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Peer Effects in Equity Research

Kenny Phua
University of Technology Sydney UTS Business School
kenny.phua@uts.edu.au

Mandy Tham
Singapore Management University Lee Kong Chian School of Business
mandytham@smu.edu.sg

Chishen Wei
Hong Kong Polytechnic University Faculty of Business
chishen.wei@polyu.edu.hk (corresponding author)

Abstract

We study the importance of peer effects among sell-side analysts who work at the same brokerage house, but cover different firms. By mapping the information network within each brokerage, we identify analysts who occupy central positions in the network. Central analysts incorporate more information from their coworkers and produce better research. Using shocks to network structures around brokerage mergers, we identify the influence of peer effects and the importance of industry expertise on analysts' performance. A portfolio strategy that exploits the forecast revisions of central analysts earns up to 24% per annum.

I. Introduction

Peer effects play an important role in the production of knowledge and information. Studies show that scientific breakthroughs and high-impact academic research rely ever more on knowledge sharing among peers.[1] Given the value of information in financial markets, access to peer expertise could be particularly

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[1]For example, see Wuchty, Jones, and Uzzi (2007), Azoulay, Graff Zivin, and Wang (2010), and Oettl (2012). A related line of literature shows that peer effects also influence household financial decisions (e.g., Maturana and Nickerson (2019), Ouimet and Tate (2020)).

useful in the production of equity research. This article examines the importance of peer effects among sell-side analysts who work at the same brokerage house, but cover different firms. We find evidence consistent with brokerage coworkers acting as a network of expertise in the production of equity research.

Equity analysts provide an ideal setting to study peer effects for several reasons. First, studies show that equity research is impactful (Barber, Lehavy, McNichols, and Trueman (2001), Loh and Stulz (2010), (2018), and Crane and Crotty (2020)). Unveiling the importance of peer effects can shed light on how these information agents facilitate price discovery in financial markets. Second, analysts produce detailed and observable output. This wealth of data provides an opportunity to precisely assess the influence of peer effects. Third, given the complexity of firm valuation and vast amount of available information, analysts may be subject to limited attention and information-processing constraints (e.g., Harford, Jiang, Wang, and Xie (2019a), Hirshleifer, Levi, Lourie, and Teoh (2019)). Thus, we hypothesize that interactions with coworkers can help analysts ease these constraints and acquire industry expertise (an attribute highly valued by institutional investors; Bagnoli, Watts, and Zhang (2008), Bradley, Gokkaya, and Liu (2017)). An anecdote suggests that such information exchange may provide a competitive advantage. In the 1990s, Lehman Brothers (a top equity research house at that time) required its analysts to cite the work of their coworkers in all presentations (Groysberg, Nanda, and Nohria (2004)).

The identification of peer effects, however, poses many challenges. First, analysts at the same brokerage house may share similar traits. For instance, some brokerages could choose to hire analysts with certain educational backgrounds or technical expertise. Such characteristics, rather than peer effects, could underlie any correlation we find in the output of analysts and their coworkers. Second, analysts working at the same brokerage may experience common shocks. For example, they may share brokerage resources, face similar incentives, or have exposure to the same news events. These common shocks could confound our ability to identify the influence of peer effects on analysts' actions and performance.

To overcome these challenges, we model the brokerage house as a network of analysts who exchange information and ideas. In this brokerage network, the propensity of an analyst to receive her coworkers' information will vary with her network position in the brokerage. We exploit this within-brokerage variation to identify peer effects.[2] A particularly attractive feature of our setting is that there are multiple brokerages at any time. Therefore, we can remove the influence of shocks that occur at the brokerage level using brokerage × year fixed effects.

We use the following approach to map the network structures of 2,718 brokerage × year cross sections in the IBES database over a 20-year period (1995–2014). We link two analysts in a brokerage network if they cover a common Global Industry Classification Standard (GICS) economic sector. It is natural to assume that analysts are more likely to interact with coworkers who cover the same industry

[2]Our approach avoids some shortcomings that accompany linear-in-means models of peer effects. These models often assume that individuals equally interact with everyone in the peer group, and vice versa. This assumption is unlikely to hold for interactions within brokerage houses where analysts are typically organized along industry sector lines. Moreover, Bramoullé, Djebbari, and Fortin (2009) and Jackson (2014) show that having knowledge of the network structure among individuals allows the econometrician to overcome the reflection problem (Manski (1993)).

sector(s) because brokerages are typically organized along sector lines (Sonney (2009)). Moreover, industry knowledge is particularly important in equity research (Brown, Call, Clement, and Sharp (2015)). Consider three analysts in a brokerage: Alice who covers utilities, Carol who covers energy, and Bob who covers both sectors. As Bob's coverage portfolio straddles the two sectors, he can receive information from both Alice and Carol. Such information exchange could help Bob form a more complete picture of the firms he covers because i) economic shocks can propagate across industry sectors (Ahern and Harford (2014)) and ii) both within- and across-industry expertise are valuable in equity research (Kadan, Madureira, Wang, and Zach (2012)).

The diffusion of ideas in a brokerage is analogous to the spread of diseases in the global aviation network. As aviation hubs are more prone to catch diseases, analysts who occupy *central* positions in the brokerage network are more likely to receive their coworkers' information and ideas.[3] We thus hypothesize that a central analyst can leverage her coworkers' expertise to ease her information-processing constraints and gain an information edge. The implication is that central analysts will produce more accurate and more informative equity research.

To better understand the central analysts in our data, we compare them with the peripheral (i.e., noncentral) coworkers employed at their respective brokerage. On average, central analysts have an additional 6 months of work experience. They cover 1.2 more sectors and 1.6 more firms than their peripheral coworkers. Firms covered by central analysts are smaller but otherwise have comparable leverage, book-to-market ratios, and analyst coverage compared with those covered by peripheral coworkers. A starker contrast emerges in the research acumen of central analysts as they are significantly more likely to be recognized as Institutional Investor star analysts.

Before proceeding with our main analysis, we first verify that information flows through our network structures. We examine the co-occurrences of forecast revisions, which we call tandem revisions because the timing of revisions is likely to coincide with the exchange of information and ideas. Specifically, we show that the network distance between analysts predicts the frequency of tandem revisions. Motivated by recent studies, we also find evidence of information exchange along social links stemming from shared ethnicity and past working relationships.[4] However, these social ties do not subsume the information flow through our constructed networks.

Next, we examine the spread of information and ideas within a brokerage by testing the following pathway. If a central analyst incorporates more of her coworkers' ideas, she should also be more likely to update those inputs when they are revealed to be erroneous. Consistent with this prediction, central analysts issue larger forecast revisions upon the revelations of their coworkers' forecast errors. In a placebo test, we find that central analysts do not respond to the forecast errors

[3] Recent studies adopt similar identifying assumptions to capture information flow, albeit not to study peer effects (Ahern (2017), Rossi, Blake, Timmermann, Tonks, and Wermers (2018), and Li and Schürhoff (2019)).

[4] Peer effects are stronger between individuals of the same ethnicity in investment decisions (Pool, Stoffman, and Yonker (2015)) and contagion of financial fraud (Dimmock, Gerken, and Graham (2018)).

of noncoworkers, which rules out the possibility that they are reacting to general information rather than their peers' information. Central analysts also weigh the quality of their coworkers' information by responding more strongly to the realized forecast errors on i) stocks covered by high-ability coworkers and ii) stocks that are strategically important (SI; Harford et al. (2019a)) to their coworkers. This finding implies that among the vast amount of information available, central analysts focus on the better ideas generated by their brokerage peers.

Our main analysis examines the relationship between analyst centrality and forecast performance. We find strong support for our hypothesis that central analysts possess an information edge as their earnings forecasts are significantly more accurate. Further tests show that analyst centrality captures both within- and cross-industry information exchange, and its effect on forecast accuracy extends beyond the merger & acquisition (M&A) setting (Hwang, Liberti, and Sturgess (2019)). Outperformance of central analysts is concentrated in hard-to-value stocks, which is consistent with the view that access to coworkers' expertise is particularly useful when valuation is complex and information-processing constraints are binding. As mentioned earlier, our regressions include brokerage × year fixed effects to capture common shocks that affect all analysts employed at the same brokerage in a given year. These fixed effects absorb brokerage-level heterogeneity such as brokerage prestige, research resources, and common analyst traits (e.g., educational background and analytical ability). Additional tests show that the peer learning effect is orthogonal to existing analyst skill or ability measures. An interesting implication emerges from our network perspective of the brokerage house. By leveraging their coworkers' industry expertise, central analysts can offset the information-processing constraints associated with complex coverage portfolios (Clement (1999)), hence offering a potential explanation for the existence of generalists (Crane and Crotty (2020)).

The network approach offers distinct advantages in the evaluation of peer effects, but it is not a panacea. Thus, we are cautious in making causal inferences. It is possible that unobservable factors that affect an analyst's performance preordain her network position. To address these issues, we exploit quasi-exogenous shocks from brokerage mergers (Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012)) that change the network structures of acquirer brokerages. Although prior studies use these shocks to examine outcomes at the stock level, we use these events to study outcomes at the analyst level. Specifically, we analyze the performance of incumbent analysts who experience changes in centrality when analysts from the target integrate into the acquirer's network.

An important feature of our identification strategy is that these mergers are staggered across time. This dissipates time-specific forces, such as macroeconomic shocks or regulatory changes, that could jointly affect performance and the reshuffling of an analyst's network position. Moreover, brokerage mergers are motivated by high-level business reasons (Derrien and Kecskés (2013)) and typically occur long after an analyst is hired. Thus, the occurrence of a merger is plausibly exogenous to influences at the individual analyst level. Of course, this does not guarantee that the change in the network position of a given analyst is entirely random. Therefore, we adopt a more stringent econometric specification by including analyst × firm × merger fixed effects to account for the endogenous decision by an analyst to cover a particular firm.[5] Our identification thus comes from the merger-induced variation in the centrality of the *same analyst* covering the *same firm*. Estimates from our difference-in-difference model show that analysts who become more central are significantly more accurate in the post-merger period.

We also examine whether brokerage conditions and the information environment moderate the role of peer effects. First, we find that the relationship between centrality and performance is stronger in midsize brokerages than in the smallest and biggest brokerages. This pattern may reflect the trade-off between stiffer in-house competition (Groysberg, Healy, and Maber (2011), Yin and Zhang (2014)) and access to higher-quality coworkers at larger brokerages. Second, we find some evidence that high turnover rates can dampen the effectiveness of information exchange among coworkers. Third, the information edge of central analysts is more pronounced after the adoption of Regulation Fair Disclosure (Reg FD). This finding suggests that analysts may lean on their coworkers' expertise when other information acquisition channels are stymied.

Our final analysis quantifies the information advantage of central analysts. We create a calendar-time portfolio strategy that exploits analysts' forecast revisions. On each day, the strategy buys (sells) stocks that receive upward (downward) forecast revisions from an analyst. We execute this strategy separately for the central and peripheral analysts within each brokerage. The portfolio strategy based on central analysts earns a significant premium of up to 24% annualized over its peripheral counterpart.[6]

Our article complements recent studies of peer effects by focusing on a professional channel rather than a social one. Peer effects are ubiquitous; they influence household financial decisions (Maturana and Nickerson (2019), Ouimet and Tate (2020)), executive decisions (Shue (2013)), stock market activities (Hong, Kubik, and Stein (2004), Hong, Kubik, and Stein (2005), and Brown, Ivković, Smith, and Weisbenner (2008)), and entrepreneurship (Lerner and Malmendier (2013)). Peers can even shape the economic attitudes that drive these outcomes (Ahern, Duchin, and Shumway (2014)).

We document that peer effects are an important input for generating equity research.[7] Our article is closest to Hwang et al. (2019), who examine M&As to show that an analyst issues more accurate earnings forecasts on acquirer firms when her coworker previously covered the target firm. M&As provide a unique setting to identify peer effects because brokerages may have strong incentives in these situations to coordinate information exchange among analysts for investment banking and/or trading business considerations. However, if coordination is costly,

[5]Jacob, Lys, and Neale (1999) and Clement, Koonce, and Lopez (2007) use analyst × firm fixed effects to capture "analyst–company alignment," which refers to the endogenous decision by an analyst to cover a particular firm. The determinants of this coverage decision include various unobservable attributes including an analyst's aptitude (natural ability), knowledge gained from learning-by-doing, and brokerage characteristics (e.g., resources, on-the-job training, and business connections).

[6]We find the largest premium with the 5-day holding period (9.6 basis points per day). This premium is also present but smaller with the 10-day and 30-day holding periods.

[7]Analysts benefit from management access (Green, Jame, Markov, and Subasi (2014)), prior industry experience (Bradley et al. (2017)), knowledge of corporate insiders' trades (Li, Mukherjee, and Sen (2021)), and support from in-house macroeconomists (Hugon, Kumar, and Lin (2015)).

information exchange may not occur during normal circumstances. We find that information exchange among coworkers is widespread and perhaps more common than previously known.

A unique feature of our network setting is the ability to trace information exchange at the within- and cross-sector levels. Documenting higher-order, cross-sector information flows between coworkers is a potentially novel contribution because most M&As occur within the same industry. Our tests also reveal that central analysts are selective in incorporating the higher-quality signals of their peers and are more skilled at forecasting complex and hard-to-value firms. Hence, peer effects represent a potential mechanism through which analysts overcome attention and information-processing constraints (Clement (1999), Harford et al. (2019a), and Hirshleifer et al. (2019)).

Our article more broadly contributes to the burgeoning literature on how networks underpin various economic phenomena. Network dynamics explain the propagation of merger activity (Ahern and Harford (2014), Harford, Schonlau, and Stanfield (2019b)), investment decisions (Hochberg, Ljungqvist, and Lu (2007), Hochberg, Ljungqvist, and Lu (2010), and Rossi et al. (2018)), and market making (Li and Schürhoff (2019)). In contrast, we use networks to identify peer effects among equity analysts. Our results suggest that information networks within organizations can help alleviate information frictions in financial markets.

II. Data and Methodology

This section describes our data and the building blocks of our brokerage networks. To capture peer effects and the propensity of an analyst to exchange information and ideas with her coworkers, we create two measures of centrality based on the position of an analyst in the brokerage network.

A. Linking Analysts in a Brokerage Network

We build an information network within each brokerage by linking an analyst to a coworker if they cover at least one common sector in the calendar year. Specifically, we construct network links based on the FY-1 forecast data from the Detailed History file of IBES. To align with common industry practice, we define sectors using 2-digit GICS (Bhojraj, Lee, and Oler (2003)). Our findings also hold using more granular industry classification schemes. Brokerage networks are updated annually to reflect structural changes due to analyst turnover or coverage reassignments.

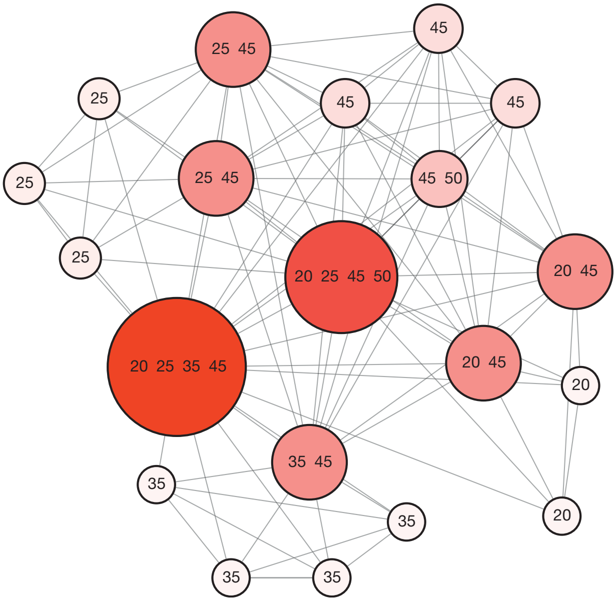
Sector overlaps represent a natural nexus of information exchange for several reasons. First, brokerages are often organized along sector lines (Sonney (2009)). This organizational structure facilitates the sharing of backend resources (e.g., data, research assistants, and support staff) and interactions among analysts covering the same sector. Second, analysts have strong economic reasons to solicit feedback from coworkers who cover the same sector(s) because industry expertise is highly valued (e.g., Brown et al. (2015)).

Figure 1 illustrates the network structure of Roth Capital Partners' brokerage in the year 2005. Each node represents an analyst, and the numbers denote the

FIGURE 1

An Example of a Brokerage Network

Figure 1 maps the network structure of Roth Capital Partners in the year 2005. The nodes and lines represent analysts and links, respectively. The numbers in each node indicate the 2-digit Global Industry Classification Standard (GICS) sectors covered by the analyst in the year. Two analysts share a link if they cover a common GICS sector. Bigger and more intensely colored nodes have more direct links to brokerage coworkers.



GICS sectors covered by the respective analyst. The lines represent links between analysts in the brokerage. Larger and more intensely colored nodes have more direct links. Notably, two analysts can cover the same number of sectors, but have different numbers of direct links. For instance, an analyst who covers GICS sectors 25 and 45 has more direct links than a coworker who covers GICS sectors 45 and 50. This example illustrates that an analyst's potential for information exchange partly depends on the composition of her coworkers' coverage portfolios.

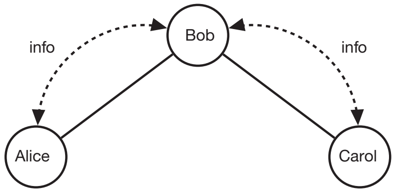
B. Measures of Analyst Centrality

Centrality measures provide a useful metric to quantify the *connectedness* of an analyst in a brokerage network. The concept of network connectedness is multifaceted. In some settings, it is sufficient to only consider direct network neighbors. In equity research, analyst expertise reaches across sectors (Kadan et al. (2012)), so we need to account for both direct and indirect connections in the brokerage network. To do so, we measure an analyst's eigenvector centrality (EIGENVECTOR) and closeness centrality (CLOSENESS) in her brokerage network. These two measures are often used in network studies and are suitable for modeling the properties of complex information flows (Borgatti (2005)). We provide technical discussions and working examples of both measures in the Supplementary Material.

FIGURE 2

A Simple Network of Three Analysts

Figure 2 presents a simple network with three analysts: Alice, Bob, and Carol. The solid lines represent the network links among the analysts. Alice is linked to Bob, Bob is linked to Carol, but Carol is not linked to Alice. Hence, the network distances of Alice–Bob and Alice–Carol are 1 and 2, respectively.



The EIGENVECTOR measure captures the breadth and richness of information and ideas received from coworkers. It is defined recursively based on the principal eigenvector of the brokerage network's adjacency matrix. Intuitively, an analyst is more central if she is linked to coworkers who are themselves central in the network. The recursive nature of EIGENVECTOR thus captures the exchange of both within- and cross-sector information.

The CLOSENESS measure captures how quickly information reaches an analyst in the network. It is a function of an analyst's total network distance to all her coworkers. We define network distance between two analysts as the length of the shortest network path between them. An analyst who is more distant from her coworkers should receive information less quickly, on average. As an example, consider a simple network presented in Figure 2 in which i) Alice is linked to Bob, ii) Bob is linked to Carol, but iii) Carol is not linked to Alice. Hence, the Alice–Bob and Alice–Carol network distances are 1 and 2, respectively.

Our centrality measures can capture dimensions of information exchange that are missed by a simple count of an analyst's direct links. Centrality quantifies two important facets of information exchange that are relevant in a finance context: the richness of information and the speed of information acquisition. Because analysts compete to incorporate novel information into forecasts quickly, we expect both measures of analyst centrality to predict better forecast performance.

C. Control Variables

This section describes the control variables for the analyst and firm characteristics used in our tests. All continuous variables are winsorized at the 1st and 99th percentile values to reduce the influence of outliers. Further details are available in the Supplementary Material.

Because analyst experience affects forecast outcomes, we calculate the logarithms of an analyst's total experience (GENERAL_EXP) and firm-specific experience (FIRM_EXP). To account for the complexity of an analyst's coverage portfolio, we control for the number of unique firms (FIRM_BREADTH) and the number of GICS sectors (INDUSTRY_BREADTH) covered by the analyst during the year. In our forecast accuracy tests, we control for analyst effort (REVISION_FREQ) and forecast nearness to earnings announcements (HORIZON). We also control for LOWBALL because Hilary and Hsu (2013) find that analysts

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strategically increase forecast error consistency through lowballing. Finally, we account for firm heterogeneity by controlling for analyst coverage (ANALYST_COV), firm size (TOTAL_ASSETS), book-to-market ratio (BOOK_TO_MARKET), leverage (LEVERAGE), and a negative earnings indicator (LOSS).

D. Descriptive Statistics

Our sample comprises 2,718 brokerage × year cross sections, 9,541 analysts, and 52,299 analyst–year observations from the years 1995–2014 using the May 2015 vintage of the IBES database. Panel A of Table 1 presents summary statistics at the analyst–year level. The median analyst covers 11 firms and 1 GICS sector. However, consistent with Sonney (2009), many analysts in our sample also cover multiple sectors. The median analyst has 12 direct links to her coworkers and is employed at a brokerage with 40 analysts. The EIGENVECTOR measure has a median (mean) of 0.130 (0.161) with an interquartile range of 0.202, whereas the

TABLE 1

Descriptive Statistics

Panel A of Table 1 reports the summary statistics of analyst characteristics at the analyst–brokerage–year level. Panel B reports the Pearson pairwise correlations among these variables in percentage points. Panel C reports the tests of differences between central and peripheral analysts. In every brokerage × year cross section, we sort the analysts by either EIGENVECTOR or CLOSENESS. Analysts in the top (bottom) tercile of EIGENVECTOR are assigned to the central (peripheral) group. We do likewise for CLOSENESS. See Section II.B and the Supplementary Material for details on EIGENVECTOR and CLOSENESS. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary Statistics

	N	Mean	Std. Dev.	p10	p25	p50	p75	p90
EIGENVECTOR	52,299	0.161	0.136	0.008	0.045	0.130	0.247	0.359
CLOSENESS	52,299	0.572	0.187	0.370	0.469	0.555	0.667	0.818
NUM_DIRECT_LINKS	52,299	16.5	15.0	3	6	12	22	36
INDUSTRY_BREADTH	52,299	1.7	1.0	1	1	1	2	3
FIRM_BREADTH	52,299	11.3	7.0	3	6	11	15	20
GENERAL_EXP	52,299	56.5	52.6	3	15	41	84	134
BROKERAGE_EXP	52,299	36.4	36.6	3	11	25	50	86
BROKERAGE_SIZE	52,299	55.7	47.4	11	19	40	83	115

Panel B. Pearson Pairwise ρ

		a	b	c	d	e	f	g
EIGENVECTOR	a							
CLOSENESS	b	62.3						
NUM_DIRECT LINKS	c	−4.2	25.1					
INDUSTRY_BREADTH	d	50.6	46.9	30.8				
FIRM_BREADTH	e	3.4	11.9	11.6	27.1			
GENERAL_EXP	f	0.2	−3.6	0.6	4.0	32.8		
BROKERAGE_EXP	g	−1.3	1.6	10.0	9.8	34.1	62.8	
BROKERAGE_SIZE	h	−46.7	−21.2	66.0	−11.3	2.3	1.8	10.0

Panel C. Differences Between Central and Peripheral Analysts

	EIGENVECTOR			CLOSENESS		
	High	Low	Diff	High	Low	Diff
INDUSTRY_BREADTH	2.4	1.2	1.2***	2.5	1.2	1.3***
FIRM_BREADTH	12.5	10.9	1.6***	12.8	10.9	1.9***
GENERAL_EXP	61.8	56.4	5.4*	62.9	56.5	6.4***
BROKERAGE_EXP	40.4	33.7	6.7***	41.3	33.4	7.9***
II_STAR (%)	11.5	10.1	1.4***	12.5	10.2	2.3***
FORECAST_BOLDNESS (%)	54.4	51.0	3.4***	54.5	51.3	3.2***
ANALYST_COV	15.0	15.6	−0.65***	14.8	15.8	−1.0***
LEVERAGE	0.49	0.52	−0.03***	0.50	0.52	−0.02***
BOOK_TO_MARKET	0.41	0.40	0.01***	0.41	0.40	0.01***
TOTAL_ASSETS ($billion)	4.5	7.4	−2.9***	4.7	7.6	−2.9***

CLOSENESS measure has a median (mean) of 0.555 (0.572) with an interquartile range of 0.198. The median analyst has 41 months of total analyst experience and has spent 25 months at her current brokerage.

Panel B of Table 1 presents Pearson correlations between our measures of analyst centrality and other variables. The positive correlation ($\rho = 62.3\%$) between EIGENVECTOR and CLOSENESS suggests that they share a common component of centrality, but are also different enough to capture distinct facets of connectedness. Both centrality measures are correlated with INDUSTRY_BREADTH ($\rho = 50.6\%$ and $\rho = 46.9\%$, respectively), but are uncorrelated with FIRM_BREADTH, GENERAL_EXP, and BROKERAGE_EXP. Analyst centrality is negatively correlated with BROKERAGE_SIZE (i.e., number of analysts employed in the brokerage) in the pooled sample. However, inclusion of brokerage × year fixed effects in our regressions accounts for this correlation.

Panel C of Table 1 compares the characteristics of central analysts to those of their peripheral coworkers. In every brokerage × year cross section, we sort the analysts into terciles by EIGENVECTOR or CLOSENESS. Analysts in the top (bottom) tercile of either centrality measure are assigned to the high-centrality (low-centrality) group. On average, a central analyst covers about 1.2 (1.3) more industry sectors and 1.6 (1.9) more firms than her peripheral coworker based on EIGENVECTOR (CLOSENESS). Central analysts have 5–6 additional months of forecasting experience and have been at their current brokerage for 7–8 months longer than their peripheral counterparts. Central analysts are also more likely to be Institutional Investor star analysts (11.5% vs. 10.1%) and tend to issue more bold forecasts (54.4% vs. 51.0%). Central analysts cover smaller firms, but otherwise these firms have comparable BOOK_TO_MARKET, LEVERAGE, and ANALYST_COV to those firms covered by peripheral coworkers.

III. Information Flow in Brokerages: Tandem Revisions

Although information flow is not directly observable in our setting, we can use the timing of forecast revisions to deduce when analysts receive new ideas and information. If analysts exchange information with one another in a brokerage, the network *structure* should predict co-occurrences of their revisions, which we term tandem revisions.

To visualize our empirical design, we revisit our example in Figure 2. The direct link between Alice and Bob suggests that Alice and Bob will frequently issue tandem revisions. In contrast, Alice is not directly linked to Carol, so we expect that they will issue fewer tandem revisions because Alice's information is likely less relevant to Carol's, and vice versa. Alice and Carol may still indirectly share information through Bob, who is directly linked to both of them.

To operationalize this idea, we perform the following procedure for every possible analyst–coworker pair in a brokerage network each year.

- Find the network distance between the analyst–coworker pair.
- Count the number of tandem revisions made by the analyst–coworker pair in the year. We classify two forecast revisions as a tandem revision if they occur within $\pm\lambda$ days of each other. We adopt various values of λ to ensure robustness.

Following equation (1), we then regress the number of tandem revisions (NUM_TANDEM) on a set of network distance indicators. For example, the $1_{\text{NETWORKDISTANCE}=2,i,j,t}$ switches on if analysts i and j are two steps apart in the brokerage network.

$$\text{(1)} \qquad \text{NUM\_TANDEM}_{i,j,t} = \sum_{n=1}^{N} \beta_n 1_{\text{NETWORKDISTANCE}=n,i,j,t} + \theta \text{CONTROLS}_{i,f,t} + \varepsilon_{i,j,t}, \quad \forall i \neq j.$$

To account for structural autocorrelation in network data, we estimate quadratic assignment procedure (QAP) regressions.[8] We first estimate specification equation (1) to obtain the baseline set of coefficient estimates. To obtain standard errors of our estimates, we next perform 500 rounds of the QAP procedure. Every round of the procedure i) permutes the NUM_TANDEM variable among analysts in the same brokerage each year and ii) reestimates equation (1) on this permuted data set. Thus, the QAP procedure produces a counterfactual distribution of coefficient estimates. To perform statistical inference, we benchmark our baseline set of coefficient estimates against this counterfactual distribution.[9] Table 2 presents results from our QAP regressions. The parentheses contain the mean coefficient estimates and their standard deviations from the counterfactual distributions.

Our results indicate that the network distance between an analyst pair predicts the frequency of tandem revisions. Column 1 of Table 2 shows that a pair of directly linked analysts makes an average of 24.4 tandem revisions per year. Information exchange among analysts also extends beyond direct connections. For example, analyst pairs who are two steps apart make an average of 17.4 tandem revisions, which represents a −29% decrease relative to the activity between directly linked analysts. The incremental change from two steps to three or more steps is smaller at −8%. These patterns suggest that analysts use both intra- and intersector information from their coworkers to make forecasts. Our findings are consistent with the evidence in Kadan et al. (2012) that sector-specific information is most relevant, but cross-sector information is also useful to analysts.

Column 2 of Table 2 includes controls for analyst-pairwise characteristics. We find that analysts who share the SAME_ETHNICITY or are EX_COLLEAGUES also tend to revise in tandem. This finding is consistent with evidence that social familiarity promotes information exchange among peers (Pool et al. (2015), Dimmock et al. (2018)). Importantly, the network distance indicators largely retain their predictive power in this augmented model, which suggests that our peer learning effect is distinct from a social familiarity effect. We also find fewer

[8]The Supplementary Material contains a supplementary discussion of structural autocorrelation in network data and the QAP procedure. OLS models tend to underestimate standard errors in a network setting (Krackhardt (1988)). To see why, we revisit the Alice-Bob-Carol setup. In predicting the number of tandem revisions made by Alice and Carol, their information has to pass through Bob. So, NUM_TANDEM between Alice-Carol is in fact correlated with NUM_TANDEM between both Alice-Bob and Bob-Carol. This problem of nonindependence becomes more complex and severe in larger networks.

[9]The benchmarking procedure is similar to statistical inference with the bootstrap procedure. For example, the p-value on a coefficient estimate is the proportion of estimates in the counterfactual distribution that are more extreme.

TABLE 2

Tandem Revisions Between Analysts and Coworkers

Table 2 presents the results from quadratic assignment procedure (QAP) network regressions. The Supplementary Material provides a detailed discussion of QAP network regressions. The unit of observation in these regressions is an analyst pair in the brokerage. The dependent variable is N_TANDEM (the number of tandem revisions made by an analyst pair in the year). If an analyst and a coworker make two revisions that occur within λ days of each other, those revisions are tandem revisions. We consider three values of λ: 3 in columns 1 and 2, 5 in column 3, and 15 in column 4. The key independent variables are the network distance indicators (corresponding network distance; DIRECT_LINK (1), LINK_AT_2_STEPS (2), and LINK_AT_MORE_STEPS (≥3)). Refer to Figure 2 for an intuitive explanation of network distances. For each variable, we construct a distribution of coefficient estimates over 500 QAP permutations. Parentheses contain the mean and standard deviation of these distributions. To obtain statistical inference, we benchmark our point estimates against these empirical distributions of coefficient estimates. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: NUM_TANDEM			
λ window	3 days	3 days	5 days	15 days
	1	2	3	4
DIRECT_LINK	24.43***	22.92***	32.96***	93.20***
	(4.40 ± 0.19)	(4.05 ± 0.21)	(5.82 ± 0.31)	(16.25 ± 0.87)
LINK_AT_2_STEPS	17.41***	15.60***	22.64***	64.83***
	(2.47 ± 0.19)	(2.08 ± 0.21)	(3.07 ± 0.30)	(8.75 ± 0.87)
LINK_AT_MORE_STEPS	16.06***	14.61***	21.30***	60.57***
	(2.71 ± 0.23)	(2.23 ± 0.24)	(3.30 ± 0.35)	(9.31 ± 1.00)
Other Predictors				
SAME_ETHNICITY		3.37***	4.83***	13.73***
		(0.65 ± 0.21)	(0.89 ± 0.30)	(2.57 ± 0.86)
EX_COLLEAGUES		20.05***	28.84***	81.69***
		(6.63 ± 0.44)	(9.63 ± 0.64)	(27.21 ± 1.83)
Δ_BROKERAGE_EXP		0.07***	0.10***	0.30***
		(0.05 ± 0.00)	(0.08 ± 0.00)	(0.22 ± 0.01)
SAME_COHORT		−0.36***	−0.60***	−1.85***
		(−1.01 ± 0.12)	(−1.53 ± 0.18)	(−4.50 ± 0.50)
No. of networks	2,660	2,660	2,660	2,660

tandem revisions between analysts who joined the brokerage in the same year (SAME_COHORT) and have similar levels of brokerage experience. Therefore, competitive pressures among coworkers may discourage information exchange, but the economic effects are relatively small. Columns 3 and 4 show that our conclusions are unchanged when we adopt other values of λ in the definition of tandem revisions.[10]

Overall, we find strong evidence that our brokerage networks capture information flow among analysts and their coworkers. Apart from sector-specific information exchange, we find evidence of cross-sector information flows, which supports the existence of cross-industry expertise documented in Kadan et al. (2012).

IV. Peer Effects and Forecast Revisions

We tackle the empirical challenge that we do not directly observe how analysts incorporate information into their forecasts. To infer the spread of information among coworkers, we test the following pathway. Suppose an analyst initially incorporates her coworkers' ideas into her forecasts, and her coworkers' views are revealed to be wrong. Then, the analyst should rationally update her forecasts to

[10]In the Supplementary Material, we repeat our analysis on a sample without forecast revisions that occur in proximity to material firm disclosures. Our conclusions remain unchanged in those robustness tests.

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unwind those inputs. We hypothesize that a central analyst will issue larger revisions to unwind her coworkers' forecast errors because she would have previously incorporated more of her coworkers' information into her forecasts.[11]

A. Revisions That Unwind Coworkers' Erroneous Information

To implement the unwinding test, we create two variables: COWORKER_OPT and SIGNED_REVISION. The variable COWORKER_OPT is defined as the proportion of optimistic forecast errors (OPT_ERR) within the past 30 days made by coworkers. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share. For an analyst i from brokerage g who makes a forecast revision on date d for firm f in year t,

$$\text{(2)}\qquad \text{COWORKER\_OPTIMISM}_{i,d} = \frac{\sum_{\substack{j\in g\\ j\neq i}} \sum_{f} \text{OPT\_ERR}_{j,f,t}}{\text{TOTAL\_\#OPT\_ERR}}, \quad \forall t \in [d-30, d],$$

$$\text{OPT\_ERR}_{j,f,t} = \begin{cases} 0, & \text{EPS\_FORECASE}_{j,f,t} \leq \text{ACTUAL\_EPS}_{f,t}, \\ 1, & \text{EPS\_FORECAST}_{j,f,t} > \text{ACTUAL\_EPS}_{f,t}. \end{cases}$$

Our dependent variable SIGNED_REVISION is defined as the signed difference between an analyst's revision value and her previous forecast value, deflated by the absolute value of the latter. A positive SIGNED_REVISION reflects an upward shift in an analyst's earnings forecast. To reduce the influence of firm-specific news on our measure, we exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within $[-1, 0]$ day of the revision.

$$\begin{aligned} \text{(3)}\qquad \text{SIGNED\_REVISION}_{i,f,d} = {} & \alpha + \beta_1(\text{CENTRALITY}_{i,d} \times \text{COWORKER\_OPT}_{i,d}) \\ & + \beta_2 \text{CENTRALITY}_{i,d} + \beta_3 \text{COWORKER\_OPT}_{i,d} \\ & + \theta \text{CONTROLS}_{i,f,d} + \eta_{g,t} + \varepsilon_{i,f,d}. \end{aligned}$$

Next, we estimate regression specification equation (3). The key variable of interest is the interaction term COWORKER_OPT × CENTRALITY. We include controls for analysts' experience, coverage portfolio complexity, and stock performance in the run-up to the forecast revision date. Our regressions also include brokerage × year fixed effects ($\eta_{g,t}$) to absorb the influence of brokerage-level shocks that might be correlated with analyst outcomes. Such shocks include on-the-job training, brokerage prestige, or research resources (e.g., Clement (1999), Hugon et al. (2015)). These fixed effects can also absorb the common traits of analysts employed by a brokerage, such as educational background or analytical ability.

Table 3 reports that central analysts are more sensitive to the revelations of their coworkers' forecast errors. Column 1 reports that $\widehat{\beta}_1$ is significantly negative, which suggests that analysts with higher EIGENVECTOR issue more negative forecast revisions when COWORKER_OPT is high. This pattern suggests that a central analyst initially incorporates more of her coworkers' ideas into her forecasts,

[11] This empirical design is similar in spirit to Clement, Hales, and Xue (2011), who study analysts' revisions in response to revisions made by competing analysts on the same stock.

but subsequently issues stronger downward revisions upon revelations that her coworkers have been optimistic.

An alternative interpretation of this finding is that central analysts possess a superior ability to process all types of information. If so, central analysts should also respond more strongly to the forecast errors of noncoworkers. To assess this alternative story, we construct a measure of GLOBAL_OPT as an analog of COWORKER_OPT, but derived from noncoworkers' forecast errors in the same 30-day window. Thereafter, we augment our regression model with interaction terms between GLOBAL_OPT and either measure of analyst centrality. Our results in column 2 of Table 3 are inconsistent with the information-processing interpretation. Central analysts do not make more negative revisions in response

TABLE 3

Response to the Revelations of Coworkers' Errors

Table 3 examines whether central analysts revise their forecasts in response to the revelation of their coworkers' errors. For every forecast revision of an analyst, we collect all instances of forecast errors that are realized within the past 30 days. We next divide the pool of forecast errors into two groups: i) those made by brokerage coworkers and ii) those made by noncoworkers. Then, we define COWORKER_OPT (GLOBAL_OPT) as the proportion of optimistic forecast errors made by brokerage coworkers (noncoworkers) in the 30-day window. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share. The dependent variable, SIGNED_REVISION, is the signed difference between an analyst's revision value and her prior forecast value, deflated by the absolute value of the latter. The key independent variables are COWORKER_OPT, GLOBAL_OPT, and their respective interactions with either EIGENVECTOR or CLOSENESS. See Section II.B and the Supplementary Material for details on EIGENVECTOR and CLOSENESS. We exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within [−1, 0] day of the revision. Standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: SIGNED_REVISION			
	1	2	3	4
a × COWORKER_OPT	−0.100*** (0.038)	−0.100*** (0.038)		
a × GLOBAL_OPT		0.013 (0.038)		
b × COWORKER_OPT			−0.049* (0.026)	−0.051* (0.026)
b × GLOBAL_OPT				0.024 (0.025)
a: EIGENVECTOR	−0.131*** (0.018)	−0.134*** (0.021)		
b: CLOSENESS			−0.099*** (0.016)	−0.104*** (0.017)
COWORKER_OPT	0.011 (0.007)	0.011 (0.007)	0.025 (0.015)	0.026* (0.015)
GLOBAL_OPT		−0.006 (0.007)		−0.017 (0.015)
GENERAL_EXP	−0.000 (0.002)	−0.000 (0.002)	−0.000 (0.002)	−0.000 (0.002)
FIRM_EXP	0.002 (0.001)	0.002 (0.001)	0.002* (0.001)	0.002* (0.001)
FIRM_BREADTH	0.000** (0.000)	0.000** (0.000)	0.001*** (0.000)	0.001*** (0.000)
INDUSTRY_BREADTH	0.004** (0.002)	0.004** (0.002)	0.002 (0.002)	0.002 (0.002)
ANALYST_COV	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
$\lvert CAR_{-5,-2} \rvert$	0.008*** (0.000)	0.008*** (0.000)	0.008*** (0.000)	0.008*** (0.000)
No. of obs.	1,232,729	1,232,729	1,232,729	1,232,729
R^2	0.005	0.005	0.005	0.005
Brokerage × year FE	Yes	Yes	Yes	Yes

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to GLOBAL_OPT, but continue to respond more strongly to COWORKER_ OPT. We find similar results using CLOSENESS in columns 3 and 4.

Overall, our findings are consistent with the view that central analysts incorporate to a greater extent information learned from their coworkers. We find support for the peer learning hypothesis, but not for explanations related to information-processing ability.

B. Accounting for the Quality of Coworkers' Information

This subsection examines whether analysts take into account the quality of their coworkers' information.

1. High-Ability Coworkers

We hypothesize that central analysts will assign greater weights to the signals from their high-ability coworkers because these colleagues are more likely to possess valuable information and insights. Therefore, we should observe that central analysts revise their forecasts more strongly in response to the forecast errors of their high-ability coworkers.

To identify high-ability coworkers, we sort analysts within a brokerage based on their median forecast accuracy in the preceding year.[12] Analysts in the top and bottom terciles of forecast accuracy are classified as high-ability and low-ability, respectively. Using this classification, we construct two variables to test our hypothesis. For every analyst's revision, we first collect the realized forecast errors of all coworkers within the past 30 days. Then, we define HI_ABILITY_OPT (LO_ABILITY_OPT) as the proportion of optimistic forecast errors made by high-ability (low-ability) coworkers. We also construct an alternative measure of coworker ability by sorting analysts within a brokerage based on their median forecast boldness in the preceding year.[13]

Table 4 reports that central analysts respond more strongly to the realized forecast errors of high-ability coworkers. Consistent with a stronger revision response to forecast errors made by high-ability coworkers, column 1 shows a significantly negative coefficient estimate on the interaction term HI_ABILITY_OPT $\times$ EIGENVECTOR. In contrast, the revision response of central analysts to LO_ ABILITY_OPT is statistically insignificant. Column 2 reports similar patterns using CLOSENESS. In columns 3 and 4, we repeat the analysis using forecast boldness as a measure of coworker ability. We continue to find that central analysts have stronger revision responses to HI_ABILITY_OPT than to LO_ABILITY_OPT. Overall, these results suggest that central analysts primarily focus on the information produced by their high-ability coworkers.

[12]To measure an analyst's forecast accuracy on a stock, we follow Clement (1999) by computing the absolute difference between the analyst's earnings-per-share forecast and the firm's actual earnings per share (i.e., the forecast error), scaled by the average firm-year forecast error.

[13]Clement and Tse (2005) show that analysts who issue bold forecasts are more skilled. We define an analyst's forecast boldness as the proportion of bold forecasts issued by an analyst in the year. Following Clement and Tse (2005), an analyst's forecast is bold if it is either above or below both her prior forecast and the prevailing consensus forecast.

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TABLE 4

Response to the Revelations of Errors Made by High-Ability Coworkers

Table 4 examines whether central analysts revise their forecasts in response to the revelation of errors made by their high-ability coworkers. The key independent variables in this panel are HI_ABILITY_OPT, LO_ABILITY_OPT, and their respective interactions with either EIGENVECTOR or CLOSENESS. In columns 1 and 2 (3 and 4), we perform a within-brokerage sort of analysts by their median forecast accuracy (median forecast boldness) in the preceding year. Next, we classify analysts in the top and bottom terciles of this sort as high-ability and low-ability analysts, respectively. For each forecast revision of a given analyst, we collect all instances of coworkers' forecast errors that are realized within the past 30 days. We then divide the pool of forecast errors into two groups: i) forecast errors made by high-ability coworkers and ii) forecast errors made by low-ability coworkers. We define HI_ABILITY_OPT (LO_ABILITY_OPT) as the proportion of optimistic forecast errors made by high-ability (low-ability) coworkers. The dependent variable, SIGNED_REVISION, is the signed difference between an analyst's revision value and her prior forecast value, deflated by the absolute value of the latter. See Section II.B and the Supplementary Material for definitions and working examples of EIGENVECTOR and CLOSENESS. We exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within [−1, 0] day of the revision. We include all control variables used in Table 3. Standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: SIGNED_REVISION			
	Measures of Analyst Ability			
	Forecast Accuracy		Forecast Boldness	
	1	2	3	4
a × HI_ABILITY_OPT	−0.140*** (0.047)		−0.106** (0.048)	
a × LO_ABILITY_OPT	−0.018 (0.044)		−0.085* (0.047)	
b × HI_ABILITY_OPT		−0.119*** (0.033)		−0.056* (0.033)
b × LO_ABILITY_OPT		−0.001 (0.032)		−0.029 (0.033)
a: EIGENVECTOR	−0.160*** (0.029)		−0.157*** (0.028)	
b: CLOSENESS		−0.141*** (0.024)		−0.153*** (0.024)
HI_ABILITY_OPT	0.014 (0.009)	0.060*** (0.019)	0.018* (0.009)	0.034* (0.019)
LO_ABILITY_OPT	0.002 (0.008)	0.001 (0.018)	−0.000 (0.008)	0.005 (0.019)
No. of obs.	1,232,729	1,232,729	1,232,729	1,232,729
R^2	0.007	0.007	0.007	0.007
Controls	Yes	Yes	Yes	Yes
Brokerage × year FE	Yes	Yes	Yes	Yes

2. Coworkers' Strategically Important Stocks

Analysts allocate more time and attention to SI stocks in their coverage portfolios. Therefore, information produced by coworkers on these stocks should be of higher quality. Following Harford et al. (2019a), a stock is SI to an analyst if it is in the top quartile of i) market capitalization, ii) institutional ownership percentage, or iii) trading volume in her coverage portfolio in the year. For every analyst's revision, we first collect all coworkers' forecast errors within the past 30 days. Then, we define SI_OPT (NON_SI_OPT) as the proportion of optimistic forecast errors on (non-) SI stocks in the 30-day window.

Table 5 reports that central analysts issue more negative forecast revisions in response to revelations of SI_OPT. Across all three measures of strategic importance, we observe a significantly negative coefficient estimate on the interaction between SI_OPT and analyst centrality. In contrast, the revision response of central

TABLE 5

Response to the Revelations of Coworkers' Errors on Strategically Important Firms

Table 5 examines whether central analysts revise their forecasts in response to the revelation of errors made on the strategically important (SI) firm covered by their coworkers. The key independent variables in this table are SI_OPT, NON_SI_OPT, and their respective interactions with either EIGENVECTOR or CLOSENESS. For each forecast revision of a given analyst, we collect all instances of coworkers' forecast errors that are realized within the past 30 days. We next divide the pool of forecast errors into two groups: i) forecast errors made on SI firms and ii) forecast errors made on non-SI firms. Then, we define SI_OPT (NON_SI_OPT) as the proportion of forecast errors made on SI (non-SI) firms in the 30-day window. Following Harford et al. (2019a), we measure the strategic importance of a firm in an analyst's coverage portfolio based on its firm size, institutional ownership, or trading volume. Specifically, a firm is (not) SI to an analyst if it is in the top (bottom) quartile of firm size, institutional ownership, or trading volume in her coverage portfolio. The dependent variable, SIGNED_REVISION, is the signed difference between an analyst's revision value and her prior forecast value, deflated by the absolute value of the latter. See Section II.B and the Supplementary Material for definitions and working examples of EIGENVECTOR and CLOSENESS. We exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within [−1, 0] day of the revision. We include all control variables used in Table 3. Standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: SIGNED_REVISION					
	Measures of Strategic Importance (SI)					
	Firm Size		Inst. Ownership		Trading Volume	
	1	2	3	4	5	6
a × SI_OPT	−0.212**		−0.322***		−0.215***	
	(0.085)		(0.093)		(0.083)	
a × NON_SI_OPT	0.122		−0.119		−0.026	
	(0.093)		(0.089)		(0.098)	
b × SI_OPT		−0.182***		−0.318***		−0.181***
		(0.069)		(0.076)		(0.067)
b × NON_SI_OPT		0.124		0.038		0.086
		(0.076)		(0.071)		(0.080)
a: EIGENVECTOR	−0.163***		−0.150***		−0.157***	
	(0.022)		(0.022)		(0.022)	
b: CLOSENESS		−0.126***		−0.118***		−0.124***
		(0.019)		(0.019)		(0.019)
SI_OPT	0.080***	0.153***	0.075***	0.209***	0.073***	0.145***
	(0.023)	(0.043)	(0.026)	(0.048)	(0.022)	(0.042)
NON_SI_OPT	−0.012	−0.066	0.009	−0.029	0.019	−0.035
	(0.026)	(0.049)	(0.025)	(0.046)	(0.028)	(0.052)
No. of obs.	1,232,729	1,232,729	1,232,729	1,232,729	1,232,729	1,232,729
R^2	0.073	0.073	0.073	0.073	0.073	0.073
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage × year FE	Yes	Yes	Yes	Yes	Yes	Yes

analysts to NON_SI_OPT is statistically insignificant. These patterns are consistent with the view that analysts selectively incorporate the high-quality information produced by their coworkers.

V. Peer Effects and Forecast Performance

In this section, we test the prediction that central analysts make more accurate earnings forecasts.

A. Forecast Accuracy

We examine whether central analysts produce more accurate earnings forecasts by estimating specification equation (4). For analyst i in brokerage g who has an earnings forecast for firm f in year t,

$$\text{(4)}\qquad \text{NORM\_FORECAST\_ERR}_{i,f,t} = \alpha + \beta_1 \text{CENTRALITY}_{i,t} + \theta \text{CONTROLS}_{i,f,t} + \eta_{g,t} + \varepsilon_{i,f,t}.$$

Following Clement (1999), we define NORM_FORECAST_ERR as the absolute difference between an analyst's EPS forecast and the firm's actual EPS, scaled by the average firm–year forecast error. The regressions include controls for forecast characteristics, analyst-level traits, and firm-level financial variables. We double-cluster standard errors at the analyst–firm and brokerage–year levels because i) an analyst's forecast errors on a particular firm may be correlated over time and ii) analysts working in the same brokerage may exhibit cross-sectional correlation in their performance.

Our specifications also include brokerage × year fixed effects ($\eta_{g,t}$), which represent network fixed effects in our setting. Bramoullé et al. (2009) show that using network fixed effects can help to identify the influence of peer effects by absorbing correlated shocks and selection effects. In our setting, brokerage × year fixed effects absorb time-varying effects of brokerage-level heterogeneity (e.g., prestige and research resources) and the common traits (e.g., educational background and analytical ability) of analysts employed at the same brokerage.

The results in Table 6 indicate that central analysts produce significantly more accurate forecasts. Column 1 shows a significantly negative relationship between EIGENVECTOR and NORM_FORECAST_ERR. The improvement in forecast accuracy from an interquartile increase in EIGENVECTOR is comparable to the effect of GENERAL_EXP.[14] The estimated loadings on the control variables are consistent with prior studies. Higher forecast accuracy is associated with shorter forecast horizons, more experience, less lowballing behavior, higher revision frequency, and greater analyst following.

Analyst centrality captures the benefits of information exchange that arise from both within- and cross-industry links to peers. To explicitly account for the dimension of within-industry information exchange, we control for the number of direct links (NUM_DIRECT_LINKS) that an analyst has with her coworkers. In column 2 of Table 6, we find that both NUM_DIRECT_LINKS and EIGENVECTOR are significantly and negatively related to NORM_FORECAST_ERR. This finding suggests that both within- and cross-industry channels of information exchange are important to analysts.

Our findings are also robust to controls for coworkers' expertise in the M&A setting. Following Hwang et al. (2019), we define PEER_M&A_EXPERTISE as an indicator that switches on if i) an analyst covers an acquirer firm and ii) her brokerage coworker covers the target firm in the preceding year. Controlling for PEER_M&A_EXPERTISE, we find that it predicts higher forecast accuracy in column 3 of Table 6. Crucially, the relationship between EIGENVECTOR and forecast error remains negative and statistically significant. This finding suggests that analyst centrality captures access to coworkers' expertise beyond the M&A

[14]The effect on forecast accuracy from an interquartile increase in GENERAL_EXP is $0.005 \times \ln\left(\frac{84}{15}\right) = 0.009$. This is comparable to an interquartile increase in EIGENVECTOR $(0.202 \times 0.050 = 0.010)$.

TABLE 6

Peer Learning and Forecast Accuracy

Table 6 reports the results from panel regressions of analyst centrality on forecast accuracy. The dependent variable NORM_FORECAST_ERR is the absolute difference between an analyst's last firm–year forecast and the actual earnings per share, deflated by the average forecast error in the firm-year. The key independent variables are EIGENVECTOR, CLOSENESS, NUM_DIRECT_LINKS, and PEER_M&A_EXPERTISE. See Section II.B and the Supplementary Material for definitions and working examples of EIGENVECTOR and CLOSENESS. The NUM_DIRECT_LINKS of an analyst is her count of directly connected coworkers in the brokerage network. We define PEER_M&A_EXPERTISE as an indicator that equals 1 if i) an analyst covers an acquirer firm and ii) her brokerage coworker covers the target firm in the preceding year, and equals 0 otherwise. Double-clustered standard errors at the brokerage–year and analyst–firm levels are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: NORM_FORECAST_ERR				
	1	2	3	4	5
EIGENVECTOR	−0.050***	−0.046**	−0.059***	−0.046**	
	(0.017)	(0.021)	(0.020)	(0.021)	
CLOSENESS					−0.049**
					(0.019)
NUM_DIRECT_LINKS		−0.001**		−0.001**	−0.001**
		(0.000)		(0.000)	(0.000)
PEER_M&A_EXPERTISE			−0.037*	−0.037*	−0.037*
			(0.021)	(0.021)	(0.021)
REVISION_FREQ	−0.009***	−0.011***	−0.011***	−0.011***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HORIZON	0.003***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GENERAL_EXP	−0.005***	−0.007***	−0.007***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FIRM_EXP	0.003*	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FIRM_BREADTH	−0.000	−0.000*	−0.000	−0.000*	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INDUSTRY_BREADTH	0.005***	0.007***	0.005**	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
LOWBALL	0.068***	0.092***	0.092***	0.092***	0.092***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
LOSS	−0.006	−0.017***	−0.017***	−0.017***	−0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ANALYST_COV	−0.004***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEVERAGE	0.008	0.000	0.000	0.000	0.000
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
BOOK_TO_MARKET	0.001	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
TOTAL_ASSETS	0.009***	0.010***	0.011***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. of obs.	403,307	403,307	403,307	403,307	403,307
R^2	0.159	0.164	0.164	0.164	0.164
Brokerage × year FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes

setting. Column 4 shows that EIGENVECTOR continues to predict higher forecast accuracy when we jointly control for NUM_DIRECT_LINKS and PEER_M&A_EXPERTISE. Our conclusions are unchanged using CLOSENESS, and we report the most complete specification in column 5.

Our findings in Table 6 speak to the information-processing constraints that analysts face. Consistent with prior studies, we find that analysts with higher INDUSTRY_BREADTH are less accurate. This pattern suggests that generalists tend to experience binding information-processing constraints compared to specialists who cover stocks in a single sector. Although INDUSTRY_BREADTH and

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analyst centrality are positively correlated, they have opposite effects on forecast accuracy in our analysis. A novel implication from our analysis is that collaborative information exchange with coworkers may partially offset the constraints from covering multiple sectors.

B. Information Edge in Hard-to-Value Stocks

Next, we test a secondary prediction that coworkers' expertise is particularly useful in the valuation of hard-to-value stocks. We employ three methods to classify such firms. First, we identify firms with high exposure to intersector trade shocks because these firms require extensive gathering and processing of information across multiple sectors. Following Ahern and Harford (2014), we construct a network of intersector trade flows from the 2007 Bureau of Economic Analysis input–output table. Firms with higher TRADE_EXPOSURE are in industries that are more exposed to customer–supplier trade shocks.[15] Second, we identify COMPLICATED firms as those operating in at least three industry segments in the Compustat Historical Segments file (Cohen and Lou (2012)). Third, we identify firms with greater information uncertainty, which makes signal extraction more challenging. We measure the information uncertainty of a firm by its FORECAST_DISPERSION, which is defined as the standard deviation of its analysts' earnings forecasts in the previous year. To test whether central analysts more accurately forecast hard-to-value stocks, we interact EIGENVECTOR (CLOSENESS) with each of the three hard-to-value measures.

Table 7 reports that central analysts are more accurate in their forecasts of hard-to-value stocks. Column 1 reports that the interaction term EIGENVECTOR × TRADE_EXPOSURE loads significantly and negatively on NORM_FORECAST_ERR. This result suggests that the information edge of central analysts is sharpest when the assimilation of cross-sector knowledge is particularly important. This finding also supports the view that brokerage networks facilitate the exchange of both sector-specific and cross-sector information. Our inferences are similar in column 2 and 3, which report significantly negative loadings on the interaction terms EIGENVECTOR × COMPLICATED and EIGENVECTOR × FORECAST_DISPERSION, respectively. We repeat our analysis with CLOSENESS in columns 4–6 and find similar results. The evidence suggests that central analysts can overcome information-processing constraints in the valuation of hard-to-value firms with the help of novel and timely perspectives from their coworkers.

C. Shocks to the Brokerage Network Structures

Although our baseline tests address brokerage-level heterogeneity, it is possible that unobservable analyst attributes may confound our inferences. In this section, we examine this issue using quasi-exogenous shocks to the brokerage network structures around brokerage mergers (Hong and Kacperczyk (2010),

[15]We first construct a network with weighted links between buyer industries and seller industries. The weight of a link between a buyer industry and a seller industry is the average of i) trade dollar value deflated by dollar value of total buyer-industry's inputs and ii) trade dollar value deflated by dollar value of total seller-industry's production. We define TRADE_EXPOSURE of an industry as its eigenvector centrality in this intersector trade network.

TABLE 7

Peer Learning and Forecast Accuracy on Hard-to-Value Stocks

Table 7 reports the results from panel regressions of analyst centrality on forecast accuracy for hard-to-value stocks. The dependent variable NORM_FORECAST_ERR is the absolute difference between an analyst's last firm–year forecast and the actual earnings per share, deflated by the average forecast error in the firm-year. The key independent variables are TRADE_EXPOSURE, COMPLICATED, FORECAST_DISPERSION, and their respective interactions with either EIGENVECTOR or CLOSENESS. See Section II.B of the main text and the Supplementary Material for definitions and working examples of EIGENVECTOR and CLOSENESS. See the Supplementary Material for definitions of TRADE_EXPOSURE, COMPLICATED, and FORECAST_DISPERSION. Control variables from Table 6 of the main text are included in the regressions. Double-clustered standard errors at the brokerage–year and analyst–firm levels are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: NORM_FORECAST_ERR					
	1	2	3	4	5	6
a: TRADE_EXPOSURE	0.220*** (0.032)			0.303*** (0.068)		
b: COMPLICATED		0.010 (0.012)			0.075*** (0.027)	
c: FORECAST_DISPERSION			0.077*** (0.016)			0.167*** (0.032)
a × EIGENVECTOR	−0.735*** (0.168)					
b × EIGENVECTOR		−0.108* (0.061)				
c × EIGENVECTOR			−0.478*** (0.073)			
a × CLOSENESS				−0.338*** (0.115)		
b × CLOSENESS					−0.145*** (0.046)	
c × CLOSENESS						−0.288*** (0.054)
EIGENVECTOR	−0.007 (0.021)	−0.056*** (0.018)	−0.006 (0.020)			
CLOSENESS				−0.037** (0.018)	−0.064*** (0.016)	−0.037** (0.017)
No. of obs.	403,307	403,307	403,307	403,307	403,307	403,307
R^2	0.168	0.166	0.166	0.168	0.166	0.166
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Kelly and Ljungqvist (2012)).[16] Prior studies use these shocks to examine outcomes at the stock level, but we repurpose these events to study outcomes at the analyst level. These shocks induce changes in analyst centrality that are relatively free of influences at the individual analyst level.

1. Identifying Assumptions and Model Setup

Brokerage mergers have two features that are useful in our setting. First, brokerage mergers are staggered across years. This diffuses any time-specific forces, such as macroeconomic shocks or regulatory changes, that may induce changes in an analyst's network position. Second, brokerage mergers are typically motivated by high-level business reasons (Derrien and Kecskés (2013)) and occur long after an analyst is hired. Thus, reverse causality is unlikely in that a brokerage merger is plausibly exogenous to the attributes and abilities of an individual analyst.

[16]The Supplementary Material contains the list of brokerage mergers used in our analysis.

To assess how changes in analyst centrality affect performance, we estimate a difference-in-difference model. We focus on the changes in centrality of incumbent analysts (i.e., analysts who work at the acquirer brokerage) around brokerage mergers. We further require that an analyst remains at the acquirer brokerage and covers the same firm after the merger. Following this stringent requirement, we include analyst × firm × merger fixed effects in our regression models. Identification thus comes from variation in the centrality of an analyst who covers the *same firm* before and after the merger. These fixed effects eliminate persistent endogenous factors (e.g., aptitude) that lead an analyst to cover a particular firm (Jacob et al. (1999), Clement et al. (2007)). We constrain our analysis to the $[-3, +3]$ year window around brokerage mergers. For analyst i who covers firm f and experiences a merger m in event time $t = 0$, we estimate the following specification:

$$
\begin{aligned}
(5)\quad \text{NORM\_FORECAST\_ERR}_{i,f,m,t} &= \beta_1(\text{POST}_{m,t} \times \Delta_C\text{ENTRALITY}_{i,m}) + \beta_2 \text{POST}_{m,t} \\
&\quad + \gamma_{i,f,m} + \theta \text{CONTROLS}_{i,f,m,t} + \varepsilon_{i,f,m,t}, \\
\Delta_C\text{ENTRALITY}_{i,m} &= \text{CENTRALITY}_{i,m,t=+1} - \text{CENTRALITY}_{i,m,t=-1}, \\
\text{POST}_{m,t} &= \begin{cases} 0, & t < 0, \\ 1, & t \geq 0. \end{cases}
\end{aligned}
$$

The treatment Δ_CENTRALITY is an analyst's centrality at 1 year after the merger ($t = +1$) less her centrality at 1 year before the merger ($t = -1$). Notably, the main effect Δ_CENTRALITY is absorbed by the analyst × firm × merger fixed effects, which are represented by $\gamma_{i,f,m}$. The POST indicator switches on in the merger-year ($t = 0$) and thereafter. We later verify that our inferences are robust to alternative empirical treatments of the merger–year observations. Our specifications include the full set of control variables used in Table 6. Standard errors are clustered at the analyst–firm level.

We assess the parallel trends assumption by plotting the NORM_FORECAST_ERR of analysts around brokerage mergers. Because the treatment is continuous, we sort analysts within every brokerage into quintiles of Δ_EIGENVECTOR for every merger event. We next assign analysts in the corresponding top (bottom) quintile to the high (low) Δ_EIGENVECTOR group. Thereafter, we track the groupwise average NORM_FORECAST_ERR in the $[-3, +3]$ year event window around the merger.

Figure 3 contains several interesting patterns. Importantly, we observe no clear pre-merger trends in differences of NORM_FORECAST_ERR in $[-3, -1]$ years between the high and low Δ_EIGENVECTOR analysts. Thus, the treatment Δ_EIGENVECTOR is unlikely to be related to latent factors that drive future performance. Analysts with high Δ_EIGENVECTOR are slightly more accurate in the pre-merger period, although this gap is less pronounced in the Δ_CLOSENESS plot. This observation does not necessarily invalidate our analysis for the following reasons. First, the accuracy gap is economically small and statistically insignificant.[17] Second, during years $-3, -1$, analysts who will gain centrality were

[17]For every t in the pre-merger period, we perform a Welch t-test for differences in mean NORM_FORECAST_ERR between the high Δ_EIGENVECTOR and low Δ_EIGENVECTOR groups. The differences in means (t-statistics) between the two groups of analysts are 0.013 (0.48), 0.021 (1.51), and 0.015 (1.06) for $t \in \{-3, -2, -1\}$, respectively.

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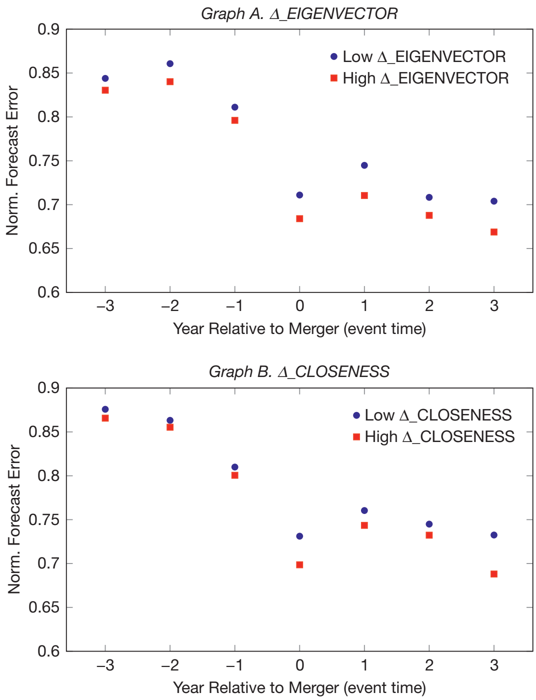
FIGURE 3

Analysts' Forecast Errors Around Brokerage Mergers

In Figure 3, we plot the dynamics of analysts' forecast performance around brokerage mergers. For every merger event, we sort analysts in the acquirer brokerage into quintiles of Δ_EIGENVECTOR. We define Δ_EIGENVECTOR as an analyst's EIGENVECTOR at event time $t = +1$ less her EIGENVECTOR at $t = -1$. We then assign analysts in the top (bottom) quintile to the high- (low-) Δ_EIGENVECTOR group. Thereafter, we track the groupwise average NORM_FORECAST_ERR in the [−3, +3]-year event window around every brokerage merger. We do likewise for CLOSENESS. We present plots using Δ_EIGENVECTOR and Δ_CLOSENESS in Graphs A and B, respectively.



not improving their accuracy relative to those analysts who will lose centrality. The absence of a pre-merger trend suggests that unobserved factors that are related to *abnormal* accuracy improvement over time are unlikely to determine treatment in our setting. Finally, our econometric specifications include analyst × firm × merger fixed effects, which absorb residual unobserved heterogeneity at the analyst–firm level.

Consistent with the view that increases in analyst centrality lead to better forecast accuracy, the accuracy gap between the two groups widens in the post-merger period. In both Graphs A and B, high Δ_CENTRALITY analysts are markedly more accurate relative to their low Δ_CENTRALITY counterparts. Because the NORM_FORECAST_ERR of both groups falls sharply in $t = 0$, we assign merger–year observations to the posttreatment period in our baseline model. Over time, we also observe that NORM_FORECAST_ERR trends downward in both groups. This trend may reflect learning-by-doing (Clement et al. (2007)), where an analyst's experience in covering a specific firm helps her make more accurate forecasts. It is also notable that both groups of analysts are more accurate in the post-merger period. Thus, organizational changes induced by mergers may lift the performance of all incumbent analysts through direct or indirect factors.

2. Difference-in-Differences Results

Table 8 presents results from the difference-in-differences analysis. Column 1 reports a significantly negative loading on POST × Δ_EIGENVECTOR. This suggests that the analysts who become more central after a brokerage merger subsequently exhibit higher forecast accuracy. Because the model includes analyst × firm × merger fixed effects, peer effects are identified through merger-induced changes in an analyst's centrality while holding fixed the covered firm and analyst. These fixed effects help to address unobserved heterogeneity such as innate ability and selection effects tied to analysts' coverage assignments. The models do not yield a main-effect estimate of Δ_EIGENVECTOR, which is invariant at the analyst × firm × merger level.

Because brokerage mergers can occur throughout the merger-year, observations that occur earlier in the calendar year may not experience treatment effects in $t = 0$. To ensure that our results are not sensitive to such measurement noise, we estimate additional specifications. In column 2 of Table 8, we assign merger–year forecasts to the pretreatment (posttreatment) period if the forecast was made before (on or after) the merger month. In column 3, we discard all merger–year observations from the analysis. Our findings are unchanged with

TABLE 8

Quasi-Exogenous Shocks to Brokerage Network Structures

Table 8 presents the results from the brokerage merger analysis. The dependent variable NORM_FORECAST_ERR is the absolute difference between an analyst's last firm–year forecast and the actual earnings per share, deflated by the average forecast error in the firm-year. For every brokerage merger event at event time $t = 0$, we track incumbent analysts who work at the acquirer before and after mergers. We further require that every analyst covers the same firm before and after the merger. In our difference-in-difference models, the treatment is an analyst's post-merger centrality ($t = +1$) less her pre-merger centrality ($t = -1$). We separately construct the treatment for EIGENVECTOR (columns 1–3) and CLOSENESS (columns 4–6). The posttreatment period is [0, +3] years after the merger. Correspondingly, the POST indicator equals 1 if an observation occurs within [0, +3] years after the merger, and equals 0 if the observation occurs within [−3, −1] years from the merger. In columns 2 and 5, we reclassify merger–year forecasts made before (on or after) the merger month to the pretreatment (posttreatment) period. In columns 3 and 6, we exclude all merger–year forecasts from our analysis. We include all control variables used in Table 6. Clustered standard errors at the analyst–firm level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The main treatment effects are absorbed by the fixed effects.

	Dependent Variable: NORM_FORECAST_ERR					
	1	2	3	4	5	6
Merger–year ($t = 0$) forecasts						
Reclassify	No	Yes	No	No	Yes	No
Exclude from sample	No	No	Yes	No	No	Yes
POST × Δ_EIGENVECTOR	−0.497***	−0.601***	−0.512***			
	(0.154)	(0.155)	(0.190)			
POST × Δ_CLOSENESS				−0.271**	−0.253**	−0.230*
				(0.109)	(0.110)	(0.135)
POST	−0.069***	−0.064***	−0.066***	−0.065***	−0.076***	−0.067***
	(0.010)	(0.010)	(0.014)	(0.010)	(0.010)	(0.014)
No. of obs.	9,963	9,963	8,221	9,963	9,963	8,221
R^2	0.291	0.290	0.328	0.290	0.290	0.328
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × firm × merger FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

these alternative specifications.[18] In columns 4–6, we repeat our analysis with Δ_CLOSENESS and obtain similar results.

Overall, the brokerage merger tests suggest that persistent analyst attributes and selection effects cannot explain our findings. However, we cannot rule out all possible interpretations, particularly time-varying analyst behavior. For example, an analyst who experiences a post-merger increase in centrality may work harder to maintain her newfound position in the brokerage. Nevertheless, an effort-based explanation and our preferred information exchange story are not necessarily mutually exclusive. Both effects can combine to produce the outcomes we observe.

VI. Additional Tests

We perform additional tests to better understand the mechanisms behind the peer effects we document. We describe the key findings in this section and report the results in the Supplementary Material.

A. Peer Learning and Measures of Analyst Ability or Skill

We perform additional analysis to show that the effect of analyst centrality on forecast accuracy is not subsumed by known measures of analyst ability or skill. We use two proxies for analyst ability. Following Clement and Tse (2005), we use FORECAST_BOLDNESS because high-ability analysts tend to make bold forecast revisions. To capture residual dimensions of forecasting skills, we identify an analyst who was recognized as an Institutional Investor star analyst (II_STAR) anytime in the prior 3 years. We continue to find that analyst centrality predicts higher forecast accuracy with the inclusion of FORECAST_BOLDNESS or/and II_STAR. Thus, the effect of analyst centrality on forecast accuracy is likely distinct from known measures of analyst ability. These findings also provide a more general setting to complement the evidence from the brokerage merger shocks to disentangle peer effects from analyst ability.

B. Peer Learning and the Brokerage Environment

We examine whether the internal brokerage environment moderates the effectiveness of peer learning. First, we focus on a key dimension of the brokerage environment (brokerage size). We find that central analysts exhibit higher forecast accuracy in all but the largest brokerages. The effect of analyst centrality on forecast accuracy is stronger in midsize brokerages than in small ones. The results support the view that at big brokerages, the effect of in-house competition, which may disincentivize information exchange, dominates the potential to interact with high-quality coworkers. The trade-off between these two effects is likely closer to the optimum for midsize brokerages than for the largest and smallest brokerages.

Second, we examine the analyst turnover rate. We find that the effect of EIGENVECTOR on forecast accuracy weakens as analyst turnover rates increase.

[18]As an additional robustness check, we assign merger-year observations to the pretreatment period. In this alternative specification, POST equals 1 if an observation occurs within $[+1, +3]$ years after the merger, and equals 0 in $[-3, 0]$ years before the merger. Our results are not sensitive to this alternative specification and are available in the Supplementary Material.

This pattern suggests that a high-turnover environment curtails peer learning as i) the brokerage is unable to retain its best analysts and ii) the integration of new employees into the brokerage requires time and effort, which draws attention and resources away from forecasting activities. Our results using CLOSENESS are more nuanced. Overall, there is suggestive evidence that a high-turnover brokerage environment is detrimental to peer learning.

C. Peer Learning and Regulation Fair Disclosure

After the adoption of Reg FD in Oct. 2000, firm managers cannot selectively release material information to analysts. Therefore, Reg FD stymied a critical information acquisition channel of analysts. We hypothesize that access to coworkers' expertise can partially fill the information void left by Reg FD. To test this hypothesis, we separately examine the effect of analyst centrality on forecast accuracy in the 5 years before (pre-Reg FD) and 5 years after (post-Reg FD) the year 2000. We find that the relationship between analyst centrality and forecast accuracy is present in the post-Reg FD period, but not in the pre-Reg FD period. Thus, our findings suggest that peer learning becomes more important in the wake of Reg FD.

VII. Calendar-Time Portfolio Strategy

We design a calendar-time portfolio strategy to quantify the information advantage of central analysts. On each day, the portfolio strategy buys (sells) stocks that receive an upward (a downward) forecast revision on an equal-weighted basis. To avoid the confounding effects of firm-level information events, we exclude a forecast revision if it coincides with the issuance of SEC Form-8Ks or earnings announcements. We then hold these long-short positions over the next 5, 10, or 30 days. We implement this portfolio strategy separately for i) analysts in the top tercile of centrality in their brokerage (central analysts) and ii) analysts in the bottom tercile of centrality in their brokerage (peripheral analysts). We then compute the *difference* in daily portfolio returns from these two implementations (Δ_L−S). If there are no stocks in any leg of our portfolio strategy on a particular day, we assign Δ_L−S to be the prevailing risk-free rate.

Table 9 presents the returns from our portfolio strategy. Although the long-short strategies of both central and peripheral analysts are profitable, the former consistently yields higher returns across all holding periods. With a 5-day holding period, the portfolio strategy earns an average daily premium (Δ_L−S) of about 9.6 basis points (24% per annum) over the peripheral portfolio strategy. This premium is also present over the 10-day and 30-day holding periods. Interestingly, these premiums are primarily driven by the short legs of our portfolio strategy. This pattern suggests that the bearish opinions of analysts are scrutinized more intensely by investors (e.g., Asquith, Mikhail, and Au (2005)).

We conduct additional tests to ensure that our inferences are robust. First, we require that every leg of the portfolio strategies has a minimum number of stocks (either 20 or 50). If this requirement is not met on a given day, we assign the Δ_L−S return on that day to be the risk-free rate. The profitability of the strategies is materially unchanged under this requirement. Second, we perform an additional

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TABLE 9

Calendar-Time Portfolio Strategies

Table 9 presents the results from the following calendar-time portfolio strategy. Every day, we form two long-short portfolios: i) long (short) stocks that receive upward (downward) forecast revisions from analysts who are in the top tercile of centrality in their brokerages and ii) long (short) stocks that receive upward (downward) forecast revisions from analysts who are in the bottom tercile of centrality in their brokerages. We hold these portfolios over [0, +5]-day, [0, +10]-day, and [0, +30]-day windows. We exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within [−1, 0] day of the revision. This table presents the average equal-weighted daily returns from these strategies. *t*-statistics are reported in parentheses.

Average Daily Portfolio Returns in Basis Points

	[0, +5] day			[0, +10] day			[0, +30] day		
	Long	Short	L−S	Long	Short	L−S	Long	Short	L−S
EIGENVECTOR									
Central	16.5	−14.4	30.9	12.6	−6.2	18.8	8.8	1.0	7.8
	(7.97)	(−6.32)	(29.36)	(6.19)	(−2.80)	(23.09)	(4.35)	(0.47)	(12.47)
Peripheral	14.7	−6.6	21.3	12.0	−1.4	13.4	8.9	4.0	4.9
	(7.64)	(−3.08)	(20.07)	(6.40)	(−0.67)	(15.43)	(4.76)	(1.97)	(6.94)
Δ_L−S			9.6			5.4			2.9
			(7.71)			(5.73)			(4.42)
CLOSENESS									
Central	15.9	−14.4	30.3	12.3	−6.2	18.5	8.7	1.0	7.7
	(7.85)	(−6.43)	(25.77)	(6.14)	(−2.85)	(23.51)	(4.35)	(0.48)	(12.70)
Peripheral	14.4	−6.8	21.2	11.9	−1.8	13.7	8.9	3.8	5.1
	(7.50)	(−3.17)	(20.27)	(6.36)	(−0.85)	(15.84)	(4.78)	(1.86)	(7.24)
Δ_L−S			9.1			4.8			2.6
			(7.49)			(5.22)			(3.84)

test to assess whether central analysts indeed have an information advantage by estimating regressions of $[0, +1]$-day cumulative abnormal returns around forecast revisions on analyst centrality. The results indicate that central analysts' forecast revisions attract larger market reactions. We report these results in the Supplementary Material. Overall, our analysis in this section reinforces the view that access to coworkers' expertise helps analysts produce more impactful research.

VIII. Conclusions

We find evidence that peer effects play an important role in the production of equity research. To identify the presence of peer effects, we model the brokerage house as a network where analysts exchange information and ideas. Using the timing of forecast revisions among analysts and their coworkers, we find that information flows through our constructed networks. For our main analysis, we use the network position of each analyst in a brokerage to construct measures of centrality. Centrality captures an analyst's access to the expertise of her brokerage coworkers. Our evidence suggests that central analysts initially incorporate more of their coworkers' views into their forecasts and subsequently unwind those inputs when these views are revealed to be erroneous. Our findings also indicate that central analysts possess an information edge as their earnings forecasts are more accurate and attract larger market reactions.

Using brokerage mergers as quasi-exogenous shocks to brokerages' network structures, we find that analysts who become more central are significantly more accurate in the post-merger period. Our econometric specifications rule out alternative explanations related to skill, aptitude, or endogenous coverage decisions.

Additional tests show that the peer learning effect is orthogonal to existing measures of analyst skill or ability. The influence of peer effects also varies with the analyst's environment. Central analysts perform better in i) small and midsize brokerages, ii) brokerages with lower analyst turnover rates, and iii) after the adoption of Reg FD. We believe that these empirical patterns are difficult to reconcile with most alternative interpretations of our results.

Overall, we find that coworkers act as a network of expertise in the production of equity research. Our findings imply that brokerage managers should consider their in-house information structures and set up appropriate incentives to facilitate information exchange. Although our study is silent on the dynamics of analysts' coverage assignments, our results show that the coverage portfolio affects how analysts interact with their coworkers. We leave a deeper examination of these issues to future research.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022000710.

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