figure 4 shows that this analyst's network density is positively correlated with earnings forecast accuracy. Because the analyst mainly focuses on one specific industry, the network centrality does not show too much time-series variation. Panel B presents that when the analyst increased network density portfolio size, he started to become a star analyst in 2002. Due to the bankruptcy of Lehman Brothers in 2008, he switched to a lower-status brokerage house, then his network density sharply decreased in 2013, and he was demoted to a smaller brokerage house in the following year. To eliminate the influence of brokerage transformations for our network-based information synergy measure, we do robust tests in Section 4.6.2 by excluding the brokerage house switched period.

[Insert Figure 3 here.]

[Insert Figure 4 here.]

## 3. Data and Variables

### *3.1 Data*

We use industry IO data from the BEA accounts. The BEA uses a single set of IO industry codes to classify both industries, we use the summary IO industry codes to define 71 industries each year and merge them with the historical six-digit NAICS classification to obtain stock-level data. We use the supply and use IO tables to identify inter-industry trade and create a network representing inter-industry relationships over the period from 1997 to 2019, because the summary IO data start in1997 and is updated yearly.

Analysts' coverage data are from the Institutional Brokers' Estimate System (I/B/E/S)'s analyst forecast dataset. We obtain the current-year annual earnings forecasts (FY1) in our sample period. Each firm $j$ in analyst $i$'s coverage portfolio has issued at least one annual earnings per share (EPS) forecast. We use the last forecast issued at least one month before fiscal year-end to measure forecast accuracy. Firm characteristics and stock returns are obtained from Compustat and CRSP. We manually collect star analyst data from All-American Research Team analysts in *Institutional Investor magazine*; the sample period for star analyst data is from 1997 to 2017 for data available.

### *3.2 Variable construction*

We follow the graph theory literature and identify two characteristics in different dimensions to measure the information synergy of each analyst's coverage portfolio. The first characteristic is network centrality, which measures the information centrality of the analyst's subgraph in the entire economic network. A network-centralized node is better positioned for information complementarity because such a position makes it possible to reach other industries' information more efficiently (Barrat et al., 2004). We consider the centrality characteristics of subgraphs in the entire industry network rather than within the subgraphs themselves because network nodes generate information synergies with all connected industries, not just the industries in the analyst's coverage. To do so, we measure an analyst's degree centrality in their coverage portfolio. Degree centrality (Centrality) is the simplest to calculate and most commonly used method of centrality measurement. It captures the number of direct edges with other industries (Borgatti, 2005). Nodes with more connections have a higher *Degree Centrality*. The method for calculation of each analyst's degree centrality is shown in Equation (2):

$$Degree\ Centrality_{i,t} = \sum_{k1 \in K_{i,t}} \left( \frac{\sum_{k1 \neq k2} X_{k1k2}}{N} * C_{k1,t} \right), \tag{2}$$

where $K_i$ is the industries covered by analyst $i$ in year $t$. $X_{k1k2}$ is 1 if there is an economic connection between industry $k1$ and industry $k2$, and 0 otherwise. $N$ is the total number of nodes in the graph. $C_{k1,t}$ is calculated as the percentages of the number of covered firms in each industry, and is used to measure an analyst's industry specialization in $k1$ in terms of the entire coverage portfolio. We construct analyst $i$'s coverage portfolio degree centrality by taking the weighted average of the degree centrality of all industry nodes covered by the analyst in each year.

The second subgraph characteristic is network density, which measures the information synergy within the coverage portfolio. It indicates the level of information transfer and complementarity between the covered industries. This variable is calculated in a different way from the centrality measure previously used in graph theory because we calculate the shortest paths in each analyst's subgraph instead of the inter-industry graph. We average the shortest weighted paths between all nodes in a subgraph to measure the coverage network density, as shown in Equation (3):

$$Density_{i,t} = \frac{1}{N} * \sum_{k1 \in K_{i,t}} (\sum_{k1 \neq k2} d_{k1k2} * C_{k1,t}), \tag{3}$$

where $N$ is the number of industries covered by analyst $i$ in year $t$. $d_{k1k2}$ is the shortest distance between two industry nodes in the weighted undirected subgraph. The weight of each edge is based on the importance of the relationship between industry $k2$ and industry $k1$ ($W_{k1k2}$). When the relationship between two industry nodes is more important, the edge linking these two industries is shorter. $C_{k1,t}$ is measured in the same way as in the degree centrality measure. Intuitively, this measure reflects the complementarity of information between industries within the portfolio covered by the analyst.

To ensure that these two network characteristic measures are comparable, we follow Clement and Tse (2005) to scale them according to Equation (4):

$$StdCentrality(Density)_{i,t} = \frac{Centrality(Density)_{i,t} - \mathrm{Min}(Centrality(Density))_t}{\mathrm{Max}(Centrality(Density))_t - \mathrm{Min}(Centrality(Density))_t}. \tag{4}$$

The standardized network characteristic measures increase with network information synergy, the range of them is between 0 to 1. In our empirical test, we use standardized network-based information synergy measures to replace original network characteristic variables.

In addition, we use equal-weighted and firm value-weighted measures to take the portfolio average in the robustness tests performed in Section 4.6.3, to reduce the influence of different industry and company characteristics. For example, analysts may strategically allocate more effort to portfolio firms that are larger or have higher institutional ownership (Harford et al., 2019). We also construct other centrality measures used in previous literature (El-Khatib et al., 2015; Phua et al., 2020), like betweenness centrality, to prove that our results are robust to different centrality measures.

We measure analyst forecast performance in two ways. The first measure is earnings forecast accuracy. The second is related to analysts' career outcomes, namely becoming a star analyst or being promoted to a high-status brokerage house from a low-status brokerage house.

For forecast accuracy, we follow Clement (1999) and Harford et al. (2019) to construct the proportional mean forecast error measure. [3] Specifically, the relative earnings forecast accuracy (*PMAFE*) is computed as the absolute forecast error (*AFE*) of analyst $i$ for firm $j$ in year $t$ minus the mean analyst absolute forecast error for firm $j$ in year $t$ (*MAFE*), which is then scaled by the mean absolute forecast error for firm $j$ in year $t$ and multiplied by minus one; see Equation (5). We then take the average of *PMAFE* to calculate the analyst's overall portfolio accuracy (*Accuracy*). Higher values of *Accuracy* correspond to more accurate forecasts.

$$PMAFE = (-1) * \frac{AFE - MAFE}{MAFE} \tag{5}$$

We control for analyst variables that are shown to affect analyst forecast accuracy (Clement, 1999; Harford et al., 2019; Jacob et al., 1999). Analyst portfolio size is measured by *Nfirm*,

[3] We also use the relative accuracy measure to verify robustness (Hong and Kubik, 2003).

which is the number of firms covered by the analyst in the current year. The literature finds that more capable analysts are assigned more companies to study. Brokerage house size is measured by *Top10broker,* which is an indicator variable that equals 1 if the analyst is employed by a top decile brokerage house in year *t*. We include the analyst's experience (*Exp*), which is the total number of years since the analyst first appeared in I/B/E/S. Studies debate whether there is an experience effect. Some literature shows find forecast accuracy increases with an analyst's general experience, while Hong and Kubik (2003) find that experienced analysts may sacrifice forecast accuracy to cater to firm managers and obtain better career outcomes. Finally, we consider firm characteristics that reflect an analyst's coverage decisions and performance: firm size (*MV*), book-to-market ratio (*B/M*), and firm profitability (*ROA*). We take the average of these firm characteristics for all companies covered by the analyst in the year. We provide detailed variable definitions in Table 1. We use star status and analyst promotion to measure an analyst's career outcome.

[Insert Table 1 here.]

### *3.3 Summary statistics*

Table 2 shows summary statistics for the key variables in our analysis. Panel A reports descriptive statistics for the full sample at the analyst-year level. The mean network centrality is 0.261 and the highest value is 0.971. Our network density characteristic only works for a network with multiple nodes, which accounts for 55.17% of our sample as shown in Panel B.

For the network density value, we focus on the diversified portfolio sample and eliminate the single-type network to make our graph network information synergy measures clearer. Specifically, in Panel C, we report the compared statistics of variables' mean between the diversified portfolio sample and the specialized portfolio sample. The former sample is composed of networks with more than one industry node. The latter sample is composed of networks with a single node. Compared with the specialized portfolio sample, the diversified portfolio samples show significantly higher forecast accuracy and better network centrality. We also find that around 55% of analysts are working for a top-decile brokerage house based on the number of analysts employed by each brokerage, and the average experience of an analyst is 8 years. These values are comparable with previous literature (Huang et al., 2019; Phua et al., 2020). Panel D of Table 2 shows the correlation coefficient between the main variables for the diversified portfolio sample. Analyst forecast performance is positively related to analyst coverage network centrality and network density. Moreover, Panel E provides that only 3% of analysts with star status, 1.6% of the analyst promoted to the higher-level brokerage house and 25% of analysts are supply chain analysts during our sample period.

[Insert Table 2 here.]

## 4. Empirical Results

### *4.1. Information synergy in network*

In this section, we verify that our network properties are able to capture network information synergy. We first examine how the network centrality of industries affects the complementarity of information across industries in the entire economic network by testing the return predictability between source industries' returns and their linked industries' returns. In particular, we calculate industry *k*'s abnormal return in month *t* ($R_{kt}$) by using each industry's value-weighted return minus the value-weighted market return (Hong et al., 2007). For each industry *k* and month *t* we estimate the following regression model:

$$\begin{aligned} Returns\_linked_{kt} &= \alpha + \beta_1 * Returns\_source_{kt} + \beta_2 * Central_k + \\ &\quad \beta_3 * Central_k \times Returns\_source_{kt} + \varepsilon_{kt} \\ Returns\_linked_{kt+1} &= \alpha + \beta_2 * Returns\_linked_{kt} + \beta_2 * Returns\_source_{kt} + \\ &\quad \beta_3 * Central_k + \beta_4 * Central_k \times Returns\_source_{kt} + \varepsilon_{kt+1}, \end{aligned} \tag{6}$$

Where $Returns\_linked_{kt}$ is the average return of source industry *k*'s linked industries and $Returns\_source_{kt}$ is industry *k*'s abnormal return $R_{kt}$. $Central_k$ is a dummy variable equal to 1 if the centrality value of industry *k* is the top quintile of all industries, and 0 otherwise. We use the interaction term of *Central* × *Returns_source* to measure the return predictability of central industries.

Panel A of Table 3 reports the results of the relation between the source industries' returns and their linked industries' returns. In Column (1), we find source industry's return is positively related to their trading partners in the same month. The coefficient of *Central* × *Returns_source* is 0.922, which indicates that the central industries' returns have a stronger relationship with their linked industries' returns. In Column (2), we use 1-month-ahead returns for the linked industries to test the return predictability of the central industry. We find that the source industries' return is positively associated with the next month's return of their trading partners, consistent with the evidence of return predictability across economically linked firms (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). The coefficient of *Central* × *Returns_source* is significantly positive, indicating that central industries' returns have strong return predictability to their trading partners' future returns relative to noncentral industries. The centrality industries transfer information to linked industries through trade flows. Analysts' research on central industries provides complementary information to other noncentral industries.

To validate that our network density measure reflects the analyst's portfolio information synergy, we calculate the correlation between network density and coverage portfolio return correlation. If the information within an analyst research portfolio is transitive and complementary, that is, the portfolio network has a higher density, which means that the return correlation between companies in the portfolio is higher. We first calculate firms' weekly returns correlation which is covered by analyst *i* in year *t*. We then average all firms' return correlation is the portfolio as the coverage portfolio return correlation in year *t*. Network density is analyst *i*'s portfolio density in year *t*. The correlation results are reported in Panel B of Table 3, portfolio network density is significantly positively related to portfolio return correlation.

Overall, these results indicate that our network properties can reflect information synergy both across and within industries in the analyst's coverage portfolio.

[Insert Table 3 here.]

### *4.2. Determinants of network-based information synergy of analyst's coverage portfolio*

Before we investigate the consequence of network information synergy on analyst performance, we examine and identify underlying determinants of an analyst's ability to construct a portfolio with a more efficient information environment. We conduct a regression analysis of our network information synergy measures by using a series of analyst ability measures studied in previous literature (Clement, 1999). Table 4 presents the results that an analyst's skill to construct a more informative portfolio is positively associated with previous forecast accuracy (*LagAccuracy*), and the number of firms followed by the analyst (*Nfirm*). Specifically, analysts employed by the high-status brokerage house (*Top10broker*) are negatively associated with network centrality, while positively associated with network density. The results suggest that analysts can share information with colleagues who cover economically related industries (Huang et al., 2019) or obtain information from extensive resources in the high-status brokerage house. Analysts take more attention to within portfolio information synergy instead of just following hub industries at the center of the economy.

[Insert Table 4 here.]

### *4.3. The impact of network-based coverage portfolio information synergy on analyst earnings forecast accuracy*

In this section, we examine how analysts' coverage portfolio information synergy influences their forecast performance.

We examine whether analysts who follow more central industries learn more complementary information and produce more accurate earnings forecasts by estimating the following panel regression model:

$$\begin{aligned} Accuracy_{it} &= \alpha + \beta_1 * Centrality_{it} + \beta_2 * Nfirm_{it} + \beta_3 Top10broke_{it} + \beta_4 * Exp_{it} \\ &+ \beta_5 * Firm\ \text{Characteritics}_{it} + FE + \varepsilon_{it}. \end{aligned} \tag{7}$$

The dependent variable $Accuracy_{it}$ is the analyst earnings forecast accuracy measure introduced in Section 3.2. The key explanatory variable is $Centrality_{it}$, which measures the information centrality of the analyst's subgraph within the entire economic network and after standardized. Table 5 present the results of this regression. The coefficient of $Centrality_{it}$ is significant and positive (at the 0.01 level) in Columns (1) and (2). These results indicate that analysts with more centralized coverage portfolios have greater forecast accuracy. This is consistent with the findings in the social network centrality paper, which show that high network centrality can provide greater information access and reduce information acquisition costs.

Similar to our results for forecast accuracy, we find analyst-level control variables are consistent with previous studies (Hong and Kubik, 2003; Harford et al., 2019). Analysts who hold a larger portfolio, work in a top decile brokerage house, and have more experience are more likely to have superior forecast performance than other analysts. When we control for firm characteristics in Column (2), we find that the average firm size of the coverage portfolio (*MV*) is significantly negatively related to analyst forecast accuracy, consistent with the finding that big companies usually have a better information environment so analysts can make more accurate forecasts (Bhushan, 1989). Our regressions also include both year and analyst fixed effects. In Column (3), we show the regression results for the full sample and find consistently positive results for our network centrality measure.

[Insert Table 5 here.]

The second network synergy measure is network density, which is the closeness of information within the analyst's subgraph; closely linked industries provide complementary information. We run the following regression and show the results in Table 5:

$$\begin{aligned} Accuracy_{it} = \alpha + \beta_1 * Density_{it} + \beta_2 * Nfirm_{it} + \beta_3 Top10broke_{it} + \beta_4 * Exp_{it} \\ + \beta_5 * Firm \text{ Characteritics}_{it} + FE + \varepsilon_{it}. \end{aligned} \tag{8}$$

The coefficients of *Density* are significantly positively related to the accuracy measures in Columns (4) and (5). For example, the coefficient of *Density* in Column (2) is 4% with a *t*-value of 3.62, after controlling for all analyst and firm characteristics and year-analyst fixed effects. These results indicate that analysts make more accurate earnings forecasts when they have a denser network, which is consistent with the prediction of our information synergy hypothesis that analysts benefit from economically interconnected industry information. In Column (6), we find that both *Centrality* and *Density* are significantly related to forecasting accuracy. Economically, the coefficient estimates in Column (6) suggest that, for a 1-standard-deviation increase in *Centrality*, the analyst's portfolio forecast accuracy increased by 0.5% (0.135*0.041=0.005). Similarly, for a 1-standard-deviation increase in *Density*, the analyst's portfolio forecast accuracy increased by 0.6% (0.208*0.032=0.006). In contrast, network density has a larger and more significant impact on analyst forecast accuracy than network centrality. Overall, our analysis in this section shows that both cross-industry and within-portfolio complementary information channels are important for analysts' information production and earnings forecast.

### *4.4. Supply chain analysts*

From the BEA IO table, we can create matrices that record the trade flows of inputs and outputs between industries. To identify specific supply chain relationships between industries in the analyst coverage network, we construct a weighted directed graph based on the percentage of supply and use between industry *k1* and industry *k2*. Network edges (arrows) in the directed graph represent input flows from supplier to customer. The analyst's subgraph and coverage portfolio synergy measures are calculated similarly to Section 3.2. Figure 5 presents an example of a directed subgraph with a supply chain relationship. We find a special industry node (in the red circle): "Other transportation equipment" (3364OT) has both an in-edge and out-edge, which means that "Other transportation equipment" has an output economic link with its customer "Motor vehicles, bodies and trailers, and parts" (3361MV) and has an input relationship with its supplier "Wholesale trade" (42). We expect this supply chain relationship to take in and transfer complementary information in both the supplier industry and customer industry.

[Insert Figure 5 here.]

For our empirical test, we define two measures to identify a supply chain relationship in an analyst's coverage network. First, we define supply chain analyst ($SC\_analyst_{i,t}$) as a dummy variable, which equals 1 when analyst *i* covers at least one node that has both an out-edge and in-edge in the directed subgraph in year *t*. Panel A of Table 6 reports the results of the statistical comparison. Consistent with the idea that information synergy arises from information complementarities along an industry's supply chain, we obverse significantly higher analyst coverage network centrality, higher network density, and lower forecast error for supply chain analysts than non-supply chain analysts.

Next, we create a continuous measure of a supply chain network, which is the proportion of nodes in the analyst's subgraph that have both an out-edge and in-edge to total the number of nodes (*Proportion_SC). Proportion_SC* measures the transferability of information between nodes in the subgraph. We expect analyst network information transferability to be positively related to analyst forecast accuracy. We regress analyst forecast accuracy on these two supply chain network measures, the regression results are presented in Panel B of Table 6. We find that both *SC_analyst* and *Proportion_SC* are significantly associated with superior forecast accuracy, indicating that more inter-industry information is incorporated into analysts' coverage portfolios through the supply chain.

[Insert Table 6 here.]

### *4.5. Analysts' coverage network and career outcomes*

The literature shows that analysts' forecast performance (Hong and Kubik, 2003) and research portfolio effort allocation (Harford et al., 2019) significantly affect their career prospects. In this section, we investigate whether analysts who cover portfolio networks with more information synergy are more likely to have better career outcomes. The *Institutional Investor* magazine uses a wide range of factors to measure the analysts' research quality and performance, among them, industry knowledge, accessibility, and stock picking should be reflected by our research portfolio information synergy measure (Brown et al., 2015). We use the logit model in Equation (9) to examine the likelihood of the analyst receiving All-Star status (*Star*). *Network Characteristics* include network centrality, network density, and supply chain analyst measures. We further control for variables that are shown in previous research to affect analysts' career outcomes. We adjust standard errors for heteroskedasticity and clustering by analyst and year and include year-fixed effects (Petersen, 2009).

$$\begin{aligned}\text{Logit}(Star_{it+1}=1) &= \alpha+\beta_1 * Network\ Characteristics_{it}+\beta_2 * Nfirm_{it}+\beta_3 * Top10broke_{it} \\ &+\beta_4 * Exp_{it}+\beta_5 * Accuracy_{it}+\beta_6 * Firm\ \text{Characteritics}_{it}+\varepsilon_{it}.\end{aligned} \tag{9}$$

Panel A of Column (1) in Table 7 shows that the higher analyst coverage network centrality increases the probability of the analyst becoming to star analyst in the next year, while Column (2) reports the coefficient on analyst network density is insignificantly positive. These results suggest analysts who cover more centralized industries are likely to be voted as star analysts because institutional investors demand more information for industries with higher economic relationships. The results of Column (3) indicate that the analyst's career outcome also benefits from complementary information from supply chain relationships.

[Insert Table 7 here.]

As most star analysts are at high-status brokerages and a large proportion of analysts have not been voted as All-star throughout their careers, we next investigate the likelihood of an analyst being promoted to a high-status brokerage house. The high-status brokerage house is defined as the top ten percent of brokerage houses that employ the most analysts each year and the low-status brokerage houses are the rest (Hong and Kubik, 2003). During our sample period, 10.65% of the analysts switch brokerage houses and 15.14% of them moved from a low-status brokerage house to a high-status brokerage house. We use the similar logit model in Equation (9) and change the dependent variable to *Promoted*, which is an indicator variable that equals 1 if the analyst promotes from a low-status brokerage house to a high-status brokerage house in a given year, and 0 otherwise. Panel B of Table 7 presents the regression results. We find that similar to Panel A, higher analyst coverage network centrality increases the probability of the analyst promoting to a high-status brokerage house both in the diversified portfolio sample and full sample. Although we do not find a significant relationship between network density and being voted as a star analyst, we find that network density shows a more significant coefficient than network centrality in predicting analyst promotion. This result is economically meaningful in our sample: A 1-standard-deviation increase in network density increases the odds of being promoted to a high-status brokerage house by 14.4%. Overall, our results are consistent with our hypothesis that analysts achieve better career outcomes when they cover more information synergy networks.

### *4.6. Robustness tests*

#### *4.6.1. Heterogeneity among the number of industries within an analyst's coverage portfolio*

Different analyst coverage portfolios are characterized by differences between the number of industries covered by the analyst. The analysts who cover more industries are more likely to acquire more information and improve coverage portfolio information synergy, while analysts have limited attention, larger portfolios allow the analyst to allocate less attention to the individual firm. To make sure that our analyst coverage network density measure is persist over the different number of industry coverage, we divide our sample into subsamples in Table 8. We repeated the regressions in Equations (8) in each subgroup based on the number of industries covered by the analyst in each year (*Nind*). The results in Table 8 indicate that except for analysts covering only two industries, the other subgroups show significant and consistent results with Table 5. Therefore, our network density measure can robustly capture the coverage portfolio information synergy of analysts who study the different numbers of industries.

[Insert Table 8 here.]

#### *4.6.2. Analyst's brokerage house stability*

The reasons for an analyst switching the brokerage house are different, for example, the brokerage house closure or merge, the analyst being promoted or fired. During the brokerage house changing period, the structure of analyst coverage is unstable, and the coverage portfolio information synergy may be influenced by other exogenous reasons. Thus, we exclude the period of analyst change brokerage house to make our sample clearer. If the analyst's brokerage house switched during the given year or is different from the last year, then we exclude this observation. Table 9 reports these subsample results, we find more significantly positive coefficients of network centrality and network density than the regression results of the whole diversified portfolio sample in Table 5. This result suggests that analysts with higher information synergy in their research portfolio experience superior forecasting accuracy, especially during the stable coverage period.

[Insert Table 9 here.]

#### ***4.6.3. Alternative measures for analyst network characteristics***

The study above shows that the information synergy of analysts' coverage portfolios measures their skills. Capable analysts have better forecast performance. In this section, we use alternative information synergy measures to confirm our results.

We first recalculate network centrality and density by using the value of firms covered in each industry to identify their level of specialization. We then perform regressions similar to Equations (7) and (8). As Table 10 shows, there are significant positive coefficients of *Centrality_VW* and Density_*VW* in Columns (1), (2), and (3). Our study is not sensitive to different portfolio industry specialization measures. Further, we use betweenness centrality as an alternative centrality measure (Borgatti, 2005), which captures how often an industry lies on the shortest paths between any pair of nodes in the network (Barrat et al., 2004). The industry as an intermediate node is like an intermediary, connecting the other two industries. The empirical results in Column (4) of Table 10 are similar to those for the degree centrality measure in our main measure. In short, these findings align with the view that industry-level information complementarity in an economic network is useful for analyst research.

[Insert Table 10 here.]

## 5. Conclusion

In this study, we construct a measure of analyst skills at the coverage portfolio level. We use portfolio information synergy as the measure of an analyst's ability to construct a more information-efficient portfolio. To measure information synergy, we use customer-supplier trade flow data from the BEA to construct an inter-industry network. We structure the analyst's research portfolio data and find the corresponding subgraph in the inter-industry graph. We then identify two network characteristics, network centrality and network density, to measure different dimensions of the subgraph information environment. We find that higher information synergy in an analyst's coverage portfolio produces superior forecast performance and career outcomes. Especially for networks with supply chain relationships, analysts benefit from information complementarity. This study systematically investigates the effect of inter-industry information complementarity on analysts' coverage portfolios.

One of the main innovations of this paper is to measure information synergy in a network setting, in which networks are defined by economic trade flows across industries. Thus, we can construct analyst skill measures at the intraportfolio level for each analyst, rather than just considering some of the characteristics of a given firm.

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**Figures and Tables**

**Figure 1.** Information structure network at the industry level.
This figure contains the inter-industry importance links based on the BEA IO matrix for 2015. A node represents an industry. An edge from industry $k1$ to industry $k2$ shows a direct economic link between them. The size of a node represents the number of edges connected to that node; bigger nodes have more direct economic links to other industries. The thickness of the edge indicates the importance of economic trade flow between industries; a thicker edge represents a more important economic tie.

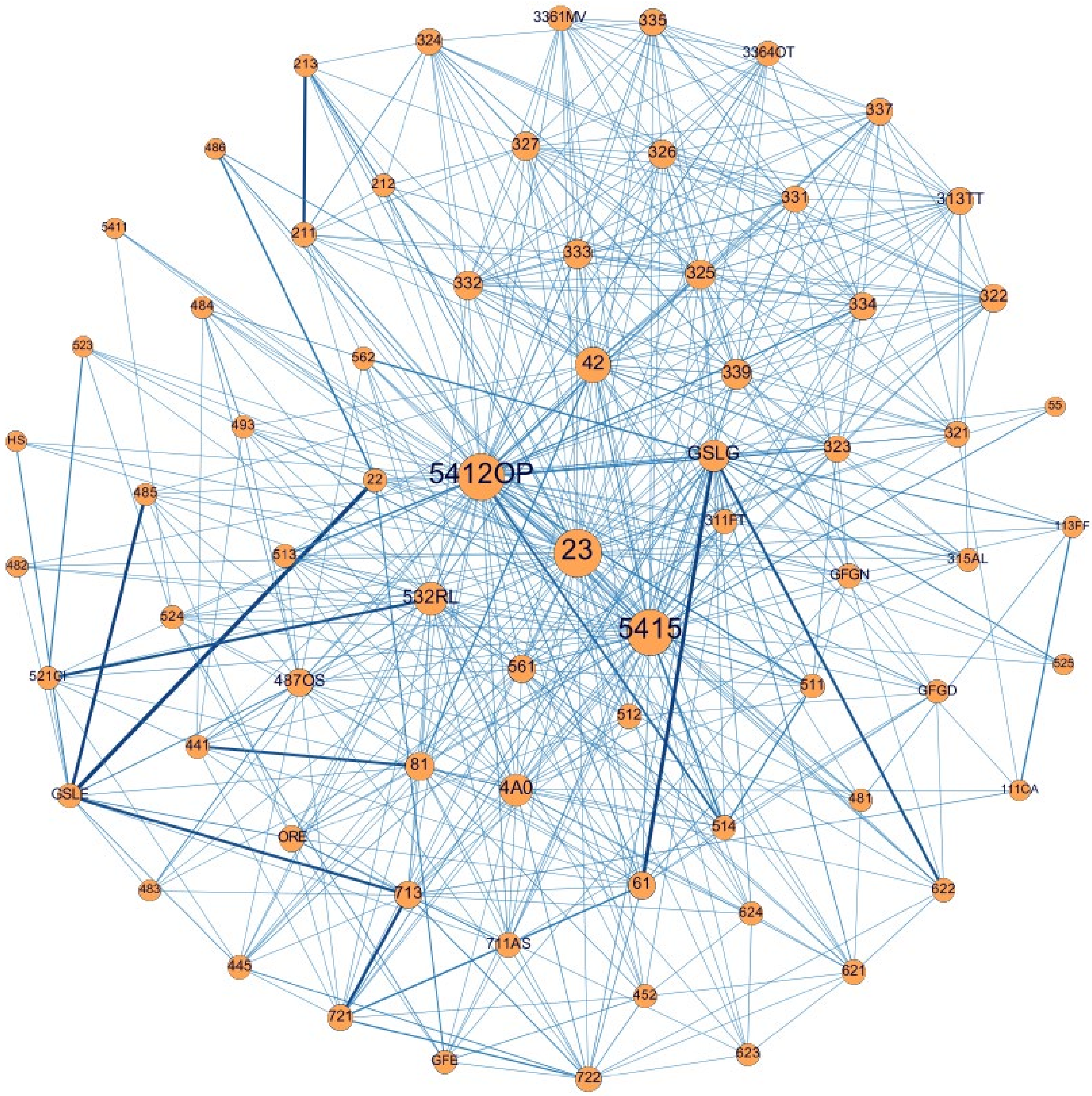
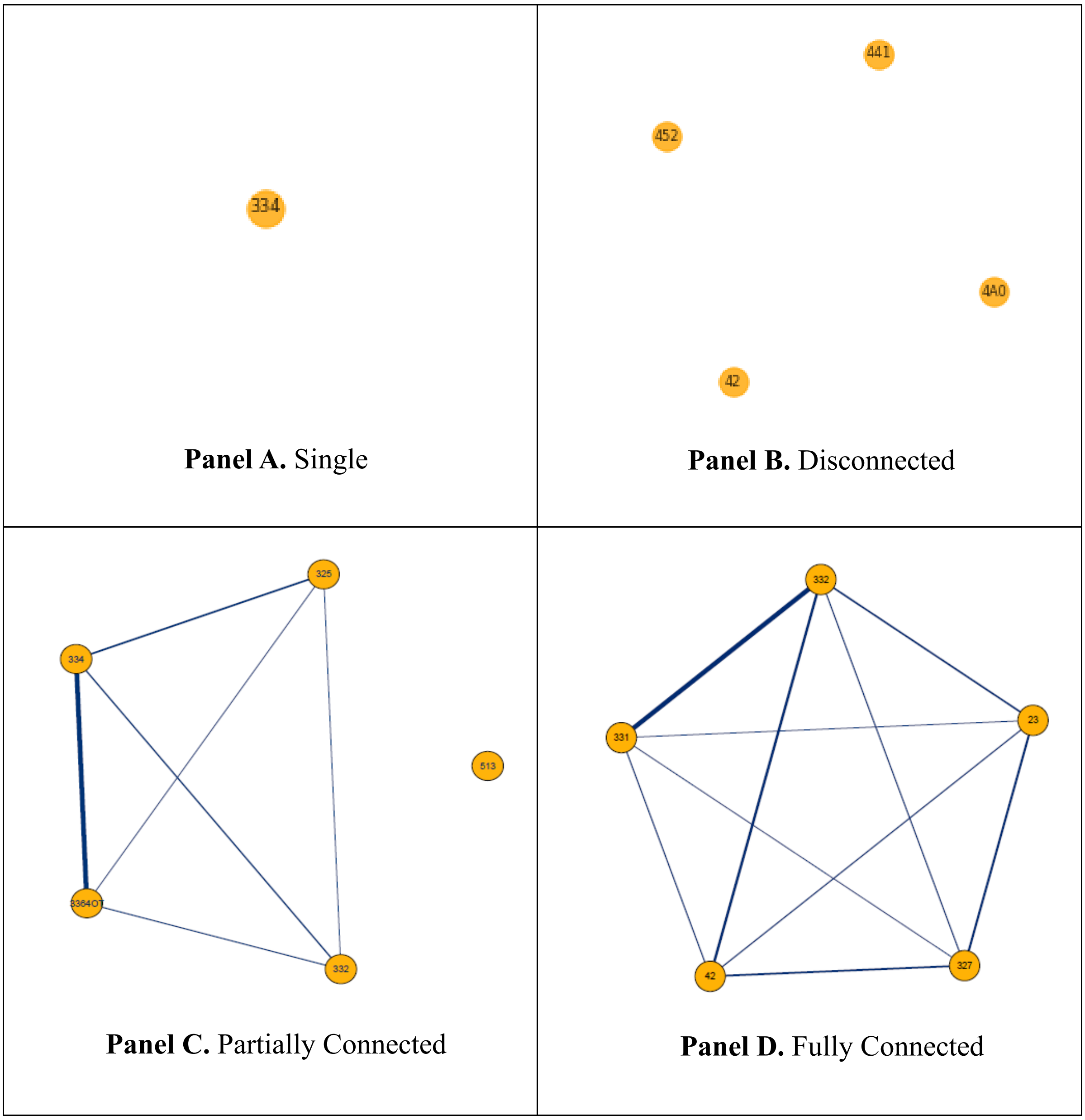


**Figure 2.** Analyst coverage network types.
The figure shows four types of analyst coverage networks. Panel A shows the situation in which the analyst covers firms in a single industry. Panel B presents a disconnected network, in which the analyst covers multiple industries with no direct economic relationship. Panel C presents a partially connected network, in which some of the industry nodes in this network have economic relationships. Panel D presents a fully connected network, in which all industries covered by the analyst have pairwise economic relationships.




**Panel A.** Single

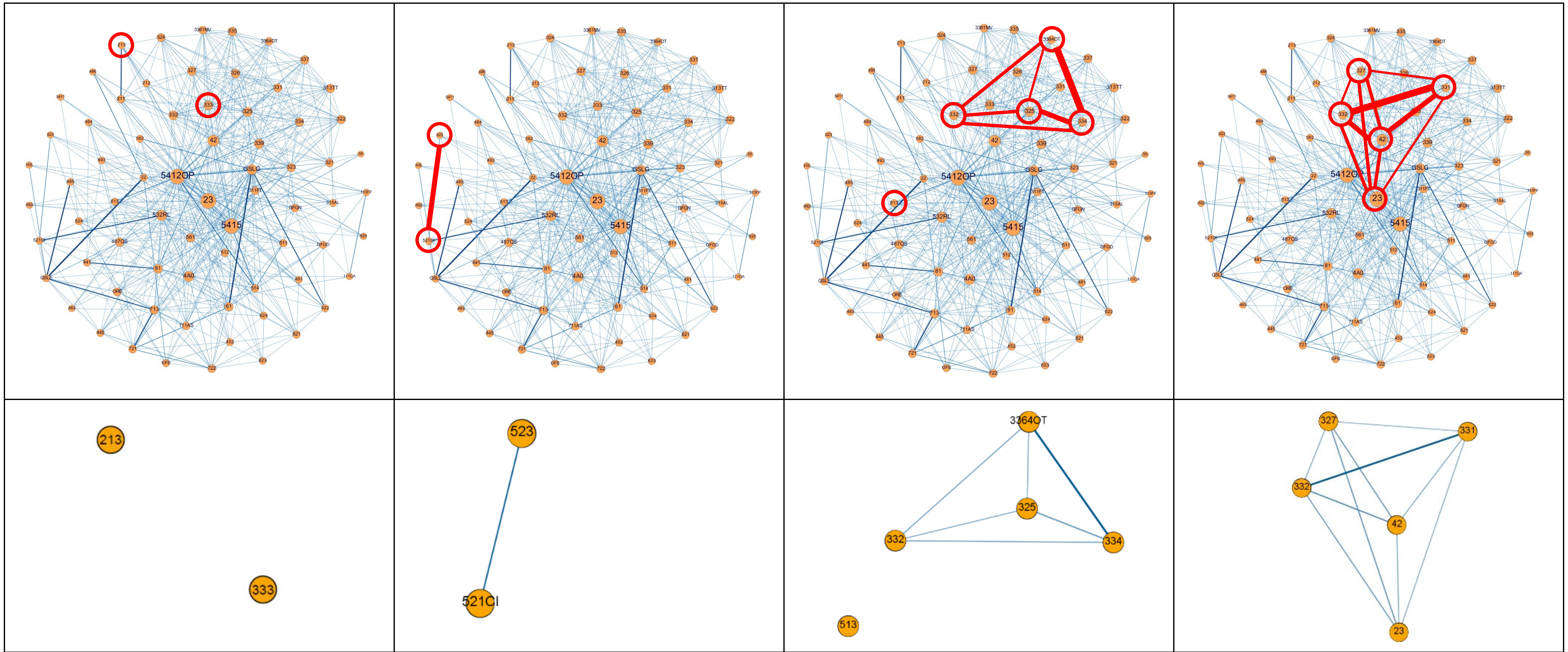
**Panel B.** Disconnected

**Panel C.** Partially Connected

**Panel D.** Fully Connected

**Figure 3. Network-based Information synergy of analyst coverage portfolio.**

This figure plots examples of an analyst's evolving coverage. The industries covered by the subgraph and the network characteristics of the subgraph are displayed below the subgraph.




| | | | |
|---|---|---|---|
| Analyst ID: 001220<br>Industry: 213, 333<br>Centrality: 0.190<br>Density: 4.5 | Analyst ID: 003740<br>Industry: 523, 521CI<br>Centrality: 0.125<br>Density: 8.533 | Analyst ID: 001445<br>Industry: 325, 332, 334, 513, 3364OT<br>Centrality: 0.273<br>Density: 6.260 | Analyst ID: 163870<br>Industry: 23, 42, 327, 331, 332<br>Centrality: 0.412<br>Density: 8.203 |

**Panel A.** In the cross-section, we show the coverage subgraphs and their network characteristics for four different analysts in 2015

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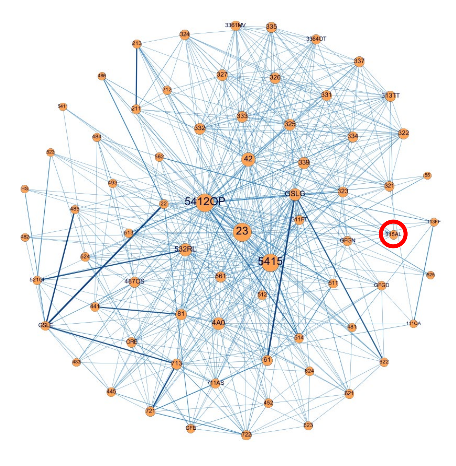
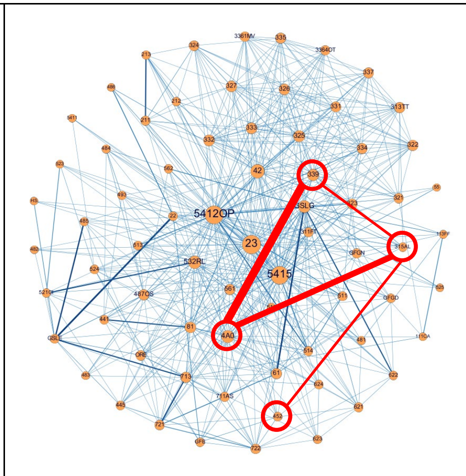
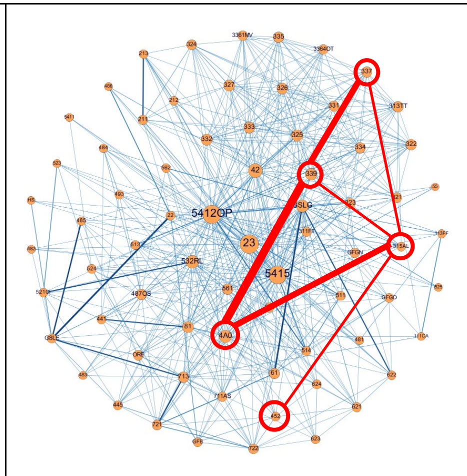
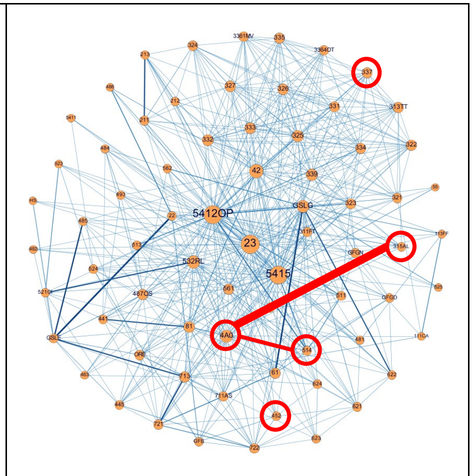
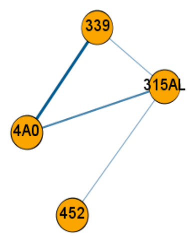
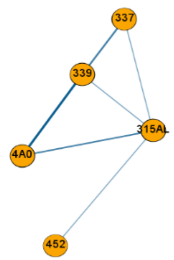
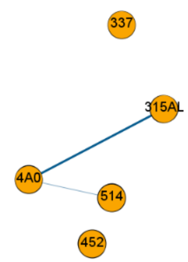
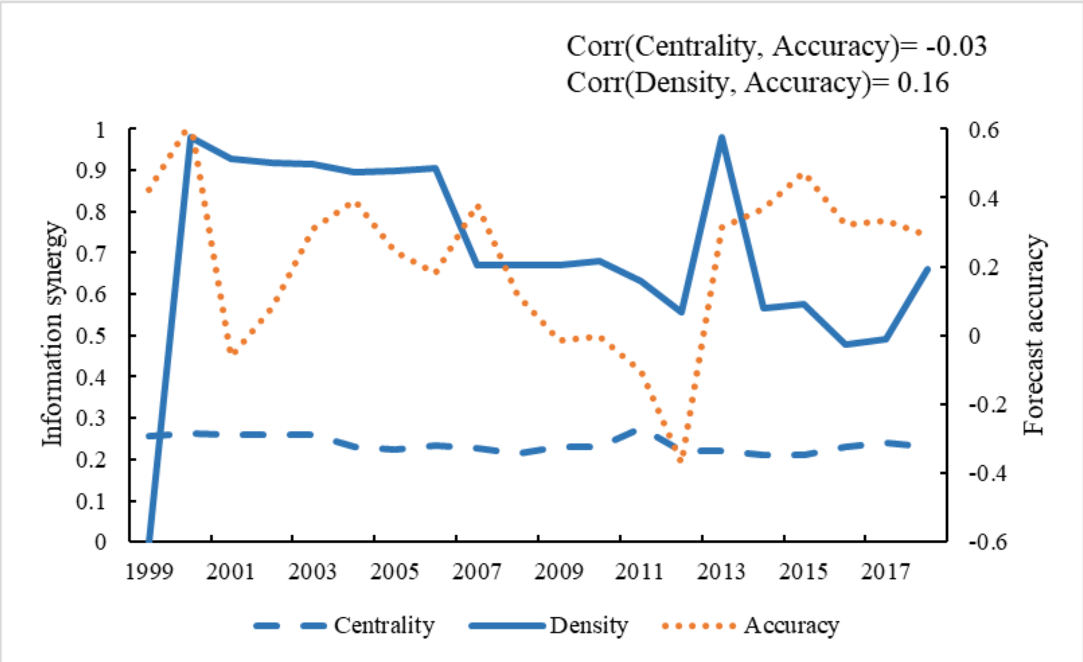
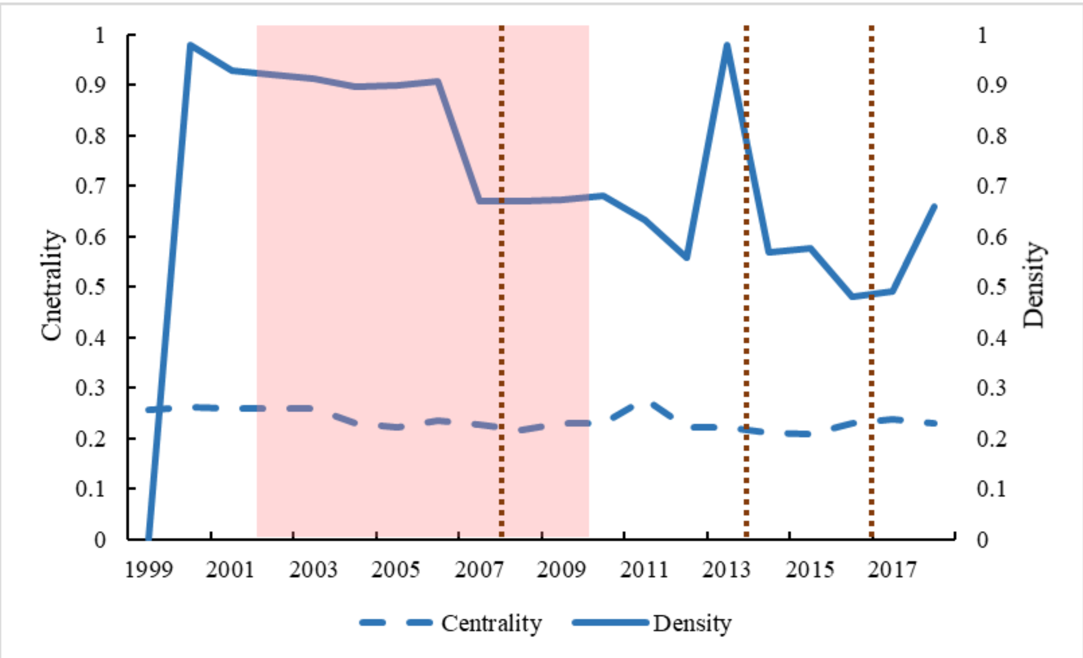
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year: 1999<br></td>
<td>Year: 2003<br></td>
<td>Year: 2004<br></td>
<td>Year: 2018<br></td>
</tr>
<tr>
<td>Industry: 315AL<br>Centrality: 0.185<br>Density: 0</td>
<td>Industry: 315AL, 339, 452, 4A0<br>Centrality: 0.202<br>Density: 7.984</td>
<td>Industry: 315AL, 339, 452, 4A0, 337<br>Centrality: 0.231<br>Density: 7.930</td>
<td>Industry: 315AL, 452, 4A0, 337, 514<br>Centrality: 0.204<br>Density: 4.259</td>
</tr>
</table>

**Panel B.** In the time series, we show the coverage subgraphs and their network characteristics for a single analyst (Analyst ID: 059339) in different four years

**Figure 4.** An example of analyst's network-based information synergy.
This figure plots an example of analyst's network-based information synergy and analyst performance. In Panel A, we show the correlation coefficients between network-based information synergy and forecast accuracy in the top of the figure. In Panel B, the red areas indicate that the analyst was a star analyst during this time period and the dashed vertical lines indicate that the analyst demoted to a lower-status brokerage this year.




**Panel A.** Analyst's network-based information synergy and forecast accuracy




**Panel B.** Analyst's network-based information synergy and career outcomes

**Figure 5.** Supply chain analyst's directed subgraph.
This figure presents an example of a directed subgraph with a supply chain relationship.

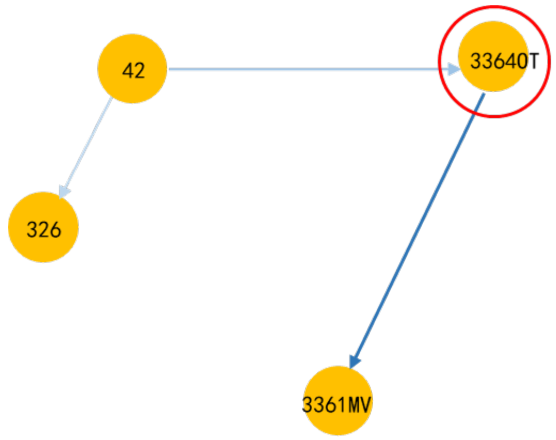


**Table 1.** Variable description.

| Variable | Definition |
|---|---|
| **Analyst performance** | |
| Proportional mean absolute forecast error (*PMAFE*) | Calculated as the difference between the absolute forecast error (*AFE*) for analyst $i$ on firm $j$ in year $t$ and the mean absolute forecast error (*MAFE*) for firm $j$ in year $t$, scaled by the mean absolute forecast error for firm $j$ in year $t$, and then multiplied by minus one. Higher *PMAFE* means more accurate forecasts. |
| Accuracy | The equal-weighted average *PMAFE* of all firms covered by analyst $i$ in year $t$. |
| Star | An indicator variable that equals 1 if analyst $i$ is named to *Institutional Investor magazine*'s All-Star Team in the next year, and 0 otherwise. |
| Promoted | An indicator variable that equals 1 if the analyst $i$ promotes from a low-status brokerage house to a high-status brokerage house in a given year, and 0 otherwise. |
| **Network properties** | |
| Centrality | The analyst's coverage network centrality, calculated as the weighted average degree of all nodes in the subgraph covered by analyst $i$ in year $t$. The degree of a node is the number of edges connected to it. Higher *Centrality* means that the subgraph is in a more central position within the inter-industry network. |
| StdCentrality | The network centrality (*Centrality*) minus the minimum centrality value and divided by the difference between the maximum and centrality value. |
| Density | The analyst's coverage portfolio density, calculated as the weighted average of the shortest distance between all nodes in a subgraph covered by analyst $i$ in year $t$ and scaled by the total number of nodes in the subgraph. Higher *Density* means that industries in the analyst's subgraph are denser linked. |
| StdDensity | The network density (*Density*) minus the minimum density value and divided by the difference between the maximum and density value. |
| **Analyst level characteristic** | |
| Nfirm | The number of firms followed by analyst $i$ in year $t$. (Analyst's portfolio size). We take natural logarithm of *Nfirm* in empirical tests. |
| Nind | The number of industries followed by analyst $i$ in year $t$. (The number of nodes in analyst *i's* coverage subgraph in year $t$). We take natural logarithm of *Nind* in empirical tests. |
| Exp | The total number of years since analyst $i$ first appeared in I/B/E/S. We take natural logarithm of *EXP* in empirical tests. |
| Top10broker | Indicator variable equal to 1 if analyst $i$ works at a top decile brokerage house in year $t$. |
| MV | The average log market capitalization of all firms covered by analyst $i$ in year $t$, and 0 otherwise. |

| | |
|---|---|
| BM | The average book-to-market ratio of all firms covered by analyst *i* in year *t*. |
| ROA | The average return of assets of all firms covered by analyst *i* in year *t*. |
| Supply chain analyst (*SC_ana*lyst) | Indicator variable equal to 1 if the analyst covers at least one node that has both an out-edge and in-edge in the directed subgraph. |
| Proportion_SC | The proportion of nodes in the analyst's directed subgraph that have both an out-edge and in-edge, relative to the total number of nodes. |

**Table 2.** Summary statistics.

This table presents the summary statistics for the analyst characteristics of our variables in the analysis. Panel A reports the mean, median, standard deviation (SD), and the first (Q1) and third (Q3) quartile values of variables. Panel B reports the frequencies of the number of different types of networks. Panel C reports the compared statistics of the mean of main variables between the diversified portfolio sample and the specialized portfolio sample. The analyst who only covers one industry belongs to the specialized portfolio sample; other analysts belong to the diversified portfolio sample. Panel D reports the correlation table based on the diversified coverage sample. The lower triangle shows the Pearson correlation coefficient, and the upper triangle shows the Spearman correlation coefficient. Panel E reports the number of star analyst, promoted analyst and supply chain analyst, respectively.

**Panel A.** Descriptive Statistics (Full Sapmle)

| VarName | Obs | Mean | SD | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| Accuracy | 79,781 | -0.048 | 0.647 | -0.224 | 0.106 | 0.326 |
| Centrality | 78,539 | 0.261 | 0.125 | 0.171 | 0.253 | 0.324 |
| StdCentrality | 79,539 | 0.244 | 0.135 | 0.138 | 0.244 | 0.314 |
| Density | 44,019 | 7.032 | 1.806 | 5.135 | 8.04 | 8.375 |
| StdDensity | 44,019 | 0.809 | 0.208 | 0.591 | 0.926 | 0.964 |
| Nfirm | 79,122 | 8.163 | 6.795 | 2.000 | 4.500 | 12.000 |
| LogNfirm | 79,122 | 1.929 | 0.791 | 1.098 | 2.079 | 2.565 |
| Nind | 79,122 | 2.421 | 1.915 | 1.000 | 2.000 | 3.000 |
| LogNind | 79,122 | 1.112 | 0.459 | 0.693 | 1.099 | 1.386 |
| Top10broker | 79,122 | 0.550 | 0.497 | 0.000 | 1.000 | 1.000 |
| Exp | 79,122 | 8.781 | 8.405 | 2.000 | 6.000 | 14.000 |
| LogExp | 79,122 | 1.822 | 1.046 | 1.099 | 1.946 | 2.708 |
| MV | 79,122 | 8.353 | 1.536 | 7.317 | 8.549 | 9.520 |
| BM | 79,122 | 0.509 | 0.330 | 0.298 | 0.436 | 0.634 |
| ROA | 79,122 | 0.013 | 0.11 | 0.003 | 0.035 | 0.068 |

**Panel B.** Descriptive Statistics (Full Sample)

| Network type | Freq. | Percent | Cum. |
|---|---|---|---|
| Single | 35,762 | 44.83 | 44.83 |
| Disconnected | 6,915 | 8.67 | 53.50 |
| Partial connected | 7,474 | 9.37 | 62.87 |
| Fully connected | 29,630 | 37.14 | 100 |
| Total | 79,781 | 100 | |

**Panel C.** Comparison: Diversified portfolio sample vs. Specialized portfolio sample

| | Diversified portfolio | | Specialized portfolio | | | |
|---|---|---|---|---|---|---|
| VarName | Obs | Mean | Obs | Mean | Mean_Diff | T-value |
| Accuracy | 44,019 | -0.002 | 35,762 | -0.104 | 0.102 | 22.16*** |
| Centrality | 44,019 | 0.285 | 35,762 | 0.232 | 0.053 | 60.04*** |
| Density | 44,019 | 7.032 | 35,762 | N/A | N/A | N/A |
| Nfirm | 43,971 | 10.649 | 35,151 | 5.053 | 5.596 | 1.32 |
| Nind | 44,019 | 3.574 | 35,151 | 1.002 | 2.572 | 2.50** |
| Top10broker | 43,971 | 0.551 | 35,762 | 0.550 | 0.001 | 0.43 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Exp | 43,971 | 10.270 | 35,151 | 6.918 | 3.352 | 56.87*** |
| MV | 43,971 | 8.400 | 35,151 | 8.295 | 0.105 | 9.53*** |
| BM | 43,971 | 0.482 | 35,151 | 0.543 | -0.061 | -26.04*** |
| ROA | 43,971 | 0.021 | 35,151 | 0.005 | 0.016 | 20.18*** |
| Star | 43,971 | 0.036 | 35,151 | 0.015 | 0.021 | 17.88*** |
| Promoted | 44,019 | 0.017 | 35,762 | 0.018 | -0.001 | -1.23 |

**Panel D.** Correlation Coefficient (Diversified portfolio sample)

| | Accuracy | Centrality | Density | Nfirm | Nind | Star |
|---|---|---|---|---|---|---|
| Accuracy | 1 | 0.010 | 0.009 | 0.040 | -0.028 | 0.045 |
| Centrality | 0.007 | 1 | 0.354 | 0.005 | 0.201 | 0.003 |
| Density | 0.022 | 0.289 | 1 | 0.330 | 0.609 | 0.029 |
| Nfirm | 0.072 | -0.039 | 0.210 | 1 | 0.482 | 0.112 |
| Nind | 0.017 | 0.127 | 0.367 | 0.490 | 1 | 0.032 |
| Star | 0.050 | 0.006 | 0.023 | 0.123 | 0.022 | 1 |

**Panel E.** Analyst type

| Analyst type | NO | YES | Total |
|---|---|---|---|
| Star analyst | 77,028 | 2,094 | 79,122 |
| Promoted | 71,296 | 1,285 | 79,781 |
| Supply chain analyst | 59,901 | 19,880 | 79,781 |

**Table 3.** Validation tests: Information synergy in network.

This table reports the relationship between network properties and information synergy in the network. Panel A presents the association between industry centrality and the predictability of stock returns. The dependent variable *Returns_linked*$_{kt}$ is the average return of source industry *k*'s linked industries. The source industry's return (*Returns_source*$_{it}$) is industry *k*'s abnormal return in month *t*. *Central* is a dummy variable equal to 1 if the network centrality (*Centrality*) of industry *k* is the top quintile of all industries. Standard errors are clustered by year and industry. The *t*-statistics are reported in parentheses. Panel B presents correlation coefficients between each analyst's coverage network density (*Density*) and coverage portfolio's return correlation. Coverage return correlation is the average return correlation between all firms' weekly returns in the portfolio covered by each analyst each year. The lower triangle shows the Pearson correlation coefficient, and the upper triangle shows the Spearman correlation coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Panel A.** Network centrality and returns predictability

| | (1)<br>Returns linked month *t* | (2)<br>Returns linked month *t* + 1 |
|---|---|---|
| Returns_linked | | 0.029 |
| | | (0.86) |
| Returns_source | 0.147*** | 0.025*** |
| | (9.18) | (3.40) |
| Central | 0.007* | 0.000 |
| | (1.66) | (1.20) |
| Central* Returns_source | 0.922*** | 0.103** |
| | (9.88) | (2.62) |
| Constant | 0.006*** | 0.007*** |
| | (5.25) | (4.92) |
| Year FE | YES | YES |
| N | 16,357 | 16,297 |
| Adjusted $R^2$ | 0.158 | 0.010 |

**Panel B.** Correlation between network density and coverage portfolio return correlation

| | Density | Coverage return correlation |
|---|---|---|
| Density | 1 | 0.106*** |
| Coverage return correlation | 0.065*** | 1 |

**Table 4.** Determinants of network-based information synergy of analyst's coverage portfolio.

This table reports the determinates of the analyst's network-based information synergy. The dependent variable is the analyst coverage network characteristics. The independent variables are the analyst's skill measures, including, the analyst's previous forecast accuracy (*LagAccuracy*), analyst portfolio size (*Nfirm*), brokerage house size (*Top10broker*), analyst experience (*Exp*), analyst's previous All-star status (*Star*) and whether the analyst promotes from a low-status brokerage house to a high-status brokerage house in a given year (*Promoted*). See Table 1 for a detailed description of the variables. Standard errors are clustered by year and analyst. The *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1)<br>Centrality | (2)<br>Centrality | (3)<br>Centrality | (4)<br>Density | (5)<br>Density |
|---|---|---|---|---|---|
| LagAccuracy | 0.008*** | 0.008*** | 0.004*** | 0.008** | 0.009** |
| | (3.78) | (3.85) | (3.05) | (2.53) | (2.58) |
| Nfirm | 0.013*** | 0.013*** | 0.020*** | 0.021*** | 0.021*** |
| | (4.65) | (4.59) | (11.71) | (5.66) | (5.65) |
| Top10broker | -0.007*** | -0.007*** | -0.008*** | 0.012** | 0.013*** |
| | (-2.90) | (-2.91) | (-3.19) | (2.79) | (2.89) |
| EXP | -0.003 | -0.003 | -0.003* | -0.004 | -0.004 |
| | (-1.66) | (-1.64) | (-1.76) | (-1.35) | (-1.32) |
| Star | | -0.001 | 0.003 | | -0.005 |
| | | (-0.16) | (0.40) | | (-0.45) |
| Promoted | | 0.015*** | 0.009 | | 0.023*** |
| | | (3.65) | (1.62) | | (3.54) |
| Constant | 0.255*** | 0.255*** | 0.214*** | 0.762*** | 0.761*** |
| | (35.07) | (34.46) | (53.75) | (79.85) | (80.09) |
| Year FE | YES | YES | YES | YES | YES |
| Analyst FE | YES | YES | YES | YES | YES |
| N | 37,058 | 37,058 | 58,807 | 37,058 | 37,058 |
| Adjusted $R^2$ | 0.018 | 0.018 | 0.018 | 0.010 | 0.011 |

**Table 5.** The impact of network-based coverage portfolio information synergy on analyst earnings forecast accuracy.

This table reports the regression results for analyst earnings forecast accuracy for the coverage sample. The dependent variable is the analyst forecast accuracy. The primary independent variable is the analyst coverage network centrality (*Centrality*) and network density (*Density*). Control variables include analyst portfolio size (*Nfirm*), analyst experience (*Exp*), brokerage house size (*Top10broker*), averaged portfolio firm size (*MV*), book-to-market ratio (*BM*), and return of assets (*ROA*). Column (4) is based on the full sample, and other columns based on the diversified portfolio sample. See Table 1 for a detailed description of the variables. Standard errors are clustered by year and analyst. The *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1)<br>Accuracy | (2)<br>Accuracy | (3)<br>Accuracy | (4)<br>Accuracy | (5)<br>Accuracy | (6)<br>Accuracy |
|---|---|---|---|---|---|---|
| Centrality | 0.070*** | 0.059** | 0.040** | | | 0.041** |
| | (3.01) | (2.44) | (1.97) | | | (1.98) |
| Density | | | | 0.040*** | 0.040*** | 0.032*** |
| | | | | (3.64) | (3.62) | (2.83) |
| Nfirm | 0.084*** | 0.087*** | 0.103*** | 0.084*** | 0.087*** | 0.087*** |
| | (9.07) | (9.36) | (11.80) | (9.68) | (10.06) | (10.08) |
| Top10broker | 0.033*** | 0.039*** | 0.052*** | 0.032*** | 0.038*** | 0.038*** |
| | (3.07) | (3.42) | (4.65) | (3.17) | (3.58) | (3.60) |
| Exp | 0.008* | 0.010* | -0.000 | 0.008* | 0.010* | 0.010* |
| | (1.74) | (1.75) | (-0.01) | (1.72) | (1.88) | (1.87) |
| MV | | -0.010*** | -0.008*** | | -0.011*** | -0.010*** |
| | | (-3.69) | (-3.30) | | (-5.33) | (-4.84) |
| BM | | -0.002 | 0.017* | | -0.004 | -0.001 |
| | | (-0.17) | (1.87) | | (-0.51) | (-0.09) |
| ROA | | -0.017 | -0.028 | | -0.009 | -0.012 |
| | | (-0.57) | (-1.27) | | (-0.32) | (-0.42) |
| Constant | -0.249*** | -0.178*** | -0.222*** | -0.262*** | -0.186*** | -0.196*** |
| | (-11.77) | (-6.16) | (-10.20) | (-15.41) | (-8.50) | (-8.25) |
| Year FE | YES | YES | YES | YES | YES | YES |
| Analyst FE | YES | YES | YES | YES | YES | YES |
| N | 43, 971 | 43, 971 | 77,798 | 43,971 | 43,971 | 43,971 |
| Adjusted $R^2$ | 0.013 | 0.014 | 0.018 | 0.013 | 0.014 | 0.018 |

**Table 6.** The impact of network-based supply chain analysts on analyst earnings forecast accuracy.

Panel A reports the comparison of analyst coverage portfolio characteristics between supply chain analysts and non-supply chain analysts in the diversified coverage sample. A supply chain analyst (*SC_ana*lyst) is an analyst who covers at least one node that has both an out-edge and in-edge in the directed subgraph. Panel B reports the regression results of analyst earnings forecast accuracy for the diversified coverage sample. The dependent variable is analyst forecast accuracy (*Accuracy*). The primary independent variables of supply chain analysts are *SC_ana*lyst and *Proportion_SC*. *Proportion_SC* is a continuous variable, which is the proportion of nodes in the analyst's subgraph that have both an out-edge and in-edge to the total number of nodes. The control variables are defined in Table 1. Standard errors are clustered by year and analyst. The *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| **Panel A.** Differences between supply-chain analysts and non-supply chain analysts | | | | |
|---|---|---|---|---|
| Variables | Dummy_scana=1 | Dummy_scana=0 | Difference | *t*-value |
| Centrality | 0.306 | 0.252 | 0.054 | 48.39*** |
| Density | 0.876 | 0.755 | 0.121 | 63.31*** |
| Accuracy | 0.018 | -0.019 | 0.037 | 8.01*** |
| Obs. | 19,800 | 24,139 | | |

| **Panel B.** Analyst performance of supply chain analyst | | |
|---|---|---|
| | Accuracy | Accuracy |
| Dummy_scana | 0.012** | |
| | (2.12) | |
| Propotion_sc | | 0.015* |
| | | (1.72) |
| Nfirm | 0.005*** | 0.006*** |
| | (6.07) | (6.24) |
| Top10broker | 0.043*** | 0.043*** |
| | (3.42) | (3.40) |
| Exp | 0.002*** | 0.002*** |
| | (4.24) | (4.26) |
| MV | -0.014** | -0.015** |
| | (-4.42) | (-4.68) |
| BM | 0.002 | 0.001 |
| | (0.23) | (0.11) |
| ROA | -0.026 | -0.026 |
| | (-0.74) | (-0.75) |
| Constant | -0.019 | -0.015 |
| | (-0.75) | (-0.62) |
| Year FE | YES | YES |
| Analyst FE | YES | YES |
| N | 43,971 | 43,971 |
| Adjusted $R^2$ | 0.010 | 0.010 |

**Table 7.** The impact of network-based coverage portfolio information synergy on analyst career outcomes.

This table reports the logit regression results for analysts' career outcomes. In Panel A, the dependent variable is *Star*, an indicator variable that equals 1 if the analyst is named to Institutional Investor magazine's All-Star Team in the next year, and 0 otherwise. In Panel B, the dependent variable is *Promoted*, an indicator variable that equals 1 if the analyst promotes from a low-status brokerage house to a high-status brokerage house in a given year, and 0 otherwise. We use coverage network density (*Density*), coverage network centrality (*Centrality*), and the continuous supply chain analyst measure (*Proportion_SC*) as the main independent variables. Columns (1), (2), and (3) are based on the diversified portfolio sample, and Column (4) is based on the full sample. The control variables include the lagged value of analyst forecast accuracy, analyst portfolio size (*Nfirm*), analyst experience (*Exp*), brokerage house size (*Top10broker*/*Log_BrokerageSize*), and firm characteristics. See Table 1 for a detailed description of the variables. Standard errors are clustered by year and analyst. The *z*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4 |
|---|---|---|---|---|
| **Panel A.** All-star analyst | | | | |
| VARIABLE | Star | Star | Star | Star |
| Centrality | 0.441** | | | 0.670*** |
| | (1.96) | | | (3.10) |
| Density | | 0.018 | | |
| | | (1.11) | | |
| Proportion_SC | | | 0.431*** | |
| | | | (4.11) | |
| Nfirm | 0.053*** | 0.028*** | 0.050*** | 0.522 |
| | (10.73) | (7.22) | (10.97) | (10.46) |
| Top10broker | 2.663*** | 2.633*** | 2.622*** | 2.514 |
| | (16.93) | (19.22) | (19.33) | (17.25) |
| Exp | 0.044*** | 0.324*** | 0.044*** | 0.049 |
| | (11.62) | (9.92) | (10.51) | (8.81) |
| Accuracy | 0.511*** | 0. 456*** | 0.514*** | 0.456*** |
| | (5.29) | (5.79) | (5.30) | (6.06) |
| MV | 0.437*** | 0.193*** | 0.46*** | 0.425*** |
| | (13.04) | (6.48) | (845) | (10.41) |
| BM | 0.260* | 0.319*** | 0.305** | 0.095 |
| | (1.78) | (2.65) | (2.03) | (0.84) |
| ROA | 2.143*** | 2.672** | 1.949*** | 2.020** |
| | (3.96) | (4.05) | (3.59) | (4.77) |
| Constant | -9.990*** | -8.533*** | -10.096*** | -10.022*** |
| | (-16.46) | (-8.73) | (-17.99) | (-21.76) |
| Year FE | YES | YES | YES | YES |
| N | 37,067 | 37,067 | 37,067 | 50,806 |
| Pseudo $R^2$ | 0.186 | 0.128 | 0.188 | 0.192 |
| **Panel B.** Analyst Promotion | | | | |
| VARIABLE | Promoted | Promoted | Promoted | Promoted |
| Centrality | 0.561* | | | 0.181* |
| | (1.93) | | | (1.87) |

| | | | | |
|---|---|---|---|---|
| Density | | 0.382** | | |
| | | (1.98) | | |
| Proportion_SC | | | 0.033 | |
| | | | (0.22) | |
| Nfirm | 0.041 | 0.041 | 0.042 | -0.016 |
| | (0.56) | (0.55) | (0.57) | (-0.29) |
| Log_BrokerageSize | 0.194*** | 0.195*** | 0.194*** | 2.665 |
| | (4.73) | (4.76) | (4.73) | (11.23) |
| Exp | 0.202*** | 0.198*** | 0.202*** | 0.303 |
| | (6.31) | (6.20) | (6.32) | (10.51) |
| Accuracy | -0.076 | -0.075 | -0.074 | 0.059 |
| | (-0.97) | (-0.96) | (-0.91) | (1.33) |
| MV | -0.033 | -0.040 | -0.039 | -0.032 |
| | (-1.02) | (-1.24) | (-1.19) | (-1.45) |
| BM | -0.463** | -0.476** | -0.508*** | -0.331*** |
| | (-2.37) | (-2.48) | (-2.62) | (2.92) |
| ROA | -1.756*** | -1.689*** | -1.758*** | -1.911 |
| | (-4.99) | (-4.81) | (-4.95) | (-9.39) |
| Constant | -4.091*** | -4.178*** | -3.883*** | -4.631 |
| | (-12.83) | (-12.75) | (-13.23) | (-21.31) |
| Year FE | 42,165 | 42,165 | 42,165 | 74,669 |
| N | YES | YES | YES | YES |
| Pseudo $R^2$ | 0.063 | 0.061 | 0.063 | 0.065 |

**Table 8.** Robustness tests: Subsample Analyses of network-based coverage portfolio density on analyst earnings forecast accuracy for different numbers of industry coverage.

This table reports the regression results for analyst earnings forecast accuracy for the different subsamples based on the different numbers of industry coverage. The dependent variable is the analyst forecast accuracy. The primary independent variable is the analyst coverage network centrality (*Centrality*) and network density (*Density*). Control variables include analyst portfolio size (*Nfirm*), analyst experience (*Exp*), brokerage house size (*Top10broker*), averaged portfolio firm size (*MV*), book-to-market ratio (*BM*), and return of assets (*ROA*). See Table 1 for a detailed description of the variables. Standard errors are clustered by year and analyst. The *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Accuracy | Accuracy | Accuracy | Accuracy | Accuracy |
| | Nind = 2 | Nind = 3 | Nind = 4 | Nind = 5 | Nind > 5 |
| Density | -0.003 | 0.059** | 0.091*** | 0.079** | 0.100*** |
| | (-0.15) | (2.22) | (2.70) | (2.34) | (2.62) |
| Nfirm | 0.011*** | 0.009*** | 0.007*** | 0.004** | -0.027 |
| | (8.94) | (6.09) | (5.10) | (2.19) | (-1.23) |
| Top10broker | 0.058*** | 0.021 | 0.019 | 0.018 | 0.043** |
| | (4.25) | (1.18) | (1.07) | (1.25) | (2.79) |
| Exp | -0.002 | 0.013 | 0.013* | 0.036*** | 0.049*** |
| | (-0.31) | (1.64) | (1.87) | (4.63) | (5.24) |
| MV | -0.013*** | -0.006 | -0.005 | -0.008 | -0.008 |
| | (-3.20) | (-1.07) | (-0.73) | (-1.20) | (-1.40) |
| BM | 0.009 | -0.002 | -0.014 | -0.028 | -0.014 |
| | (0.56) | (-0.07) | (-0.60) | (-0.94) | (-0.28) |
| ROA | 0.015 | 0.040 | -0.062 | -0.108 | 0.041 |
| | (0.29) | (0.63) | (-0.68) | (-1.59) | (0.38) |
| Constant | 0.058*** | 0.021 | 0.019 | 0.018 | 0.043** |
| | (4.25) | (1.18) | (1.07) | (1.25) | (2.79) |
| Year FE | YES | YES | YES | YES | YES |
| Analyst FE | YES | YES | YES | YES | YES |
| N | 16360 | 10474 | 6814 | 4168 | 6153 |
| Adjusted $R^2$ | 0.015 | 0.013 | 0.012 | 0.012 | 0.021 |

**Table 9.** Robustness tests: Subsample Analyses of network-based information synergy on analyst earnings forecast accuracy when the analyst did not change the brokerage house period. This table reports the regression results for analyst earnings forecast accuracy for the coverage sample only in the year in which the analyst did not change the brokerage house. The dependent variable is the analyst forecast accuracy. The primary independent variable is the analyst coverage network centrality (*Centrality*) in Panel A and network density (*Density*) in Panel B, respectively. Control variables include analyst portfolio size (*Nfirm*), analyst experience (*Exp*), brokerage house size (*Top10broker*), averaged portfolio firm size (*MV*), book-to-market ratio (*BM*), and return of assets (*ROA*). See Table 1 for a detailed description of the variables. Standard errors are clustered by year and analyst. The *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Accuracy | Accuracy | Accuracy |
| Centrality | 0.117*** | | 0.099*** |
| | (4.41) | | (3.65) |
| Density | | 0.049*** | 0.030** |
| | | (3.46) | (2.10) |
| Nfirm | 0.005*** | 0.017*** | 0.016*** |
| | (8.79) | (3.09) | (2.95) |
| Top10broker | 0.039*** | 0.038*** | 0.038*** |
| | (3.29) | (3.24) | (3.25) |
| Exp | 0.016*** | 0.005*** | 0.005*** |
| | (2.93) | (8.49) | (8.68) |
| MV | -0.010*** | -0.011*** | -0.010*** |
| | (-3.53) | (-4.10) | (-3.63) |
| BM | -0.015 | -0.021* | -0.014 |
| | (-1.36) | (-1.86) | (-1.26) |
| ROA | -0.042 | -0.032 | -0.036 |
| | (-1.31) | (-0.98) | (-1.14) |
| Constant | -0.056** | -0.047* | -0.074** |
| | (-2.12) | (-1.77) | (-2.63) |
| Year FE | YES | YES | YES |
| Analyst FE | YES | YES | YES |
| N | 39,270 | 39,259 | 39,259 |
| Adjusted $R^2$ | 0.012 | 0.012 | 0.012 |

**Table 10.** Robustness tests: Alternative measures for network-based information synergy.

This table reports the regression results for the impact of network-based information synergy on analyst earnings forecast accuracy for the diversified coverage sample. The dependent variable is the analyst forecast accuracy. Centrality_VW is the value-weighted measure of an analyst's portfolio degree centrality. Density_VW is the value-weighted measure of an analyst's portfolio density. Centrality_between is the value-weighted measure of an analyst's portfolio betweenness centrality. The control variables include analyst portfolio size (*Nfirm*), analyst experience (*Exp*), brokerage house size (*Top10broker*), averaged portfolio firm size (*MV*), book-to-market ratio (*BM*), and return of assets (*ROA*). See Table 1 for a detailed description of the variables. Standard errors are clustered by year and analyst. The *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1)<br>Accuracy | (2)<br>Accuracy | (3)<br>Accuracy | (4)<br>Accuracy |
|---|---|---|---|---|
| Centrality_VW | 0.013*** | | 0.043*** | |
| | (2.58) | | (2.60) | |
| Density_VW | | 0.008** | 0.007** | |
| | | (2.53) | (2.00) | |
| Centrality_Between | | | | 0.234*** |
| | | | | (2.94) |
| Nfirm | 0.025* | 0.017*** | 0.015*** | 0.005*** |
| | (7.94) | (7.17) | (2.72) | (7.56) |
| Top10broker | 0.049*** | 0.049*** | 0.048*** | 0.044*** |
| | (4.47) | (4.33) | (4.32) | (3.46) |
| Exp | 0.004*** | 0.004*** | 0.003*** | 0.002*** |
| | (7.31) | (7.15) | (7.15) | (4.24) |
| MV | -0.011*** | -0.011*** | -0.011*** | -0.016*** |
| | (-4.37) | (-4.55) | (-4.56) | (-5.20) |
| BM | 0.000 | 0.005 | 0.004 | 0.016 |
| | (0.02) | (0.55) | (0.47) | (1.38) |
| ROA | -0.033 | -0.028 | -0.030 | -0.029 |
| | (-1.07) | (-0.87) | (-0.94) | (-0.84) |
| Constant | 0.004 | -0.020 | -0.017 | 0.007 |
| | (0.19) | (-0.95) | (-0.87) | (0.31) |
| Year FE | YES | YES | YES | YES |
| Analyst FE | YES | YES | YES | YES |
| N | 43,971 | 43,971 | 43,971 | 43,957 |
| Adjusted $R^2$ | 0.006 | 0.006 | 0.010 | 0.006 |