Cross-industry Technological Link and Information Spillovers in Analyst Research

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ABSTRACT

This paper provides evidence of within-brokerage information spillover effects—an analyst's research on one firm benefits another analyst's research on another technologically similar firm in a different industry. I develop a Technological Connectedness (TC) measure based on the similarity in patent distribution between firms covered by different analysts. I show that analysts with high TC provide more accurate earnings forecasts, issue more informative forecast revisions, exert greater price impact, and make more profitable stock recommendations. I establish causality using three different identification strategies: contemporaneous revisions among connected analysts, colleague turnover, and brokerage mergers. Lastly, I find that such technological information spillovers attenuate technology momentum in stock returns.

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1 Introduction

While a large body of accounting and finance literature has shown that social networks facilitate information transmission in various context,[1] much less is known about the nature of information being transmitted. This paper contributes to this literature by documenting that equity analysts working at the same brokerage house exchange technological information on firms in different industries.[2] Such information transmission arises from information spillover across technologically similar firms in different industries and is distinct from information transmission through other traditional economic linkages such as industry connections, supply chain relationships, and geographic proximity.

A growing strand of literature suggests that analysts colleagues working in the same brokerage house interact with each other and share value-relevant information on economically related firms, for example, those in the same industry (Phua et al., 2023), along a supply chain (Huang et al., 2022), and located in the same geographical area (Chen et al., 2022). Another dimension of economic connection that has considerable value implications but has not received much attention from the literature is technological linkage. Technological link exists between firms that operate in similar technology areas and are closely aligned in terms of technological expertise. This technological affinity transcends traditional industry boundaries and is typically not readily discernible from firms' financial reports. Firms with minimal overlap in product space, or even those in different industries, can share similarities in technological expertise. For example, Boeing Corp (Aircraft industry) and 3M Corp (Business Supplies industry) are not in the same industry, neither do they compete in the same product market, however, the technologies used by these two firms, as captured by their existing patents distribution, are highly similar.[3] Figure 1 shows the average pairwise technological

[1]For example, social interaction among mutual fund managers (Hong et al., 2005; Pool et al., 2015), individual investors (Ivković and Weisbenner, 2007), executives (Shue, 2013), analysts (Cohen et al., 2010; Fang and Huang, 2017; Bradley et al., 2020; Chen et al., 2022), and between mutual fund managers and corporate board members (Cohen et al., 2008).

[2]Note that this paper focuses on information exchange among individual analysts, which is distinct from analysts working in teams (e.g., Fang and Hope, 2021; Gao et al., 2022).

[3]Following prior studies, I calculate technological similarity as the cosine similarity in distribution of patent classes between pairs of firms (Jaffe, 1986; Bloom et al., 2013; Lee et al., 2019). As of 2015, the technological similarity between Boeing Corp and 3M Corp is 0.704 out of 1. Section 2.2 discusses this measure in details.

similarity across firms between pairs of industries. It is quite common that two different industries exhibit technological similarity, and in many cases cross-industry similarity is even higher than within-industry similarity.[4]

In this paper, I investigate whether colleagues who cover technologically linked firms in different industries share information, and how such interaction affects analyst forecast performance and market efficiency. Based on the findings that communication and interaction within an organization play instrumental roles in the flow of technical information (Allen et al., 1984), and people in a network of contacts are more inclined to engage in social interactions and discuss things they share in common (Burt, 1995), I conjecture that analysts covering technologically similar firms, albeit in different industries, have more opportunities to interact with each other and exchange technological information. These analysts should therefore gain a better understanding of how these complex technological factors impact their covered firms and transmit this information to the market, which therefore, leads to improved forecasting performance and market efficiency.

Figure 2 illustrates my empirical prediction. Consider four otherwise identical analysts working at two different brokerage houses. Analyst a and Analyst b work at brokerage house XYZ, while Analyst c and Analyst d work at brokerage house EFG. Firm A is covered by both Analyst b and Analyst c, Firm B is covered by Analyst a, and Firm C is covered by Analyst d. All three firms are in different industries. Assuming that the technological similarity between Firm A and Firm B ($TechSimilarity_{A,B}$) is higher than that between firm A and firm C ($TechSimilarity_{A,C}$), I anticipate that interactions and knowledge-sharing between Analyst a and Analyst b are more frequent than that between Analyst c and Analyst d. Accordingly, Analyst b would have a better assessment of the impact of technological factors on Firm A, compared to Analyst c. This improved understanding is expected to translate into better forecasting performance.

Whether one will observe improved forecast performance due to sharing of technological information is unclear ex ante. Information about technological factors is complex and hard-to-process, especially when it comes to assessing how a given firm will be affected by any particular techno-

[4] Appendix A1 shows that 23 out of 48 Fama-French Industries exhibit higher cross-industry than within-industry technological similarity. For example, the technological similarity between Candy & Soda (code = 3) and Shipping Containers (code = 39) is 0.22, while the within Candy & Soda industry average technological similarity is only 0.11.

logical factor (Cohen et al., 2013; Hirshleifer et al., 2013; Hirshleifer et al., 2018). Although information events impacting one firm has value implications for another technologically-linked peer firm, investors often fail to recognize such technological linkage. Due to sluggish price adjustment to technological information, equity prices exhibit significant technology momentum (Qiu et al., 2018; Lee et al., 2019; Bekkerman et al., 2023). Accordingly, it is possible that analysts covering technologically similar firms fail to identify such underlying linkage, and hence no information is exchanged. In addition, since complex information degrades analyst earnings forecast accuracy (Plumlee, 2003; Bradshaw et al., 2009; Lehavy et al., 2011), the complex nature of technological factors may increase processing costs to such a level that analysts ultimately choose not to receive additional technological information from their colleagues. Furthermore, analysts may compete not internally for resources and senior management attention but also, externally for institutional clients (Hugon et al., 2023), which will impede knowledge sharing. All these factors could result in no association between observed technological linkage among analyst colleagues and forecast performance.

To test my predictions, I develop a "technological connectedness" ($TechConnect$) measure to capture the technological information sharing between the focal analyst and her colleagues. This $TechConnect$ measure is at the analyst-firm-quarter level, calculated as the weighted average pairwise cosine similarity in distribution of patent classes (Jaffe, 1986) between the focal firm and all other distinct firms (different industry) covered by the focal analyst's colleagues in a given quarter.[5] The measure ranges from 0 to 1. A value of 1 means the focal firm is technologically identical to the firms covered by colleagues, whereas a value of 0 means that they have no overlap in technological space. The design of this measure mechanically sidesteps industry information sharing (Phua et al., 2023). In addition, I also control for the industry connectedness with colleagues, calculated as the fraction of marketcap in each industry covered by other analysts. To ensure that the $TechConnect$ measure is not a rediscovery of previously documented within brokerage information sharing channels, I further control for supply chain connections (Huang et al., 2022), geographical connections

[5]The weight for each firm is based on the dollar value of all patents it owns. One should expect the value of technological information to be positively associated with the value of the technology per se, and analysts should benefit more from more valuable technological information.

(Chen et al., 2022), and conglomerate connections (Cohen and Lou, 2012).[6] I expect that analysts are more likely to obtain pertinent and valuable technological information from their colleagues when there is a greater technological overlap in their coverage. Accordingly, $TechConnect$ should be positively associated with forecast performance.

I begin by analyzing the quarterly earnings forecasts issued by a large sample of sell-side analysts from 1995 to 2021. After controlling for other factors that affect analyst forecast accuracy and including firm-year-quarter fixed effects and broker fixed effects, I find that analysts that are more technologically connected to their colleagues provide more accurate earnings forecasts. A one standard deviation increase in $TechConnect$ reduces analyst's absolute forecast error by 0.241 basis points, which is equivalent to making forecasts 2.4 days closer to the earnings announcement date or having an additional 3.8 years of firm-specific experience. Further, to investigate whether colleagues' characteristics influence the effectiveness of $TechConnect$, I separately calculate $TechConnect$ based on different types of colleagues. The baseline results are more pronounced if analysts' colleagues are technologically specialised, more accurate in the past, and more experienced. This result is consistent with the intuition that more accurate and relevant colleagues share more useful information and serve as a more valuable information source (e.g., Bradley et al., 2019; Do and Zhang, 2020). I also find that the effect of $TechConnect$ is stronger if colleagues are of the same gender or same cohort as the focal analyst, consistent with the finding that individuals interact more with peers sharing commonalities (e.g., Pool et al., 2015; Dimmock et al., 2018). I also examine on which types of firms can analysts benefit most from information sharing. The results show that the improvement in accuracy is higher for firms that are smaller, younger, have less analyst coverage, more innovative, and higher earnings volatility. These findings indicate that the per unit value of technological information is higher for firms whose earnings are harder to predict. Furthermore, The effect of $TechConnect$ is stronger after the passage of the Regulation Fair Disclosure (Reg FD) in October 2000, indicating that such alternative source of information is more useful when analysts no longer have direct access to the management.

[6] In fact, the correlations between $TechConnect$ and other connectedness measures are low, ranging from -0.096 between $TechConnect$ and supply chain connection, to 0.168 between $TechConnect$ and industry connection, indicating small overlaps between $TechConnect$ and existing information sharing channel.

The identification of information sharing among analyst colleagues poses challenges (Manski, 1993). First, information sharing among colleagues is ultimately unobservable to researchers. It might happen through various private channels, such as in-person discussions, conference calls, and emails. Second, it is difficult to disentangle the treatment effect (i.e., information sharing) from the selection effect (e.g., Hwang et al., 2019). Brokerage houses may endogenously choose to hire analysts with certain technological expertise. They may also choose to cover firms that are aligned with their expertise. Such hiring decisions or coverage choices, rather than peer effects, could underlie any correlation uncovered between $TechConnect$ and analyst performance. In addition, analysts working at the same brokerage may share common brokerage resources,[7] follow the same training program, be driven by similar incentives, or have exposure to the same brokerage-level shocks. These confounding factors could potentially bias my inference on the influence of peer effects on analysts' performance.

To mitigate these concerns, in my regression specifications, I include broker fixed effects and brokerage-quarter level control variables, which essentially account for a range of time-invariant or -variant characteristics of a brokerage house, such as hiring preference, coverage portfolio decisions, and broker-level specialization. In a stricter specification, I also include analyst fixed effects to explicitly isolates variation within an analyst's portfolio (i.e., forecast accuracy of high $TechConnect$ vs. low $TechConnect$ stocks for the same analyst). To further allay the endogeneity concerns, I implement three identification strategies. These strategies are designed to isolate the effects of colleague information sharing while effectively controlling for the confounding factors. First, I examine the co-occurrences of forecast revisions of highly connected colleagues since the timing of revisions is likely to reflect the exchange of information and ideas. I find that, conditional on covering technologically similar firms, two analysts are more likely to revise earnings forecast within the same day if they work at the same brokerage house, compared to two other analysts who are not colleagues. Second, I exploit colleague turnovers and test whether analyst forecast accuracy improves (deteriorates) after a colleague who covers a technologically highly connected firm joins (departs) the brokerage

[7] For example, macroeconomists (Hugon et al., 2016), high-quality directors of research (Bradley et al., 2019), in-house debt research expertise (Hugon et al., 2023), and quantitative researchers (Birru et al., 2022).

house. This test rules out the possibility that analysts' access to other brokerage resources is driving the results. I find that analyst departure decreases the focal analyst's accuracy while analyst arrival does not have a significant impact. Lastly, using mergers of brokerage houses as quasi-exogenous shocks following Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012), I analyze the accuracy of incumbent analysts who experience changes in $TechConnect$ due to colleague turnover after mergers. I employ a stringent econometric specification by including $Merger \times Analyst \times Firm$ fixed effects to focus on the variation in $TechConnect$ for the same analyst covering the same firm. Results from a difference-in-difference model suggest that $TechConnect$ is positively associated with forecast accuracy.

In addition to forecast accuracy, further analyses examine other aspects of analyst forecast performance. My results show that analysts whose coverage firm is more technologically connected to that of colleagues are more likely to issue bold negative revisions (Clement and Tse, 2005). This is consistent with previous findings that negative information draws more attention (Ferrara and Yang, 2015; Hirshleifer et al., 2021). In addition, revisions from high $TechConnect$ analysts exert stronger investor reactions to their forecast revisions. This observation is consistent with the idea that information sharing enhances forecast informativeness in a way that investors recognize and respond to. Lastly, I examine the profitability of buy and sell recommendation (e.g., Cohen et al., 2010), respectively. Profitability of stock recommendations are more straightforward measures of performance as they provide direct, actionable information to investors. The results show that both analysts' buy and sell recommendations generate significantly positive abnormal return (Daniel et al., 1997).

The findings that analysts with high $TechConnect$ have better forecast performance imply that one should observe less technology momentum in stock prices (Lee et al., 2019). Consistent with these implications, I find that technology momentum effects attenuate as the average $TechConnect$ across all analysts covering a firm increases. I also find that the effect of $TechConnect$ on technology momentum is stronger after the passage of Reg FD. These findings suggest that information sharing among technologically connected analysts facilitates more efficient pricing of technological information.

Furthermore, I examine the $TechConnect$ within an individual analyst portfolio. Specifically, an analyst is more accurate on a firm when it is more technologically similar to other firms within the analyst's portfolio, compated to other analysts. This indicates that not only can analysts obtain useful technological information from their colleagues, they can also reuse such information generated from other firms in their portfolio. This finding corroborates my key conjecture that information from technologically similar firms is beneficial in facilitating analysts making earnings forecast.

This study contributes to the literature in several ways. First, I add to the broad literature on information transmission through social networks (e.g., Hong et al., 2005; Ivković and Weisbenner, 2007; Cohen et al., 2010; Pool et al., 2015; Fang and Huang, 2017; Gu et al., 2019; Bradley et al., 2020). My work is closely related to the studies showing the benefits of information sharing among analyst colleagues that follow the firms in the same industry (Phua et al., 2023), firms located in the same geographical area (Chen et al., 2022), or industries along a supply chain (Huang et al., 2022). I extend this strand of literature by identifying a specific type of information sharing that contributes to analyst performance: access to complementary information about technologically linked firms through colleague collaboration. My evidence reveals the nature of information being transmitted through social network and uncovers a potential mechanism through which analysts overcome attention and information-processing constraints (Clement, 1999; Harford et al., 2019; Hirshleifer et al., 2019).

Second, this paper complements prior studies on the sources of analyst expertise (e.g., Clement, 1999; Malloy, 2005; Kadan et al., 2012; Li et al., 2023) and determinants of analyst career outcome (e.g., Hong and Kubik, 2003; Harford et al., 2019). I show analysts' ability to gather technological information from their colleagues and such ability has positive effect on their forecast performance, and consequently, leading to more favourable career outcomes.

Third, by documenting that analysts with high $TechConnect$ issue more accurate and informative earnings forecast, and more profitable stock recommendations, I offer novel evidence on analysts' roles as information intermediaries in effectively communicating firm information to investors (e.g., Chen et al., 2010; Li et al., 2015; Bradshaw et al., 2017; Martens and Sextroh, 2021). In particular, previous studies show that analyst research generates value from two sources: the

discovery of private information and interpretation of public information (Ivković and Jegadeesh, 2004; Asquith et al., 2005). I contribute to this literature by documenting a flow of information from colleagues to the focal analyst to better understand the sources of the value of analyst research.

Finally, this paper is also relevant to the literature on analyst and anomalies (e.g., Ali and Hirshleifer, 2020; Engelberg et al., 2020). The finding that $TechConnect$ moderates technology momentum builds on the findings of Lee et al. (2019) to shed light on the technology momentum phenomenon, and presents evidence suggesting that a relation exists between stock price momentum and exchange of information via interactions among analyst colleagues (Jegadeesh and Titman, 2001).

2 Data and Variables

2.1 Data sources and sample selection

I draw on three sets of data: analyst forecast data, firm information data, and the Google patent data. Analyst quarterly forecasts and stock recommendations are from the Institutional Broker Estimate System (I/B/E/S) database. The sample period is from January 1995 to March 2022.[8] I use the Unadjusted Detail file and adjust the forecasted EPS based on the split-adjusting factor in Center for Research in Security Prices (CRSP).[9] The Unadjusted Detail file contains analysts' forecasts for one-quarter-ahead quarterly earnings forecasts. To avoid stale or erroneous reported forecasts, I truncate the sample where forecast horizon (days to earnings announcement when analysts issue the forecasts) exceeds 90 days (Kumar et al., 2022). I additionally exclude observations where the date when an analyst forecast becomes effective (ACTDATS) and the forecast review date (REVDATS), or the forecast announcement date (ANNDATS), precedes the analyst forecast announcement date (ANNDATS). Consistent with prior literature (e.g., Hilary and Hsu (2013); Kumar et al. (2022)), when

[8] I choose 1995 as the starting date of the sample because analyst forecast in I/B/E/S are often delivered in batches prior to 1995 and thus subject to data errors. The data accuracy improves after 1995 (Clement et al., 2011; Hilary and Hsu, 2013; Cuculiza et al., 2021).

[9] I/B/E/S Adjusted Detail file provides forecasted EPS data that adjusts for stock splits and rounds the reported EPS to two decimal places. Payne and Thomas (2003) suggest that this rounding method results in loss in information and biased research results. A detailed guidance on how to adjust for EPS can be found at Wharton Research Data Services.

evaluating forecast accuracy, I only consider the last forecast before earning announcement for each analyst-firm-quarter.

Firm information is drawn from CRSP-COMPUSTAT merged data set (CCM). I only include common stocks (SHRCD = 10 or 11) listed on NYSE, AMEX, and Nasdaq (EXCHCD = 1, 2, or 3). The I/B/E/S sample is merged with the CCM using IBES-CRSP Link provided by the Wharton Research Data Services (WRDS). Institutional ownership data is from Thomson Reuters.

To measure technological connectedness, I use the CRSP-matched Google patent data generously provided by Kogan et al. (2017). Specifically, Kogan et al. (2017) use Optical Character Recognition (OCR) technology and several textual analysis algorithms to extract relevant information from Google Patents, and then match the identified assignees to CRSP unique identifiers (PERMNO). This data set covers around 2 million patents with application and issuing dates between 1926 and 2022.

The final sample consists of analysts and firms in the intersection of the above-mentioned datasets from January 1995 to March 2022. The sample contains 892,319 analyst-firm-quarter observations, representing 10,163 unique analysts, 704 unique brokerage houses, and 4,069 unique firms.

2.2 Main variables

Analyst forecast accuracy is measured by absolute forecast error $AFE_{i,j,t}$ (Kumar et al., 2022; Gerken and Painter, 2023), defined as the absolute value of the analyst's most recent earnings forecast minus the actual earnings per share for the firm-quarter, scaled by share price at the beginning of the quarter. Formally, $AFE_{i,j,t}$ is calculated as

$$AFE_{i,j,t} = \frac{Abs(Forecast_{i,j,t} - Actual_{j,t})}{Price_{j,t-1}}, \tag{1}$$

where $Forecast_{i,j,t}$ is analyst i's most recent forecast for firm j's earnings per share in quarter t, $Actual_{j,t}$ is firm j's actual earnings per share in quarter t, and $Price_{j,t-1}$ is firm j's stock price at

the beginning of quarter t.[10]

To capture technological information sharing among analysts, I develop an analyst-firm-quarter variable, Technological Connectedness ($TechConnect_{i,j,t}$). I begin by measuring pairwise patent similarity between firms as in Jaffe (1986) and Bloom et al. (2013). This patent similarity measure essentially captures the closeness between two firms in in multidimensional technology space. Specifically, a firm's patents are distributed across 669 Cooperative Patent Classification (CPC) technology classes as assigned by the United States Patent and Trademark Office (USPTO).[11] I define the pairwise technological similarity, $TechSimilarity_{f,g,t}$, as the cosine similarity across patent classes between firm f and g,

$$TechSimilarity_{f,g,t} = \frac{T_{ft}T'_{gt}}{(T_{ft}T'_{ft})^{1/2}(T_{gt}T'_{gt})^{1/2}}, \tag{2}$$

where $T_{ft} = (T_{ft1}, T_{ft2}, \cdots T_{ft669})$ is a vector of firm f's proportional share of patents across 669 USPTO technology classes. I consider all effective patents that a firm possesses in a rolling window of five years ending in the year before the forecast date. The grant date is treated as the effective date of the patent.[12] $TechSimilarity_{f,g,t}$ is bound by (inclusive) 0 and 1. A value close to 1 means that firm f is technologically similar to firm g, while a value of 0 means that firm f has no technological

[10] As robustness checks, in Appendix A5, I employ three alternative measures of forecast accuracy: standardized $AFE_{i,j,t}$ (Clement and Tse, 2003; Do and Zhang, 2020; Li et al., 2023), proportional mean absolute forecast error $PMAFE_{i,j,t}$ (Clement, 1999; Malloy, 2005; Bradley et al., 2020), and accuracy score $Score_{i,j,t}$ (Hong et al., 2000; Huang et al., 2022), the results are quantitatively similar.

[11] Patent classification is a system for organizing all U.S. patent documents and other technical documents into specific technology groupings based on common subject matter. On January 1, 2013, the USPTO moved from using the United States Patent Classification (USPC) system to the Cooperative Patent Classification (CPC) system. Thus, I assess a firm's patents using the 669 CPC patent classes, the number of patent classes is close to 642 reported by McLemore et al. (2022). Within each technology class, subclasses further delineate processes, structural features, and functional features of the subject matter. Over time, the USPTO has continued to fine tune its classification system, either by adding new classes or by adjusting the subclasses within a given class. These revisions do not significantly affect my methodology, as I only use the major classes available at a given point in time in constructing technological connectedness. Additional details are available at https://www.uspto.gov/.

[12] There are two important dates in the life of each patent: the application date and the grant date. The application date is the date on which the inventor(s) filed for a new patent with the USPTO; the grant date is the date on which the patent is formally issued by the USPTO. The lag between these two dates is on average two to three years. Unless there is a federal holiday, the USPTO issues patents every Tuesday, and its publication, Official Gazette, lists detailed information on the patents granted on that day. After the American Inventors Protection Act (AIPA) came into effect on November 30, 2000, the USPTO began publishing patent applications 18 months after the application date. I choose the grant date as the patent effective date to ensure investors and analysts are exposed to this public information. Nevertheless, my measure of connectedness does not rely on the premise that patent information is publicly available because the technological similarity between firms may already be known by analysts through other information channels (either private or public) before the patent information is publicized.

overlap with firm g.

After obtaining pairwise patent similarity, I then calculate $TechConnect_{i,j,t}$ of analyst i who covers firm j in quarter t as the weighted average $TechSimilarity$ between firm j and all other K firms covered by her colleagues in the most recent year (quarter $t-3$ to quarter t). Formally, $TechConnect_{i,j,t}$ is defined as:

$$TechConnect_{i,j,t} = \Sigma_{k=1,j\neq k}^{K} \frac{PatentValue_{k,t}}{\Sigma_{k=1,j\neq k}^{K} PatentValue_{k,t}} \times TechSimilarity_{k,j,t}, \tag{3}$$

where $TechSimilarity_{k,j,t}$ is the most recent patent similarity measure between firm k and firm j at quarter t, $PatentValue_{k,t}$ is the total value of patents of firm k at quarter t (Kogan et al., 2017). Intuitively, information on technologies that are more valuable is more beneficial to the focal analyst. I exclude pairs of firms where $TechSimilarity_{k,j,t}$ is zero. To mechanically avoid the $TechConnect_{i,j,t}$ capturing industry information sharing, I require firm k to be in a different industry from firm j using Fama-French 48 industry classification.[13]

Moreover, since analyst i may reuse technological information from other firms in her portfolio when analyzing firm j, I impose the condition that firm j must be different from any other firms covered by analyst i in quarter t. Finally, I exclude colleagues who left the brokerage house before quarter t in which analyst i makes the earnings forecast.

2.3 Control variables

To ensure that the technological connectedness is not a rediscovery of existing channels of within-brokerage information sharing, I control for several other channels. First, I include supply chain connection with other colleagues as in Huang et al. (2022). Supply chain connection, $SupplyChainConnect_{i,j,t}$, is defined as the economic connection between the industry that firm j belongs to and all other industries covered by analyst i's colleagues in quarter t, based on the Benchmark Input-Output Accounts prepared by the Bureau of Economic Analysis (Menzly and Ozbas,

[13] As reported in the robustness checks in Appendix A6, the results are unaffected without this restriction or using different industry classification methods.

2010). The economic connection between two industry is their mutual dependence as both a supplier and a customer. Second, to control for same-industry information sharing, I calculate the percentage of firms that are in the same industry as firm j among all the other firms covered by other colleagues ($IndustryConnect_{i,j,t}$). In addition, to control for geographic information transmission (Chen et al., 2022), I calculate the number of peer colleagues that cover firms located in the same Metropolitan Statistical Area ($GeographyConnect_{i,j,t}$). Lastly, I identify "pseudo-conglomerate" firms to firm j to control for information spillover between conglomerate firms and stand-alone firms. For focal firms that have more than one business line, I create an indicator of $ConglomerateConnect_{i,j,t}$ that takes the value of one if colleagues cover at least one "pseudo-conglomerate" peer firms, i.e., single-line firms that collectively span the focal firms' lines of business (Cohen and Lou, 2012).[14]

Following prior literature (Clement, 1999; Clement and Tse, 2003; Bradley et al., 2020), I include analyst characteristics that are known to affect forecast accuracy, such as brokerage firm size ($BrokerageSize$) to control for the analyst's brokerage firm resources, number of companies followed ($NumFirms$) and number of industries followed ($NumIndustries$) to control for the analyst's portfolio complexity, firm-specific experience ($FirmExperience$) general experience ($AnalystTenure$), all-star status ($Star$) (Stickel, 1992), and analyst locality ($Local$) (Malloy, 2005) to control for the analyst's forecasting ability. I further include forecast horizon ($ForecastHorizon$) to account for forecast timeliness.

Furthermore, it is possible that $TechConnect$ is a proxy for brokerage-level specialization or hiring preference. For example, brokerage houses may specialize in firms that share technological similarity, and they may intentionally hire analysts that cover technologically similar firms. To alleviate this concern, I also control for two brokerage-quarter characteristics: industry concentration ($Broker_IndCon$) of all firms the brokerage covers, which is akin to the Herfindahl-Hirschman index, and the average value of patents of all coverage firms ($Broker_PatentVal$). All continuous variables are winsorized at 1% and 99% to minimize the effect of outliers. Appendix A8 provides detailed descriptions of each variable.

[14]The results are not affected if I instead use the percentage of firms from which the focal firm generates industry segment sales.

2.4 Descriptive statistics

Appendix A2 presents descriptive statistics for the sample. The average analyst in the sample has 7.4 years of experience and covers 10.2 firms operating in 2.8 industries (based on Fama-French 48 industry classification). The mean forecast error is -12.1 basis points, which is consistent with Kumar et al. (2022) that the average forecast is pessimistic.

In terms of officemates, the average brokerage house has 40.2 analysts. Among them, 19.7 colleagues cover at least one technologically linked firm (where $TechSimilarity$ is greater than zero). On average, an analyst-firm is technologically linked to 88.2 firms in different industries.Analysts typically have 9.08 colleagues covering firms within the same Metropolitan Statistical Area. This number is similar to the average of 7.31 local peers reported by Chen et al. (2022). For an analyst's covered firm, the sum of its input produced by her colleagues' industries and its output used by her colleagues' industries amounts to 74.6% of its total output ($SupplyChainConnect$). This is consistent with the 69.8% reported by Huang et al. (2022). Further, only 6.9% of other firms in terms of marketcap is in the same industry as the focal firm ($IndustryConnect$), which is consistent with the organizational structure of industry-specialization (Sonney, 2009). Lastly, an average focal firm generate industry segment sales from 15.4% of other firms ($ConglomerateConnect$).

The main independent variable, $TechConnect$, has a mean of 0.087, meaning that, on average, a firm shares 8.7% of its technological expertise with firms in different industries covered by the analyst's colleagues. To put it into context, the average technological similarity ($TechSimilarity$) between any two firms is only 5.9%. To further understand the variation in $TechConnect$, I regress it on a host of variables. Column (1) of Table 1 reports the results of a pooled ordinary least squares (OLS) regression that includes all firm-, analyst-, and brokerage-level characteristics as independent variables. These variables explain only 14% of the variation in $TechConnect$. In Column (2), I focus on the firm characteristics by including analyst-quarter fixed effects. The R-squared rises to 49%, suggesting that much of the variation of $TechConnect$ comes from analyst portfolio heterogeneity. For the firm characteristics, $TechConnect$ increases with market capitalization, R&D expense, and analyst coverage but decreases with institutional

ownership. Additionally, for coverage firms within an analyst portfolio, $TechConnect$ is positively associated with $ConglomerateConnect$ and $GeographyConnect$ but negatively associated with $SupplyChainConnect$. I note that $TechConnect$ is not related to $IndustryConnect$ because the construction of $TechConnect$ mechanically excludes any same-industry information sharing.

Column (3) examines the relationship between analyst characteristics and $TechConnect$ by including firm-year-quarter fixed effects. The R-squared further increases to 69%, implying significant firm heterogeneity in $TechConnect$. The industry concentration and average patent value of coverage firms for a brokerage house are positively associated with $TechConnect$, while all-star status is negatively associated. Notably, within the same firm, analysts with higher $TechConnect$ also exhibit higher other connectedness measures, suggesting that brokerages tend to cover economically linked firms. Lastly, no other analyst characteristics show a significant relationship with $TechConnect$.

3 Main Empirical Results

3.1 Analyst forecast accuracy and technological connectedness with colleagues

To test the relation between analysts' forecast accuracy and their technological connectedness with colleagues, I estimate the following regression:

$$\begin{aligned} AFE_{i,j,t} =& \beta_0 + \beta_1 TechConnect_{i,j,t} + \beta_2 SupplyChainConnect_{i,j,t} + \\ & \beta_3 IndustryConnect_{i,j,t} + \beta_4 ConglomerateConnect_{i,j,t} + \\ & \beta_5 GeographyConnect_{i,j,t} + \beta_6 ForecastHorizon_{i,j,t} + \beta_7 FirmExperience_{i,j,t} + \\ & \beta_8 AnalystTenure_{i,j,t} + \beta_9 NumFirms_{i,j,t} + \beta_{10} NumIndustries_{i,j,t} + \\ & \beta_{11} Star_{i,j,t} + \beta_{12} Local_{i,j,t} + \beta_{13} BrokerageSize_{i,j,t} + \\ & \beta_{14} Broker_IndCon + \beta_{15} Broker_PatentVal + \\ & Firm \times year \times quarter\ FE + Broker\ FE + \varepsilon_{i,j,t}. \end{aligned} \tag{4}$$

The main specification includes firm-year-quarter fixed effects to essentially compare forecast accuracy across analysts covering the same firm. I also include brokerage fixed effects that help to absorb effects of brokerage-level heterogeneity such as institutional prestige and research resources, as well as common traits among analysts at the same brokerage, such as educational background and analytical ability. I double-cluster standard errors at the analyst and firm levels to address the time-series correlation of an analyst's own forecast errors and the cross-sectional correlation in forecasting performance for analysts covering the same firm (Petersen, 2009).

Table 2 reports the regression results for earnings forecast accuracy. The coefficients on $TechConnect$ in all three columns are negative and statistically significant, supporting my prediction that information sharing with colleagues who cover technologically-linked firms improves analysts' earnings forecast accuracy. In Column (1), all other connectedness measures are excluded and they are added back in Column (2). The magnitude and significance of $TechConnect$ are nearly unchanged from Column (1) to Column (2), indicating that $TechConnect$ is a unique channel that is distinct from information sharing on firms along supply chain, industry, conglomerate, or geography linkages.[15] The coefficients on control variables are mostly consistent with previous studies. For example, analysts' forecast accuracy improves with firm experience, brokerage size, and all-star status but deteriorates with forecast horizon. The coefficient on $IndustryConnect$ is negative and significant, indicating that analysts are more accurate when more colleagues are covering the same industry (Phua et al., 2023). Consistent with Chen et al. (2022), the coefficient on $GeographyConnect$ is also negative and significant, suggesting that analysts with more local peers provide more accurate earnings forecasts. Column (3) next shows that the coefficient on $TechConnect$ remains large and significant even when including the stricter analyst fixed effects. With this specification, I am essentially comparing forecast accuracy across firms within an analyst portfolio. This result indicates that the effect of $TechConnect$ is unlikely to be driven by brokerage-level heterogeneity.

In terms of economic magnitude, using the coefficients obtained from the main model in Column (2), a one standard deviation increase in $TechConnect$ reduces the AFE by 0.241 basis points (-1.894

[15] In addition, the correlation between $TechConnect$ and $SupplyChainConnect$, $IndustryConnect$, $ConglomerateConnect$, and $GeographyConnect$ is -0.096, 0.168, 0.007, and 0.015, respectively.

$\times$ 0.127=0.241), which is a 1.71% improvement relative to the sample median of 14.06 basis points. To put this result into perspective, AFE of all-star analysts is 0.453 basis points lower than non-star analysts. In addition, such an improvement is equivalent to making forecast 2.4 days closer to the earnings announcement date (0.241%/0.099= 2.4), or having additional 3.8 years of firm-specific experience (0.241%/0.064=3.8).

To further gauge the the economic significance of the effects of technological connectedness, I compare the improvement in accuracy to the extant literature on network effects of analysts. Huang et al. (2022) find that a one standard deviation in supply chain connectedness to colleagues is equivalent to the benefit of issuing forecast five days closer to the earnings announcement in an annual earnings forecast setting. Bradley et al. (2020) show that forecasts made by analysts with professional senior management connections are 2.21% more accurate than those of analysts without such ties. Chen et al. (2022) show that having one more local peer in a brokerage house increase forecast accuracy by 4.4%. Overall, $TechConnect$ appears to represent a unique form of within-brokerage information sharing, resulting in economically significant improvements in forecast accuracy that are comparable to other network effects documented in the literature.

3.2 Conditional effects of technological connectedness

In this section, I explore the determinants of the usefulness of technological information sharing. First, I explore peer analyst characteristics. Analysts are more likely to seek information from higher-quality colleagues. For example, Bradley et al. (2019) show that effects from high-quality research directors on analyst performance are more beneficial compared to low-quality ones. Do and Zhang (2020) find that peer effects from star analysts, who are characterized by superior performance, can significantly improve other analysts' performance. Accordingly, one would expect that, conditional on the same level of technological connectedness, analysts benefit more from colleagues who are more experienced or skilled. Further, prior studies show that individuals sharing similarity engage in more social interaction (e.g., Pool et al., 2015; Dimmock et al., 2018), which could potentially promote technological information exchange among analyst peers.

To empirically test these predictions, I separately calculate two types of $TechConnect$ ($TechConnect_True$ and $TechConnect_False$) based on various characteristics of analyst peers. For colleague skill and experience, I categorize analyst colleagues into two groups based on whether they are technologically specialized, have performed well in the past, and are experienced. An analyst is considered tech-specialized, well-performing, and experienced if her portfolio-average $PatentValue$, $PastPerformance$, and $AnalystTenure$ are above the sample median, respectively. For peer similarity, I categorize analyst colleagues based on whether they are of the same gender or from the same cohort as the focal analyst. I define same-cohort analysts as those join the brokerage in the same year.

I then replace $TechConnect$ in Equation 3.1 with these two new variables, $TechConnect_True$ and $TechConnect_False$, and rerun the regression. The prediction is that the coefficients on $TechConnect_True$ are higher than that on $TechConnect_False$, that is, the per-unit benefit of technological information sharing is higher from colleagues that are more skilled, experienced, and similar. Columns (1) to (3) of Panel A in Table 3 report the results for colleague skill and experience, and Columns (4) to (5) report the results for colleague similarity. The coefficients on $TechConnect_True$ are all negative and significant, while the coefficients on $TechConnect_Low$ are insignificant with the exception for same cohort result. The χ^2 tests show that the magnitudes of the coefficients on $TechConnect_True$ significantly exceed that on $TechConnect_False$ except for Column (3).[16] These results indicate that information sharing from colleagues is more valuable if they are more technologically specialised, more accurate, more experienced, and if they share similarity with the focal analyst.

Next, I examine firm-level characteristics that might affect the effects of $TechConnect$ on forecast accuracy. The first one is firm size ($FirmSize$). Harford et al. (2019) find that analysts allocate their attention and effort to larger firms in their portfolios. Accordingly, colleagues may serve as more important complementary information sources when the analyst exerts less effort on covering the firm. Second, I consider the firm's information environment. The reliance on information

[16]Nevertheless, the horse-race regression in Column (3) yields a significant coefficient on $TechConnect_True$ but an insignificant coefficient on $TechConnect_False$.

sharing should be negative associated with information transparency and availability. I use firm's age and analyst coverage as proxies for information environment ($FirmAge$ and $NumAnalysts$). Next, I examine innovation intensity ($InnovationIntensity$), which is calculated as the logarithm of one plus total number of citations of a firm's patents, deflated by the logarithm of its marketcap. Firms that are more innovation-intensive are more sensitive to economic shocks to its tech-peers (Lee et al., 2019). Information sharing helps analyst to better understand how these shocks would affect the focal firm. In addition, more innovation-intensive firms are likely to be hard to value (Hirshleifer et al., 2013), making the per unit information shared by colleagues more valuable. Lastly, I examine earnings volatility ($EarningsVolatility$). I expect that the marginal benefit of information sharing to increase when earnings are difficult to predict.

Table 3, Panel B reports the results. The coefficients on all interaction terms are significant, which supports my prediction that analysts benefit more from technological information sharing when the focal firm is smaller, younger, has more analyst coverage, engages in more intensive innovation activities, and exhibits high earnings uncertainty.

Lastly, I examine whether the passage of Regulation Fair Disclosure (Reg FD) affects the effect of $TechConnect$ on forecast accuracy. Studies have shown that Reg FD puts an end to the practice of selective disclosure and private earnings guidance (Agrawal et al., 2006; Wang, 2007; Cohen et al., 2010). As these information sources become unavailable after Reg FD, I expect the benefits of alternative information sources, including technological information from colleagues, to increase. Panel C of Table 3 presents the regression results using subsamples partitioned by the end of the year 2000. Consistent with my expectation, the effect of $TechConnect$ on forecast accuracy is significant after but not before Reg FD.

4 Identification Strategies

In this section, I address the endogeneity concern that omitted variables might be correlated with both analyst's forecast accuracy and $TechConnect$. To that end, I employ three different identification strategies. Section 4.1 discusses my first identification strategy that uses contemporaneous

forecast revisions as evidence of information flow. Section 4.2 presents the second identification strategy using analyst turnover as exogenous source of variation in $TechConnect$. Section 4.3 discusses the last identification strategy that uses a DiD approach by relying on brokerage mergers as quasi-natural experiments.

4.1 Information flow in brokerages: co-occurrences of forecast revisions

Because information flow among colleagues is not directly observable, as the first identification strategy, I use the timing of forecast revisions to infer whether analysts receive new ideas and information from their technologically connected colleagues. If highly-connected analysts exchange information with one another in a brokerage, the technological connectedness should predict co-occurrences of their revisions, which I term tandem revisions. When an analyst makes a revision, presumably due to arrival of new information, a highly-connected colleague is more likely to issue a revision than other analysts in a different brokerage house. Using again Figure 2 to illustrate, contemporaneous forecast revision is more likely to occur between Analyst a and Analyst b, than between Analyst a and Analyst c. To test this prediction, I construct a panel data by documenting all pairs of forecast revisions for every calendar month in each year. Each observation consists of two forecast revisions from two firm-analyst combinations in a given calendar year-month, where both firms and both analysts are required to be different. Appendix A3 presents a hypothetical example of how I convert the forecast revision data into the panel dataset. Based on the 284901 forecast revisions in the original data, I obtain a final panel data consists of 19825779 observations, spanning 326 months. In each month, there are on average 66018 unique pairs of firm-analyst, representing 455 unique forecast revisions.

Using the panel data, I estimate the following regression with standard errors clustered at the

revision pair and year-month levels:[17]

$$
\begin{aligned}
Tandem_Revision_{f,g,i,j,t} = \\
&\beta_0 + \beta_1 HighConnect_{f,g,t} \times SameBroker_{i,j,t} + \beta_2 HighConnect_{i,j,t} + \\
&\sum_{n}^{N} \beta_n SameBroker_{i,j,t} \times \text{Firms-pair Control}_{f,g,t} + \\
&\sum_{k}^{K} \beta_k SameBroker_{i,j,t} \times \text{Analysts-pair Control}_{i,j,t} + \\
&\sum_{f}^{F} \beta_f \text{Firms-pair Control}_{f,g,t} + \sum_{m}^{M} \beta_m \text{Analysts-pair Control}_{i,j,t} + \\
&+ \text{Year-month FE} + \epsilon_{f,g,i,j,t},
\end{aligned}
\tag{5}
$$

where $Tandem_Revision_{f,g,i,j,t}$ is a dummy variable that takes the value of one if analyst i, covering firm f, and analyst j, covering firm g (where $f \neq g$ and $i \neq j$), make forecast revisions contemporaneously in month t. Contemporaneous forecast revisions are defined as those occurring within twenty-four hours of each other. $HighConnect_{f,g,t}$ equals one if firms f and g are highly similar in terms of technological expertise, as measured by $TechSimilarity_{f,g,t}$. Firms are considered highly similar when firm g's $TechSimilarity_{f,g,t}$ is in the top 10th percentile ($HighConnect10$) or 20th percentile ($HighConnect20$) of all firms relative to firm f. Analyst-pair control variables include indicator of whether two analysts work at the same brokerage house ($SameBroker_{i,j,t}$), are of the same gender ($SameGender_{i,j,t}$), are of the same ethnicity ($SameEthnicity_{i,j,t}$), or have previously been colleagues ($ExColleague_{i,j,t}$). Firm-pair control variables include indicator of whether two firms are in the same industry ($SameIndustry_{f,g,t}$), are in the same Metropolitan Statistical Area ($SameGeography_{f,g,t}$), are part of the same supply chain ($SameSupplyChain_{f,g,t}$), or have conglomerate connections ($SameConglomerate_{f,g,t}$). These firm-level variables effectively absorb any economic shocks that may cause analysts to make forecast revisions simulta-

[17] Since the unit of analysis is the revision pair-year-month, clustering standard errors at the year-month level addresses the cross-sectional correlation across revision pairs. Tandem revision between two firm-analyst could be correlated with another two firm-analyst due to common economic shock to the firms or similarity of the analysts. Clustering standard errors at the revision pair level addresses the autocorrelation within each pair of firm-analyst, where two analysts' revision timings in the current month may be correlated with their revision timings in subsequent months.

neously. $ExperienceDiff_{i,j,t}$ and $FirmExperienceDiff_{i,j,t}$ represent the absolute differences in general experience and firm-specific experience between analyst i and analyst j, respectively. $MarketcapDiff_{f,g,t}$ is the absolute difference in the logarithm of the market capitalization between firm f and firm g.

Table 4 reports the results. Column (1) and (2) present results using all pairs while Column (3) and (4) exclude pairs of firm-analyst in which firms are in the same industry. The coefficients on $HighConnect$ are all highly significant, suggesting that analysts respond simultaneously to common technological shocks. On the other hand, the coefficients on $SameBroker$ are mostly insignificant, ruling out the possibility of brokerage-level timing alignment of forecast revisions. The coefficients of interest on the interaction terms of $HighConnect \times SameBroker$ are statistically significant in all four columns. In my main specification in Column (3), the coefficient on $HighConnect10 \times SameBroker$ is 0.906, indicating that, conditional on high technological similarity, the probability of contemporaneous forecast revisions between two highly-connected analysts at the same brokerage is 0.906% higher than between two highly-connected analysts at different brokerage houses. To put this economic magnitude into perspective, consider that the unconditional probability of an analyst issuing a forecast revision for a firm is 24.2%. A back-of-the-envelope calculation would suggest a probability of 5.9% that two analysts make forecast revisions on the same day by chance ($0.242^2 = 0.059$). The 0.906% increase is equivalent to a 15.4% improvement relative to the baseline probability of 5.9%. Also as a comparison, the coefficient on $SameIndustry$ in Column (1) is 0.864, suggesting that analysts covering firms in the same industry are 0.864% more likely to issue revisions contemporaneously than analysts covering firms in different industries. Further, I note that the coefficients on $HighConnect20 \times SameBroker$ are smaller and less significant than the coefficients on$HighConnect10 \times SameBroker$ in either sample, which supports my conjecture that the probability of contemporaneous revisions increases with the strength of technological link between two firms.

Several additional findings emerge from the regression results. The coefficients on both $SameIndustry \times SameBroker$ and $SameGeography \times SameBroker$ are positive and significant, aligning with previous studies on information sharing in industry and geographic dimensions

(Phua et al., 2023; Chen et al., 2022). However, the coefficient on $SameSupplyChain \times SameBroker$ is negative and significant, suggesting that although analysts obtain information on economically related industries along a supply chain, there is a significant lead-lag effect in information transmission. Lastly, in the same brokerage, analysts that are of the same gender, joined the brokerage in the same year, and have similar years of experience are more likely to issue forecast revisions contemporaneously. This is consistent with prior work showing that people share similarity interact more (e.g., Pool et al., 2015; Dimmock et al., 2018).

4.2 Colleague turnover and information sharing

Next, I exploit cases in which an analyst covering firm j experiences an arrival or departure of a colleague who covers a firm that has strong technological link (i.e., high $TechSimilarity_{f,g,t}$) with firm j (hereafter, a "highly connected colleague"). If the underlying mechanism of the increase in forecast accuracy is due to social interaction among analyst colleagues, one would expect the forecast accuracy of the focal analyst to be affected by colleague turnovers. When a highly-connected analyst leaves, knowledge transfer and social learning cease, negatively affecting focal analysts' performance. Conversely, when a highly connected analyst arrives, the additional information should enhance the focal analyst's performance. Therefore, I expect an improvement (reduction) in forecast accuracy with the arrival (departure) of a highly connected colleague.

I define highly connected colleague as someone who covers a firm whose $TechSimilarity_{f,g,t}$ with the focal firm is in the top n percentile of the sample $TechSimilarity_{f,g,t}$ values (n is set to 10, 20, 30, respectively). To isolate the effect of the turnover of highly-connected colleagues, I only focus on the cases where only one colleague is arriving (departing), and during the quarter when she arrives (departs), there should be no other colleague departing (arriving).[18] Further, I also require that the arriving (departing) colleague to cover an economically-important firm whose total value of patents must be above the median of all firms that a brokerage covers in a given year. For each turnover event, I compare the affected analyst's forecast accuracy on firm j in the quarter when the

[18] Do and Zhang (2020) show that the arrival (departure) of a star analyst has a positive (negative) effect on incumbents' forecasting performance. To avoid capturing the same effect, in an untabulated test, I exclude the cases where the arriving (departing) highly-connected colleague is also a star analyst. The results are unaffected by this additional restriction.

highly connected colleague is hired ($Arrival$ equals one) or in the quarter after the highly connected colleague departs ($Departure$ equals one) with that of the prior quarter. Specifically, I use the two adjacent quarters in the regression for any firm-analyst affected by a turnover event, and I include event fixed effects (i.e., firm $\times$ analyst $\times$ colleagues turnover). The regression specification is the same as in Equation 3.1, except that $TechConnect$ is replaced with an indicator of departure or arrival of colleagues, and only event fixed effects are included. Formally, I estimate the following regression with standard errors clustered at the firm and analyst levels:

$$AFE_{i,j,t} = \beta_0 + \beta_1 Arrival\ (Departure) + \beta_2 Controls + Event\ FE + \varepsilon_{i,j,t}. \tag{6}$$

Table 5 reports the results. Panel A shows the effects of the departure of a highly connected colleague. In Column (1), the coefficient on the departure dummy is positive and significant (coefficient = 6.814, t-stat = 2.54), which indicates that the focal analyst's AFE increases by 6.814 basis points after a highly-connected colleague leaves the brokerage house. Column (2) and (3) define highly-connected colleagues using alternative $TechSimilarity_{f,g,t}$ thresholds. The magnitude and significance reduce monotonically and the coefficient in Column (3) is no longer significant. Column (4) show results of falsification tests. I falsely define highly-connected colleague as someone who covers a firm whose $TechSimilarity_{f,g,t}$ with the focal firm is zero (i.e., no technological similarity). The falsification test yields coefficient that is insignificant and close to zero, further supporting my prediction that technological information sharing improves analysts' forecast accuracy. Finally, to put these results into perspective, I examine the effect of the turnover of a same-industry colleague in Column (5). The coefficient is small and insignificant, suggesting that the departure of a highly connected colleague has a substantially larger impact on the focal analyst's forecast accuracy than the departure of a same-industry colleague.

Table 5, Panel B, shows the effects of the arrival of a highly connected colleague. The coefficients on $Arrival$ in all columns are insignificant, implying that the arrival of a highly connected colleague does not have an immediate effect on the focal analyst's performance. This may be due to frictions in incorporating new information or adjusting to a new colleague.

Overall, these results suggest that the arrival and departure of highly connected colleagues have asymmetric effects, with the impact of a departure being more pronounced than that of an arrival.

4.3 Brokerage mergers as exogenous shocks

To further mitigate endogeneity concerns, I exploit brokerage mergers as quasi-exogenous shocks to the brokerage network structures (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012) that result in variation in $TechConnect$. Using mergers as shocks is ideal because they are driven by strategic motivations at the business level (Derrien and Kecskés, 2013), and hence exogenous to analyst attributes. In addition, these events occurred in various points in time, mitigating concerns about macroeconomic shocks or seasonal effects that could simultaneously affect both brokerage coverage decisions and analysts' performance. I obtain the list of mergers from Chen et al. (2018), who compile it from Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012). Appendix A7 presents the names and I/B/E/S codes of targets and acquirers. My main regression specification involves 19 mergers, representing 130 unique analysts and 203 unique firms.

To evaluate the impact of the changes in $TechConnect$ on analyst's forecast accuracy, I estimate a difference-in-differences model. I focus on the incumbent analysts that remain at the same brokerage and cover the same firm throughout the merger event. Identification thus comes from variation in the $TechConnect$ due to turnover of colleagues. Following this stringent requirement, I include $Merger \times Analyst \times Firm$ fixed effects. These fixed effects help to address unobserved heterogeneity at the analyst-firm level, such as innate ability, selection effects related to analysts' coverage assignments (Clement et al., 2007), and an analyst's average optimism regarding the firm (Kumar et al., 2022).

In my main analysis, I first skip two months symmetrically around the event date to avoid data errors, as it can be difficult to pinpoint the exact date of analyst turnover. I then focus on an analyst's first (last) three forecasts for the first (last) three fiscal quarters after (before) the brokerage merger, within an 18-month window symmetrically surrounding the event. I require each analyst to issue at least one forecast in each of the three fiscal quarters both before and after the event within this time

window. For analyst i, who covers firm j and experiences a merger m at event time 0, I estimate the following specification:

$$\begin{aligned} AFE_{i,j,m,t} =& \beta_0 + \beta_1 Post \times \Delta TechConnect_{i,j,m,t} + \beta_2 Post + Controls_{i,j,m,t} + \\ & Merger \times Analyst \times Firm\ FE + \epsilon_{i,j,m,t}, \end{aligned} \tag{7}$$

where $Post$ is a binary indicator that switches on after the merger date, and $\Delta TechConnect_{i,j,m,t}$ represents the treatment effect, calculated as the change in $TechConnect_{i,j,m,t}$ for analyst i covering firm j from quarter $t-1$ to quarter $t+1$ around the merger event m. Note that $\Delta TechConnect_{i,j,m,t}$ is absorbed by the fixed effects in the model. In other words, $\Delta TechConnect_{i,j,m,t}$ takes the same value across all quarters for each merger-analyst-firm. The control variables are the same as those in Equation 3.1. Standard errors are two-way clustered at the analyst and firm levels.

I verify the parallel trends assumption by plotting the average AFE of analysts who experience large changes in $\Delta TechConnect_{i,j,m,t}$. Since the treatment is continuous, for each merger event, I sort analysts into quintiles based on $\Delta TechConnect_{i,j,m,t}$ and calculate the average AFE of analysts in the top and bottom quintiles, corresponding to the high and low groups, respectively.[19] I then calculate the groupwise average AFE for each of the six quarters surrounding the events.

Figure 3 shows the accuracy pattern of two analyst groups. There is no clear pre-merger trend in AFE differences between the two groups, suggesting that the treatment, $\Delta TechConnect_{i,j,m,t}$, is unlikely to be related to latent factors affecting future forecast accuracy. Analysts with high $\Delta TechConnect_{i,j,m,t}$ are slightly more accurate than those with low $\Delta TechConnect_{i,j,m,t}$ in the pre-merger period. The difference widens in the first two quarters after the events, implying that the benefit of information sharing is greatest in this initial period but gradually fades. Notably, the accuracy gap is mainly driven by an increase in the AFE of the low group, while the accuracy of the high group remains largely unchanged. This is consistent with my colleague turnover test in Table 5, which shows that a decrease in $TechConnect$ has a more pronounced impact on forecast accuracy than an increase.

[19] $\Delta TechConnect_{i,j,m,t}$ ranges from -0.318 to 0.179, with the 80th and 20th percentiles at 0.004 and -0.007, respectively.

Table 6 reports the results from the difference-in-differences analysis. The coefficient for $\Delta TechConnect$ is not reported because it is invariant at the $Merger \times Analyst \times Firm$ level. Column (1) shows the main analysis. The coefficient for $\Delta TechConnect \times Post$ is negative and highly significant (coefficient = -285.503, t-stat = -3.84), suggesting that analysts who experience an increase in $TechConnect$ following a brokerage merger subsequently exhibit higher forecast accuracy. A coefficient of -285.503 implies that a one-standard deviation increase in $\Delta TechConnect$ leads to a 9.13 basis points (-285.503 * 0.032 = -9.13) decrease in AFE. To ensure robustness to different sample selection methods, I examine analyst's 8 and 10 forecasts, evenly distributed around the event date, within time windows of 30 and 42 months in Columns (2) and (3), respectively. The coefficient on $\Delta TechConnect \times Post$ continues to be negative and highly significant in Column (2). However, the magnitude is substantially smaller—a one-standard deviation increase in $\Delta TechConnect$ leads to only a 1.94 basis points (-32.366 * 0.06) decrease in AFE .[20] In Column (3), the coefficient is no longer significant. This may be because, as the time window expands, other factors begin to influence forecast accuracy, such as regular analyst turnover or changes in the focal analyst's characteristics.

Overall, the brokerage merger tests suggest that persistent analyst attributes and selection effects cannot explain my findings. However, one cannot rule out all other possible interpretations, particularly those involving time-varying analyst behavior. For example, analysts may work harder due to the more supporting working environment. Nonetheless, my information-sharing explanation is not in conflict with this possibility. Both forces could interact to generate the results I observe.

5 Other analyst performance measures

This section examines additional aspects of analyst performance beyond forecast accuracy. Three additional performance measures are used: the informativeness and price impact of forecast revisions, and the profitability of stock recommendations. I then explore the asset pricing implications of information sharing, testing whether technology momentum for a firm is attenuated when infor-

[20] The standard deviation of $\Delta TechConnect$ is slightly different from specification (1) due to the difference in sample size.

mation sharing is more prevalent.

5.1 Informativeness of analyst forecast revisions

If analysts obtain technological information from colleagues and gain a better understanding of the covered firm, one should expect that their forecast revisions to be more informative. I test this prediction by examining the relation between technological connectedness and tendency to issue bold forecasts. Clement and Tse (2005) demonstrate that bold forecasts tend to be more accurate than other forecasts and likely reflect relevant private information. Accordingly, the following regression model is estimated:

$$BoldPositive_{i,j,t}(BoldNegative_{i,j,t}) = \beta_0 + \beta_1 TechConnect_{i,j,t} + Controls_{i,j,t} + \delta + \varepsilon_{i,j,t}. \tag{8}$$

The dependent variable is a dummy variable that takes a value of one if the analyst issues either a bold positive ($BoldPositive$) or bold negative revision ($BoldNegative$). A bold positive (negative) forecast is defined as a forecast revision that is both above (below) the analyst's prior forecast and the consensus forecast immediately before the revision (Malloy, 2005; Clement and Tse, 2005; Kumar et al., 2022). δ represents either firm-year-quarter or broker-quarter fixed effects. Control variables are the same as in Table 2 plus analyst's past performance. When including broker-quarter fixed effects, I exclude the broker-quarter controls $BrokerageSize$, $Broker_IndCon$, and $Broker_PatentVal$. I also control for a range of firm characteristics, including market capitalization, R&D expense, institutional ownership, and twelve-month stock price momentum.

Table 7 reports the results of the bold forecast regressions. Columns (1) and (2) show that the coefficients on $BoldPositive$ are insignificant, while Columns (3) and (4) indicate that the coefficients on $BoldNegative$ in both specifications are positive and significant. This suggests that analysts with higher $TechConnect$ are more likely to issue bold negative forecast revisions, either cross-sectionally or within a brokerage house.

These results suggest that negative technological information is more likely to be transmitted

among analyst colleagues, making the focal analyst more inclined to issue a bold negative earnings forecast revision in response to such information. This finding is consistent with prior literature indicating that negative information spreads faster than positive information in social networks (Ferrara and Yang, 2015), and that analysts tend to pay more attention to a firm's negative information (Hirshleifer et al., 2021).

5.2 Price impact of analyst's bold forecast revisions

Next, I investigate whether the market recognizes the forecast revisions made by analysts who presumably have better understanding of the technological information due to their interactions with colleagues. I expect stronger market reactions to bold forecast revisions issued by analysts who are more technologically connected to their colleagues. I estimate the following regression model to test my prediction:

$$CAR_{j,t} = \beta_0 + \beta_1 TechConnect_{i,j,t} + Controls_{i,j,t} + \delta + \varepsilon_{i,j,t}. \tag{9}$$

where the dependent variable $CAR_{i,j,t}$ is the [0,+2]-day cumulative market-adjusted return. δ represents either quarter or broker-quarter fixed effects. The regression specification is similar to Bradley et al. (2017). I separately estimate this regression using the positive and negative news samples. I classify forecast revision as positive (negative) news if the revision is above (below) both the analyst's prior forecast and the prevailing consensus forecast.

Table 7 reports the results. Models 1 and 2 present the results for earnings upgrades. Model 1 indicates that market reactions to analysts' upward revisions are indeed more pronounced. The coefficient of 1.311 on $TechConnect$ suggests that a one-standard-deviation increase in $TechConnect$ leads to a 0.166 basis point increase in market reactions (0.127 * 1.311 = 0.166). The control variables generally have the expected signs; for instance, market reactions are positively related to the absolute change in earnings forecasts and negatively related to firm size. The result is quantitatively similar in Column (2) when I include broker-quarter fixed effects.

Models 3 to 4 repeat the above analyses for earnings downgrade. I find that the effect of

$TechConnect$ on market reactions is stronger for negative news. The coefficient of -2.229 on $TechConnect$ in Column (3) implies that a one-standard deviation increase in $TechConnect$ leads to 0.166 basis points increase in market reactions (0.127*-2.229=0.283), which is 70% stronger than the effects for positive news. This results resonates with the results in Table 7 that analysts tend to spread negative information to the market. The results remain robust after including broker-quarter fixed effects in Column (4).

Overall, these results indicate that, conditional on the direction and magnitude of forecast revisions, the stock market reacts more strongly to revisions issued by analysts with higher technological connectedness. This finding supports my prediction that the market recognizes the quality of information produced by these analysts.

5.3 Profitability of analyst recommendations

In this section, I investigate whether information transfers from colleagues to analysts through technological connections also translate into more informative stock recommendations. Following prior literature on the investment value of stock recommendations (Barber et al., 2001; Cohen et al., 2010; Bradley et al., 2020), I focus on stocks that are upgraded or downgraded in comparison with prior recommendations, as well as those reiterated, resumed, or initiated with an I/B/E/S rating of "Strong Buy" or "Buy" (or "Sell" and "Strong Sell"). The upgrade, downgrade, or reiteration must occur within 365 days of the previous recommendation. Stocks are updated when an analyst revises a recommendation or when the outstanding recommendation becomes stale (defined as no activity for at least one year). The analysis is conducted at the recommendation level: if multiple analysts make recommendations on a single stock, all recommendations are included in the data.

I skip two trading days after the recommendation day t, meaning that the investment starts at the end of day $t+2$. By waiting two trading days, I ensure that the profitability of the recommendation is not driven by its immediate price impact. I calculate the abnormal daily return of each stock based on the outstanding buy/sell recommendations. Abnormal stock returns are measured using the characteristic-adjusted returns of Daniel et al. (1997) (DGTW). Finally, I regress abnormal returns

on $TechConnect$, controlling for a range of firm, analyst, and broker characteristics on a daily basis. For ease of interpretation, the coefficients are converted to monthly values (e.g., Cohen et al., 2010; Bradley et al., 2020). The following regression model is estimated:

$$\begin{aligned} RET_{j,t}(DGTW) = &\beta_0 + \beta_1 HighTechConnect_{i,j,t}(TechConnect_{i,j,t}) + Controls_{i,j,t} + \\ &Month\ FE + Analyst \times year\ FE + \varepsilon_{i,j,t}. \end{aligned} \tag{10}$$

where $RET_{j,t}$ is the Daniel et al. (1997) (DGTW) characteristic-adjusted daily stock returns generated from day 3 until the recommendation is dropped from the portfolio. This number is converted into monthly return for ease of interpretation. $HighTechConnect_{i,j,t}$ is an indicator that takes a value of one if $TechConnect_{i,j,t}$ is above the 90th percentile of the sample, and zero if it is zero. This variable captures the recommendation profitability of high-connected analysts relative to analysts with no $TechConnect$. In alternative specifications, I replace $HighTechConnect_{i,j,t}$ with $TechConnect$. I include month fixed effects to absorb macroeconomic shocks and analyst-year fixed effects to control for analyst's time-variant and time-invariant characteristics. Control variables include $SupplyChainConnect$, $IndustryConnect$, $GeographyConnect$, $ConglomerateConnect$, firm-specific experience, firm size, book-to-market ratio, institutional ownership, twelve-month stock price momentum, and past-month return.

Table 9 presents the results. The coefficients of interest are significant in three of four specifications. Column (1) documents that abnormal monthly returns to buy recommendations are 1.033% higher for analysts with high technological connectedness, compared to analysts that have no connection at all. Likewise, Column (3) shows that highly-connected analysts generate economically and statistically significant abnormal returns with their sell recommendations. However, the magnitude is slightly smaller than buy recommendations (0.897%).

Overall, the results are consistent with the notion that analysts obtain value-relevant technological information, both positive and negative, from their colleagues.

6 Additional Tests

In this section, I conduct two additional tests. I first study the asset pricing implication of such information sharing. I test whether technology momentum for a firm is attenuated when information sharing is more prevailing. Next, I examine whether analysts benefit from technologial information from other firms in their coverage portfolios

6.1 Technological information sharing and technology momentum

The picture that emerges from the results thus far is that information sharing on technologically connected firms can help analysts improve forecast quality. If analyst colleagues facilitate a better understanding of technological information, implications exist for the technology momentum between technologically connected firms as documented by previous studies (Qiu et al., 2018; Lee et al., 2019; Bekkerman et al., 2023). Extensive studies present evidence that analyst research is an important channel through which information is impounded in stock prices (e.g., Womack, 1996; Barber et al., 2001; Gleason and Lee, 2003; Jegadeesh et al., 2004). My findings imply that analysts could play a role in diminishing technology momentum because they obtain technological information from colleagues, process it, and propagate it to the public through earnings forecasts. I expect that the technology momentum in stock returns will be attenuated when technological information sharing is more pervasive. To assess this conjecture, I test whether technology momentum is less pronounced for firms followed by analysts with high average $TechConnect$ through the following panel regression model:

$$\begin{aligned} MonthlyReturn_{i,t} =& \beta_0 + \beta_1 FirmTC_{i,t-2,t} \times TECHRET_{i,t-1} + \\ & \beta_2 FirmTC_{i,t-2,t} + \beta_3 TECHRET_{i,t-1} + \\ & Control_{i,t-1} + Date\ FE + \varepsilon_{i,t}. \end{aligned} \tag{11}$$

where $MonthlyReturn_{i,t}$ is the focal firm's monthly return, $FirmTC_{i,t-2,t}$ is the averaged $TechConnect$ across all analysts covering firm j in quarter t weighted by each analyst's firm-specific experience in the most recent three months, $TECHRET_{i,t-1}$ is the the weighted return of a port-

folio of firms that share similar technology as the focal firm as in Lee et al. (2019), and the control variables include lagged industry return ($INDRET_{t-1}$) (Moskowitz and Grinblatt, 1999), lagged firm size ($Marketcap_{t-1}$), book-to-market ratio (BM_{t-1}), gross profitability (GP_{t-1}), asset growth (AG_{t-1}), R&D intensity (RD_{t-1}), the firm's own lagged monthly return ($MonthlyReturn_{t-1}$), and month $t-13$ to $t-1$ price momentum (MOM).

Table 10 presents the results from estimating Equation 11. In column (1), I first replicate the basic specification in Lee et al. (2019) without considering the effect of technological information sharing. The point estimate of 0.011 for technology momentum is similar in magnitude to Qiu et al. (2018) and Lee et al. (2019).[21] A coefficient of 0.011 on $TECHRET_{t-1}$ indicates that the average monthly return spread of the focal firms in the top and bottom deciles of $TECHRET_{t-1}$ is 1.1%. The coefficients on the control variables also have expected signs. For example, stock return is positively associated with book-to-market ratio, gross profitability while negatively associated with firm size, asset growth, and last-period return. In Column (2), the estimate on β_1 is negative and significant at the 10% level, suggesting that technological information sharing among analyst colleagues attenuate the technology momentum effect.

My results in Panel C of Table 2 suggest that the benefits of technological information from colleagues increase after the passage of Regulation Fair Disclosure (Reg FD). Accordingly, I posit that the effect of $FirmTC_{i,t-2,t}$ to be stronger after Reg FD. Consistent with my prediction, Column (3) shows that β_1 is insignificant while Column (4) shows that both the magnitude and significance of β_1 increases relative to Column (2). Lastly, the finding in Table 1 suggests that $TechConnect$ is significantly associated with analyst coverage, which is shown to reduce technology momentum (Lee et al., 2019). To ensure the effect of $TechConnect$ is not endogenously related to analyst coverage, I assign firms into five groups based on quintiles of analyst coverage, I then include analyst coverage-date fixed effects in Column (5).[22] Hence, I am essentially comparing the effect of $TechConnect$ across firms share similar analyst coverage. The results still hold.

[21] Lee et al. (2019) reports a coefficient of 0.583 using the same specification between 2000 and 2012.
[22] The 20th, 40th, 60th, 80th percentile of analyst coverage are 5, 8, 12, 17, respectively.

6.2 Technological link within analyst portfolio

If an analyst can use technological information from other colleagues, an interesting question is whether she can reuse such information from other firms in her portfolio. I hypothesize that, relative to other analysts covering firm j, analyst i is more accurate on firm j if other firms in the analyst's portfolio are more technologically similar to firm j. To test this conjecture, for analyst i covering firm j, I calculate the portfolio level technological connectedness, $TechConnect_Port$. The calculation is the same as $TechConnect$ except that I use other firms in analyst's coverage portfolio. Similarly to Equation 3.1, I calculate other portfolio-level economic connections and run the regression as in Table 2.

Table 11 shows the results. I include firm-year-quarter fixed effects in Column (1) and additionally include broker fixed effects in Column (2).[23] The coefficients on $TechConnect_Port$ are negative and highly significant in both columns, indicating that technological information from one firm can be beneficial for another firm within the same analyst's portfolio, even if the firms operate in different industries.

7 Robustness Checks

7.1 Alternative measure for analyst forecast accuracy

I repeat the analysis using three alternative accuracy measures: normalized forecast accuracy (Clement and Tse, 2005), proportional mean absolute forecast error (Clement, 1999), and standardized performance score (Hong et al., 2000). Since these accuracy measures already remove firm-year-quarter fixed effects, I replace it with quarter fixed effects in all specifications.

Appendix A5 reports the results. I continue to find that analysts with high technological connectedness to their colleagues provide more accurate earnings forecasts. In five out of six columns, the coefficients on $TechConnect$ are negative and significant at the 1% level.

[23] Note that I no longer include analyst fixed effects because there could be little variation in $TechConnect$ within an analyst's portfolio. For example, if an analyst covers two firms that are technologically similar, then the $TechConnect_Port$ for these two firms would be identical.

7.2 Alternative specifications to construct technological connectedness

I consider six alternative approaches for constructing $TechConnect$. First, I remove the industry restriction, meaning that all firms covered by colleagues are included in calculating $TechConnect$. Next, I apply five different industry classification methods: two-digit Standard Industrial Classification (SIC) codes, the Fama-French 30 (17) industry classification codes, and three (two)-digit North American Industry Classification System (NAICS) codes. Using these six alternative specifications, the regressions are re-run as shown in Columns (2) and (3) of Table 2.

Appendix A6 presents the regression results. The coefficients on $TechConnect$ are significant at the 5% level in ten out of twelve specifications, suggesting that the results are not sensitive to the industry classification method used. The coefficients on $TechConnect$ are not significant when using two-digit NAICS codes and the Fama-French 17 industry classification codes in Columns (10) and (12), respectively. This is likely due to the coarse industry definitions, which exclude many firms from the $TechConnect$ calculation, leading to a loss of information.

8 Conclusions

This paper provides evidence on the nature of information that is transmitted through social networks. I exploit the fact that firms in different industries can be close in technological space, and show that analysts working in the same brokerage house share technological information on firms in different industries. I develop a Technological Connectedness (TC) measure to capture such information sharing. I show that analysts with high TC deliver more accurate earnings forecasts, especially when their colleagues are more skilled and experienced. The benefits of technological information sharing is more pronounced for analysts covering smaller, younger, more innovative firms and firms whose earnings are difficult to predict. In addition, analysts with high TC provide more informative forecast revisions, exert a greater impact on stock prices, and make more profitable stock recommendations. Furthermore, I find that the technology momentum effect is less pronounced for firms covered by analysts with high TC. Thus, one implication of technological information sharing among analysts colleagues for the capital market is that prices impound technology-related infor-

mation more efficiently. Lastly, I show that analyst also reuse technological information from other firms to facilitate earnings forecast on the focal firm.

Overall, this study extends the literature by identifying a specific information-sharing channel that enhances analyst performance. It also deepens the understanding of analysts' roles as information intermediaries by showing that analysts can facilitate the flow of technological information across industries through collaboration with colleagues. This suggests that brokerage managers should evaluate their internal information structures and implement effective incentives to encourage information sharing.

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9 Figures

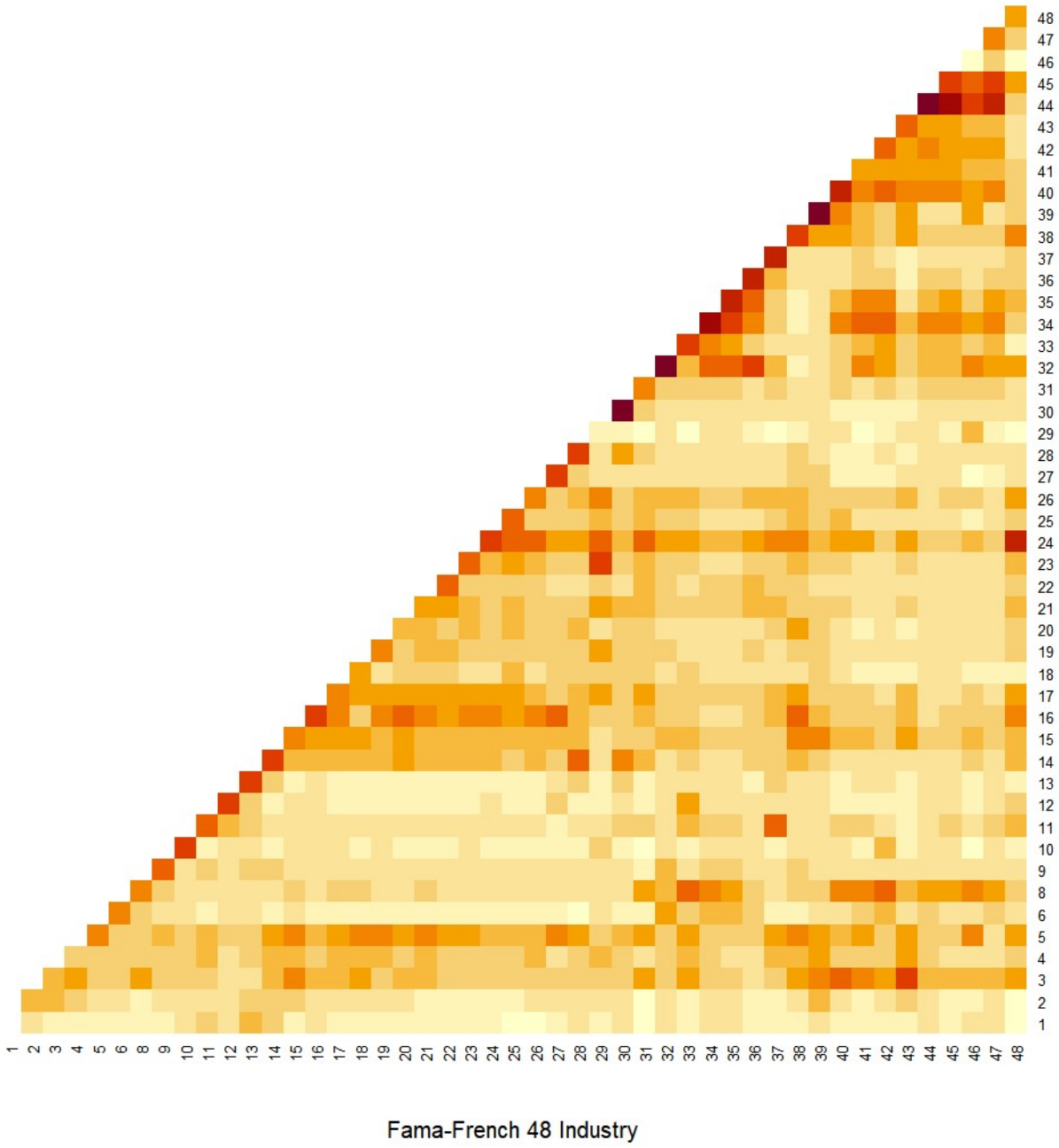
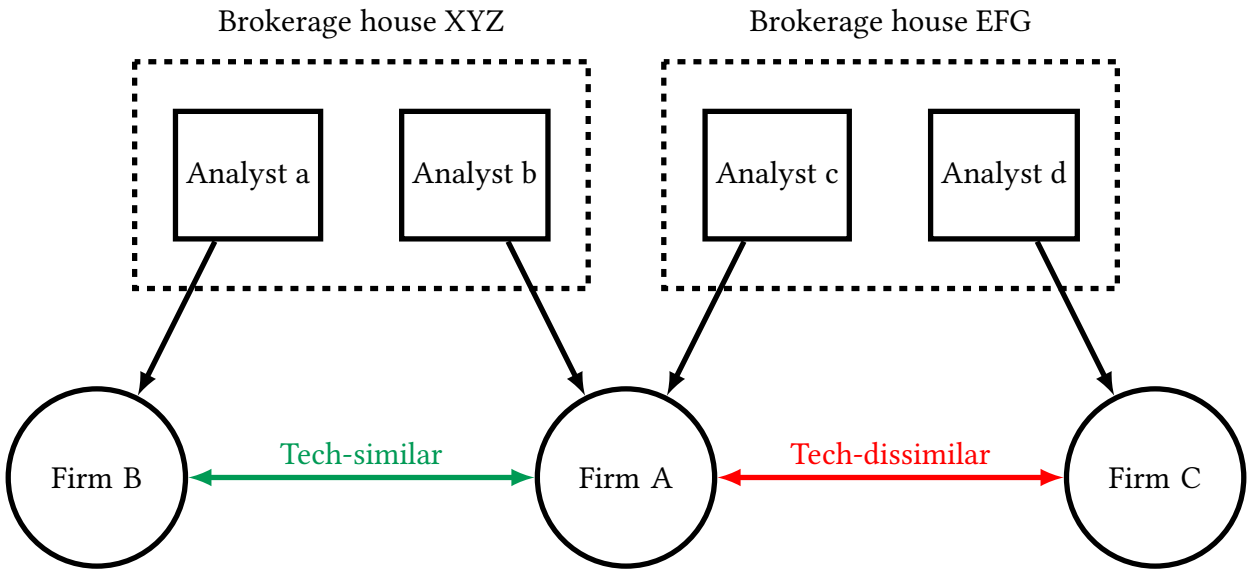


Figure 1: Cross-industry technological similarity heatmap. This figure illustrates the average technological similarity of firms across different industries. The technological similarity is calculated for every pair of firms, then averaged either within an industry or across different industries. The diagonal entries reflect the average technological similarity between firms within an industry, while the off-diagonal entries show the average technological similarity between firms from pairs of different industries.



Hypothesis: All else equal, if $TechSimilarity_{A,B} > TechSimilarity_{A,C}$, the forecasting performance of Analyst b for Firm A is better than that of Analyst c.

Figure 2: The identification strategy. This figure illustrates my empirical design and the main testable hypotheses. Analyst a and Analyst b work at brokerage house XYZ, while Analyst c and Analyst d work at brokerage house EFG. Analyst b and Analyst c cover firm A, Analyst a covers firm B, and Analyst d covers firm C. If the technological similarity between firm A and firm B ($TechSimilarity_{A,B}$) is higher than that between firm A and firm C ($TechSimilarity_{A,C}$), I expect that the forecasting performance of Analyst b on firm A to be better than that of Analyst c.

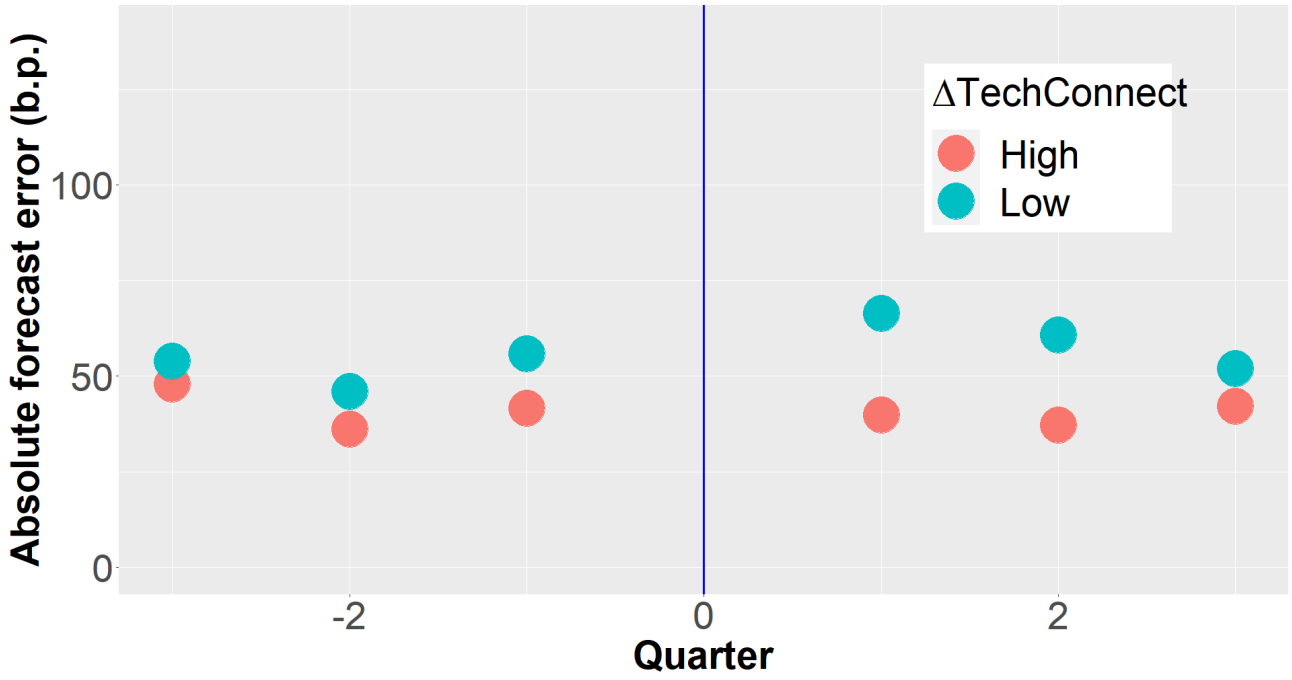


Figure 3: Analysts' absolute forecast errors around brokerage mergers. This figure plots absolute forecast error of analysts' first (last) 3 forecasts after (before) brokerage mergers in an 20-month window around the event. The closest two months around the merger date are dropped to avoid data error. I define $\Delta TechConnect$ as an analyst's $TechConnect$ at event time +1 minus that at event time -1. Analysts are assigned into high (low) group if their $\Delta TechConnect$ is above (below) the median $\Delta TechConnect$ (median $\Delta TechConnect = 0$). Then the absolute forecast error is averaged within each group for the 6 forecasts around the merger event.

10 Tables

Table 1: Determinants of technological connectedness. This table shows the relationship between analyst's Technological Connectedness ($TechConnect_{i,j,t}$) and other variables. The dependent variable, $TechConnect_{i,j,t}$, is the average technological similarity ($TechSimilarity_{f,g,t}$) between firm j covered by analyst i and all other unique K firms covered by analyst i's colleagues in the most recent four quarters, weighted by each firm k's total patent value ($PatentValue_{k,t}$). All coefficients are multiplied by 100 for ease of interpretation. Variable definitions are in Appendix A8.

	TechConnect		
	(1)	(2)	(3)
SupplyChainConnect	-1.759***	-0.488**	0.830*
	(-5.60)	(-2.18)	(1.87)
IndustryConnect	13.528***	-1.428	9.496***
	(7.75)	(-0.82)	(7.18)
ConglomerateConnect	0.559	0.712***	1.035***
	(1.36)	(2.71)	(4.62)
GeographyConnect	0.093***	0.032**	0.041***
	(4.47)	(2.25)	(2.69)
FirmSize	0.674***	1.380***	
	(4.27)	(13.48)	
BM	-0.923	0.274	
	(-1.60)	(0.62)	
IO	-1.550*	-1.710***	
	(-1.82)	(-3.20)	
RD	-0.244***	0.490***	
	(-2.86)	(9.17)	
NumAnalysts	0.338***	0.115***	
	(8.37)	(5.40)	
FirmExperience	-0.059*	0.041*	-0.007
	(-1.81)	(1.67)	(-0.61)
AnalystTenure	0.172***		0.002
	(5.40)		(0.16)
Local	-1.428***		-0.043
	(-2.97)		(-0.17)
NumFirms	-0.186***		0.006
	(-7.40)		(0.61)
NumIndustries	0.459***		-0.038
	(4.88)		(-1.12)
Star	-0.776***		-0.442***
	(-3.02)		(-4.20)

(The table is continued on the next page.)

Table 1 (continued)

BrokerageSize	-0.028***		-0.016***
	(-4.20)		(-3.43)
Broker_IndCon	4.691**		14.224***
	(2.00)		(7.08)
Broker_PatentVal	0.563***		0.362***
	(6.79)		(6.19)
Analyst-quarter FE		yes	
Firm-year-quarter FE			yes
Observations	769,024	822,762	788,242
Adj. R2	0.14	0.49	0.69

Table 2: Analyst technological connectedness and forecast accuracy. This table examines analyst's technological connectedness and forecasting accuracy. The dependent variable is the absolute forecast error (AFE) of analyst i covering firm j at quarter t, defined as the difference between forecasted earning per share and actual earning per share at fiscal quarter t, scaled by the firm's stock price at the beginning of the quarter. The key independent variable, $TechConnect_{i,j,t}$, is the average technological similarity ($TechSimilarity_{f,g,t}$) between firm j covered by analyst i and all other unique K firms covered by analyst i's colleagues in the most recent four quarters, weighted by each firm k's total patent value ($PatentValue_{k,t}$). The firms used for the calculation of $TechConnect_{i,j,t}$ must be in a different Fama-French 48 industry as firm j and different from all other firms that analyst i covers in quarter t. Variable definitions are in Appendix A8. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

	AFE		
	(1)	(2)	(3)
TechConnect	-2.042***	-1.894***	-1.345**
	(-3.12)	(-2.91)	(-2.09)
SupplyChainConnect		-0.270	-0.157
		(-1.35)	(-0.76)
IndustryConnect		-1.104**	-1.065*
		(-2.02)	(-1.85)
ConglomerateConnect		-0.511	-0.157
		(-0.97)	(-0.31)
GeographyConnect		-0.016*	-0.014
		(-1.66)	(-1.53)
ForecastHorizon	0.099***	0.099***	0.171*
	(22.18)	(22.18)	(1.82)
FirmExperience	-0.063***	-0.064***	-0.059***
	(-3.90)	(-3.92)	(-3.44)
AnalystTenure	0.039***	0.039***	26.798
	(2.63)	(2.62)	(0.78)
NumFirms	0.017	0.016	-0.023
	(1.30)	(1.25)	(-1.36)
NumIndustries	0.063	0.063	0.058
	(1.52)	(1.52)	(1.08)
Star	-0.455***	-0.453***	-0.544***
	(-2.64)	(-2.64)	(-2.64)
Local	0.096	0.143	-0.111
	(0.47)	(0.70)	(-0.56)

(The table is continued on the next page.)

Table 2 (continued)

BrokerageSize	-0.019***	-0.015***	0.003
	(-3.54)	(-2.73)	(0.60)
Broker_IndCon	2.739**	3.004***	1.428
	(2.52)	(2.70)	(1.61)
Broker_PatentVal	0.116	0.118*	0.112
	(1.64)	(1.66)	(1.63)
Firm-year-quarter FE	yes	yes	yes
Broker FE	yes	yes	
Analyst FE			yes
N	788,245	788,245	788,245
Adj. R^2	0.81	0.81	0.82

Table 3: Technological connectedness: conditional on different colleagues and firm characteristics. This table reports how colleague characteristics or firm characteristics affects the relation between an analyst's forecast accuracy of a firm and technological connectedness ($TechConnect$). Panel A shows $TechConnect$ calculated using different types of colleagues. Colleagues are divided into two groups based on whether they are technology-specialised, well performing, experienced, same gender or same cohort as the focal analyst i. Technology-specialised, well performing, experienced colleagues are defined as analysts whose portfolio average $PatentValue$, $PastPerformance$, and $AnalystTenure$ are above the sample median of each variable, respectively. Panel B interacts $TechConnect$ and several firm characteristics, including the logarithm of marketcap ($FirmSize$), number of months since first observation in CRSP ($FirmAge$), number of covering analysts ($NumAnalysts$), innovation intensity ($InnovationIntensity$), and earnings volatility ($EarningsVolatility$). Panel B splits the sample into pre- and post-Regulation Fair Disclosure (Reg FD), i.e., pre- and post-2001. Appendix A8 provides detailed description of variables. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

Panel A: Technological connectedness conditional on different types of colleagues

	AFE				
	(1)	(2)	(3)	(4)	(5)
	Tech Specialized	High PastPerformance	Experienced	Same Gender	Same Cohort
TechConnect_True	-2.035***	-1.895***	-1.292**	-2.310***	-2.233***
	(-3.04)	(-3.69)	(-2.14)	(-3.96)	(-3.82)
TechConnect_False	-0.199	-0.338	-0.545	0.524	-0.608*
	(-0.43)	(-0.81)	(-1.11)	(1.00)	(-1.65)
χ^2 $(H_0 : True = Flase)$	4.74**	6.64***	0.86	12.92***	5.97**
Controls	yes	yes	yes	yes	yes
Firm-year-quarter FE	yes	yes	yes	yes	yes
Broker FE	yes	yes	yes	yes	yes
N	788,242	788,242	788,242	788,242	788,242
Adj. R^2	0.81	0.81	0.81	0.81	0.81

(The table is continued on the next page.)

Table 3 (continued)

Panel B: Firm characteristics and the effects of technological connectedness

	AFE				
	(1)	(2)	(3)	(4)	(5)
TechConnect × FirmSize	1.287***				
	(3.45)				
TechConnect × FirmAge		0.014***			
		(3.54)			
TechConnect × NumAnalysts			0.191**		
			(2.30)		
TechConnect × InnovationIntensity				-5.416**	
				(-2.38)	
TechConnect × EarningsVolatility					-1.239***
					(-2.69)
TechConnect	-13.132***	-5.179***	-4.766***	2.598	-7.488***
	(-3.77)	(-4.39)	(-3.26)	(1.490)	(-3.14)
Controls	yes	yes	yes	yes	yes
Firm-year-quarter FE	yes	yes	yes	yes	yes
Broker FE	yes	yes	yes	yes	yes
N	788,242	788,242	788,242	570,897	750,923
Adj. R^2	0.82	0.81	0.81	0.81	0.81

(The table is continued on the next page.)

Table 3 (continued)

Panel C: Technological connectedness and Reg FD

	AFE	
	(1) Pre–Reg FD	(2) Post–Reg FD
TechConnect	-2.577	-1.575**
	(-1.40)	(-2.27)
Controls	yes	yes
Firm-year-quarter FE	yes	yes
Broker FE	yes	yes
N	122,592	665,650
Adj. R^2	0.79	0.82

Table 4: Technological connectedness and co-occurrence of analyst forecast revisions. This table presents the results of panel regressions analyzing the relationship between technological connectedness and propensity of contemporaneous forecast revisions. The panel data is constructed by documenting all pairs of forecast revisions for every calendar month. Each revision pair consists of analyst i, covering firm f, and analyst j, covering firm g, where $f \neq g$ and $i \neq j$. The dependent variable, $Tandem_Revision_{f,g,i,j,t}$, is a dummy variable that takes the value of one if analyst i, covering firm f, and analyst j, covering firm g, make forecast revisions contemporaneously in month t. Contemporaneous forecast revisions are defined as those occurring within twenty-four hours of each other. $HighConnect_{f,g,t}$ equals one if firms f and g are highly similar in terms of technological expertise, as measured by $TechSimilarity_{f,g,t}$. Firms are considered highly similar when firm g's $TechSimilarity_{f,g,t}$ is in the top 10th percentile ($HighConnect10$) or 20th percentile ($HighConnect20$) of all firms relative to firm f. Analyst-level dummy variables include whether two analysts work at the same brokerage house ($SameBroker_{i,j,t}$), are of the same gender ($SameGender_{i,j,t}$), are of the same ethnicity ($SameEthnicity_{i,j,t}$), or have previously been colleagues ($ExColleague_{i,j,t}$). Firm-level dummy variables include whether two firms are in the same industry ($SameIndustry_{f,g,t}$), are in the same Metropolitan Statistical Area ($SameGeography_{f,g,t}$), are part of the same supply chain ($SameSupplyChain_{f,g,t}$), or have conglomerate connections ($SameConglomerate_{f,g,t}$). $ExperienceDiff_{i,j,t}$ and $FirmExperienceDiff_{i,j,t}$ represent the absolute Diffs in general experience and firm-specific experience between analyst i and analyst j, respectively. $MarketcapDiff_{f,g,t}$ is the absolute Diff in the logarithm of the market capitalization between firm f and firm g. All coefficients are multiplied by 100. In parentheses are t-statistics based on standard errors two-way clustered by firm and year-month.

	Tandem Revision			
	(1)	(2)	(3)	(4)
	All pairs		Exclude same-industry pairs	
HighConnect10 × SameBroker	0.884**		0.906**	
	(2.11)		(2.19)	
HighConnect20 × SameBroker		0.735*		0.739*
		(1.90)		(1.91)
HighConnect10	0.520***		0.568***	
	(6.94)		(7.62)	
HighConnect20		0.476***		0.507***
		(7.62)		(8.21)
SameIndustry	0.864***	0.723***		
	(7.92)	(7.12)		
SameIndustry × SameBroker	3.561***	3.720***		
	(5.93)	(7.17)		
SameGeography × SameBroker	1.525***	1.647***	0.887**	1.020**
	(3.78)	(4.27)	(2.26)	(2.33)

(The table is continued on the next page.)

Table 4 (continued)

SameSupplyChain × SameBroker	-0.481***	-0.599***	-0.427**	-0.555***
	(-2.60)	(-3.15)	(-2.23)	(-2.75)
SameConglomerate × SameBroker	0.358	0.005	1.427**	0.800
	(0.56)	(0.01)	(2.33)	(1.59)
SameGender × SameBroker	0.501**	0.587**	0.407	0.482*
	(2.03)	(2.53)	(1.57)	(1.96)
SameEthnicity × SameBroker	0.177	-0.033	0.368	0.110
	(0.65)	(-0.14)	(1.26)	(0.43)
SameCohort × SameBroker	0.989*	0.910	0.753	0.759
	(1.73)	(1.59)	(1.33)	(1.38)
ExColleague × SameBroker	-0.027	-0.063	0.036	0.006
	(-0.03)	(-0.07)	(0.04)	(0.01)
ExperienceDiff × SameBroker	-0.070**	-0.048	-0.094***	-0.074**
	(-2.40)	(-1.58)	(-3.18)	(-2.48)
FirmExperienceDiff × SameBroker	-0.049	-0.058	-0.030	-0.036
	(-1.32)	(-1.62)	(-0.77)	(-0.99)
MarketcapDiff × SameBroker	0.079	0.079	0.084	0.085
	(1.21)	(1.31)	(1.25)	(1.42)
SameGeography	0.013	0.013	0.161*	0.174**
	(0.15)	(0.17)	(1.83)	(2.06)
SameSupplyChain	-0.014	0.011	0.024	0.047
	(-0.42)	(0.34)	(0.67)	(1.41)
SameConglomerate	0.539***	0.457***	0.480***	0.436***
	(4.66)	(4.40)	(3.71)	(3.89)
SameGender	-0.003	-0.039	0.017	-0.020
	(-0.06)	(-0.91)	(0.37)	(-0.45)
SameEthnicity	0.030	0.036	0.026	0.030
	(0.57)	(0.71)	(0.49)	(0.58)
SameCohort	0.047	0.028	0.071	0.045
	(0.39)	(0.24)	(0.58)	(0.39)
ExColleague	0.144	0.121	0.104	0.088
	(1.55)	(1.45)	(1.07)	(1.03)
ExperienceDiff	-0.003	-0.004	-0.002	-0.004
	(-0.61)	(-0.93)	(-0.43)	(-0.81)
FirmExperienceDiff	0.001	0.000	-0.002	-0.002
	(0.17)	(0.06)	(-0.39)	(-0.45)
MarketcapDiff	-0.038**	-0.048***	-0.029*	-0.035**
	(-2.51)	(-3.35)	(-1.86)	(-2.45)

(The table is continued on the next page.)

Table 4 (continued)

SameBroker	0.556	0.706	0.675	0.809*
	(1.11)	(1.46)	(1.28)	(1.65)
Year-month FE	yes	yes	yes	yes
Observations	21,314,626	26,753,101	19,825,779	24,695,587
Adj. R^2	0.002	0.002	0.002	0.002

Table 5: Turnover of technologically-connected colleagues and analyst forecast accuracy. This table examines the impact of turnover of technologically-connected colleague on analyst's forecast accuracy. A turnover event is defined as the arrival or departure of a technologically connected colleague for analyst i, who covers firm j in quarter t. Specifically, the event includes both the quarter in which the highly connected colleague arrives (departs) and the preceding (subsequent) quarter. I only use cases where a single colleague arrives (departs), with no other analysts departing (arriving) concurrently. I also require that the arriving (departing) colleague to cover an economically-important firm whose total value of patents must be above the median of all firms that a brokerage covers in a given year. The independent variable $TechConnect$ in the regression in Table **??** is replaced with $Arrival_{i,j,t}(Departure_{i,j,t})$, which is a dummy variable taking value of one if a technologically connected colleague arrives (departs) for analyst i covering firm j at quarter t. Technologically connected colleagues are defined as those covering at least one firm whose patent similarity ($TechSimilarity_{f,g,t}$) with firm j is above the top n% percentile. Column (1) to (3) reports the main tests where n is set to 10, 20, and 30, respectively. Column (4) conducts a falsification test where $TechSimilarity_{f,g,t}$ is falsely required to be 0 for two technological connected colleagues. Column (5) reports results of turnover of colleague covering the same Fama-French 48 industry. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

Panel A: Departure of highly connected colleague

	(1)	(2)	(3)	(4)	(5)
	Technologically connected colleagues				
	top 10%	top 20%	top 30%	No connection	Same-industry colleague
Departure	6.814**	3.133*	0.571	1.376	-0.599
	(2.54)	(1.78)	(0.35)	(0.68)	(-0.28)
Controls	yes	yes	yes	yes	yes
Event FE	yes	yes	yes	yes	yes
N	8,343	17,023	25,138	55,130	3,032
Adj. R^2	0.547	0.543	0.533	0.535	0.55

Panel B: Arrival of highly connected colleague

	(1)	(2)	(3)	(4)	(5)
	Technologically connected colleagues				
	top 10%	top 20%	top 30%	No connection	Same-industry colleague
Arrival	-0.534	0.124	-1.009	2.443	2.907
	(-0.27)	(0.09)	(-0.79)	(1.53)	(1.05)
Controls	yes	yes	yes	yes	yes
Event FE	yes	yes	yes	yes	yes
N	11,107	23,088	33,497	60,079	4,102
Adj. R^2	0.532	0.545	0.540	0.520	0.50

Table 6: Brokerage mergers as quasi-exogenous shocks to analyst technological connectedness. This table presents the results from the brokerage merger analysis. For each merger event, I track the incumbent analysts who remain at the acquiring brokerage and cover the same firm pre- and post-merger. I use each analyst's 6, 8, and 10 forecasts, evenly distributed around the event date, within time windows of 18, 30, and 42 months in Columns (1), (2), and (3), respectively. Forecasts occurring within one month of the event date are excluded. $\Delta TechConnect_{i,j,m,t}$ is the treatment effect, calculated as the difference in $TechConnect_{i,j,m,t}$ for analyst i covering firm j from quarter $t-1$ to quarter $t+1$ around the merger event m. The variable $Post$ is a binary indicator equal to one for post-event observations and zero for pre-event observations. The treatment, $\Delta TechConnect_{i,j,m,t}$, is absorbed by the Merger $\times$ Analyst $\times$ Firm fixed effects. All control variables are the same as in Table 2. Standard errors are two-way clustered at the analyst and firm levels.

	AFE		
	(1)	(2)	(3)
	6 quarters	8 quarters	10 quarters
$\Delta TechConnect\times$ post	-285.503***	-32.366***	9.567
	(-3.84)	(-2.85)	(0.28)
Post	7.589	-4.576	-6.429
	(1.00)	(-0.56)	(-1.14)
SupplyChainConnect	-102.076*	-51.506	27.136
	(-1.69)	(-1.22)	(1.21)
IndustryConnect	-92.963**	-160.741*	-8.811
	(-2.12)	(-1.93)	(-0.15)
ConglomerateConnect	-5.526	4.787	4.370
	(-0.59)	(0.72)	(0.93)
GeographyConnect	-0.496	0.379	-0.010
	(-0.59)	(0.71)	(-0.02)
ForecastHorizon	0.082	0.123**	0.193***
	(1.42)	(2.46)	(3.67)
FirmExperience	-11.147	1,362.695	802.308
	(-0.01)	(1.08)	(0.77)
AnalystTenure	-1.087	-1,360.508	-793.871
	(0.00)	(-1.08)	(-0.76)
NumFirms	0.580	0.573	0.999*
	(0.52)	(0.64)	(1.66)
NumIndustries	0.071	-1.783	0.032
	(0.03)	(-0.63)	(0.02)
Star	0.335	0.763	3.510
	(0.06)	(0.16)	(0.73)

(The table is continued on the next page.)

Table 6 (continued)

Local	38.724**	11.474	6.383
	(2.24)	(0.93)	(0.93)
BrokerageSize	0.821**	0.071	-0.548**
	(2.12)	(0.23)	(-2.32)
Broker_IndCon	198.268	21.343	100.775
	(1.49)	(0.22)	(0.76)
Broker_PatentVal	5.426	-2.507	2.808
	(0.75)	(-0.46)	(0.78)
Merger-Analyst-Firm FE	yes	yes	yes
N	1,368	3,016	3,689
Adj. R^2	0.50	0.44	0.44

Table 7: Technological connectedness and bold forecast. This table examines the relationship between technological connectedness and the boldness of analyst forecasts. BoldPositive (BoldNegative) is a dummy variable taking value of one if the analyst issues a bold positive (negative) revision. Bold positive (negative) forecast is defined as the forecast revision both above (below) the analyst's prior forecast and the consensus forecast immediately before the forecast revision (Clement and Tse, 2005). Consensus forecast is the average value of all forecasts outstanding for a given firm. All coefficients are multiplied by 100 for ease of interpretation. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. Appendix A8 provides detailed description of variables. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)
	Dependent variable:			
	BoldPositive		BoldNegative	
TechConnect	0.053	-0.167	1.738**	4.670***
	(0.07)	(-0.13)	(2.24)	(4.00)
SupplyChainConnect	-0.098	0.666	0.034	0.004
	(-0.42)	(1.38)	(0.14)	(0.01)
IndustryConnect	-1.062*	0.162	1.940***	-1.676
	(-1.87)	(0.16)	(2.98)	(-1.43)
ConglomerateConnect	0.670*	-0.357	0.437	1.510***
	(1.70)	(-0.76)	(0.86)	(3.35)
GeographyConnect	0.014	0.008	0.001	-0.005
	(1.31)	(0.36)	(0.08)	(-0.20)
FirmExperience	0.052**	0.112***	0.086***	0.167***
	(2.49)	(3.49)	(3.61)	(4.33)
AnalystTenure	-0.101***	-0.136***	-0.087***	-0.034
	(-6.25)	(-6.33)	(-4.59)	(-1.19)
NumFirms	0.094***	0.111**	0.109***	0.034
	(4.91)	(2.27)	(4.51)	(0.49)
NumIndustries	-0.048	-0.224**	0.037	0.724***
	(-0.94)	(-2.40)	(0.59)	(5.41)
Star	0.143	-0.047	-0.486*	0.574
	(0.66)	(-0.13)	(-1.95)	(1.19)
Local	0.377	-0.870**	0.000	-0.416
	(1.60)	(-2.31)	(0.00)	(-0.81)
BrokerageSize	0.009**		0.037***	
	(2.42)		(8.11)	
Broker_IndCon	1.205		1.058	
	(1.44)		(0.99)	
Broker_PatentVal	-0.005		-0.382***	
	(-0.09)		(-5.28)	
PastPerformance	0.082***	0.087***	-0.039***	-0.039**
	(8.38)	(7.32)	(-3.35)	(-2.37)
ForecastHorizon	-0.277***	-0.242***	-0.328***	-0.396***
	(-51.23)	(-34.64)	(-64.12)	(-59.31)

(The table is continued on the next page.)

Table 7 (continued)

FirmSize		0.598***		0.202*
		(5.50)		(1.87)
RD		-0.101		-0.600***
		(-1.26)		(-7.14)
IO		1.506*		2.502***
		(1.83)		(2.79)
MOM		3.016***		-3.865***
		(10.62)		(-14.95)
Firm-year-quarter FE	yes		yes	
Brokerage-quarter FE		yes		yes
N	700,499	690,852	700,499	690,852
Adj. R^2	0.35	0.10	0.42	0.15

Table 8: Technological connectedness and market reaction. This table examines the relationship between technological connectedness and price impact of bold forecast revisions. The dependent variable is the [0,+2]-day cumulative market-adjusted abnormal return around the announcement of a forecast revision by analyst i for firm j in quarter t. All coefficients are multiplied by 100. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. Appendix A8 provides detailed description of variables. *p < .1; **p < .05; ***p < .01.

	CAR(0,2)			
	(1)	(2)	(3)	(4)
	Positive news		Negative news	
TechConnect	1.311***	1.253***	-2.229***	-2.039***
	(3.95)	(3.37)	(-4.08)	(-3.28)
SupplyChainConnect	0.009	-0.004	-0.033	-0.043
	(0.14)	(-0.06)	(-0.45)	(-0.59)
IndustryConnect	-0.408	-0.271	-0.380	-0.238
	(-1.33)	(-0.76)	(-0.94)	(-0.42)
GeographyConnect	-0.001	-0.001	-0.003	0.003
	(-0.14)	(-0.25)	(-0.50)	(0.45)
ConglomerateConnect	-0.178*	-0.155*	0.330***	0.267***
	(-1.92)	(-1.71)	(3.46)	(2.77)
ForecastHorizon	-0.010***	-0.007***	0.016***	0.016***
	(-4.39)	(-3.09)	(6.05)	(7.02)
FirmExperience	-0.008	-0.007	0.016	0.013
	(-0.94)	(-0.76)	(1.53)	(1.08)
AnalystTenure	0.021**	0.019**	-0.021***	-0.019**
	(2.41)	(2.20)	(-2.90)	(-2.14)
NumFirms	-0.030***	-0.017**	0.034***	0.034***
	(-3.92)	(-2.23)	(4.61)	(4.07)
NumIndustries	0.055***	0.052**	0.017	-0.001
	(2.90)	(2.32)	(0.67)	(-0.05)
Star	-0.069	-0.006	0.022	-0.059
	(-1.12)	(-0.08)	(0.33)	(-0.71)
Local	-0.039	0.062	0.320***	0.207*
	(-0.52)	(0.62)	(3.00)	(1.90)
BrokerageSize	-0.001		0.002	
	(-0.67)		(1.27)	
Broker_IndCon	-1.038***		1.428***	
	(-2.76)		(3.18)	
Broker_PatentVal	-0.125***		0.013	
	(-3.40)		(0.39)	
FirmSize	-0.331***	-0.303***	0.443***	0.388***
	(-8.28)	(-7.72)	(8.13)	(6.72)
BM	-0.291**	-0.298**	1.332***	1.192***
	(-2.40)	(-2.54)	(8.04)	(7.57)

(The table is continued on the next page.)

Table 8 (continued)

MOM	0.103	0.152	0.004	-0.046
	(0.93)	(1.34)	(0.03)	(-0.29)
PastPerformance	-0.003	0.001	-0.003	0.000
	(-0.81)	(0.18)	(-0.51)	(0.09)
Abs(SignedRevision)	74.773***	72.875***	-62.551***	-61.099***
	(5.60)	(5.07)	(-5.22)	(-4.82)
Quarter FE	yes		yes	
Brokerage-quarter FE		yes		yes
N	45,085	45,093	73,413	73,427
Adj. R^2	0.04	0.10	0.05	0.08

Table 9: Technological connectedness and recommendation profitability. This table examines analyst technological connectedness and characteristic-adjusted stock returns to buy/sell recommendations. The dependent variable is the Daniel et al. (1997) (DGTW) characteristic-adjusted daily stock returns. The unit of analysis is daily return, but coefficients have been adjusted to represent monthly returns in percent. Buy (Sell) recommendations are those upgraded (downgraded) in comparison with prior recommendations as well as those reiterated, resumed, and initiated with an I/B/E/S rating of "Strong Buy" or "Buy" ("Hold", "Sell", and "Strong Sell") (Cohen et al., 2010; Bradley et al., 2020). The upgrade, downgrade, and reiteration must be made within 365 days of the previous recommendation. I skip two trading day after the recommendation date t, and purchase the stock at the close of day $t + 2$. $HighTechConnect$ is a dummy variable that takes a value of one if a firm-analyst has $TechConnect$ above the 90th percentile of the sample, and zero if $TechConnect$ equals zero. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

	Daily risk-adjusted return (DGTW) × 30			
	(1)	(2)	(3)	(4)
	Buy recommendation		Sell recommendation	
HighTechConnect	1.033**		-0.897*	
	(2.20)		(-1.71)	
TechConnect		0.716		-1.178*
		(1.07)		(-1.71)
SupplyChainConnect	-0.253	-0.035	-0.226	-0.063
	(-0.81)	(-0.27)	(-0.83)	(-0.50)
IndustryConnect	-0.302	0.124	-1.105	-1.087
	(-0.22)	(0.14)	(-0.76)	(-1.11)
GeographyConnect	0.029	0.016*	-0.017	0.003
	(1.42)	(1.74)	(-1.10)	(0.38)
ConglomerateConnect	-0.098	-0.104	-0.047	-0.077
	(-0.25)	(-0.60)	(-0.14)	(-0.51)
FirmExperience	-0.011	-0.016	-0.067	0.008
	(-0.28)	(-0.74)	(-1.43)	(0.36)
FirmSize	-0.114	0.008	0.315**	0.253***
	(-0.93)	(0.14)	(2.37)	(4.23)
BM	-0.184	-0.044	0.324	-0.180
	(-0.39)	(-0.19)	(0.68)	(-0.70)
IO	-2.373**	-0.082	1.054	1.110**
	(-2.47)	(-0.18)	(1.29)	(2.42)
MOM	0.136	-0.228	0.108	-0.204
	(0.37)	(-1.29)	(0.30)	(-1.09)
RET	-37.585***	-46.070***	-24.251***	-33.350***
	(-7.04)	(-11.45)	(-3.67)	(-7.14)
Month FE	yes	yes	yes	yes
Analyst-year FE	yes	yes	yes	yes
N	1,369,580	3,530,595	1,372,835	3,582,457
Adj. R^2	0.002	0.001	0.002	0.002

Table 10: Firm-level analyst technological connectedness and technology momentum.. This table reports the return predictability of tech-peer return ($TECHRET_{t-1}$) (Qiu et al., 2018; Lee et al., 2019), conditional on firm-level analyst technological connectedness. The sample period is from 1995 to 2021. The dependent variable is the focal firm's monthly return $MonthlyReturn_{i,t}$. The main explanatory variable is the interaction terms between tech-peer return ($TECHRET_{t-1}$) and $FirmTC_{t-2,t}$, calculated as the averaged $TechConnect$ across all analysts covering firm j in the most recent 3 months. Other explanatory variables include tech-peer return ($TECHRET_{t-1}$), focal firm's value- weighted industry return ($INDRET_{t-1}$) (Moskowitz and Grinblatt, 1999), firm marketcap, book-to-market ratio, gross profitability, asset growth, R&D intensity, the firm's own lagged monthly return, and month $t-13$ to $t-1$ price momentum. All explanatory variables except for $FirmTC_{t-2,t}$ are based on the last non-missing available observation for each month t and are assigned to deciles ranging from zero to one. The sample excludes financial firms (one-digit SIC code = 6) and stocks with a price less than $1 at portfolio formation. Panel A reports results using the full sample and subsamples splitted by the implementation of Regulation Fair Disclosure (Reg FD) in 2000 (i.e., 1995 to 2000 and 2001 to 2021). In parentheses are t-statistics based on standard error two-way clustered by firm and month. *p < .1; **p < .05; ***p < .01.

	MonthlyReturn$_t$				
	(1)	(2)	(3)	(4)	(5)
	Full sample		Before Reg FD	After Reg FD	
FirmTC$_{t-2,t}$ × TECHRET$_{t-1}$		-0.039*	-0.002	-0.047**	-0.041**
		(-1.928)	(-0.032)	(-2.236)	(-2.011)
TECHRET$_{t-1}$	0.011***	0.006	0.013	0.004	0.004
	(2.663)	(1.509)	(1.011)	(1.186)	(1.176)
FirmTC$_{t-2,t}$		0.023*	-0.014	0.030**	0.026*
		(1.694)	(-0.331)	(2.207)	(1.926)
INDRET$_{t-1}$	-0.001	0.002	0.017*	-0.001	-0.001
	(-0.188)	(0.623)	(1.851)	(-0.359)	(-0.237)
Marketcap$_{t-1}$	-0.008*	-0.006	0.015	-0.010**	-0.011**
	(-1.959)	(-1.454)	(1.166)	(-2.201)	(-2.234)
BM	0.006**	0.003	0.019**	0.001	0.001
	(2.390)	(1.260)	(2.211)	(0.392)	(0.377)
GP	0.013***	0.013***	0.010	0.013***	0.013***
	(4.324)	(4.542)	(1.308)	(4.306)	(4.319)
AG	-0.011***	-0.009***	-0.017*	-0.007**	-0.007**
	(-4.361)	(-3.059)	(-1.872)	(-2.410)	(-2.353)
RD	0.006	0.004	0.036*	-0.003	-0.003
	(1.196)	(0.778)	(1.950)	(-0.670)	(-0.654)

(The table is continued on the next page.)

Table 10 (continued)

MonthlyReturn$_{t-1}$	-0.015***	-0.010***	-0.020**	-0.009***	-0.009***
	(-4.384)	(-3.511)	(-2.271)	(-2.910)	(-2.958)
MOM	-0.001	0.001	0.018	-0.004	-0.003
	(-0.116)	(0.138)	(1.134)	(-0.750)	(-0.685)
Date FE	yes	yes	yes	yes	
Analyst coverage-date FE					yes
N	257,969	144,426	23,075	121,351	121,351
Adj. R^2	0.150	0.191	0.190	0.191	0.193

Table 11: Technological link within analyst portfolio. This table reports tests of technological link within an analyst portfolio on forecast accuracy. Similar to the construction of $TechConnect_{i,j,t}$, I measure the within portfolio technological link $TechConnect_Portfolio_{i,j,t}$ between firm j and all other firms covered by analyst i as the average $TechSimilarity$ between firm j and all other unique firms that analyst i has covered in the most recent year (quarter $t-3$ to quarter t, at least two quarters of observations are required). $TechConnect_Port_{i,j,t}$ is constructed using all firms other than firm j. All other connection measures are constructed in the same way as in Table 2 but only using the firms within an analyst portfolio. Firms that are dropped from analyst i's coverage before quarter t are excluded within the one-year rolling window. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

	AFE	
	(1)	(2)
TechConnect_Port	-4.083***	-3.955***
	(-3.427)	(-3.186)
SupplyChainConnect_Port	8.612	7.007
	(1.638)	(1.462)
IndustryConnect_Port	1.839	2.440
	(0.602)	(0.748)
ConglomerateConnect_Port	-2.227	-2.143
	(-1.156)	(-1.082)
GeographyConnect_Port	-1.505	-1.180
	(-0.967)	(-0.755)
ForecastHorizon	0.102*	0.103*
	(1.880)	(1.922)
FirmExperience	0.148	0.183
	(1.008)	(1.169)
AnalystTenure	-0.047	-0.061
	(-0.795)	(-0.907)
NumFirms	0.059	0.084
	(0.704)	(0.922)
NumIndustries	-0.708	-0.657
	(-1.510)	(-1.483)
Star	-0.372	-0.015
	(-0.567)	(-0.013)
Local	-1.117	-0.857
	(-1.635)	(-1.443)
BrokerageSize	-0.027	0.046
	(-1.385)	(1.064)

(The table is continued on the next page.)

Table 11 (continued)

Broker_IndCon	3.814	13.873
	(1.428)	(1.309)
Broker_PatentVal	0.194	0.509
	(0.539)	(1.206)
Analyst_IndCon	-9.291**	-9.683**
	(-2.055)	(-2.151)
Analyst_PatentVal	0.250	0.181
	(1.292)	(0.976)
Firm-year-quarter FE	yes	yes
Broker FE		yes
N	743,193	743,193
Adj. R^2	0.72	0.72

11 Appendix

Table A1: Average technological similarity within and across industries. This table reports the average pairwise $TechConnect$ between firms in the same industry or in different industries. The industry definition is based on Fama-French 48 industry classification. The second column shows the average pairwise $TechConnect$ of firms within an industry. The last three columns report the top three technologically similar industries in terms of average $TechConnect$ in a descending order from left to right. Definition of $TechConnect$ is reported in Appendix A8.

Industry code (name)	Within industry	Top 3 other industry		
1 (Agriculture)	0.26	13 (0.15)	14 (0.07)	2 (0.06)
2 (Food Products)	0.23	3 (0.15)	4 (0.13)	39 (0.12)
3 (Candy & Soda)	0.11	**39 (0.22)**	4 (0.21)	5 (0.15)
4 (Beer & Liquor)	0.09	**3 (0.21)**	39 (0.15)	2 (0.13)
5 (Tobacco Products)	0.30	39 (0.22)	3 (0.15)	15 (0.14)
6 (Recreation)	0.09	**32 (0.09)**	35 (0.07)	44 (0.06)
8 (Printing and Publishing)	0.11	**44 (0.19)**	45 (0.15)	42 (0.12)
9 (Consumer Goods)	0.08	38 (0.08)	13 (0.07)	24 (0.06)
10 (Apparel)	0.30	42 (0.07)	16 (0.05)	24 (0.04)
11 (Healthcare)	0.12	**12 (0.12)**	37 (0.10)	13 (0.09)
12 (Medical Equipment)	0.27	11 (0.12)	27 (0.07)	5 (0.07)
13 (Pharmaceutical Products)	0.35	1 (0.15)	11 (0.09)	9 (0.07)
14 (Chemicals)	0.16	16 (0.11)	38 (0.11)	24 (0.11)
15 (Rubber and Plastic Products)	0.14	**39 (0.22)**	16 (0.17)	5 (0.14)
16 (Textiles)	0.30	24 (0.20)	15 (0.17)	38 (0.16)
17 (Construction Materials)	0.11	**24 (0.13)**	16 (0.13)	38 (0.11)
18 (Construction)	0.06	**39 (0.09)**	25 (0.08)	24 (0.07)
19 (Steel Works Etc)	0.07	**24 (0.10)**	16 (0.09)	38 (0.07)
20 (Fabricated Products)	0.07	**38 (0.13)**	16 (0.13)	24 (0.12)
21 (Machinery)	0.08	**24 (0.10)**	16 (0.09)	38 (0.08)
22 (Electrical Equipment)	0.09	**24 (0.09)**	26 (0.07)	16 (0.07)
23 (Automobiles and Trucks)	0.13	24 (0.12)	16 (0.10)	38 (0.09)
24 (Aircraft)	0.22	16 (0.20)	38 (0.15)	26 (0.13)
25 (Shipbuilding, Railroad Equipment)	0.13	24 (0.10)	38 (0.08)	23 (0.08)
26 (Defense)	0.12	**24 (0.13)**	16 (0.11)	38 (0.09)
27 (Precious Metals)	0.25	16 (0.15)	5 (0.13)	24 (0.11)
28 (Non-Metallic & Industrial Metal Mining)	0.09	**14 (0.10)**	38 (0.08)	24 (0.08)
29 (Coal)	NA	33 (0.05)	40 (0.03)	31 (0.03)
30 (Petroleum and Natural Gas)	0.18	14 (0.09)	28 (0.07)	24 (0.05)

(The table is continued on the next page.)

Table A1 (continued)

31 (Utilities)	0.06	**44 (0.08)**	45 (0.07)	24 (0.06)
32 (Communication)	0.29	35 (0.17)	34 (0.15)	36 (0.12)
33 (Personal Services)	0.09	**34 (0.12)**	45 (0.11)	44 (0.10)
34 (Business Services)	0.22	44 (0.21)	35 (0.20)	45 (0.19)
35 (Computers)	0.23	34 (0.20)	32 (0.17)	45 (0.14)
36 (Electronic Equipment)	0.15	32 (0.12)	35 (0.11)	34 (0.09)
37 (Measuring and Control Equipment)	0.12	11 (0.10)	24 (0.08)	5 (0.06)
38 (Business Supplies)	0.20	39 (0.17)	16 (0.16)	24 (0.15)
39 (Shipping Containers)	0.46	15 (0.22)	3 (0.22)	5 (0.22)
40 (Transportation)	0.15	**44 (0.22)**	45 (0.17)	47 (0.13)
41 (Wholesale)	0.07	**44 (0.15)**	45 (0.13)	34 (0.11)
42 (Retail)	0.14	**44 (0.22)**	45 (0.17)	47 (0.14)
43 (Restaurants, Hotels, Motels)	0.10	**44 (0.15)**	3 (0.14)	45 (0.12)
44 (Banking)	0.47	45 (0.32)	47 (0.24)	40 (0.22)
45 (Insurance)	0.23	**44 (0.32)**	34 (0.19)	47 (0.18)
46 (Real Estate)	0.01	**44 (0.07)**	45 (0.07)	47 (0.06)
47 (Trading)	0.15	**44 (0.24)**	45 (0.18)	34 (0.16)
48 (Other)	0.08	**24 (0.10)**	16 (0.07)	38 (0.07)

Table A2: Descriptive statistics. This table shows summary statistics for the variables from the sample from 1995 to 2021. Variable definitions are in Appendix A8.

	Moments				Percentiles											
	Mean	Standard Deviation	Skewness	Kurtosis	Min	1st	5th	10th	25th	Median	75th	90th	95th	99th	Max	Observations
Panel A: Analyst level variables																
ForecastError	-12.1	77.8	-0.43	14.1	-389	-389	-114	-63.3	-23.7	-6.08	1.94	28.9	72.4	341	341	892319
AFE	38.7	68.6	3.30	14.6	0	0	0	0.163	4.76	14.1	38.2	96.6	176	389	389	892319
TechConnect	0.087	0.127	2.05	7.30	0	0	0	0	0	0.031	0.123	0.262	0.364	0.626	0.626	843388
Number of linked colleagues	19.7	21.4	0.94	3.01	0	0	0	0	0	12	35	52	59	78	121	843388
Number of linked firms	88.2	103	1.03	2.90	0	0	0	0	0	43	157	258	297	359	486	843388
SupplyChainConnect	0.746	0.697	2.41	11.7	0	0	0	0	0.324	0.649	0.959	1.28	2.08	4.46	4.46	856010
IndustryConnect	0.069	0.134	3.62	17.67	0	0	0	0	0.002	0.020	0.075	0.170	0.310	0.821	0.821	856010
ConglomerateConnect	0.154	0.361	1.92	4.69	0	0	0	0	0	0	0	1	1	1	1	856010
GeographyConnect	9.08	9.38	1.40	4.68	0	0	0	0	2	6	13	22	29	42	42	856010
ForecastHorizon	54.9	30.8	-0.26	1.49	3	4	7	12	24	62	86	90	90	90	90	892319
FirmExperience	3.69	4.14	1.79	6.52	0	0	0	0.096	0.729	2.24	5.21	9.47	12.5	18.4	27.2	892319
AnalystTenure	7.38	5.87	0.91	3.15	0	0.022	0.466	0.997	2.63	5.95	10.9	16.2	19.2	23.7	27.2	892319
NumFirms	10.2	5.92	2.26	17.3	1	2	3	4	6	9	13	17	20	28	88	892319
NumIndustries	2.83	1.87	1.60	8.10	1	1	1	1	1	2	4	5	6	9	29	892319
Star	0.165	0.372	1.80	4.24	0	0	0	0	0	0	0	1	1	1	1	831142
Local	0.108	0.310	2.53	7.41	0	0	0	0	0	0	0	1	1	1	1	828136
BrokerageSize	40.2	27.9	0.68	3.00	1	1	5	8	16	36	61	78	87	122	147	892319
Broker_IndCon	0.120	0.127	3.16	13.8	0.043	0.043	0.045	0.048	0.054	0.074	0.122	0.235	0.398	0.774	0.774	892319
Broker_PatentVal	9.223	1.427	-1.61	5.70	3.95	3.95	6.01	7.26	8.70	9.67	10.1	10.5	10.8	11.3	11.3	891006
PastPerformance	49.1	7.10	-0.40	4.57	0	30	37	40	45	49	54	58	60	65	88	664175
Accuracy	0.576	0.365	-0.37	1.73	0	0	0	0	0.267	0.647	0.941	1	1	1	1	877393
PMAFE	-0.085	0.605	0.87	4.58	-1	-1	-1	-0.926	-0.483	-0.091	0.200	0.626	1	2.11	2.11	888821
Score	50	32.2	-0.03	1.81	0	0	0	0	23	50	77	97	100	100	100	892319
BoldPositive	0.092	0.289	2.82	8.95	0	0	0	0	0	0	0	0	1	1	1	1011162
BoldNegative	0.163	0.369	1.82	4.33	0	0	0	0	0	0	0	1	1	1	1	1011162
Revision	0.344	0.475	0.66	1.43	0	0	0	0	0	0	1	1	1	1	1	1011162
SignedRevision	-0.0018	0.008	-2.58	15.9	-0.047	-0.047	-0.015	-0.008	-0.002	0.000	0.001	0.003	0.006	0.022	0.022	348100
TechConnect_Port	0.294	0.319	0.69	2.05	0	0	0	0	0	0.173	0.558	0.805	0.897	0.980	0.980	892319
SupplyChainConnect_Port	0.069	0.129	2.73	11.1	0	0	0	0	0	0	0.092	0.223	0.324	0.664	0.664	892319
IndustryConnect_Port	0.563	0.397	-0.23	1.39	0	0	0	0	0.133	0.638	0.988	1	1	1	1	892319
ConglomerateConnect_Port	0.082	0.233	2.90	10.2	0	0	0	0	0	0	0	0.360	0.768	1	1	892319
GeographyConnect_Port	0.230	0.280	1.33	3.60	0	0	0	0	0.020	0.102	0.343	0.724	0.871	1	1	892319
Analyst_IndCon	0.645	0.280	-0.01	1.61	0.153	0.153	0.222	0.278	0.389	0.625	1	1	1	1	1	892319
Analyst_PatentVal	7.773	2.429	-0.34	2.29	1.95	1.95	3.47	4.36	5.98	7.97	9.75	10.8	11.3	12.0	12.0	843359
Panel B: Firm level variables																
TechSimilarity	0.059	0.150	3.70	17.8	0	0	0	0	0	0	0.03	0.18	0.37	1	1	62229670
FirmSize	8.38	1.90	0.012	2.59	1.34	4.24	5.27	5.89	7.00	8.37	9.73	10.9	11.5	12.5	14.9	892319
BM	0.474	0.357	1.49	5.66	0.016	0.016	0.073	0.118	0.222	0.383	0.631	0.945	1.183	1.892	1.892	870906
IO	0.659	0.204	-0.92	3.80	0.014	0.014	0.255	0.379	0.554	0.693	0.802	0.893	0.940	0.987	0.987	891762
RD	0.199	0.879	7.29	58.4	0	0	0	0	0	0	0.122	0.234	0.428	7.61	7.61	892319
MOM	0.172	0.531	1.79	8.73	-0.771	-0.771	-0.528	-0.375	-0.130	0.105	0.358	0.717	1.10	2.67	2.67	876708
FirmAge	232	140	0.253	2.06	1	9	27	48	111	225	336	435	480	519	528	892319
EarningsVolatility	-4.598	1.21	-0.24	3.46	-8.23	-8.23	-6.57	-6.02	-5.33	-4.61	-3.81	-3.06	-2.59	-1.74	-1.74	849818
NumAnalysts	11.5	7.30	0.90	3.48	1	2	2	3	6	10	16	22	26	33	45	892319
PatentValue	18836	64422	8.40	114	0.014	2	8	19	92	785	7351	44894	107946	286863	1717839	642357
NumCitations	7147	26873	9.71	139	0	0	5	16	83	541	3205	14757	30923	128486	596652	642357
InnovationItensity	0.75	0.300	-0.03	3.37	0.00	0.00	0.22	0.35	0.55	0.77	0.95	1.11	1.21	1.44	4.21	642357
Daily risk-adjusted return (DGTW)	0.00006	0.022	0.24	5.64	-0.072	-0.072	-0.035	-0.024	-0.010	0.000	0.010	0.024	0.037	0.080	0.080	7758208
CAR(0,2)	-0.001	0.064	-0.15	5.85	-0.227	-0.227	-0.109	-0.069	-0.027	-0.001	0.025	0.066	0.103	0.210	0.210	892298
TECHRET	0.017	0.075	0.63	10.1	-0.561	-0.178	-0.102	-0.071	-0.024	0.019	0.056	0.096	0.131	0.232	1.66	426192
MonthlyReturn	0.017	0.192	8.19	422	-0.937	-0.387	-0.227	-0.159	-0.069	0.005	0.080	0.185	0.284	0.608	17.6	416614

Table A3: Hypothetical example of revision panel data construction. This table provides a hypothetical example of how panel data is constructed for the revision regression in equation (5). All pairs of forecast revisions for each calendar month are included, with each observation consisting of two distinct firm-analyst pairs, where both firms and both analysts are different. Each pair is entered into the dataset only once to avoid double counting. Tandem revision is a binary indicator that takes the value of one if the two revisions occur within 24 hours of each other.

Panel A: Hypothetical raw data

Firm	Analyst	Date	Fama-French 48 industry	Gender
A	1	Sep 2	16	Male
B	2	Sep 2	16	Male
C	3	Sep 9	8	Male
C	4	Sep 20	8	Female
D	5	Sep 20	34	Female

Panel B: Permuted data

Firm1	Analyst1	Firm2	Analyst2	Tandem Revision	Same industry	Same gender
A	1	B	2	1	1	1
A	1	C	3	0	0	1
A	1	C	4	0	0	1
A	1	D	5	0	0	0
B	2	C	3	0	0	1
B	2	C	4	0	0	1
B	2	D	5	0	0	0
C	3	D	5	0	0	0
C	4	D	5	1	0	0

Table A4: Robustness tests: Poisson regressions. This table presents robustness tests for the main results in Table 2. I use Poisson regression to address the skewness concern of the dependent variable (Cohn et al., 2022). In addition, I take the square root of some of the positively skewed independent variables, namely, TechConnect, SupplyChainConnect, IndustryConnect, and Broker_IndCon. After transformation, the skewness of these variables decreases to 0.75, 0.94, 1.55, and 2.18, respectively. The regression specification is the same as in Equation 3.1. Variable definitions are in Appendix A8. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

	AFE	
	(1)	(2)
TechConnect (squared root)	-0.037***	-0.031**
	(-2.72)	(-2.39)
SupplyChainConnect (square root)	-0.018*	-0.009
	(-1.66)	(-0.78)
IndustryConnect (square root)	-0.026***	-0.011
	(-2.62)	(-1.01)
ConglomerateConnect	-0.013	-0.009
	(-1.03)	(-0.82)
GeographyConnect	-0.001**	0.000
	(-2.06)	(-1.59)
ForecastHorizon	0.003***	0.004*
	(24.42)	(1.79)
FirmExperience	-0.002***	-0.002***
	(-3.59)	(-3.83)
AnalystTenure	0.001***	0.468
	(2.61)	(0.57)
Local	0.003	-0.006
	(0.45)	(-0.99)
NumFirms	0.000	-0.001
	(0.63)	(-1.58)
NumIndustries	0.002*	0.001
	(1.70)	(1.00)
Star	-0.012**	-0.012**
	(-2.44)	(-2.08)
BrokerageSize	0.000**	0.000
	(-2.11)	(1.20)
Broker_IndCon (square root)	0.074***	0.028
	(2.73)	(1.19)

(The table is continued on the next page.)

Table A4 (continued)

Broker_PatentVal	0.003*	0.002
	(1.91)	(1.11)
Firm-year-quarter FE	yes	yes
Broker FE	yes	
Analyst FE		yes
N	782,040	782,011
Adj. Pseudo R^2	0.81	0.81

Table A5: Robustness checks: Alternative measure for analyst forecast accuracy. This table presents results of robustness checks for analyst forecasts accuracy. The independent variables are the same as in Equation 3.1. For model (1) and (2), the dependent variable is normalized forecast accuracy measure suggested by Clement and Tse (2005), which is defined as: $Accuracy_{i,j,t} = \frac{MaxAFE_{j,t} - AFE_{i,j,t}}{MaxAFE_{j,t} - MinAFE_{j,t}}$. For model (3) and (4), the dependent variable is Proportional mean absolute forecast error (Clement, 1999), $PMAFE_{i,j,t}$, calculated as $PMAFE_{i,j,t} = \frac{(AFE_{i,j,t} - MAFE_{j,t})}{MAFE_{j,t}}$, where $AFE_{i,j,t}$ is the absolute difference between analyst's predicted EPS and the actual earnings for company j announced at the fiscal quarter end, $MAFE_{j,t}$ is the mean $AFE_{i,j,t}$ for firm j at quarter t. For model (5) and (6), the dependent variable is standardized score as in Hong et al. (2000): $Score_{i,j,t} = 100 - (\frac{rank_{i,j,t} - 1}{number\ of\ analyst_{j,t} - 1})$, where $rank_{i,j,t}$ is the accuracy (absolute forecast error) ranking of analyst i covering firm j in quarter t, $number\ of\ analyst_{j,t}$ is the number of analysts covering firm j in quarter t. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Accuracy		PMAFE		Score	
TechConnect	0.064***	0.037***	-0.053***	-0.027***	1.633***	0.492
	(6.18)	(4.49)	(-4.28)	(-2.78)	(3.62)	(1.35)
SupplyChainConnect	0.003	0.001	-0.005	-0.001	-0.059	-0.121*
	(1.52)	(0.41)	(-1.44)	(-0.41)	(-0.99)	(-1.67)
IndustryConnect	0.029***	0.016**	-0.011	-0.012	1.317***	1.159**
	(4.00)	(2.26)	(-0.99)	(-1.25)	(2.76)	(2.42)
ConglomerateConnect	-0.005**	-0.003*	-0.003	0.000	-0.293***	-0.265***
	(-2.48)	(-1.67)	(-0.90)	(-0.14)	(-3.51)	(-3.10)
GeographyConnect	0.000	0.000	0.000	0.000	0.008	0.002
	(1.01)	(-0.08)	(-1.58)	(-1.37)	(1.36)	(0.38)
ForecastHorizon	-0.001***	-0.001***	0.003***	0.003***	-0.085***	-0.086***
	(-33.88)	(-22.18)	(32.99)	(25.36)	(-41.12)	(-30.47)
FirmExperience	0.001***	0.001***	-0.002***	-0.002***	0.032*	0.029*
	(4.20)	(4.37)	(-5.45)	(-5.17)	(1.85)	(1.87)
AnalystTenure	-0.001***	-0.070***	0.001***	0.093***	-0.063***	-0.637
	(-3.35)	(-3.96)	(2.65)	(3.66)	(-3.41)	(-0.98)
NumFirms	0.000	0.000	0.000	0.000	-0.065***	-0.015
	(-0.83)	(0.36)	(1.14)	(-0.16)	(-4.15)	(-0.92)
NumIndustries	-0.003***	-0.002***	0.002*	0.002**	0.095**	-0.013
	(-5.33)	(-3.01)	(1.67)	(2.13)	(2.11)	(-0.25)
Star	0.007***	0.004	-0.010**	-0.003	0.714***	0.294
	(2.72)	(1.49)	(-2.05)	(-0.72)	(3.17)	(1.32)
Local	-0.005*	-0.001	0.014***	0.007*	-0.235	-0.022

(The table is continued on the next page.)

Table A5 (continued)

	(-1.89)	(-0.56)	(2.97)	(1.68)	(-1.38)	(-0.14)
BrokerageSize	0.000**	0.000	0.000***	0.000	0.020***	0.001
	(2.13)	(-0.47)	(-2.87)	(0.42)	(3.01)	(0.21)
Broker_IndCon	-0.040***	-0.013	0.079***	0.033**	-3.188***	-0.538
	(-3.02)	(-1.28)	(3.73)	(2.10)	(-2.84)	(-0.61)
Broker_PatentVal	0.004***	0.001	-0.002	-0.001	-0.057	-0.125*
	(4.11)	(1.57)	(-1.59)	(-0.43)	(-0.76)	(-1.75)
Quarter FE	yes	yes	yes	yes	yes	yes
Broker FE	yes		yes		yes	
Analyst FE		yes		yes		yes
N	775,459	775,459	775,459	775,459	775,459	775,459
Adj. R^2	0.02	0.03	0.02	0.04	0.01	0.02

Table A6: Robustness checks: Alternative specification for technological connectedness. This table presents results of robustness checks using different specifications when constructing $TechConnect$. Column (1) reports results without industry restrictions. Other alternative classification methods include two-digit Standard Industrial Classification (SIC) codes, Fama-French 30 (17) industry classification, and two (three)-digit North American Industry Classification System (NAICS). The regression specifications are the same as in Equation 3.1. In parentheses are t-statistics based on standard error two-way clustered by firm and analyst. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)
	No industry restriction		SIC industry code		FF 30 industry	
TechConnect	-2.073***	-1.507**	-2.246***	-1.647**	-1.830***	-1.306**
	(-3.07)	(-2.25)	(-3.43)	(-2.55)	(-2.91)	(-2.02)
Firm-year-quarter FE	yes	yes	yes	yes	yes	yes
Broker FE	yes		yes		yes	
Analyst FE		yes		yes		yes
N	789,131	789,131	789,131	789,131	789,131	789,131
Adj. R^2	0.81	0.82	0.81	0.82	0.81	0.82
	(7)	(8)	(9)	(10)	(11)	(12)
	NAICS 3-digit		NAICS 2-digit		FF 17 industry	
TechConnect	-2.141***	-1.535**	-1.678***	-1.064	-1.174*	-0.640
	(-3.28)	(-2.33)	(-2.71)	(-1.57)	(-1.91)	(-1.00)
Firm-year-quarter FE	yes	yes	yes	yes	yes	yes
Broker FE	yes		yes		yes	
Analyst FE		yes		yes		yes
N	789,131	789,131	789,131	789,131	789,131	789,131
Adj. R^2	0.81	0.82	0.81	0.82	0.81	0.82

Table A7: List of mergers of brokerage houses. EventDate is the merger date provided in Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012), and Chen et al. (2018).

EventDate	Target	Target code	Acquirer	Acquirer code
1997/5/31	Dean Witter Discover & Co.	232	Morgan Stanley Group, Inc.	192
1998/1/9	Principal Financial Securities	495	EVEREN Capital Corp.	829
1998/2/17	Jensen Securities Co.	932	DA Davidson & Co.	79
1999/10/1	EVEREN Capital Corp.	829	First Union Corp., Charlotte, NC (Wachovia)	282
2000/5/31	Wit Capital, Ltd.	1836	SoundView Technology Group	114
2000/6/12	JC Bradford & Co.	34	PaineWebber Group, Inc.	189
2000/10/15	Donaldson Lufkin & Jenrette	86	Credit Suisse First Boston	100
2000/12/31	Chase Manhattan	125	JP Morgan	873
2001/2/28	Wasserstein Perella & Co.	1496	Dresdner Kleinwort. Wasser- stein Perella & Co., Inc.	1746
2001/5/31	ING Financial Markets	112	ABN Amro	54
2001/6/30	Epoch Partners, Inc.	1980	Goldman Sachs	118
2001/8/31	SunTrust Equitable Securities	96	Robinson-Humphrey—subsidiary of Smith Barney	238
2001/9/18	Josephthal Lyon & Ross	933	Fahnestock & Co. (Oppenheimer)	98
2001/10/31	Wachovia Securities	147	Wheat First Union merged with IJL Wachovia	282
2005/3/22	Parker/Hunter, Inc.	860	Janney Montgomery Scott LLC	142
2007/1/31	Ryan Beck & Co.	881	Stifel Financial	260
2007/9/30	Cochran, Caronia Securities, LLC	1915	Fox-Pitt Kelton	110
2007/10/31	A. G. Edwards & Sons	94	Wachovia Corp	282
2008/1/31	CIBC World Markets	211	Oppenheimer	98

Table A8: Variable definitions. This table provides the definitions of our key variables. Panel A presents analyst level variables. Panel B shows the construction of firm characteristics. All accounting related data are obtained from Compustat Quarterly and Annual file. Pricing related data, such as Market Capitalization and Price, are obtained from both CRSP and Compustat, and I rely on CRSP as the primary data source for pricing data. For each month end, I use the most recent data that is available in CRSP or Compustat to compute each firm characteristic. The final outputs for individual firm value are at monthly frequency. In order to populate the data to monthly frequency, I carry forward the most recent quarterly or annual data item, whichever is most recently available at a given time stamp, to the subsequent months before the next filing data becomes available. I add a two month lag when matching the most recent filing data to ensure it is publicly available.

Variable	Definition	Data source
Panel A: Analyst level variables		
ForecastError	Forecast error, calculated as forecasted earning per share minus actual earning per share for fiscal quarter t, scaled by the firm's stock price at the beginning of the quarter.	I/B/E/S
AFE	Absolute value of forecast error.	I/B/E/S
TechConnect	Technological connectedness with colleagues within a brokerage house, which is the technological link between analyst i who covers firm j in quarter t and her colleagues, calculated as the average $TechSimilarity$ between firm j and all other firms covered by her colleagues in the most recent year (quarter $t-3$ to quarter t). Formally, $TechConnect_{i,j,t} = \frac{\Sigma_{k=1,k\neq j}^{N} TechSimilarity_{k,j,t}}{N}$, where $TechSimilarity_{k,j,t}$ is the most recent patent similarity measure between firm k and firm j at quarter t. I require firm k to be in a different industry as firm j (using Fama-French 48 industry classification) and different than any other firms that analyst i covers in quarter t. Colleagues who leave the brokerage house before analyst i makes the earnings forecast at quarter t within the one-year rolling window are excluded.	I/B/E/S and KPSS patent data (Kogan et al., 2017)

(The Appendix is continued on the next page.)

Appendix (continued)

Variable	Definition	
SupplyChainConnect	Supply chain connectedness with colleagues within a brokerage house (Huang et al., 2022) based on the reliance of one industry on another. Specifically, the importance of industry j to industry i is the ratio of the sum of i's input commodity k produced by j (i.e., j's importance to i as its upstream industry) and i's output commodity used by j (i.e., j's importance to i as its downstream industry) to industry i's total output: $Importance_{i,j,t} = \frac{\sum_k \left(\begin{array}{l} k \; used \; by \; i_t \times \% \; of \; k \; produced \; by \; j_t + \\ k \; used \; by \; j_t \times \% \; of \; k \; produced \; by \; i_t \end{array} \right)}{Total \; output \; of \; i_t}$. Next, I measure the supply chain connectedness between analyst l, who covers industry i, and her colleagues as the sum of the $Importance_{i,j,t}$ of all industries covered by her colleagues for industry i during the most recent four quarters. I use the 2002 Benchmark Input-Output (IO) Surveys provided by the Bureau of Economic Analysis (BEA). To measure industry classifications for the sample firms, I match six-digit North American Industry Classification System (NAICS) codes provided by Compustat to the 71 IO industry codes using the concordance tables provided by the BEA. See Ahern and Harford (2014) for a more detailed description of the IO tables.	Compustat and Bureau of Economic Analysis (BEA).
IndustryConnect	Industry connectedness with colleagues within a brokerage house, defined as the percentage of distinct firms (in terms of marketcap) covered by colleagues that are in the same Fama French 48 industry as the focal firm in the most recent four quarters.	Compustat and I/B/E/S
ConglomerateConnect	Conglomerate connectedness with colleagues within a brokerage house. $ConglomerateConnect_{i,j,t}$ takes a value of one if colleagues are covering industries that the focal conglomerate firm generates sales from. Conglomerate firms are defined as the firms that operate in more than one industry and whose aggregate sales from all reported segments account for more than 80% of the total sales of the firm. I extract firms' segment accounting and financial information from Compustat segment files.	Compustat and I/B/E/S

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Appendix (continued)

Variable	Definition	
GeographyConnect	Geographical connectedness with colleagues within a brokerage house, defined as the number of analysts working in the same brokerage office who cover different firms headquartered in the same Metropolitan Statistical Area (Chen et al., 2022).	Compustat and I/B/E/S
ForecastHorizon	Forecast horizon, calculated as number of days from the forecast date to the earning announcement date. In regressions it is divided by one thousand for better visualization.	I/B/E/S
FirmExperience	Firm-specific experience, calculated as number of days since the first forecast of analyst i on firm j. In all regressions it is divided by 3650.	I/B/E/S
BrokerageSize	The size of the brokerage house that employs the target analyst, measured by the total number of analysts employed by the brokerage. In all regressions it is divided by one thousand.	I/B/E/S
AnalystTenure	Analyst general experience, which is measured as the number of days since the first forecast of an analyst according to I/B/E/S. In all regressions it is divided by 3650.	I/B/E/S
NumFirms	Number of companies the target analyst follows. In all regressions it is divided by one thousand.	I/B/E/S
NumIndustries	Number of industries covered by analysts in their portfolio (Fama-French 48 industry). In all regressions it is divided by one thousand.	I/B/E/S
Star	An indicator variable taking value of one if the analyst is an all-star analyst in a year.	Institutional Investor All-America Research Team analysts

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Appendix (continued)

Variable	Definition	
Local	An indicator variable taking value of one if the analyst is located in the same Metropolitan Statistical Area as the covered firm.	Compustat and I/B/E/S
Broker_IndCon	Industry concentration, calculated as $\Sigma_{i=1}^{N}(\frac{N_Firms_i}{Total_N_Firms})^2$, where N_Firms_i is the number of firms in industry i and $Total_N_Firms$ is the total number of firms covered by a brokerage house in quarter t	I/B/E/S
Broker_PatentVal	Average value of patents of all coverage firms at a brokerage house in a given quarter	I/B/E/S and KPSS patent data (Kogan et al., 2017)
BoldPositive (BoldNegative)	The forecast revision both above (below) the analyst's prior forecast and the consensus forecast immediately before the forecast revision (Clement and Tse, 2005). The consensus forecast is calculated as the average of available forecasts for a firm.	I/B/E/S
Signed_Revision	Signed forecast revision, calculated as the difference between the revised forecast and the old forecast, scaled by beginning-of-quarter stock price.	I/B/E/S
PastPerformance	A normalized ranking measure of analyst performance as in Hong et al. (2000), calculated as the average performance score, $Score_{i,j,t}$, across all firms in the most recent eight quarters in an analyst portfolio, where $Score_{i,j,t} = 100 - (\frac{rank_{i,j,t}-1}{number\ of\ analyst_{j,t}-1})$, and $rank_{i,j,t}$ is the accuracy (absolute forecast error) ranking of analyst i covering firm j in quarter t, $number\ of\ analyst_{j,t}$ is the number of analysts covering firm j in quarter t.	I/B/E/S
Accuracy	Normalized forecast accuracy measure as in Clement and Tse (2005), which is calculated as: $Accuracy_{i,j,t} = \frac{MaxAFE_{j,t}-AFE_{i,j,t}}{MaxAFE_{j,t}-MinAFE_{j,t}}$, where $AFE_{i,j,t}$ is the absolute forecast error of analyst i's forecast on firm j at quarter t, $MaxAFE_{j,t}$ and $MinAFE_{j,t}$ are the largest and smallest $AFE_{i,j,t}$ for firm j at quarter t, respectively.	I/B/E/S

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Appendix (continued)

Variable	Definition	
PMAFE	Proportional mean absolute forecast error (Clement, 1999), which is defined as the difference between the absolute forecast error $AFE_{i,j,t}$ of analyst i for firm j at quarter t and the mean absolute forecast error for firm j at quarter t. This difference is then scaled by the mean absolute forecast error for firm j at quarter t. Formally, $PMAFE_{i,j,t}$ is calculated as $PMAFE_{i,j,t} = \frac{(AFE_{i,j,t} - MAFE_{j,t})}{MAFE_{j,t}}$, where $AFE_{i,j,t}$ is the absolute difference between analyst's predicted EPS and the actual earnings for company j announced at the fiscal quarter end, $MAFE_{j,t}$ is the mean $AFE_{i,j,t}$ for firm j at quarter t.	I/B/E/S
Score	Standardized accuracy score as in Hong et al. (2000): $Score_{i,j,t} = 100 - (\frac{rank_{i,j,t}-1}{number\ of\ analyst_{j,t}-1})$, where $rank_{i,j,t}$ is the accuracy (absolute forecast error) ranking of analyst i covering firm j in quarter t, $number\ of\ analyst_{j,t}$ is the number of analysts covering firm j in quarter t.	I/B/E/S
Analyst_IndCon	Industry concentration of an analyst's portfolio, calculated as $\Sigma_{i=1}^{N}(\frac{N_Firms_i}{Total_N_Firms})^2$, where N_Firms_i is the number of firms in industry i and $Total_N_Firms$ is the total number of firms covered by an analyst in quarter t	I/B/E/S
Analyst_PatentVal	Average value of patents of all coverage firms of an analyst in a given quarter	I/B/E/S and KPSS patent data (Kogan et al., 2017)
Panel B: Firm level variables		

(The Appendix is continued on the next page.)

Appendix (continued)

Variable	Definition	
TechSimilarity	The pairwise technological similarity, $TechSimilarity_{f,g,t}$, is the cosine similarity across technology classes between firm f and g (Jaffe, 1986; Bloom et al., 2013), formally, $TechSimilarity_{f,g,t} = \frac{T_{ft}T'_{gt}}{(T_{ft}T'_{ft})^{1/2}(T_{gt}T'_{gt})^{1/2}}$, where $T_{ft} = (T_{ft1}, T_{ft2}, \cdots T_{ft669})$ is a vector of firm f's proportional share of patents across 669 USPTO technology classes over the rolling past five years as of time t. The grant date is used as the effective date of the patent. $TechSimilarity_{f,g,t}$ is bound by (inclusive) 0 and 1. A value close to 1 means that firm f is technologically similar to firm g, while a value of 0 means that firm i has no technological overlap with firm g.	KPSS patent data (Kogan et al., 2017)
FirmSize	Logarithm of market cap of a firm, calculated as share price times shares outstanding.	CRSP
FirmAge	Firm's age since the first observation in CRSP (months).	CRSP
RD	Sum of most-recent four-quarter Research and Development Expense (XRDQ) as a fraction of sum of most-recent four-quarter revenue (REVTQ).	Compustat
BM	Book-to-market, calculated as book equity for the most recent fiscal quarter end divided by the market equity (from CRSP) at the end of current quarter. We measure book equity as stockholders' book equity (Compustat quarter item SEQQ), plus balance sheet deferred taxes and investment tax credit (TXDITCQ) if available, minus the book value of preferred stock. If SEQ is not available, we measure stockholders' equity as the book value of common equity (item CEQQ) plus the par value of preferred stock (item PSTKQ), or the book value of assets (item ATQ) minus total liabilities (item LTQ). Depending on availability, we use redemption (item PSTKRQ), or par value (item PSTKQ) for the book value of preferred stock.	CRSP and Compustat
IO	Institutional ownership, calculated as percentage split-adjusted shares owned by institutional investors.	Thomson Reuters

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Appendix (continued)

Variable	Definition	
MOM	Momentum, month t-13 to month t-1 cumulative return.	CRSP
EarningsVolatility	Earnings volatility, calculated as the logarithm of standard deviation of quarterly deflated earnings over the past eight quarters. Deflated earnings are computed as quarterly earnings (NIQ) divided by one-quarter lagged total asset (ATQ).	Compustat
NumAnalysts	Number of analysts that have issued earnings forecasts for a firm in a given fiscal quarter.	I/B/E/S
PatentValue	Value of innovation in millions of nominal dollars value for all the patents of a firm. This is calculated as the sum of the variable $xi_nominal$ provided by Kogan et al. (2017) for each patent that a firm holds in a five-year window.	KPSS patent data (Kogan et al., 2017)
NumCitations	Number of total citations of a firm's patents. This is calculated as the sum of the variable $cites$ provided by Kogan et al. (2017) for each patent that a firm holds in a five-year window.	KPSS patent data (Kogan et al., 2017)
InnovationIntensity	Firm's innovation intensity, calculated as the logarithm of one plus total number of citations of a firm's patents deflated by the logarithm of its marketcap.	CRSP and KPSS patent data (Kogan et al., 2017)
Daily risk-adjusted return (DGTW)	Daily risk-adjusted return following Daniel et al. (1997)	CRSP
CAR(0,2)	Three-day cumulative return since the announcement of stock recommendation.	CRSP
MonthlyReturn$_{i,t}$	Monthly return of firm i in month t	CRSP

(The Appendix is continued on the next page.)

Appendix (continued)

Variable	Definition	
$\text{TECHRET}_{i,t}$	The average monthly return of technology-linked firms in the technology space, weighted by pairwise technology closeness (Lee et al., 2019): $TECHRET_{it} = \frac{\sum_{j \neq i} TechSimilarity_{ijt} \cdot RET_{jt}}{\sum_{j \neq i} TechSimilarity_{ijt}}$	CRSP and KPSS patent data (Kogan et al., 2017)