3-2023

Peer effects in equity research

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Citation

PHUA, Kenny; THAM, Mandy; and WEI, Chi Shen. Peer effects in equity research. (2023). *Journal of Financial and Quantitative Analysis*. 58, (2), 647-676.

Available at: https://ink.library.smu.edu.sg/lkcsb_research/6782

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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.

`Keywords:` Peer effects, Analysts, Limited attention, Networks
`JEL classification:` D83, G14, G24

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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 useful in the production of equity research. This paper 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; Loh and Stulz, 2018; 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 education backgrounds or technical expertise. Such characteristics, rather than peer effects, could underlie any correlation we find in the output of

[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)

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 I/B/E/S database over a twenty 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 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

[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).

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., non-central) coworkers employed at their respective brokerage. On average, central analysts have an additional six 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 to 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 of non-coworkers, which rule-outs the possibility that they

[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; 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).

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 (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 relation 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 mergers & acquisitions (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 $\times$ 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, analytical ability). Additional tests show that the peer learning effect is orthogonal to existing measures of analyst skill or ability. 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. While prior studies use these shocks to examine outcomes at the stock level, we utilize 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 $\times$ firm $\times$ 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-differences 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 relation between centrality and performance is stronger in mid-sized 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,

[5] Jacob, Lys, and Neale (1999) and Clement, Koonce, and Lopez (2007) use analyst $\times$ 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, business connections).

the strategy buys (sells) stocks that receive upwards (downwards) forecast revisions from an analyst. We execute this strategy separately for the central and peripheral analysts within each brokerage. The portfolio strategy earns a significant premium of up to 24% annualized over its peripheral counterpart.[6]

Our paper complements recent peer effects studies 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; 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 paper 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 co-worker 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, 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.,

[6]We find the largest premium with the five-day holding period (9.6 basis points per day). This premium is also present but smaller with the ten-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).

2019a; Hirshleifer et al., 2019).

Our paper 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; 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.

II.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 I/B/E/S. To align with common industry practice, we define sectors using two-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 -

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 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.

II.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 multi-faceted. 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 Internet Appendix.

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`, and (ii) `Bob` is linked to `Carol`, but (iii) `Carol` is not linked to `Alice`. Hence, the `Alice-Bob` and `Alice-Carol` network distances are one and two, respectively.

- Figure 2 -

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.

II.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 Internet Appendix.

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 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).

II.D Descriptive statistics

Our sample comprises 2,718 brokerage $\times$ year cross-sections, 9,541 analysts, and 52,299 analyst-year observations from the years 1995–2014 using the May 2015 vintage of the I/B/E/S database. Panel A presents summary statistics at the analyst-year level. The median analyst covers 11 firms and one 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, while the 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.

- Table 1 here -

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 $\times$ year fixed effects in our regressions accounts for this correlation.

Panel C compares the characteristics of central analysts to those of their peripheral coworkers. In every brokerage $\times$ 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 five to six additional months of forecasting experience and have been at their current brokerage for seven to eight months longer than their peripheral counterparts. Central analysts are also more likely to be Institutional Investor star analysts (11.5% versus 10.1%) and tend to issue more bold forecasts (54.4% versus 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.

1. Find the network distance between the analyst-coworker pair.
2. 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 $\mathbb{1}_{\text{network distance}=2,i,j,t}$ switches on if analysts i and j are two steps apart in the brokerage network.

$$(1) \qquad \mathit{NUM\_TANDEM}_{i,j,t} = \sum_{n=1}^{N} \beta_n \mathbb{1}_{\text{network distance}=n,i,j,t} + \theta\, \mathit{controls}_{i,f,t} + \epsilon_{i,j,t} \quad \forall i \neq j$$

To account for structural autocorrelation in network data, we estimate quadratic assignment procedure (QAP) regressions.[8] We first estimate specification (1) to obtain the baseline set of coefficient estimates. To obtain standard error of our estimates, we next

[8]The Internet Appendix 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.

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) re-estimate equation (1) on this permuted dataset. 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.

- Table 2 here -

Our results indicate that the network distance between an analyst-pair predicts the frequency of tandem revisions. Column 1 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 inter-sector 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 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 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.

[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.

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 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]

IV.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

[10]In the Internet Appendix, 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.

[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.

analyst i from brokerage g who makes a forecast revision on date d for firm f in year t:

$$(2) \qquad COWORKER\_OPTIMISM_{i,d} = \frac{\sum_{\substack{j \in g \\ j \neq i}} \sum_f OPT\_ERR_{j,f,t}}{\text{total } \# OPT\_ERR} \qquad \forall t \in [d-30, d]$$

$$OPT\_ERR_{j,f,t} = \begin{cases} 0 & \text{EPS forecast}_{j,f,t} \leq \text{actual EPS}_{f,t} \\ 1 & \text{EPS forecast}_{j,f,t} > \text{actual EPS}_{f,t} \end{cases}$$

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 upwards 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.

$$\begin{aligned} (3) \qquad SIGNED\_REVISION_{i,f,d} = \alpha &+ \beta_1(CENTRALITY_{i,d} \times COWORKER\_OPT_{i,d}) \\ &+ \beta_2 CENTRALITY_{i,d} + \beta_3 COWORKER\_OPT_{i,d} \\ &+ \theta controls_{i,f,d} + \eta_{g,t} + \epsilon_{i,f,d} \end{aligned}$$

Next, we estimate regression specification (3). The key variable of interest is the interaction term COWORKER_OPT $\times$ 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 $\times$ 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 shows that central analysts are more sensitive to the revelations of their coworkers' forecast errors. Column 1 reports that $\hat{\beta}_1$ 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, but subsequently issues stronger downwards revisions upon revelations that her coworkers have been optimistic.

- Table 3 here -

An alternative interpretation of this finding is that central analysts possess superior ability to process all types of information. If so, central analysts should also respond more strongly to the forecast errors of non-coworkers. To assess this alternative story, we construct a measure of GLOBAL_OPT as an analog of COWORKER_OPT, but derived from non-coworkers' 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 are inconsistent with the information-processing interpretation. Central analysts do not make more negative revisions in response 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 learnt from their coworkers. We find support for the peer learning hypothesis but not for explanations related to information-processing ability.

IV.B Accounting for the quality of coworkers' information

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

IV.B.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

[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.

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 Panel A here -

Panel A of Table 4 shows 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.

IV.B.2 Coworkers' strategically important stocks

Analysts allocate more time and attention to strategically important 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 strategically important (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-) strategically important stocks in the 30-day window.

[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.

- Table 4 Panel B here -

Panel B of Table 4 shows 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 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.

V.A Forecast accuracy

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

$$(4) \quad \mathit{NORM\_FORECAST\_ERR}_{i,f,t} = \alpha + \beta_1 \mathit{CENTRALITY}_{i,t} + \theta \mathit{controls}_{i,f,t} + \eta_{g,t} + \epsilon_{i,f,t}$$

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, analytical ability) of analysts employed at the same brokerage.

- Table 5 here -

The results in Table 5 indicate that central analysts produce significantly more accurate forecasts. Column 1 shows a significantly negative relation 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, 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. Crucially, the relation 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 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.

[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 ($0.202 \times 0.050 = 0.010$).

Our findings in Table 5 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 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.

V.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 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 6 here -

Table 6 shows that central analysts are more accurate in their forecasts of hard-to-

[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.

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 through 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.

V.C Shocks to the brokerage network structures

While 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; 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.

V.C.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 Internet Appendix contains the list of brokerage mergers used in our analysis.

To assess how changes in analyst centrality affect performance, we estimate a difference-in-differences 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.

$$(5) \quad NORM\_FORECAST\_ERR_{i,f,m,t} = \beta_1 \left(POST_{m,t} \times \Delta\_CENTRALITY_{i,m}\right) + \beta_2 POST_{m,t} + \gamma_{i,f,m} + \theta controls_{i,f,m,t} + \epsilon_{i,f,m,t}$$

$$\Delta\_CENTRALITY_{i,m} = CENTRALITY_{i,m,t=+1} - CENTRALITY_{i,m,t=-1}$$

$$POST_{m,t} = \begin{cases} 0 & t < 0 \\ 1 & t \geq 0 \end{cases}$$

The treatment Δ_CENTRALITY is an analyst's centrality at one year after the merger ($t = +1$) less her centrality at one 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 5. 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 group-wise average NORM_FORECAST_ERR in the $[-3, +3]$ year event window around the merger.

- Figure 3 here -

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 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 $\times$ firm $\times$ 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 subfigures (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 post-treatment period in our baseline model. Over time, we also observe that NORM_FORECAST_ERR trends downwards 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.

[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.

V.C.2 Difference-in-differences results

Table 7 presents results from the difference-in-differences analysis. Column 1 reports a significantly negative loading on POST $\times$ 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 $\times$ firm $\times$ 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 $\times$ firm $\times$ merger level.

- Table 7 here -

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, we assign merger-year forecasts to the pre-treatment (post-treatment) 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 these alternative specifications.[18] In columns 4 to 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.

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

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 Internet Appendix.

VI.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 skill, we identify analyst who were recognized as an Institutional Investor star analyst (II_STAR) anytime in the prior three 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.

VI.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 mid-sized 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 tradeoff between these two effects is likely closer to the optimum for mid-sized brokerages than for the largest and smallest brokerages.

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

VI.C Peer learning and Regulation Fair Disclosure

After the adoption of Reg FD in October 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 five years before (pre-Reg FD) and five years after (post-Reg FD) the year 2000. We find that the relation 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 upwards (a downwards) 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 five, ten, 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 8 here -

Table 8 presents the returns from our portfolio strategy. While the long-short strategies of both central and peripheral analysts are profitable, the former consistently yields higher returns across all holding periods. With a five-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 ten-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 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 Internet Appendix. 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 mid-sized brokerages, (ii) brokerages with lower analyst turnover rates, and (iii) after the adoption of Regulation Fair Disclosure. 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. While 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.

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Figure 1. An Example of a Brokerage Network

This figure 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 two-digit 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.

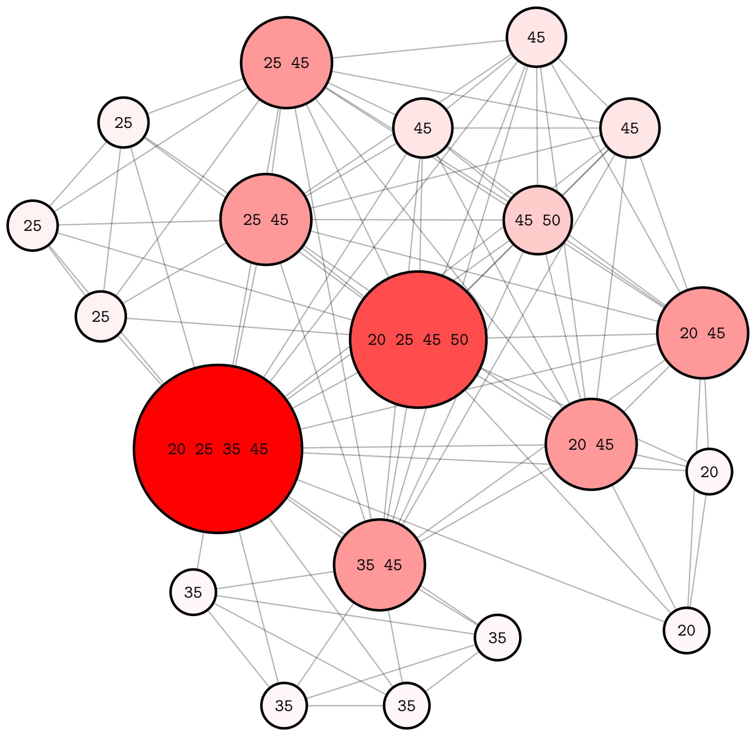


Figure 2. A Simple Network of Three Analysts

This figure 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.

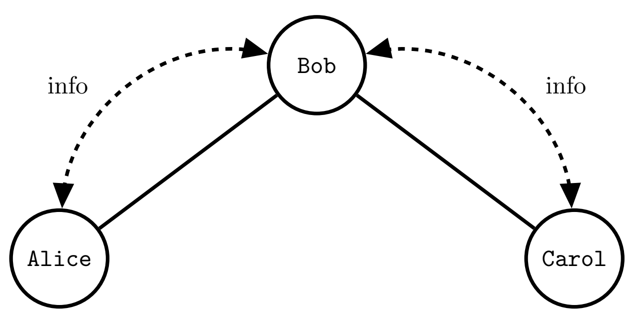
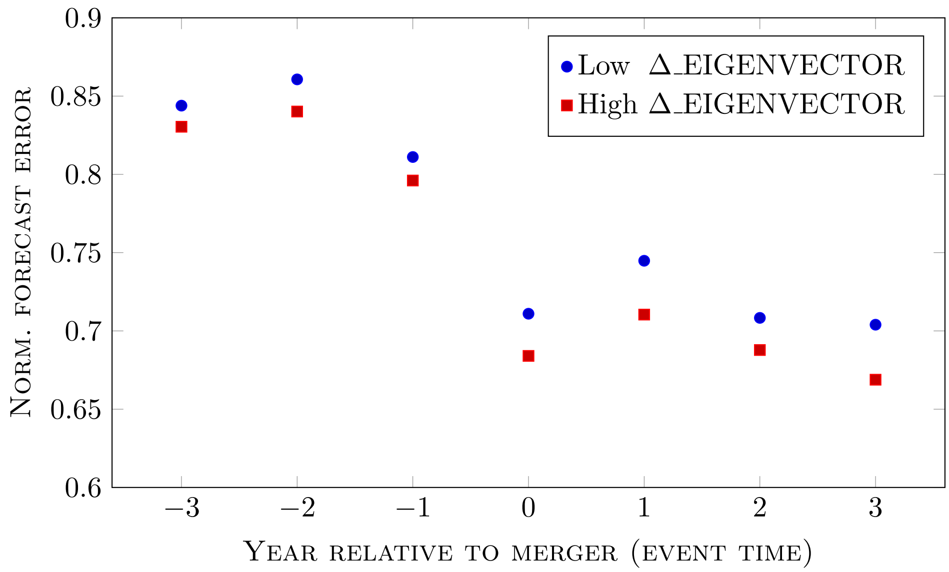
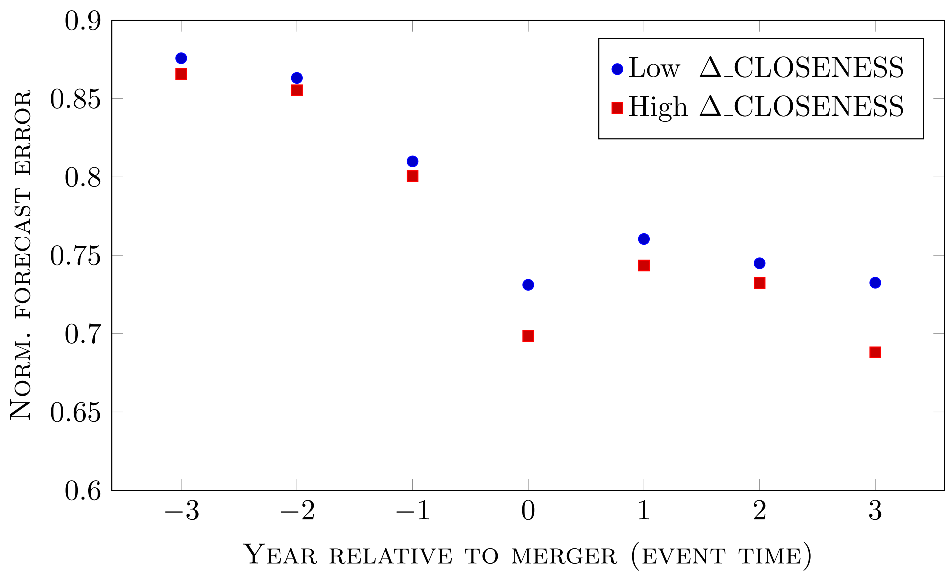


Figure 3. Analysts' Forecast Errors Around Brokerage Mergers

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 subfigures (a) and (b), respectively.



(a) Δ_EIGENVECTOR



(b) Δ_CLOSENESS

Table 1. Descriptive Statistics

Panel A reports summary statistics of analyst characteristics at the analyst-brokerage-year level. Panel B reports Pearson pairwise correlations among these variables in percentage points. Panel C reports 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 Internet Appendix for details on EIGENVECTOR and CLOSENESS. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary statistics

	N	Mean	S.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 ($bn)	4.5	7.4	−2.9 ***	4.7	7.6	−2.9 ***

Table 2. Tandem Revisions Between Analysts and Coworkers

This table presents results from quadratic assignment procedure (QAP) network regressions. The Internet Appendix 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 ($\geq$ 3). Refer to Figure 2 for an intuitive explanation on 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

	1	2	3	4
λ window	3 days	3 days	5 days	15 days
DIRECT_LINK	24.43***	22.92***	32.96***	93.20***
	(4.400.19)	(4.050.21)	(5.820.31)	(16.250.87)
LINK_AT_2_STEPS	17.41***	15.60***	22.64***	64.83***
	(2.470.19)	(2.080.21)	(3.070.30)	(8.750.87)
LINK_AT_MORE_STEPS	16.06***	14.61***	21.30***	60.57***
	(2.710.23)	(2.230.24)	(3.300.35)	(9.311.00)
Other predictors				
SAME_ETHNICITY		3.37***	4.83***	13.73***
		(0.650.21)	(0.890.30)	(2.570.86)
EX_COLLEAGUES		20.05***	28.84***	81.69***
		(6.630.44)	(9.630.64)	(27.211.83)
Δ_BROKERAGE_EXP		0.07***	0.10***	0.30***
		(0.050.00)	(0.080.00)	(0.220.01)
SAME_COHORT		−0.36***	−0.60***	−1.85***
		(−1.010.12)	(−1.530.18)	(−4.500.50)
Num. of networks	2,660	2,660	2,660	2,660

Table 3. Response to the Revelations of Coworkers' Errors

This table 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 non-coworkers. Then, we define COWORKER_OPT (GLOBAL_OPT) as the proportion of optimistic forecast errors made by brokerage coworkers (non-coworkers) 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 Internet Appendix 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***	–0.100***		
	(0.038)	(0.038)		
a × GLOBAL_OPT		0.013		
		(0.038)		
b × COWORKER_OPT			–0.049*	–0.051*
			(0.026)	(0.026)
b × GLOBAL_OPT				0.024
				(0.025)
a: EIGENVECTOR	–0.131***	–0.134***		
	(0.018)	(0.021)		
b: CLOSENESS			–0.099***	–0.104***
			(0.016)	(0.017)
COWORKER_OPT	0.011	0.011	0.025	0.026*
	(0.007)	(0.007)	(0.015)	(0.015)
GLOBAL_OPT		–0.006		–0.017
		(0.007)		(0.015)
GENERAL_EXP	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
FIRM_EXP	0.002	0.002	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
FIRM_BREADTH	0.000**	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
INDUSTRY_BREADTH	0.004**	0.004**	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
ANALYST_COV	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
$\mid \text{CAR}_{-5,-2} \mid$	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	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	Y	Y	Y	Y

Table 4. Panel A. Response to the Revelations of Errors Made by High-ability Coworkers

This table examines whether central analyst 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 tercile 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 Internet Appendix 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

	1	2	3	4
	Measures of analyst ability			
	Forecast accuracy		Forecast boldness	
a × HI_ABILITY_OPT	−0.140***		−0.106**	
	(0.047)		(0.048)	
a × LO_ABILITY_OPT	−0.018		−0.085*	
	(0.044)		(0.047)	
b × HI_ABILITY_OPT		−0.119***		−0.056*
		(0.033)		(0.033)
b × LO_ABILITY_OPT		−0.001		−0.029
		(0.032)		(0.033)
a: EIGENVECTOR	−0.160***		−0.157***	
	(0.029)		(0.028)	
b: CLOSENESS		−0.141***		−0.153***
		(0.024)		(0.024)
HI_ABILITY_OPT	0.014	0.060***	0.018*	0.034*
	(0.009)	(0.019)	(0.009)	(0.019)
LO_ABILITY_OPT	0.002	0.001	0.000	0.005
	(0.008)	(0.018)	(0.008)	(0.019)
Observations	1,232,729	1,232,729	1,232,729	1,232,729
R^2	0.007	0.007	0.007	0.007
Controls	Y	Y	Y	Y
Brokerage × Year FE	Y	Y	Y	Y

Table 4. Panel B. Response to the Revelations of Coworkers' Errors on Strategically Important Firms

This table examines whether central analyst revise their forecasts in response to the revelation of errors made on the strategically important firm covered by their coworkers. The key independent variables in this panel 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 strategically important (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 strategically important (non-SI) firms in the 30-day window. Following Harford, Jiang, Wang, and Xie (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) strategically important 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 Internet Appendix 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

	1	2	3	4	5	6
	Measures of strategic importance (SI)					
	Firm size		Inst. ownership		Trading volume	
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)
Observations	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	Y	Y	Y	Y	Y	Y
Brokerage × Year FE	Y	Y	Y	Y	Y	Y

Table 5. Peer Learning and Forecast Accuracy

This table reports result 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 Internet Appendix 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 one if (i) an analyst covers an acquirer firm and (ii) her brokerage coworker covers the target firm in the preceding year, and equals zero 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)
Observations	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	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y

Table 6. Peer Learning and Forecast Accuracy on Hard-to-value Stocks

This table reports result 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 Internet Appendix for definitions and working examples of EIGENVECTOR and CLOSENESS. See the Internet Appendix for definitions of TRADE_EXPOSURE, COMPLICATED, and FORECAST_DISPERSION. Control variables from Table 5 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***			0.303***		
	(0.032)			(0.068)		
b: COMPLICATED		0.010			0.075***	
		(0.012)			(0.027)	
c: FORECAST_DISPERSION			0.077***			0.167***
			(0.016)			(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	–0.056***	–0.006			
	(0.021)	(0.018)	(0.020)			
CLOSENESS				–0.037**	–0.064***	–0.037**
				(0.018)	(0.016)	(0.017)
Observations	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	Y	Y	Y	Y	Y	Y
Brokerage × Year FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y

Table 7. Quasi-exogenous Shocks to Brokerage Network Structures

This table presents 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-differences 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 to 3) and CLOSENESS (columns 4 to 6). The post-treatment period is $[0, +3]$ years after the merger. Correspondingly, the POST indicator equals one if an observation occurs within $[0, +3]$ years after the merger, and equals zero 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 pre-treatment (post-treatment) period. In columns 3 and 6, we exclude all merger-year forecasts from our analysis. We include all control variables used in Table 5. Clustered standard errors at the analyst-firm level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. NOTE: 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	N	Y	N	N	Y	N
Exclude from sample	N	N	Y	N	N	Y
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)
Observations	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	Y	Y	Y	Y	Y	Y
Analyst × Firm × Merger FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y

Table 8. Calendar-time Portfolio Strategies

This table presents results from the following calendar-time portfolio strategy. Every day, we form two long-short portfolios: (i) long (short) stocks that receive upwards (downwards) forecast revisions from analysts who are in the top tercile of centrality in their brokerages, and (ii) long (short) stocks that receive upwards (downwards) 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)

Internet Appendix to

PEER EFFECTS IN EQUITY RESEARCH

Kenny Phua, Mandy Tham, and Chishen Wei*

The Internet Appendix contains supplementary information, additional tests, and robustness checks for the paper "PEER EFFECTS IN EQUITY RESEARCH". Contents of the Internet Appendix are organized as follows.

Section I	Definitions and working examples of the two measures of analyst centrality.
Section II	Discussion on the mechanics of quadratic assignment procedure regressions.
Section III	Robustness check of the tandem revisions analysis.
Section IV	List of brokerage mergers, and robustness check of the difference-in-differences analysis.
Section V	Additional tests of the mechanisms behind peer effects and forecast accuracy.
Section VI	Robustness check of the calendar-time portfolio strategies.
Section VII	Supplementary test that examines relation between analyst centrality and market reactions around forecast revisions.
Section VIII	Detailed definitions of variables used in analyses.

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I Definitions of analyst centrality

In this section, we provide detailed definitions of eigenvector centrality and closeness centrality with the aid of figures and working examples.

I.A Eigenvector centrality

A node in a network has high eigenvector centrality if its direct neighbors also have high eigenvector centrality. The `PageRank` algorithm of Google's search engine has a similar recursive nature; websites are more important if they receive more weblinks from other important websites. In our setting, this recursive nature allows eigenvector centrality to capture an analyst's access to intra- and inter-sector information produced in the brokerage network.

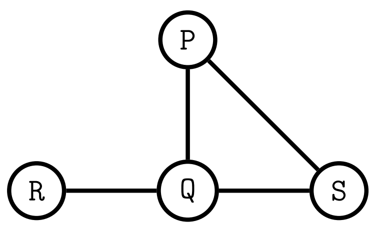


Figure 1. Circles are nodes in the network. Lines represent links between nodes.

To motivate the mathematical intuition behind eigenvector centrality, consider a simple network structure in Figure 1 and its corresponding adjacency matrix $\mathbf{M}$. The adjacency matrix represents links between nodes in the network. Since we have four nodes—P, Q, R, and S—in this example, $\mathbf{M}$ is a 4×4 matrix.

$$\mathbf{M} = \begin{array}{cc} \begin{array}{cccc} \mathtt{P} & \mathtt{Q} & \mathtt{R} & \mathtt{S} \end{array} & \\ \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} & \begin{array}{c} \mathtt{P} \\ \mathtt{Q} \\ \mathtt{R} \\ \mathtt{S} \end{array} \end{array} \tag{1}$$

For example, the element $\mathbf{m}_{1,2}$ equals one because `P` and `Q` are linked in the network, whereas $\mathbf{m}_{1,3}$ equals zero because `P` and `R` do not share a link. Because M represents an unweighted network, its elements are binary. The diagonal elements of $\mathbf{M}$ are all zeroes because there are no self-loops (i.e., a node linked to herself) in this network. $\mathbf{M}$ is symmetric because it represents an undirected network in which links between nodes are reciprocal. We base our working examples henceforth on an unweighted and undirected network, characteristic of the brokerage networks we construct in the main text.

To kick off the working example, we define a 4×1 vector $\mathbf{k}$ that describes the nodes' endowment on some arbitrary centrality measure. Without loss of generality, we choose $\mathbf{k}$ to indicate the number of direct links that the nodes have. For example, `P` and `Q` have two and three direct links in the network, respectively.

$$\mathbf{k} = \begin{array}{c} \begin{bmatrix} 2 \\ 3 \\ 1 \\ 2 \end{bmatrix} \end{array} \begin{array}{l} \texttt{P} \\ \texttt{Q} \\ \texttt{R} \\ \texttt{S} \end{array} \tag{2}$$

Nodes receive and transmit some network flows to their neighbors in the network. Mathematically, we can realize this operation by multiplying $\mathbf{M}$ and $\mathbf{k}$.

$$\mathbf{Mk} = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ 3 \\ 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \\ 3 \\ 5 \end{bmatrix} \tag{3}$$

In this multiplication, every node "receives" her direct neighbors' centrality scores and "distributes" her centrality score to them. Thus, the product $\mathbf{M} \cdot \mathbf{k}$ gives us the summed centrality scores of every node's neighbors. For example, `P` has a value of 5 in the product because it is linked to `Q` (who began with a score of 3) and `S` (who began with a score of 2). We can repeat this multiplication indefinitely to spread the initial vector $\mathbf{k}$ further. For the purpose of exposition, we work out two additional steps of this multiplication.

$$\mathbf{M}^2\mathbf{k} = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} 5 \\ 5 \\ 3 \\ 5 \end{bmatrix} = \begin{bmatrix} 10 \\ 13 \\ 5 \\ 10 \end{bmatrix} \tag{4}$$

$$\mathbf{M}^3\mathbf{k} = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} 10 \\ 13 \\ 5 \\ 10 \end{bmatrix} = \begin{bmatrix} 23 \\ 25 \\ 13 \\ 23 \end{bmatrix} \tag{5}$$

In the first round, a node receives flows from her neighbors. In the second round, a node receives flows from her neighbors who have themselves received flows from their own neighbors. As this process perpetuates, each node receives flows from other nodes that are increasingly further from it. At the limit, the vector $\lim_{n\to\infty} \mathbf{M}^n\mathbf{k}$ should represent the flows from the entire network arriving at each node. In the context of our paper, $\lim_{n\to\infty} \mathbf{M}^n\mathbf{k}$ reflects the information received by each analyst from all her coworkers in the brokerage network.

Additional rounds of multiplication will produce vectors with increasingly larger elements. However, there is an equilibrium at which the *proportion* of flows received by each node remains constant. At this equilibrium, the vector contains centrality values that fully reflects the centrality of every node's neighbors. This is exactly the recursive nature of eigenvector centrality. We can search for this equilibrium by choosing the initial vector $\mathbf{k}^*$ such that for some scalar λ,

$$\mathbf{M}\mathbf{k}^* = \lambda\mathbf{k}^* \tag{6}$$

Upon closer inspection, we can solve for this equilibrium by setting $\mathbf{k}^*$ as the eigenvector of the adjacency matrix $\mathbf{M}$. At this equilibrium, increasing rounds of multiplication always produces a scalar inflation of $\mathbf{k}^*$—the proportion of flows arriving at each node in the network is constant. Thus, the eigenvector centrality of a node is given by her element in the eigenvector of the network's adjacency matrix.

I.B Closeness centrality

The closeness centrality of a node is the average length of the shortest paths (i.e., geodesics) between itself and all other nodes in the network. In other words, a node with high closeness centrality is positioned near all other nodes in the network. Therefore, such a node can receive network flows earlier than others.

However, network flows may not strictly travel along geodesics, and instead take a circuitous route to reach a node. Nevertheless, it turns out that closeness centrality is still a valid index of information reception speed in our context of peer learning. The key intuition is that information or ideas can be duplicated and distributed in parallel. If all possible paths—including geodesics—are followed, then the net effect is *on average* the same as the one implied by a geodesic-only transmission (Borgatti, 2005). Thus, the rank ordering of how quickly analysts receive information still corresponds to the ordering provided by closeness centrality. In the main text, the brokerage × year fixed effects in regressions produce a similar effect to rank ordering within brokerage networks.

We begin our working example by considering a network from the perspective of node `X` in Figure 2. The number in each of the other nodes indicates the geodesic length between it and node `X`.

We next sum up the lengths of all those geodesics and normalize its reciprocal by $N-1$, where N is the number of nodes in the network, to obtain node `X`'s closeness centrality. So, more positive values of closeness centrality reflect greater proximity to all other nodes in the network.

$$\text{closeness centrality}_{\text{node }\mathtt{X}} = \frac{8-1}{1+1+2+2+2+2+3} = 0.54 \tag{7}$$

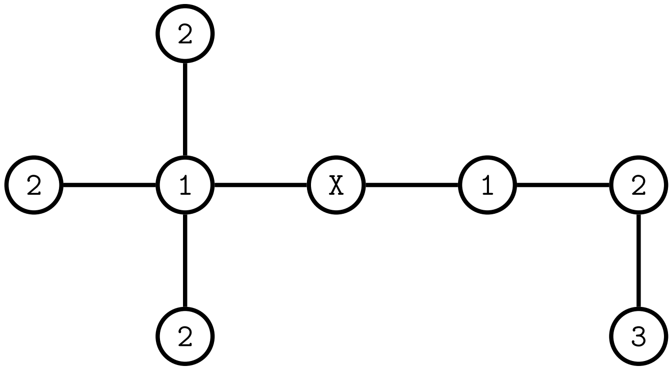


Figure 2. Circles are nodes in the network. Lines represent links. The number in each node indicates the length of the shortest path (i.e., geodesic) between it and node `X`.

Figure 3 illustrates the same network from the perspective of node `Y`. We also compute node `Y`'s closeness centrality as a comparison to node `X`'s.

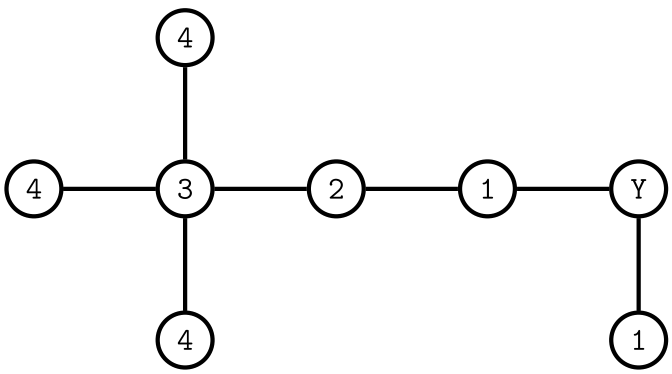


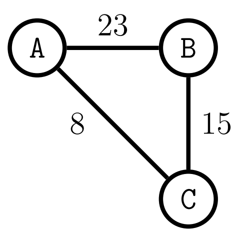
Figure 3. Circles are nodes in the network. Lines represent links. The number in each node indicates the shortest path (i.e., geodesic) length between it and node `Y`.

$$\text{closeness centrality}_{\text{node }\mathtt{Y}} = \frac{8-1}{1+1+2+3+4+4+4} = 0.37 \tag{8}$$

Though nodes `X` and `Y` have the same number of direct neighbors, `X` has a higher closeness centrality than `Y`.

II Discussion on QAP regressions

To facilitate a discussion of the QAP regressions, we first consider the network in Figure 4. Nodes represent analysts in a brokerage, and a link between two analysts represents the number of tandem revisions made between them.[1] We can express the structure of tandem revisions in the network as a 3 × 3 adjacency matrix **R**. Since an analyst cannot make tandem revisions with herself, the diagonal elements of **R** are zeroes.



$$\mathbf{R} = \begin{array}{c} \\ \\ \end{array}\begin{array}{cc} \begin{array}{ccc} \mathtt{A} & \mathtt{B} & \mathtt{C} \end{array} & \\ \begin{bmatrix} 0 & 23 & 8 \\ 23 & 0 & 15 \\ 8 & 15 & 0 \end{bmatrix} & \begin{array}{c} \mathtt{A} \\ \mathtt{B} \\ \mathtt{C} \end{array} \end{array}$$

Figure 4. This figure presents the structure of tandem revisions in a stylized network. Nodes represent analysts in a brokerage network. A link between two analysts represents the number of tandem revisions made between them. We can also express the structure of tandem revisions in this network as a 3 × 3 adjacency matrix R.

Suppose we want to test whether pairwise differences in experience (Δ experience) and age (Δ age) between two analysts predict the frequency of tandem revisions made by them. Notwithstanding an abuse of notations, we estimate the following ordinary least squares (OLS) regression.

$$(9) \qquad \underbrace{\begin{array}{cc} \begin{array}{ccc} \mathtt{A} & \mathtt{B} & \mathtt{C} \end{array} & \\ \begin{bmatrix} 0 & 23 & 8 \\ 3 & 0 & 15 \\ 8 & 15 & 0 \end{bmatrix} & \begin{array}{c} \mathtt{A} \\ \mathtt{B} \\ \mathtt{C} \end{array} \end{array}}_{\mathbf{R}} = \beta_1 \underbrace{\begin{array}{cc} \begin{array}{ccc} \mathtt{A} & \mathtt{B} & \mathtt{C} \end{array} & \\ \begin{bmatrix} 0 & 5 & 2 \\ 5 & 0 & 17 \\ 2 & 17 & 0 \end{bmatrix} & \begin{array}{c} \mathtt{A} \\ \mathtt{B} \\ \mathtt{C} \end{array} \end{array}}_{\Delta \text{ experience}} + \beta_2 \underbrace{\begin{array}{cc} \begin{array}{ccc} \mathtt{A} & \mathtt{B} & \mathtt{C} \end{array} & \\ \begin{bmatrix} 0 & 4 & 10 \\ 4 & 0 & 1 \\ 10 & 1 & 0 \end{bmatrix} & \begin{array}{c} \mathtt{A} \\ \mathtt{B} \\ \mathtt{C} \end{array} \end{array}}_{\Delta \text{ age}}$$

However, the standard errors of the estimated coefficients on Δ experience and Δ age will be underestimated in this regression. This downward bias stems from structural

[1] The main text contains a detailed definition of tandem revisions.

autocorrelation (Krackardt, 1987; Krackhardt, 1988) as analysts exchange information with one another in the network. To see why, notice that information can flow from `A` to `B`, and then from `B` to `C`. Therefore, the frequency of tandem revisions between `A` and `C` is likely correlated with frequencies between `A-B` and `B-C`. These correlations imply a violation of independence among observations, thereby leading to underestimated standard errors.

To break up the structural autocorrelation, we repeatedly permute the structure of the dependent variable (i.e., tandem revisions) by scrambling the nodes' identities but not the values of the links. Equivalently, we are concurrently swapping the rows and columns on $\mathbf{R}$. For example, `A` and `B` may swap positions in the tandem revisions network in one of the permutations. Figure 5 presents the structure of the tandem revisions network before and after the permutation.

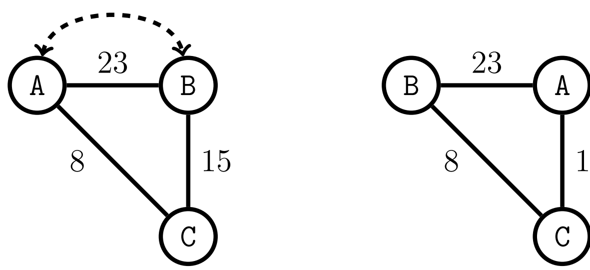


Figure 5. This figure shows an example of a permutation in QAP regressions. Nodes represent analysts in a brokerage network. A link between two analysts represents the number of tandem revisions made between them. In the left subfigure, `A` and `B` swap positions while keeping the link values constant. The right subfigure shows the outcome of the permutation.

Importantly, the independent variables do not undergo these permutations. Thus, the permutations essentially remove the relation between the dependent and independent variables. Using the permuted tandem revisions network $\mathbf{R}^*$, we then estimate equation (10) and store the coefficient estimates β_1^* and β_2^*. The intuition is that because structural autocorrelation makes it "too easy" to reject the null hypothesis, we should find that Δ experience and Δ age spuriously predict the frequency of tandem revisions even with permuted data.

$$(10) \quad \underbrace{\begin{array}{cc} \begin{matrix} \texttt{A} & \texttt{B} & \texttt{C} \end{matrix} & \\ \begin{bmatrix} 0 & 23 & 15 \\ 23 & 0 & 8 \\ 15 & 8 & 0 \end{bmatrix} & \begin{matrix} \texttt{A} \\ \texttt{B} \\ \texttt{C} \end{matrix} \end{array}}_{\mathbf{R}^*} = \beta_1^* \underbrace{\begin{array}{cc} \begin{matrix} \texttt{A} & \texttt{B} & \texttt{C} \end{matrix} & \\ \begin{bmatrix} 0 & 5 & 2 \\ 5 & 0 & 17 \\ 2 & 17 & 0 \end{bmatrix} & \begin{matrix} \texttt{A} \\ \texttt{B} \\ \texttt{C} \end{matrix} \end{array}}_{\Delta \text{ experience}} + \beta_2^* \underbrace{\begin{array}{cc} \begin{matrix} \texttt{A} & \texttt{B} & \texttt{C} \end{matrix} & \\ \begin{bmatrix} 0 & 4 & 10 \\ 4 & 0 & 1 \\ 10 & 1 & 0 \end{bmatrix} & \begin{matrix} \texttt{A} \\ \texttt{B} \\ \texttt{C} \end{matrix} \end{array}}_{\Delta \text{ age}}$$

We repeat the permutations and regressions many times to form an empirical distribution of coefficient estimates. To perform statistical inference, we benchmark the coefficient estimates from the naïve regression in equation (9) against this empirical distribution. Akin to a percentile bootstrap procedure, the p-value is the proportion of the empirical distribution that is more extreme than the coefficient estimate.

III Tandem revisions

We re-estimate the quadratic assignment procedure (QAP) regressions in Table 2 on a sample that excludes forecast revisions with recent material firm disclosures. This exclusion helps to address concerns that tandem revisions may be primarily driven by confounding firm news.

- Table 1 here -

Table 1 reports the results. In columns 1 to 3, we exclude a forecast revision if it coincides with the firm's issuance of a SEC Form-8K or earnings announcement within $[-1, 0]$ days of the revision. Our conclusions on within-brokerage information exchange remain qualitatively unchanged. Across all three $\lambda \in \{3, 5, 15\}$ windows, analyst-coworker pairs who are directly linked make the most tandem revisions. Consistent with the idea that there is inter-sector information exchange among coworkers, we continue to observe tandem revisions between indirectly linked analyst-coworker pairs, albeit at lower frequencies. Our conclusions are also unchanged using a more stringent filter that excludes forecast revisions with material firm disclosures within $[-3, 0]$ days of the revision in columns 4 to 6. Overall, this robustness test supports our view that tandem revisions reflect information exchange among brokerage coworkers.

IV Difference-in-differences analysis

We first present the list of brokerage mergers used in our difference-in-differences analysis.

- Table 2 here -

Next, we perform a robustness check of Table 7 in the main text. We now show that our findings from the difference-in-differences analysis are robust to alternative definitions of the POST indicator variable.

In this robustness check, we assign merger-year observations to the pre-treatment period. Correspondingly, the POST_ALT indicator equals one if an observation occurs within $[+1, +3]$ years after the merger, and equals zero if the observation occurs within $[-3, 0]$ years from the merger.

- Table 3 here -

We re-estimate the difference-in-differences models of the main text with POST_ALT and present results in Table 3. In column 1, we find that the interaction term POST_ALT $\times$ Δ_EIGENVECTOR loads significantly and negatively on NORM_FORECAST_ERR. In column 2, we reclassify merger-year observations made after (on or before) the merger month to the post-treatment (pre-treatment) period.[2] We continue to find that increases in EIGENVECTOR are associated with higher forecast accuracy in the post-merger period. In column 3, we obtain similar results when we exclude all merger-year observations from our analysis. The results are similar using Δ_CLOSENESS in columns 4 to 6.

[2]Note that this reclassification is different from the one in the main text because merger-year forecasts are now assigned to the pre-treatment period.

Overall, we find that our difference-in-differences results are robust to alternative empirical treatments of merger-year observations. Our results in this robustness check echo our finding that analysts who become more central after brokerage mergers subsequently exhibit higher forecast accuracy.

V Additional tests

We perform additional tests to better understand the mechanisms behind the peer effects we document. First, we examine whether analyst centrality is orthogonal to various measures associated with analyst performance. Second, we examine whether the brokerage environment moderates the role of peer effects. Third, we test whether peer learning becomes more important after the adoption of Regulation Fair Disclosure.

V.A Peer learning and measures of analyst skill or ability

The results from our difference-in-differences models in Table 6 of the main text suggest that unobservable analyst characteristics cannot fully explain our findings. Nevertheless, it is possible that the effect of analyst centrality is subsumed by measures of analyst skill or ability. We focus on two proxies for analyst skill. First, we add FORECAST_BOLDNESS to the regression model because Clement and Tse (2005) find that high-ability analysts tend to issue bold forecast revisions. Next, we identify whether an analyst was recognized as an Institutional Investor star analyst (II_STAR) anytime in the prior three years to capture any residual dimensions of forecasting skill.[3]

- Table 4 here -

Table 4 shows that the effect of analyst centrality on forecast accuracy is not subsumed by these measures of skill or ability. Column 1 shows that EIGENVECTOR continues to predict higher forecast accuracy with the inclusion of FORECAST_BOLDNESS. Our results

[3]The use of the three-year window in the definition of II_STAR captures the notion that analyst ability is a persistent trait.

are unchanged with the inclusion of II_STAR in column 2. In column 3, we jointly control for both FORECAST_BOLDNESS and II_STAR, and continue to find that analysts with higher EIGENVECTOR are significantly more accurate. Interestingly, both FORECAST_BOLDNESS and II_STAR retain their statistical significance in this specification. Thus, these two measures are likely to capture distinct dimensions of analyst skill. In column 4, we include analyst fixed effects to rule out the possibility that time-invariant dimensions of analyst ability are behind these findings. Using this stricter specification, we find that the measures of analyst ability are statistically insignificant, but the loading on EIGENVECTOR remains negative and significant at the 10% level. In columns 5 to 8, we find that CLOSENESS also has explanatory power on forecast accuracy beyond the two measures of analyst ability.

Overall, our results suggest that the effect of analyst centrality on forecast performance is distinct from that of analyst skill or ability. Our analysis here also complements the difference-in-differences analysis in Table 6 of the main text. In that analysis, we find that analysts who become more central after brokerage mergers are not significantly more accurate in the pre-merger period, suggesting that analyst ability does not drive analyst centrality. Our findings in this section provide a more generalized setting to disentangle peer effects from analyst ability.

V.B Peer learning and the brokerage environment

Characteristics of the internal brokerage environment, such as culture and organizational structure, may moderate the effectiveness of peer learning. One dimension that captures many of these attributes is brokerage size. On one hand, bigger brokerages are more prestigious and have more resources, so they can attract better analysts (Clement, 1999; Jacob, Lys, and Neale, 1999). Thus, the benefits of peer learning could be amplified in bigger brokerages because analysts can leverage the expertise of more able coworkers. However, bigger brokerages also tend to have more intense competition (Groysberg, Healy, and Maber, 2011), which can disincentivize information exchange among analysts.

Another key dimension of the brokerage environment is the analyst turnover rate (Jacob et al., 1999). The effect of turnover on the quality of information exchange is unclear, ex ante. High turnover rates may bring in fresh ideas from outsiders and remove underperformers, but may also reflect the inability of a brokerage to retain its best analysts. Assimilating new employees into the brokerage also requires time and effort, which may draw attention and resources away from forecasting activities.

To assess the effect of the brokerage environment on peer learning, we create subsamples that are split at the 30^{th} and 70^{th} percentiles of either brokerage size or analyst turnover rates in each year.[4] The split based on brokerage sizes produces roughly equal analyst turnover rates across subsamples, and vice versa. Hence, brokerage sizes and analyst turnover rates are likely to proxy for distinct elements of the brokerage environment. Panel A of Table 5 reports results from seemingly unrelated regressions. Central analysts exhibit higher forecast accuracy in all but the biggest brokerages (columns 3 and 6). Interestingly, we also find that the effect of analyst centrality is stronger in mid-sized brokerages than in small ones. Taken together, our results support the view that at big brokerages, the effect of in-house competition may dominate the potential to interact with high-quality coworkers. The tradeoff between these two effects is likely closer to the optimum for mid-sized brokerages than for brokerages in the extreme terciles.

- Table 5 Panel A here -

In Panel B, we find that the effect of EIGENVECTOR on forecast accuracy declines with analyst turnover rates. For example, the effect of EIGENVECTOR in the low-turnover brokerages (-0.112^{***}) is nearly four times larger than in the high-turnover brokerages (-0.030). This pattern is consistent with our hypothesis that a high-turnover brokerage environment curtails information exchange among coworkers. Our results using CLOSENESS are more nuanced. We find that CLOSENESS has the strongest effect in low-turnover brokerages, but remains statistically significant in mid- and high-turnover brokerages. Overall, there is suggestive evidence that a high-turnover brokerage environment is detrimental to peer learning.

[4] Specifically, a brokerage is classified as small (big) if it is smaller (bigger) than the 30^{th} (70^{th}) percentiles of brokerage sizes. Otherwise, the brokerage is classified as mid-sized. Similarly, a brokerage is classified as low-turnover (high-turnover) if its analyst turnover rate is lower (higher) than the 30^{th} (70^{th}) percentiles of analyst turnover rates. Otherwise, the brokerage is classified as mid-turnover.

- Table 5 Panel B here -

Taken together, our findings suggest that the internal brokerage environment moderates the effectiveness of peer learning. In-house competition and coworkers' quality could act as countervailing forces on information exchange within brokerages. There is also some evidence that peer learning is less effective in brokerages with high analyst turnover rates. In the next section, we examine how the external information environment affects peer learning.

V.C Peer learning and Regulation Fair Disclosure

Before the adoption of Reg FD in October 2000, firm managers could release material information to analysts without simultaneously disclosing it to other investors. While there were concerns that Reg FD would hinder analysts' ability to understand firm performance, analysts' forecast accuracy did not deteriorate much after its adoption (Heflin, Subramanyam, and Zhang, 2003). Mohanram and Sunder (2006) attribute this pattern to a substitution towards other forms of information discovery. In a similar vein, we hypothesize that access to coworkers' expertise can partially fill the information void left by Reg FD. Thus, we expect the relation between analyst centrality and performance to be stronger after Reg FD.

To ensure that subsample sizes are comparable before and after Reg FD, we restrict our analysis to the $[-5, +5]$ year window around year 2000.[5] We then estimate seemingly unrelated regressions and report estimation results in Table 6.

- Table 6 here -

We find that the relation between analyst centrality and forecast accuracy is present in the post-Reg FD period but not in the pre-Reg FD period. The pre-post differences are statistically significant at the 1% level for both EIGENVECTOR and CLOSENESS.

[5]Since our I/B/E/S sample begins in 1995 and ends in 2014, the post-2000 subsample will be substantially larger than the pre-2000 subsample. Should we not adopt this truncation and find that analyst centrality has a stronger effect post-2000, it is unclear whether this contrast is driven by an increased importance of peer learning or a difference in statistical power across both subsamples.

Overall, our findings suggest that peer learning becomes more important after Reg FD stymied analysts' access to firm managers.

VI Calendar-time portfolio strategy

We perform robustness tests of Table 8 in the main text by imposing a minimum number of stocks in every leg of our calendar-time portfolio strategy.

- Table 7 here -

For brevity, Table 7 only presents the Δ L$-$S returns, which are the returns of the long-short portfolio strategy executed on central analysts' revisions less that executed on peripheral analysts' revisions. In columns 1 to 3, we employ three different holding periods (five-day, ten-day, and 30-day) while requiring every leg of the portfolio strategy to have a minimum number (either 20 or 50) of stocks. If this requirement is not met on a particular day of the portfolio strategy, then we assign the Δ L$-$S returns on that day to be the risk-free rate. For ease of comparison, we replicate the baseline Δ L$-$S returns from the main text in columns 4 to 6. Imposing the above requirement produces the largest change in Δ L$-$S returns for the combinations of five-day holding period and a minimum of 50 stocks in every portfolio leg (EIGENVECTOR: 8.1 bps versus 9.6 bps, CLOSENESS: 7.1 bps versus 9.1 bps). Elsewhere, the requirement does not cause the profitability of our portfolio strategies to be materially different.

Overall, the profitability of our portfolio strategy holds even when we mitigate the influence of sparse portfolio cells.

VII Market reactions around forecast revisions

We perform a supplementary test to the calendar-time portfolio strategy in Section VII of the main text. Specifically, we estimate regressions of $[0, +1]$ day cumulative abnormal returns around forecast revisions on analyst centrality following equation (11).

$$\text{(11)} \qquad |\,\text{CAR}_{i,f,d,d+1}\,| = \alpha + \beta_1 CENTRALITY_{i,d} + \theta controls_{i,f,d} + \epsilon_{i,f,d}$$

The unit of analysis is a forecast revision issued by an analyst i for firm f. The dependent variable is the absolute $[d, d+1]$ day market-adjusted cumulative abnormal returns (CAR) around the forecast revision date d. We double-cluster standard errors (i) by calendar-week to capture common time-varying macroeconomic shocks, and (ii) by firm because market reactions to forecast revisions may be correlated over time for a firm. Among other control variables, we also control for forecast boldness (Clement and Tse, 2005) and stock performance in the run-up to the forecast revision date. To avoid the confounding effects of firms' information disclosures, we exclude a forecast revision if the firm issues a SEC Form-8K or an earnings announcement within $[-1, 0]$ day of the revision. This filter also addresses concerns that central analysts are merely more adept at timing their revisions to coincide with material firm news.

- Table 8 here -

Table 8 shows that central analysts attract larger market reactions around their forecast revisions. Column 1 reports a positive and statistically significant association between EIGENVECTOR and the absolute $[0, +1]$ day CAR. A one-standard-deviation-shock to EIGENVECTOR elicits a +0.10% larger market reaction in the two-day window. As a benchmark, a bold forecast (Clement and Tse, 2005) attracts a +0.19% larger market reaction than a herding one. In column 2, we find that CLOSENESS attracts a comparable premium around forecast revisions. Our results are robust to the inclusion of brokerage $\times$ year fixed effects in columns 3 and 4. Overall, our findings suggest that analysts obtain an information edge from richer and quicker access to coworkers' expertise.

VIII Variable definitions

We provide detailed definitions of variables used in our analyses below.

ANALYST_COV Number of analysts who made at least one forecast for the firm in the year.

ANALYST_TURNOVER_RATE Total number of analysts who join and leave the brokerage in the year, normalized by the average of brokerage sizes in the year and the previous year.

BOOK_TO_MARKET Ratio of firm book value to its market capitalization in the year.

BROKERAGE_EXP Number of months between an analyst's earliest appearance in the brokerage (in the I/B/E/S dataset) and the date of her forecast.

BROKERAGE_SIZE Number of analysts employed by the brokerage in the year.

CLOSENESS A network centrality measure that captures the idea that an analyst is central in the brokerage network if she is separated from all her coworkers by short network paths in aggregate. See Section II.B of the main text and the Internet Appendix for details and a working example.

COWORKER_OPT Proportion of coworkers' forecast errors that are optimistic and realized in the past 30 days relative to analyst's forecast revision. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share.

COMPLICATED Indicator that equals one if the firm has operations in at least three industry segments, and equals zero otherwise.

EIGENVECTOR A network centrality measure that captures the idea that an analyst is more central in the brokerage network if her directly connected coworkers are also central. See Section II.B of the main text and the Internet Appendix for details and a working example.

EX_COLLEAGUES Indicator that equals one if an analyst and her coworker have a past working relationship at other brokerages, and equals zero otherwise.

FIRM_BREADTH Number of firms covered by the analyst in the year.

FIRM_EXP Logarithm of the number of months between an analyst's earliest forecast of the firm in I/B/E/S and her firm-year forecast.

FORECAST_BOLDNESS Proportion of bold forecasts made by the analyst for the firm in the year. Following Clement and Tse (2005), an analyst's revision is bold if it is either above or below both her prior forecast value and the prevailing consensus forecast value. Standard deviation of earnings forecasts among analysts who cover the firm in the previous year.

GENERAL_EXP Logarithm of number of months between an analyst's earliest appearance in I/B/E/S and her firm-year forecast.

GLOBAL_OPT Proportion of non-coworkers' forecast errors that are optimistic and realized in the past 30 days relative to the analyst's forecast revision. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share.

HI_ABILITY_OPT Proportion of high-ability coworkers' forecast errors that are optimistic and realized in the past 30 days relative to analyst's forecast revision. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share. A coworker is high-ability if the median forecast error (median forecast boldness) in her coverage portfolio is in the bottom (top) tercile of the brokerage in the preceding year.

HORIZON Number of days elapsed between the analyst's firm-year forecast and the actual earnings announcement. We exclude all forecasts that are more than 365 days old or issued within 30 days from the earnings announcement date.

II_STAR Indicator that equals one if the analyst is recognized as an Institutional Investor star analyst anytime in the prior three years, and equals zero otherwise.

INDUSTRY_BREADTH Number of unique two-digit GICS sectors covered by the analyst in the year.

LEVERAGE Sum of short-term debt and long-term borrowings, deflated by total assets.

LOSS Indicator that equals one if the actual earnings per share of the firm is negative, and equals zero otherwise.

LO_ABILITY_OPT Proportion of low-ability coworkers' forecast errors that are optimistic and realized in the past 30 days relative to analyst's forecast revision. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share. A coworker is low-ability if the median forecast error (median forecast boldness) in her coverage portfolio is in the top (bottom) tercile of the brokerage in the preceding year.

LOWBALL Number of times over the past three years that lowballing forecasts were issued for the firm by the analyst. Three conditions must be met for a forecast to be classified as lowball. (i) The forecast value must be below the actual earnings per share (EPS) value. (ii) The absolute difference between forecast value and actual EPS value must be either greater than \$0.03 or higher than 5% of the actual EPS value. (iii) the difference between the forecast value and the consensus value must be greater than \$0.03 or higher than 5% of the consensus value.

NON_SI_OPT Proportion of coworkers' forecast errors made on non-strategically-important (non-SI) firms that are optimistic and realized in the past 30 days relative to an analyst's forecast revision. Following Harford, Jiang, Wang, and Xie (2019), a firm is non-strategically-important to a coworker if it is in the bottom quartile of size, institutional ownership, or trading volume in her coverage portfolio. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share.

NORM_FORECAST_ERR Absolute difference between an analyst's last firm-year forecast value and the actual EPS, deflated by the average firm-year forecast error.

NUM_DIRECT_LINKS Count of an analyst's directly connected coworkers in the brokerage network.

REVISION_FREQ Number of firm-year forecast revisions issued by the analyst.

PEER_M&A_EXPERTISE Indicator that equals one if (i) an analyst covers an acquirer firm and (ii) her brokerage coworker covers the target firm in the preceding year, and equals zero otherwise.

SAME_COHORT Indicator that equals one if an analyst and her coworker join the brokerage in the same year, and equals zero otherwise.

SAME_ETHNICITY Indicator that equals one if an analyst and her coworker have the same ethnic origins, and equals zero otherwise. Using a predictive model trained on Florida voter registration data (Sood and Laohaprapanon, 2018), we determine an analyst's ethnicity based on her last name found in the I/B/E/S detailed recommendations file. Under this model, an analyst belongs to one of the following ethnic categories: (i) asian, (ii) hispanic, (iii) non-hispanic black, or (iv) non-hispanic white. We use the `ethnicolr` library in Python to implement this model.

SIGNED_REVISION Signed difference between an analyst's revision value and her previous forecast value, scaled by the absolute value of the latter.

SI_OPT Proportion of coworkers' forecast errors made on strategically important (SI) firms that are optimistic and realized in the past 30 days relative to an analyst's forecast revision. Following Harford et al. (2019), a firm is strategically important to a coworker if it is in the top quartile of size, institutional ownership, or trading volume in her coverage portfolio. A forecast error is optimistic if the forecast value exceeds the firm's actual earnings per share.

NUM_TANDEM Number of tandem revisions between two analysts. If an analyst and her coworker make two revisions that occur within λ days of each other, those revisions are tandem revisions. We consider three values of $\lambda \in \{3, 5, 15\}$ for robustness.

TRADE_EXPOSURE Eigenvector centrality of an industry in a network of intersector trade (e.g., Ahern and Harford, 2014). The link between buyer-industry and seller-industry is weighted by 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.

Δ_BROKERAGE_EXP Absolute difference in BROKERAGE_EXP between an analyst and her coworker. See above for definition of BROKERAGE_EXP.

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Table 1. Tandem Revisions Between Analysts and Coworkers (Excl. Material Events)

This table presents results from a robustness check of Table 2 in the main text. In the construction of NUM_TANDEM, we exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within either $[-1, 0]$ day (columns 1 to 3) or $[-3, 0]$ day (columns 4 to 6) of the revision. The unit of observation in these regressions is an analyst-pair in the brokerage. The dependent variable is NUM_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 of the main text for an intuitive explanation on 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

	1	2	3	4	5	6
	Excl. revision if material event occurs within window:					
	$[-1, 0]$ day			$[-3, 0]$ day		
λ window	3 days	5 days	15 days	3 days	5 days	15 days
DIRECT_LINK	5.48***	8.01***	22.79***	4.00***	5.73***	16.53***
	(1.11 ± 0.06)	(1.60 ± 0.09)	(4.43 ± 0.26)	(0.78 ± 0.05)	(1.09 ± 0.07)	(3.06 ± 0.20)
LINK_AT_2_STEPS	3.72***	5.53***	16.01***	2.77***	4.05***	11.88***
	(0.59 ± 0.06)	(0.89 ± 0.09)	(2.54 ± 0.26)	(0.43 ± 0.05)	(0.64 ± 0.07)	(1.85 ± 0.20)
LINK_AT_MORE_STEPS	3.07***	4.58***	13.30***	2.24***	3.30***	9.74***
	(0.11 ± 0.07)	(0.20 ± 0.10)	(0.57 ± 0.28)	(0.03 ± 0.05)	(0.09 ± 0.07)	(0.24 ± 0.21)
Other predictors						
SAME_ETHNICITY	1.02***	1.49***	4.22***	0.72***	1.03***	2.92***
	(0.43 ± 0.06)	(0.61 ± 0.08)	(1.68 ± 0.24)	(0.33 ± 0.04)	(0.46 ± 0.06)	(1.25 ± 0.18)
EX_COLLEAGUES	1.41***	2.16***	6.17***	0.87***	1.32***	3.76***
	(-0.58 ± 0.10)	(-0.75 ± 0.15)	(-2.07 ± 0.44)	(-0.60 ± 0.07)	(-0.80 ± 0.11)	(-2.23 ± 0.32)
Δ_BROKERAGE_EXP	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(-0.00 ± 0.00)	(-0.00 ± 0.00)	(-0.01 ± 0.00)	(0.00 ± 0.00)	(-0.01 ± 0.00)	(-0.01 ± 0.00)
SAME_COHORT	1.50***	2.07***	5.75***	1.21***	1.62***	4.57***
	(0.76 ± 0.04)	(1.02 ± 0.05)	(2.80 ± 0.15)	(0.66 ± 0.03)	(0.86 ± 0.04)	(2.40 ± 0.12)
Num. of networks	2,660	2,660	2,660	2,660	2,660	2,660

Table 2. List of Brokerage Mergers

We compile the list of brokerage mergers from Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012). This table documents the 16 mergers used in the difference-in-differences test in Table 6 of the main text. We exclude mergers if their pre-treatment and post-treatment effects overlap in time. For example, we exclude Merrill Lynch because it acquired Advest in 2005 and Petrie Parkman in 2006. In our difference-in-differences framework, an analyst-firm observation at Merrill Lynch would then be subject to pre-treatment and post-treatment effects concurrently around the 2005–2006 period, thus obfuscating our estimations.

Merger year	Acquirer	Target
1997	Morgan Stanley	Dean Witter Reynolds
1998	D.A. Davidson	Jensen Securities
1998	EVEREN Capital	Principal Financial Securities
2000	Soundview	Wit Capital
2000	PaineWebber	J.C. Bradford
2000	Credit Suisse First Boston	Donaldson, Lufkin & Jenrette
2001	Dresdner Bank	Wasserstein Perella
2001	First Union	Wachovia Securities
2001	Suntrust Equitable Securities	Robinson-Humphrey
2004	UBS	Schwab Soundview
2005	Janney Montgomery Scott	Parker/Hunter
2005	Citigroup	Legg Mason Wood Walker
2007	Stifel Financial	Ryan Beck & Co.
2007	Fox-Pitt Kelton	Cochran Caronia Securities
2007	Wachovia Securities	A.G. Edwards & Sons
2008	Fahnestock	CIBC World Markets

Table 3. Robustness Check: Difference-in-differences Regressions

NOTE: The main treatment effects are absorbed by the fixed effects. We present results from OLS regressions in this table. 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 each analyst covers the same firm before and after the merger. In our difference-in-differences 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 to 3) and CLOSENESS (columns 4 to 6). The post-treatment period is $[+1, +3]$ years after the merger. Correspondingly, the POST_ALT indicator equals one if an observation occurs within $[+1, +3]$ years after the merger, and equals zero if the observation occurs within $[-3, 0]$ years from the merger. In columns 2 and 5, we reclassify merger-year forecasts made after (on or before) the merger month to the post-treatment (pre-treatment) period. In columns 3 and 6, we exclude all merger-year forecasts from our 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. The Internet Appendix contains the list of brokerage mergers used in this test. We include all control variables used in Table 5 of the main text. Clustered standard errors at the analyst-firm level 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
Merger-year ($t = 0$) forecasts						
Reclassify	N	Y	N	N	Y	N
Exclude from sample	N	N	Y	N	N	Y
POST_ALT × Δ_EIGENVECTOR	–0.441***	–0.618***	–0.512***			
	(0.164)	(0.156)	(0.190)			
POST_ALT × Δ_CLOSENESS				–0.207*	–0.288***	–0.230*
				(0.118)	(0.111)	(0.135)
POST_ALT	–0.033***	–0.059***	–0.066***	–0.034***	–0.060***	–0.067***
	(0.011)	(0.011)	(0.014)	(0.011)	(0.011)	(0.014)
Observations	9,963	9,963	8,221	9,963	9,963	8,221
R^2	0.289	0.290	0.328	0.289	0.290	0.328
Controls	Y	Y	Y	Y	Y	Y
Analyst × Firm × Merger FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y

Table 4. Peer Learning and Analyst Ability

We present results from OLS regressions in this table. 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, FORECAST_BOLDNESS, and II_STAR. See Section II.B of the main text and the Internet Appendix for definitions and working examples of EIGENVECTOR and CLOSENESS. We define FORECAST_-BOLDNESS as the proportion of bold forecast revisions issued by the analyst for the firm in the previous year. Following Clement and Tse (2005), a forecast revision is bold if it is either higher or lower than both the analyst's previous forecast value and the prevailing consensus value. The indicator II_STAR equals one if the analyst is recognized as an Institutional Investor star analyst anytime in the prior three years, and equals zero otherwise. We include all control variables used in Table 5 of the main text. 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	7	8
EIGENVECTOR	−0.089***	−0.091***	−0.088***	−0.064*				
	(0.024)	(0.025)	(0.025)	(0.039)				
CLOSENESS					−0.116***	−0.118***	−0.115***	−0.055*
					(0.023)	(0.023)	(0.023)	(0.031)
Proxies for ability								
FORECAST_BOLDNESS	−0.027***		−0.027***	−0.003	−0.027***		−0.027***	−0.008
	(0.005)		(0.005)	(0.006)	(0.005)		(0.005)	(0.005)
II_STAR		−0.018***	−0.017***	−0.002		−0.017***	−0.017***	−0.010
		(0.006)	(0.006)	(0.010)		(0.006)	(0.006)	(0.009)
Observations	403,307	403,307	403,307	403,307	403,307	403,307	403,307	403,307
R^2	0.186	0.186	0.186	0.450	0.186	0.186	0.186	0.450
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Brokerage × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Analyst FE	N	N	N	Y	N	N	N	Y
Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y

Table 5. Panel A. Peer Learning and Brokerage size

In this panel, we present results from seemingly unrelated regressions on subsamples split on brokerage size. A brokerage is classified as small if its size is smaller than the 30th percentile of brokerage sizes in the year. A brokerage is classified as mid-sized if its size is between the 30th and 70th percentiles of brokerage sizes in the year. A brokerage is classified as big if its size is bigger than the 70th percentile of brokerage sizes in the year. 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 and CLOSENESS. See Section II.B of the main text and the Internet Appendix for details of their definitions and working examples. We include all control variables used in Table 5 of the main text. Clustered standard errors at the brokerage-year level 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
Brokerage size	Small	Mid	Big	Small	Mid	Big
EIGENVECTOR	−0.036*	−0.176***	−0.076			
	(0.021)	(0.031)	(0.055)			
CLOSENESS				−0.063***	−0.104***	−0.001
				(0.023)	(0.026)	(0.042)
Subsample means						
Brokerage size	12.3	41.9	108.2	12.3	41.9	108.2
Analyst turnover rate	0.596	0.531	0.585	0.596	0.531	0.585
Observations	122,756	158,367	116,860	122,756	158,367	116,860
Controls	Y	Y	Y	Y	Y	Y
Brokerage × Year FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y

Table 5. Panel B. Peer Learning and Analyst Turnover Rate

In this panel, we present results from seemingly unrelated regressions on subsamples split on analyst turnover rate. A brokerage is classified as low-turnover if its analyst turnover rate is lower than the 30$^{\text{th}}$ percentile of analyst turnover rates in the year. A brokerage is classified as mid-turnover if its analyst turnover rate is between the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles of analyst turnover rates in the year. A brokerage is classified as high-turnover if its analyst turnover rate is higher than the 70$^{\text{th}}$ percentile of analyst turnover rates in the year. Analyst turnover rate is the total number of analysts who join and leave the brokerage in the year, normalized by the average of brokerage sizes in the year and the previous year. 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 and CLOSENESS. See Section II.B of the main text and the Internet Appendix for details of their definitions and working examples. We include all control variables used in Table 5 of the main text. Clustered standard errors at the brokerage-year level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Normalized forecast error

	1	2	3	4	5	6
Analyst turnover rate	Low	Mid	High	Low	Mid	High
EIGENVECTOR	−0.112***	−0.059**	−0.030			
	(0.028)	(0.030)	(0.028)			
CLOSENESS				−0.092***	−0.047*	−0.078***
				(0.027)	(0.026)	(0.026)
Subsample means						
Brokerage size	21.2	34.3	22.8	21.2	34.3	22.8
Analyst turnover rate	0.280	0.520	0.854	0.280	0.520	0.854
Observations	121,819	157,434	118,730	121,819	157,434	118,730
Controls	Y	Y	Y	Y	Y	Y
Brokerage × Year FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y

Table 6. Peer Learning and Regulation Fair Disclosure

In this table, we present results from seemingly unrelated regressions on subsamples split on pre- and post-adoption of Regulation Fair Disclosure (Reg FD). The pre-Reg FD period is between the years 1995 and 2000. We restrict the post-Reg FD sample to observations between the years 2001 and 2006 to maintain comparable subsample sizes. 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 and CLOSENESS. See Section II.B of the main text and the Internet Appendix for details of their definitions and working examples. Standard errors reported in parentheses are clustered at the brokerage-year level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: NORM_FORECAST_ERR

	1	2	3	4
Reg FD regime	Pre ['95–'00]	Post ['01–'06]	Pre ['95–'00]	Post ['01–'06]
a: EIGENVECTOR	0.048	−0.068**		
	(0.035)	(0.030)		
b: CLOSENESS			0.005	−0.092***
			(0.031)	(0.025)
REVISION_FREQ	−0.026***	−0.015***	−0.026***	−0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
HORIZON	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
FIRM_EXP	0.002	−0.002	0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)
GENERAL_EXP	0.004	0.008***	0.008***	0.005
	(0.004)	(0.003)	(0.004)	(0.003)
FIRM_BREADTH	0.001	−0.001**	−0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
INDUSTRY_BREADTH	−0.001	0.006*	0.009**	0.002
	(0.003)	(0.004)	(0.003)	(0.004)
LOWBALL	0.047***	0.045***	0.047***	0.045***
	(0.009)	(0.008)	(0.009)	(0.008)
LOSS	−0.002	−0.006	−0.006	−0.002
	(0.007)	(0.006)	(0.006)	(0.007)
ANALYST_COV	−0.001***	−0.003***	−0.001***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
LEVERAGE	0.000	0.008	0.007	−0.001
	(0.012)	(0.011)	(0.011)	(0.012)
BOOK_TO_MARKET	0.005	0.000	0.005	0.000
	(0.004)	(0.002)	(0.002)	(0.004)
TOTAL_ASSETS	0.001	0.008***	0.001	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Wald χ^2 test	Δ **a**: (2) − (1)		Δ **b**: (4) − (3)	
	−0.116**		−0.096**	
Observations	91,007	113,952	91,007	113,952
Brokerage × Year FE	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y

Table 7. Robustness Check: Calendar-time Portfolio Strategies

This table presents results from a robustness check of Table 8 in the main text. The calendar-time portfolio strategy is as follows. Every day, we form two long-short portfolios: (i) long (short) stocks that receive upwards (downwards) forecast revisions from analysts who are in the top tercile of centrality in their brokerages, and (ii) long (short) stocks that receive upwards (downwards) 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 differences in equal-weighted daily returns between these two long-short portfolios (Δ_L−S returns). In columns 1 to 3, we assign Δ_L−S returns on that day to be the risk-free rate if the number of stocks in any leg of the two long-short portfolios is below a certain threshold (either 20 or 50). In columns 4 to 6, we present the Δ_L−S returns from Table 7 of the main text for ease of comparison. t-statistics are reported in parentheses.

Average daily Δ_L−S returns in basis points

		1	2	3		4	5	6
Holding window (day)		$[0, +5]$	$[0, +10]$	$[0, +30]$		$[0, +5]$	$[0, +10]$	$[0, +30]$
		EIGENVECTOR				EIGENVECTOR		
Min. # stocks per leg	20	9.6	5.3	2.9	Baseline (main text)	9.6	5.4	2.9
		(7.83)	(5.73)	(4.42)		(7.71)	(5.73)	(4.42)
	50	8.1	5.4	2.9				
		(7.57)	(5.88)	(4.36)				
		CLOSENESS				CLOSENESS		
	20	9.1	4.8	2.5		9.1	4.8	2.6
		(7.55)	(5.21)	(3.84)		(7.49)	(5.22)	(3.84)
	50	7.1	4.7	2.5				
		(7.14)	(5.23)	(3.78)				

Table 8. Peer Learning and Market Reactions to Forecast Revisions

We present results from OLS regressions in this table. The dependent variable is the absolute $[0, +1]$ day market-adjusted cumulative abnormal returns around the forecast revision date. The key independent variables are EIGENVECTOR and CLOSENESS. See Section II.B of the main text and the Internet Appendix for details of their definitions and working examples. We exclude a forecast revision if the firm issues SEC Form-8Ks or earnings announcements within $[-1, 0]$ day of the revision. Double-clustered standard errors at the week and firm levels are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: $|\,\mathrm{CAR}_{0,+1}\,|$

	1	2	3)	4
EIGENVECTOR	0.744***		0.794***	
	(0.111)		(0.141)	
CLOSENESS		0.532***		0.812***
		(0.058)		(0.119)
BOLD_FORECAST	0.186***	0.185***	0.113***	0.112***
	(0.013)	(0.013)	(0.011)	(0.011)
REVISION_MAGNITUDE	0.013**	0.013**	0.011**	0.011**
	(0.006)	(0.006)	(0.005)	(0.005)
INDUSTRY_BREADTH	−0.108***	−0.104***	−0.089***	−0.097***
	(0.012)	(0.011)	(0.014)	(0.013)
FIRM_BREADTH	−0.010***	−0.012***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
GENERAL_EXP	0.048***	0.054***	0.014	0.013
	(0.013)	(0.013)	(0.009)	(0.009)
FIRM_EXP	−0.028***	−0.028***	−0.035***	−0.035***
	(0.007)	(0.007)	(0.006)	(0.006)
ANALYST_COV	−0.001	−0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
LEVERAGE	0.390***	0.399***	0.487***	0.490***
	(0.088)	(0.088)	(0.077)	(0.077)
TOTAL_ASSETS	−0.426***	−0.423***	−0.414***	−0.413***
	(0.013)	(0.013)	(0.012)	(0.012)
BOOK_TO_MARKET	0.208***	0.209***	0.133***	0.134***
	(0.067)	(0.067)	(0.048)	(0.048)
ROA VOLATILITY	0.004	0.004	0.004*	0.004*
	(0.002)	(0.002)	(0.003)	(0.003)
NUM_FORECASTS	0.150***	0.150***	0.140***	0.139***
	(0.009)	(0.009)	(0.008)	(0.008)
$\|\,\mathrm{CAR}_{-5,-2}\,\|$	0.091***	0.090***	0.062***	0.062***
	(0.004)	(0.004)	(0.003)	(0.003)
BROKERAGE_SIZE	0.185***	0.154***		
	(0.015)	(0.011)		
Observations	1,232,729	1,232,729	1,232,729	1,232,729
R^2	0.120	0.121	0.302	0.302
Brokerage × Year FE	N	N	Y	Y
Clustered SE	Y	Y	Y	Y