Internet Appendix to

PEER EFFECTS IN EQUITY RESEARCH

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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.

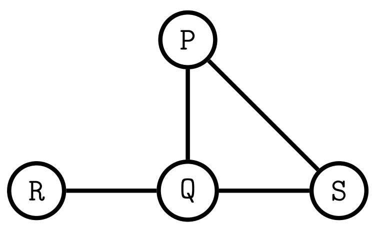


Figure 1. Circles are nodes in the network. Lines represent links between nodes.

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

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

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.

(2)
$$\mathbf{k} = \begin{array}{cc} \begin{bmatrix} 2 \\ 3 \\ 1 \\ 2 \end{bmatrix} & \begin{array}{c} \mathtt{P} \\ \mathtt{Q} \\ \mathtt{R} \\ \mathtt{S} \end{array} \end{array}$$

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

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

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.

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

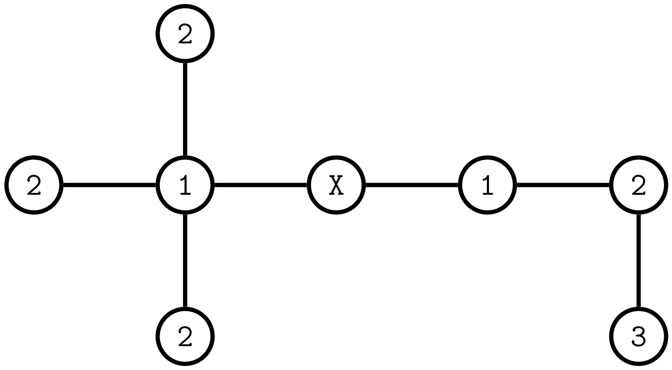


Figure 2. Circles are nodes in the network. Lines represent links. The number in each node indicates the length of the shortest path (i.e., geodesic) between it and node `X`.

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.

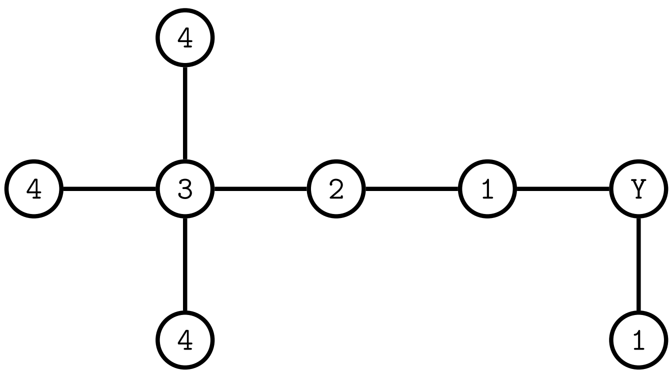


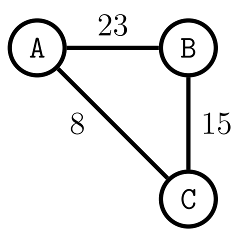
Figure 3. Circles are nodes in the network. Lines represent links. The number in each node indicates the shortest path (i.e., geodesic) length between it and node `Y`.

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

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.



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

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.

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

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 **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.

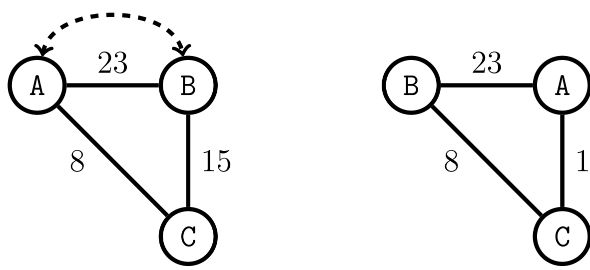


Figure 5. This figure shows an example of a permutation in QAP regressions. Nodes represent analysts in a brokerage network. A link between two analysts represents the number of tandem revisions made between them. In the left subfigure, `A` and `B` swap positions while keeping the link values constant.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

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

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 × 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).

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

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 30^{th} percentile of brokerage sizes in the year. A brokerage is classified as mid-sized if its size is between the 30^{th} and 70^{th} percentiles of brokerage sizes in the year. A brokerage is classified as big if its size is bigger than the 70^{th} 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^{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^{th} and 70^{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^{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 ($\Delta\_L{-}S$ returns). In columns 1 to 3, we assign $\Delta\_L{-}S$ 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 $\Delta\_L{-}S$ returns from Table 7 of the main text for ease of comparison. t-statistics are reported in parentheses.

Average daily $\Delta\_L{-}S$ 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