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Cross-industry information sharing and analyst performance

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Abstract:

This study shows that analyst research benefits from the sharing of information about economically connected industries among colleagues. Measuring the intensity of potential information sharing with the level of economic connection between an analyst's industry and her colleagues' industries, we find that it is positively correlated with an analyst's earnings forecast accuracy, stock recommendation profitability, coverage breadth, and report frequency after controlling for other determinants including broker or analyst fixed effects. We also find that analysts are more likely to issue reports when highly connected colleagues produce information. We show that sharing information with colleagues covering downstream (upstream) industries benefits an analyst's revenue (expense) forecasts, and that an analyst's performance improves (deteriorates) after an economically connected colleague joins (departs) the brokerage firm. Cross-sectionally, information sharing benefits an analyst's research more when her colleagues have higher research quality, and when she and her colleagues have stronger social ties. Finally, we find that investors recognize the benefits of information sharing: they react more strongly to research reports issued by analysts whose covered industries have a higher level of economic connection to those of colleagues, and are more likely to vote such analysts as All-Stars.

Key words: Financial analyst, information sharing, economically connected industries, forecast accuracy, recommendation profitability, social network, All-Star ranking

JEL Code: G29, M14, M40, M41

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Cross-Industry Information Sharing and Analyst Performance

1. Introduction

In this study, we identify a new channel through which analysts collect information, namely the sharing of information about economically connected industries among colleagues.[1] We examine the effects of this sharing on an analyst's research quality and productivity, and on the market's recognition of her research performance. Our findings show that an analyst's research quality and productivity are both positively correlated with the level of economic connection between her industry and those covered by her colleagues working for the same brokerage house, suggesting that information sharing among colleagues is beneficial to analyst research performance. These findings contribute to the literature, which has primarily focused on the roles of analysts as industry specialists (e.g., Boni and Womack, 2006; Kadan et al., 2012; Parsons et al., 2019). We, however, argue that cross-industry information sharing among colleagues is an important analyst activity that has been underexplored. Investigating the activity of cross-industry information sharing furthers our understanding of the sources of analysts' information, the economic determinants of their performance, and the diffusion of this information in the market.[2]

The practice of information sharing has been observed anecdotally, as this description concerning Goldman Sachs (Groysberg, 2010):

If a chemicals analyst noticed that plastic prices had dipped unexpectedly, for example, he would inform colleagues who covered industries that could be affected by the price differential. The beneficial effect on research quality was enormous. "When a company reported, the analyst would think horizontally across the analytical staff about who would be impacted," Einhorn [head of Goldman Sachs global research] explained. "And that provided a bond between various analysts."

[1] We use "analysts working for the same brokerage house" and "colleagues" interchangeably in this paper.
[2] For brevity, we use "information sharing" as shorthand for "information sharing among colleagues covering economically connected industries."

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Brokerage firms' organizational mechanisms for promoting colleague collaboration and such activities' benefits for analyst rankings are further noted in this description from Lehman Brothers (Groysberg, 2010):

> *Balog and other Lehman research executives pushed analysts to include collaborative work in their annual business plans. That way, they came to understand that team-specific collaborative achievements would help determine their yearly bonus... When Lehman Brothers was rated the best research department on Wall Street in the 1990s, its analysts benefited from team-based research processes that heightened their awareness of developments in related sectors and their ability to evaluate such developments knowledgeably...*

Although information sharing among colleagues has long been recognized in practice, little research has focused on this activity. In our study, we document and examine this activity, its determinants, and its implications for analyst performance and market perception.

There are several forces driving information sharing among colleagues covering economically connected industries. The first is the economic connection among industries, specifically between supplier and customer industries. We posit that any shocks to commodity prices, consumer demand, or technological advancement should ripple through the layers of the supply chain (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016). Information impacting one industry thus has value implications for firms in both its upstream and downstream industries (Menzly and Ozbas, 2010). The second force is the need for analysts to specialize to gain a competitive advantage. Analysts face intense competition in discovering and interpreting new information and providing industry knowledge, and specialization or in-depth study is then necessary for them to exploit commonalities within firms in the same industry (Kini et al., 2009; Parsons et al., 2019). An analyst with colleagues who specialize in upstream and downstream industries can more efficiently obtain information from her colleagues instead of gathering it on her own. The third force is the intrinsic motivation to collaborate, which can be manifested in feelings of competence, self-efficacy, and altruism (Osterloh and Frey, 2000; Lin, 2007).

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Recognizing the benefits of information sharing for both employees and the firm, organizations often encourage collaboration through formal and informal mechanisms (Tsai, 2002; Inkpen and Tsang, 2005). For example, brokerage houses might co-locate colleagues covering related industries, organize conferences to bring colleagues together, and acknowledge collaborative efforts in performance evaluations (Hill and Teppert, 2010).

Although information sharing yields a number of benefits to analysts, they also have reasons not to collaborate. First, because analysts in the same brokerage house must share the year-end bonus pool, they have incentives to outperform each other (Groysberg et al., 2011; Yin and Zhang, 2014). These analysts also compete for promotions, such as being promoted to research executive (Wu and Zang, 2009; Bradley et al., 2019). Prior research shows that such intrafirm tournament incentives can impede knowledge sharing and can even lead to sabotage among employees (Bonner et al., 2000; Brown and Heywood, 2009; Harbring and Irlenbusch, 2011). Research also shows that social comparisons and resulting feelings of envy can lead to similar consequences (Nickerson and Zenger, 2008; Tai et al., 2012; Charness et al., 2014). Social comparisons are more likely to occur among colleagues because they work in close proximity and have frequent interactions (Festinger, 1954; Kulik and Ambrose, 1992; Kilduff et al., 2010).

Several recent studies investigate the effects of information sharing among analysts and their colleagues and find evidence that analysts learn from colleagues who likely do not view them as competitors, such as directors of research, macroeconomists, quantitative analysts, debt analysts, and mentors (Hugon et al., 2016; Birru et al., 2019; Do and Zhang, 2019; Hugon et al., 2019). Hwang et al. (2019) find that analysts obtain information from colleagues when their covered firms are involved in an M&A. Our study differs from these in two aspects. First, we examine the practice of information sharing among those whom analysts might deem competitors. For the

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reasons discussed above, whether such activity takes place remains an empirical question. Second, the nature of the information being shared differs from that previously examined. We take advantage of the variations in industry economic connections to explore the sharing of industry information among colleagues who analyze upstream and downstream industries.

In our study, we predict that the sharing of industry-related information among colleagues improves analysts' performance. To measure the intensity of potential information sharing, we utilize the extent to which an analyst's industry is economically connected to the industries covered by her colleagues.[3] We posit that if information sharing does take place, it should benefit the analyst's research performance more when there is a higher level of economic connection between her industry and her colleagues' industries.

We use data from the Benchmark Input-Output Surveys of the Bureau of Economic Analysis (hereafter, BEA) to estimate the economic connection among industries. Specifically, we measure the level of reliance between industries that are suppliers and customers (i.e., the sum of one industry's input commodities made by the other, and its output commodities used by the other). To measure the connection between an analyst and her colleagues, we aggregate the reliance between the analyst's industry and those of her colleagues. During our sample period of 1982 to 2017, we find the average connection between an analyst and her colleagues to be economically significant at 69.8%; that is, the industries covered by her colleagues have a combined value of input and output commodities that amounts to 69.8% of her industry's total output.

[3] Information sharing likely occurs through unobservable channels, such as face-to-face discussion, phone calls, text messages, or email exchanges. Accordingly, researchers have limited ability to document how and when such communications take place. We attempt to detect information sharing by documenting its varying effect on analysts' research performance due to different levels of economic connectedness among colleagues' industries. If such activity does not occur, the level of economic connectedness with colleagues' industries should not explain analysts' research performance.

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Using this measure, we find evidence that information sharing among colleagues improves analyst research performance. First, we find that both earnings forecast accuracy and stock recommendation profitability are positively correlated with analysts' industry connection with colleagues, after we control for broker fixed effects and other factors that the literature has found can explain research quality. This finding suggests that colleagues share information useful in analyst research from their own industries. Second, we find that analysts with a higher level of industry connection with their colleagues cover larger firms and issue reports more frequently. This suggests that information sharing among colleagues lowers an analyst's information acquisition costs and increases her productivity. Third, we find that analysts with colleagues who cover highly connected industries are more likely to issue reports around the date when their connected colleagues issue reports, which provides further direct evidence of colleagues sharing information.

Industry connection is higher for analysts working for larger brokerage firms because they have more colleagues. However, it is unlikely that our findings are driven by larger brokerage firms' general resources because we include broker fixed effects in all of our empirical analyses. We thus show that analysts with more industry connections with colleagues exhibit higher research quality and productivity among those who work for the same broker and thus have similar access to various general brokerage resources, including working with the same research director, team of quantitative analysts, macroeconomists (Hugon et al., 2016; Birru et al., 2019; Bradley et al., 2019), and other support staff (Mikhail et al., 1997; Clement, 1999; Gao et al., 2019).[4] To further address the potential endogeneity concern such as brokerage firms assigning

[4] Arguably, having colleagues who cover economically connected industries can also be considered a broker resource. However, throughout this paper, we use "broker resource" to refer to other types of broker support that are distinct from the sharing of upstream/downstream industry-related information.

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more capable analyst to better connected industries, we conduct a number of additional tests. First, we rerun our analyses, replacing broker fixed effects with analyst fixed effects, and separately using a change specification. Our results continue to suggest that for a given analyst, her performance is better when she has greater industry connectedness with colleagues. Second, we replicate our empirical analyses using a matched sample design in which we match each analyst with a high level of industry connection to another analyst with a low level of industry connection from the same broker-year and of similar industry experience and coverage breadth. The results indicate that analysts who work for the same broker in the same year, and who have similar experience and coverage, perform better when their colleagues' industries are more economically connected to theirs. Third, we rerun our analyses and separately measure the colleagues' industry connection of upstream versus downstream industries, and find upstream connectedness benefits expense forecasts but not revenue forecasts, and downstream connectedness benefits revenue forecasts but not expense forecasts. Last, we examine the effect of colleague turnover, which is arguably an exogenous change in information sharing. We find that analyst performance improves after the brokerage house hires an industry-connected colleague, and deteriorates when an industry-connected colleague departs. The results of these empirical tests indicate that analyst research benefits from information sharing among colleagues covering economically connected industries, and that this effect cannot be explained by general brokerage resources, analysts' selection of a particular brokerage house, or brokerage firms assigning better analysts to more connected industries.

We next examine the cross-sectional variation in the effect of information sharing on analyst performance. We show evidence that the effect of information sharing is more salient when an analyst has colleagues of higher research ability (measured by forecast accuracy,

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recommendation profitability, and industry experience), and when she and her colleagues have stronger social ties (measured by longer relationship, working in the same city, or graduated from the same school), which imply more frequent informal contact, smoother collaboration, and more willingness to share information.

Finally, we use investor responses to analyst reports and their analyst All-Star rankings in *Institutional Investor* (hereafter *II*) (Groysberg et al., 2011) to examine whether investors recognize the benefit of analysts' information sharing. The results from these analyses show that, after we control for analyst forecast performance, productivity, and other economic factors, analysts with higher industry connection to their colleagues elicit stronger investor reaction to their research reports and are more likely to be ranked as *II* All-Stars. This effect is economically significant: a one standard deviation increase in information sharing increases analysts' odds of being ranked as *II* All-Stars by 11.8% (1.7% relative to the unconditional probability of 14.4%). These results are consistent with investors recognizing the benefit of information sharing to analysts' industry knowledge, written reports, and idea generation.

Our study extends the research on financial analysts, as previously the focus has been on the role of analysts as industry specialists (e.g., Clement, 1999; Jacob et al., 1999; Piotroski and Roulstone, 2004; Boni and Womack, 2006; Kini et al., 2009), that they produce information that is highly specialized along industry lines, and that they contribute to information segmentation in the market (e.g., Menzly and Ozbas, 2010; Parsons et al., 2019).[5] We, however, show that analysts covering economically connected industries share information, which benefits their research quality and productivity. Thus, our findings contribute to the literature by revealing the

[5] Menzly and Ozbas (2010) argue that cross-predictability in a limited-information model requires the assumption that informed investors specialize. They address this assumption by presenting evidence for the specialization of equity analysts and money managers. Similarly, Parsons et al. (2019) use analyst industry specialization to explain the geographic lead-lag effect in firms.

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role of analysts in the gradual diffusion of information in the market. They can both specialize in their own industries and facilitate the efficient flow of information across economically connected industries.

Second, our study contributes to the recent literature on learning from colleagues (e.g., Hugon et al., 2016; Birru et al., 2019; Bradley et al., 2019; Do and Zhang, 2019; Hugon et al., 2019; Hwang et al., 2019). This research finds that analysts benefit from in-house colleagues who are macroeconomists, quantitative researchers, research directors, and debt analysts; *II* All-Star colleagues covering the *same* industry; and colleagues covering the other company in an M&A transaction. We contribute to this research by documenting a new type of information that analysts share with colleagues, which is related to upstream and downstream industries, and that varies even among analysts working for the same broker. Our evidence reveals that analysts may even collaborate with peers who they regard as competitors.

On a broader level, our paper contributes to the literature by identifying a new determinant of analyst coverage decisions, forecast performance, and investor recognition (Mikhail et al., 1997; Clement, 1999; Emery and Li, 2009; Givoly et al., 2009; Bradshaw et al., 2013). We show that the costs of specializing in one industry can be mitigated by information sharing with colleagues who cover upstream and downstream industries. Our findings also suggest to brokerage houses that encouraging information sharing on industries along the supply chain can improve analysts' research quality and productivity, and enhance their reputation among investors. In addition, our paper provides guidance to investors by helping them identify analysts who possess better cross-industry knowledge and superior research quality.

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2. Hypotheses development

Our study is based on the notion that analysts covering economically connected industries have incentives to share information. Information from one industry has been found to have value implications for both its upstream and downstream industries (Menzly and Ozbas, 2010; Huang and Kale, 2013; Aobdia et al., 2014). Shocks to commodity prices, consumer demand, or production, and technological advancements ripple through the supply chain (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016), leading to highly correlated fundamentals for companies in closely connected industries (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010).

Not surprisingly, institutional investors value industry knowledge in analyst reports (Bradshaw, 2011; Brown et al., 2015; Lowengard, 2017), so analysts face intense competition in discovering and interpreting industry information (Huang et al., 2018). Analyst industry knowledge can come from experience, as most analysts have previously worked in the industry they cover (Bradley et al., 2017). Financial analysts typically specialize in one industry (Boni and Womack, 2006; Kadan et al., 2012), presumably to exploit commonalities within their covered firms (Clement, 1999; Gilson et al., 2001).[6] Such specialization incentivizes analysts to obtain information on related industries from their colleagues. Prior studies have shown that analysts rely on colleagues for macroeconomic news (Hugon et al., 2016) and common anomaly mispricing signals (Birru et al., 2019).[7] In addition, employees have intrinsic motivations to share information with colleagues, including feelings of competence and self-efficacy, and enjoyment in helping others (Osterloh and Frey, 2000; Lin, 2007).

[6] Prior studies also examine country-level specialization by analysts (e.g., Kini et al., 2009; Sonney, 2009). We use I/B/E/S analysts covering U.S. firms in our sample. The vast majority of these analysts are industry specialists and do not follow firms in other countries (Kini et al. 2009).

[7] Prior research also examines analysts' sharing of information with non-colleagues (e.g., Cohen et al., 2010; Green et al., 2014; Fang and Huang, 2017; Gu et al., 2019). Such sharing activities can improve an analyst's relationships and expand her social connections, leading to better career outcomes (Li et al., 2016).

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Organizations recognize the benefits of knowledge sharing and facilitate it through both formal and informal mechanisms (Tsai, 2002; Inkpen and Tsang, 2005). Anecdotal evidence indicates that brokerage houses co-locate analysts who cover related industries, organize conferences for firms in related industries, acknowledge collaboration in analyst performance evaluations (Hill and Teppert, 2010), and host corporate retreats and other social bonding events.

Although sharing information has its benefits, analysts have reasons not to share with colleagues, particularly those they regard as potential competitors for compensation or promotion opportunities. In terms of compensation, analysts receive a year-end bonus that comprises a substantial proportion of their annual pay (Groysberg et al., 2011). This is allocated from the broker's annual bonus pool (Yin and Zhang, 2014; Brown et al., 2015). Such zero-sum games can encourage individualism and reduce coordination (Lazear, 1989; Baiman and Rajan, 1995; Berger et al., 2013; Arnold et al., 2019). In terms of promotion opportunities, analysts compete with colleagues for internal promotions to positions such as research executive and director of research (Wu and Zang, 2009; Bradley et al., 2019). These intrafirm tournament incentives and sentiments can impede knowledge sharing, and even lead to sabotage (Bonner et al., 2000; Chen, 2003; Brown and Heywood, 2009; Harbring and Irlenbusch, 2011; Charness et al., 2014). In addition, analysts might refrain from sharing due to the social comparisons they make with their colleagues. Management research shows that employees are more likely to compare themselves to those they are more closely located to or with whom they interact more frequently (Festinger, 1954; Kulik and Ambrose, 1992). Such social comparisons can lead to feelings of envy and jealousy that might hinder collaboration among colleagues (Nickerson and Zenger, 2008; Kilduff et al., 2010; Tai et al., 2012).

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Our study allows us to investigate whether collaboration exists in an analyst setting among competitors. Previous studies examine information sharing when the information comes from research directors, macroeconomists, quantitative analysts, debt analysts, or mentors working for the same brokerage house (Hugon et al., 2016; Bradley et al., 2019; Birru et al., 2019; Do and Zhang, 2019; Hugon et al., 2019). However, these colleagues either work in a different functional area or already have higher status in the brokerage than the analyst, and thus they likely do not view her as a competitor for bonuses or promotions. By contrast, we study whether analysts share information with peers in the same department, with similar status, and with whom they interact frequently given the related nature of the industries they cover. In a recent study, Hwang et al. (2019) find that analysts learn from colleagues when their respective covered firms are involved in an M&A. Our study is broader in scope, as we examine information sharing among colleagues who cover firms in economically connected industries.

The question of whether analysts share information with colleagues in such a setting is an empirical one. If analysts do share information, we predict that such activity should result in an improvement in analyst research performance when the level of economic connectedness between the analyst and her colleagues is high. This leads to our first hypothesis:

H1: Analyst performance benefits more from information sharing with colleagues when the colleagues cover industries that are more economically connected to the industry covered by the analyst.

In addition to examining whether information sharing benefits analyst research, we examine the nature of this effect by exploring potential cross-sectional variations resulting from colleague research quality and analyst-colleague social ties. First, we examine whether information sharing yields greater benefits when colleagues exhibit higher research quality. The intuition for this is simply that analysts are more likely to seek information from higher-quality colleagues, and the

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information acquired from such colleagues are more useful and timely. Consistent with this intuition, Do and Zhang (2019) and Bradley et al. (2019) find the quality of analysts' mentors and research directors is positively related to their beneficial effect on analyst performance. However, higher-quality colleagues have higher opportunity costs in sharing their time and lower expectations for reciprocal relations, and as such, they might be less willing to share information (Hardin, 1982; Cabrera and Cabrera, 2002; Fulk et al., 2004; Levine and Prietula, 2012). We develop the following hypothesis to empirically test this conjecture:

H2a: Analyst performance benefits more from information sharing with colleagues when the colleagues covering the economically connected industries exhibit higher research quality.

We also investigate whether colleagues can share information more effectively when they have stronger social ties. A collaborative relationship may take time to develop and preexisting social ties may facilitate the development of this relation through an understanding of each other's strengths, information needs, communication styles, and work schedules. A preexisting relationship, which can include geographic proximity, can facilitate interaction and encourage information sharing, and preexisting social ties may make analysts more willing to help each other (Cohen et al., 2010). However, analysts who know each other well may also be more likely to compare themselves to each other (Festinger, 1954; Kulik and Ambrose, 1992; Kilduff et al., 2010), which can lead to feelings of envy and jealousy (Nickerson and Zenger, 2008; Tai et al., 2012; Charness et al., 2014). We thus have our final hypothesis:

H2b: Analyst performance benefits more from information sharing with colleagues covering economically connected industries when the analyst and her colleagues have stronger preexisting social ties.

3. Empirical measure and research design

3.1. Empirical measures and descriptive statistics of industry interdependence and economic connection

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To construct our measure of industry economic interdependence, we follow prior studies (Fan and Goyal, 2006; Menzly and Ozbas, 2010; Ahern, 2012) and obtain the Benchmark Input-Output Accounts prepared by the BEA for our sample period of 1982 to 2017. They consist of Make and Use tables showing the dollar values of the production and consumption of commodities, including goods and services, by each industry in each year, respectively. In providing a summary of the supply chains across the economy, these data allow us to measure how much an industry's production relies on inputs from other industries.

To construct our measure, we begin by specifying that, for every industry pair i and j, the importance of j to i is the ratio of the sum of industry i's input commodities made by industry j (i.e., j's importance to i as its upstream industry) and industry i's output commodities used by industry j (i.e., j's importance to i as its downstream industry), to industry i's total output. That is, the importance of one industry to another depends on its role as both a supplier and a customer (Acemoglu et al., 2012; Baqaee, 2018).[8] Thus, our measure of industry interdependence is:

$$Importance_{i,j,t} = \frac{\sum_k \begin{pmatrix} Commodity\ k\ used\ by\ industry\ i_t \times \%\ of\ Commodity\ k\ made\ by\ industry\ j_t + \\ Commodity\ k\ used\ by\ industry\ j_t \times \%\ of\ Commodity\ k\ made\ by\ industry\ i_t \end{pmatrix}}{Total\ output\ of\ industry\ i_t}$$

where $Importance_{i,j,t}$ indicates the importance of industry j to industry i in year t.

To obtain our industry codes, we follow BEA's industry definitions and classify our firm-year observations into the corresponding industries based on the firms' historical NAICS codes (or current NAICS code if historical ones are not available) obtained from COMPUSTAT. The

[8] In an additional analysis, we examine industry j's importance to industry i as a supplier and as a customer separately, and find that the analyst's expense forecast accuracy benefits from colleague coverage of supplier industries, and her revenue forecast accuracy benefits from colleague coverage of customer industries. See Section 5.2 for details.

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descriptive statistics of $Importance$ (reported in Panel A of Table 2) show that the mean (median) value of $Importance$ is 1.5% (0.4%). The literature considers any relationship of at least 1% or 5% to be sufficiently economically significant to identify vertical mergers (Guckin et al., 1991; Matsusaka, 1996; Fan and Goyal, 2006), so we use this range as a benchmark. For our sample, we find that around 32% of the industry pairs have an $Importance$ value greater than 1%, and around 7% of the industry pairs have an $Importance$ value greater than 5%. The average cross-sectional standard deviation of $Importance$ for our sample is 4.8%, suggesting a wide variation in the economic interdependence across industries in the U.S. economy.

Our untabulated results show that the economic connection between industries changes over time, with an average time-series standard deviation of 0.6% for a given industry pair, larger than the median value of $Importance$ (0.4%). We observe that some industry pairs experience large changes. For example, the $Importance$ of Warehousing and Storage (BEA industry code 493) to Primary Metals (BEA industry code 331) increased from 0% in 1982 to 1.66% in 2017.

Next, we measure the economic connection between an analyst's industry and her colleagues' industries as the sum of the $Importance$ of all of the industries covered by her colleagues to her industry.[9] We label this variable as $Ind\_Connect_{l,i,t}$, where analyst l covers industry i in year t:

[9] An alternative approach is to focus on companies with direct trading relationships and measure the importance of colleague coverage at the company level. We do not choose this approach for the following reasons. First, one company can have many potential customers (suppliers) in a downstream (upstream) industry. Therefore, focusing on direct trading relationships likely understates the prevalence of information sharing among analysts. Second, after 1997, firms voluntarily disclose major customers (customers that contribute to greater than 10% of the company's total revenues) under SFAS No. 131, creating a selection bias in the data. Third, major customers are usually much larger than the disclosing companies (Cohen and Frazzini, 2008). As a result, it is difficult to detect information flow from suppliers to customers (Menzly and Ozbas, 2010). Nonetheless, in a sensitivity test, we control for the number of an analyst's covered firms that have direct suppliers or customers covered by herself and the number of an analyst's covered firms that have direct suppliers or customers covered by her colleagues, and continue to find

$$Ind\_Connect_{l,i,t} = \sum_{j}^{J_{l,t}} Importance_{i,j,t},$$

where $J_{l,t}$ are industries covered by analyst l's colleagues in year t, and industry j is one of $J_{l,t}$.[10] Intuitively, this measure reflects the sum of industry i's input commodities made by industries covered by analyst l's colleagues, and industry i's output commodities used by industries covered by analyst l's colleagues.

[Insert Table 1 here]

[Insert Table 2 here]

As mentioned, our sample consists of data on all of the analysts included in I/B/E/S from 1982 to 2017 and for whom we have the data needed to measure our required variables. Based on this condition, we have yields 72,033 analyst-year observations or 221,328 analyst-industry-year observations. The mean value of $Ind\_Connect$ indicates that, on average, an analyst's colleagues cover industries that make and use 69.8% of the total output of the industry she follows, which is economically significant. There are substantial variations in industry connection to colleagues: the third quartile of $Ind\_Connect$ is 0.952, indicating that the analyst's colleagues cover industries that account for 95.2% of her industry's outputs, while those in the first quartile cover only 38.5%.

The variation in $Ind\_Connect$ arises from two sources. The first is the number of industries covered by the analyst's colleagues. An analyst with more extensive colleague industry

significant results for $Ind\_Connect$ (tabulated in Internet Appendix Table IA1 Panel A). We also exclude colleagues who cover firms with direct suppliers or customers relation with the firms covered by the analyst in calculating economic connection ($IC\_Connect\_NoDirect$) and find that all our results are similar except one measure of research productivity (tabulated in Internet Appendix Table IA1 Panel B). These results are consistent with analysts benefiting from information sharing from colleagues who cover economically connected industries even though their covered firms do not have a direct relation.

[10] If two colleagues cover the same industry j, we only count $Importance_j$ once in calculating $Ind\_Connect$.

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coverage—either because she has a greater number of colleagues or her colleagues on average cover a broader set of industries—likely has a higher $Ind\_Connect$. In our sample, analysts who work for larger brokers have a higher $Ind\_Connect$ (a Pearson correlation between employer size and $Ind\_Connect$ of 0.56, as seen in Table 2, Panel C). Therefore, we include broker size and broker fixed effects in all of our empirical analyses to control for the effect of other types of brokerage resources correlated with brokerage size.

The second source is the variation in the importance of the economic connection between the analyst's industry and those of her colleagues. We find that the average cross-sectional standard deviation of $Ind\_Connect$ within each broker-year is 14.0%, that is, 20% of the average level of $Ind\_Connect$ (69.38%). This finding indicates that analysts who work for the same broker in the same year, that is, analysts who have identical colleagues (excluding themselves), have vastly different levels of economic connectedness with colleagues, driven by the varying degrees of the economic interdependence among industries.

Thus, the $Ind\_Connect$ for an analyst who works for the same broker changes over time because of colleague turnovers, changes in colleague industry coverage, or changes in economic connections among industries. Our untabulated analyses show that the average time-series standard deviation of $Ind\_Connect$ for each analyst–broker pair is 16.1%.[11]

3.2. Empirical measures of analyst performance and research design to test H1

We focus on two dimensions of analyst research performance: research quality and productivity. We measure research quality by earnings forecast accuracy and stock recommendation profitability, which are considered analysts' most important and visible

[11] In Section 5.3, we use colleague turnover (i.e., the hiring or departure of a colleague who covers an economically important industry) and find the results are consistent with those of our main analyses. That is, analyst performance improves (deteriorates) after the hiring (departure) of such a colleague.

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quantitative outputs. We measure research productivity with the market cap of analyst-covered firms and report issuance frequency. Performance is measured at the analyst-industry-year level.

Research quality: Earnings forecast accuracy and stock recommendation profitability

We follow previous studies (Hong et al., 2000) and calculate the relative earnings forecast accuracy of analyst l for company p in year t as follows:

$$Accuracy_{l,p,t} = 100 - \left[\frac{Rank\_FE_{l,p,t} - 1}{Number\ of\ Analysts_{p,t} - 1}\right] \times 100,$$

where $Number\ of\ Analysts_{p,t}$ is the number of analysts issuing earnings forecasts for company p in year t, and $Rank\_FE_{l,p,t}$ is the ranking of the absolute forecast error (i.e., the absolute value of the difference between the forecasted and actual earnings per share) of her last annual earnings forecast for the company issued at least one month prior to the fiscal year end. The analyst with the lowest (highest) absolute forecast error receives the first (last) rank and has an $Accuracy_{l,p,t}$ of 100 (0). Next, to obtain an analyst's earnings forecast accuracy for a given industry-year, we take the average of $Accuracy_{l,p,t}$ across all of the companies analyst l covers in industry i in year t ($Accuracy_{l,i,t}$). This specification measures the analyst's relative forecast accuracy compared to that of her peers who follow the same industry.

We measure stock recommendation profitability in a similar manner. We calculate the return obtained from following analyst l's recommendation for company p in year t. Using the market-adjusted buy-and-hold return, we assume a long position for buy and strong buy recommendations, and a short position for hold, sell, and strong sell recommendations.[12] We specify an investment window starting from two days after the recommendation announcement

[12] In a sensitivity test, we exclude all hold recommendations in calculating stock recommendation profitability and find similar results as our main analyses.

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date and ending on either 364 days after the recommendation announcement date or 2 days before the next recommendation announcement date, whichever is earlier. Next, we rank all of the analysts following company p in year t and normalize their rankings from 0 to 100, with the most profitable analyst receiving a $Rec\_Profit_{l,p,t}$ of 100. Finally, we use the average $Rec\_Profit_{l,p,t}$ across all of the companies that analyst l covers in industry i in year t to obtain her relative stock recommendation profitability for the industry-year ($Rec\_Profit_{l,i,t}$).

Research productivity: Covered firms' market cap and report issuance frequency

We suggest that in addition to the benefits for research quality, research productivity may also increase due to analysts' information sharing. Specifically, when an analyst is able to obtain value-relevant information from her colleagues, she can use such information directly in her research and can also allocate more time and effort to acquiring information in her own industry, both of which increase her research output.

To measure research productivity, we use the total market cap covered in an industry and the number of reports issued for firms in that industry. The research suggests covering larger firms allows an analyst to gain visibility and generate more trading commissions for her brokerage house (Hong and Kubik, 2003). Groysberg et al. (2011) find a positive relation between covered companies' market cap and an analyst's compensation. As for our measures of research quality, we use the normalized ranking of market cap covered in the industry ($Ind\_MV_{l,i,t}$) to control for differences in task difficulty and company size across industries.

Our second measure of research productivity is the frequency of analyst reports issued for firms in a given industry ($Ind\_Freq_{l,i,t}$). We use a normalized ranking similar to that of $Ind\_MV_{l,i,t}$. Following Frankel et al. (2006), we use earnings forecast revisions on I/B/E/S to

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identify issuance of reports. The number of reports is widely used by brokerage houses as an action-based performance measure to evaluate analysts (Groysberg et al., 2011). Prior research suggests that more frequent report issuance generates more trading commissions and investment banking fees for brokerages (Krigman et al., 2001; Juergens and Lindsey, 2009). Thus, analysts have incentives to issue frequent reports.

Research design to test H1

To test HI, we use the following pooled OLS regression model:

$$Analyst\ Performance = \alpha + \beta \cdot Ind\_Connect + \sum_m \gamma_m Control\_Performance_m + Broker\ FE + Industry\_Year\ FE + \varepsilon, \quad (1)$$

where $Analyst\ Performance$ consists of $Accuracy$, Rec_Profit, Ind_MV, and Ind_Freq. Our main variable of interest is $Ind\_Connect$. From H1, we expect that the coefficient for $Ind\_Connect$ will be positive. That is, information sharing among colleagues creates greater performance benefits when these colleagues cover industries that are more economically connected to the analyst's industry.

As discussed in Section 3.1, it is essential that we control for other types of brokerage resources because analysts working for larger brokers tend to have a higher $Ind\_Connect$. Larger brokerage houses generally have higher reputations, and are more likely to support analyst research through training programs, distribution networks, and easier access to firm management, databases, research, and administrative assistance. These brokerage houses also tend to have better research directors, macroeconomists, and quant analysts. Such resources can attract higher-quality analysts, leading to a positive correlation between analyst performance and $Ind\_Connect$. To address this endogeneity concern, we include broker size (measured as the total number of analysts working for the broker) and broker fixed effects in our estimation

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(Stickel, 1995; Clement, 1999; Jacob et al., 1999).[13, 14] Thus, we can compare variations among analysts within a broker—that is, whether analysts who cover industries that are more economically connected with those of colleagues perform better than other analysts in the same broker.[15]

In addition to controlling for brokerage characteristics, we follow the literature (e.g., Mikhail et al., 1997; Clement, 1999; Jacob et al., 1999; Hong and Kubik, 2003; Clement and Tse, 2005) and control for a number of analyst characteristics that might be correlated with performance, such as industry experience (Ind_Expr), the number of industries followed ($NInd$), the number of companies followed in the industry ($NFirm$), the average number of reports issued per covered company in the industry ($Freq$), and the average forecast horizon ($Horizon$). Finally, we control for the following firm characteristics that reflect an analyst's coverage selection and can affect her performance: firm size (MV, the average log market cap of companies followed by the analyst in the industry-year), market-to-book ratio (MTB, the average market-to-book ratio of firms followed by the analyst in the industry-year), and firm profitability (ROA, the average return on assets of firms followed by the analyst in the industry-year). We also include industry-year fixed effects to control for industry-wide and time-series variations. The definitions of the variables are provided in the Appendix. We winsorize all continuous variables that are not based on normalized ranks at the top and bottom 1%. The standard errors are estimated with two-way clustering at the analyst and industry-year levels (Petersen, 2009).

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[13] In a sensitivity analysis, we control for analyst quality by replacing brokerage fixed effects with analyst fixed effects in our regressions and find similar results (tabulated in Internet Appendix Table IA2).

[14] Our empirical results remain the same if we use an alternative measure of broker size that is based on the number of industries covered by the broker.

[15] In a sensitivity analysis, we exclude broker fixed effects from our regressions, and find that $Ind\_Connect$ is significantly positive and the economic magnitude of the effect of information sharing is larger (tabulated in Internet Appendix Table IA3).

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4. Empirical results

4.1. Descriptive statistics

From the descriptive statistics reported in Panel B of Table 2, we see that the median analyst in our sample covers two industries and five companies, issues 13 reports a year, and has 48 colleagues.[16] In Panel C, we further see that $Ind\_Connect$ is positively correlated with all of the analyst performance measures (significant at the 0.01 level), consistent with our prediction that information sharing benefits analyst research.

4.2. Relation between analyst performance and the economic importance of colleagues' covered industries

Table 3 reports the empirical results for our analysis of the relation between the analyst's performance and the economic connectedness of the industries covered by her colleagues (i.e., H1). Column 1 presents the results for analyst forecast accuracy ($Accuracy$). In Column 1, we see that the coefficient for $Ind\_Connect$ is positive and significant (at the 0.01 level), supporting our prediction that information sharing from colleagues covering related industries improves analyst earning forecast accuracy. The results further show that forecast accuracy is positively correlated with both industry experience (Ind_Expr) and the number of industries followed ($NInd$), which is consistent with previous findings (e.g., Clement, 1999; Jacob et al., 1999). Furthermore, forecast accuracy is positively correlated with the number of companies covered in the industry ($NFirm$) and the number of forecasts issued per company in the industry ($Freq$), as these measures capture the analyst's effort and her breadth of knowledge, but as expected is negatively correlated with forecast horizon ($Horizon$). Finally, we find that forecast accuracy is

[16] The low average numbers of firms covered and reports issued are driven by the sample analysts in the earlier years. In 2008–2017, the median analyst covers 9 firms and issues 33 reports per year.

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negatively correlated with broker size ($BSize$) when broker fixed effects are included in the regression, but the correlation is either insignificant (Internet Appendix Table IA2 and IA3) or significantly positive (Internet Appendix Table IA4) when broker fixed effects are not included.

[Insert Table 3 here]

Table 3, Column 2 reports the results for stock recommendation profitability (Rec_Profit). Again, we find the coefficient on $Ind\_Connect$ to be positive and significant (at the 0.10 level), suggesting that information sharing from colleagues covering economically connected industries enables the analyst to provide more profitable recommendations. Similar to our results for forecast accuracy, we find positive significant correlations for $NInd$, $NFirm$, and $Freq$.

Columns 3 and 4 report the results for our two analyst research productivity measures. We find positive correlations (significant at the 0.10 level) for both measures of productivity—that is, the market cap covered in the industry (Ind_MV) and the report issuance frequency for the industry (Ind_Freq)—after we control for brokerage size, experience, and portfolio complexity. These results suggest that information sharing about economically connected industries allows an analyst to focus more on her own industry.

4.3. Cross-sectional tests on the relation between analyst performance and the economic connectedness of colleague industries

In this section, we examine the cross-sectional variations in the effect of information sharing on analyst performance as predicted in H2.

To test H2a, wherein analyst research benefits more from information sharing when the connected colleagues are of higher quality, we measure colleague research quality using their forecast accuracy, recommendation profitability, industry experience, and *II* star status. We separately calculate the sum of the $Importance$ of the industries covered by colleagues whose

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research quality is above and below the sample median (or who are star and non-star rated) and label them $IC\_High\_Quality$ and $IC\_Low\_Quality$, respectively. To examine whether our information sharing effect varies with colleague quality, we replace $Ind\_Connect$ in Eq. (1) with $IC\_High\_Quality$ and $IC\_Low\_Quality$ and predict that information sharing from high-quality colleagues has a larger impact than that from low-quality colleagues. That is, the estimated coefficient on $IC\_High\_Quality$ should be significantly larger than that on $IC\_Low\_Quality$.

[Insert Table 4 here]

Table 4 reports the results. Panel A presents our comparison of the effects of information sharing from more accurate colleagues (IC_High_Acc) with those from less accurate colleagues (IC_Low_Acc) on the analyst's research quality ($Accuracy$ and Rec_Profit) and productivity (Ind_MV and Ind_Freq). The results show that the coefficients on IC_High_Acc are significantly greater than those on IC_Low_Acc for both forecast accuracy and report frequency (at the 0.05 and 0.01 levels, respectively). Panel B presents our comparison of the effects of information sharing from more profitable colleagues (IC_High_Profit) with those from less profitable colleagues (IC_Low_Profit). We see that the coefficients on IC_High_Profit are significantly greater than those on IC_Low_Profit for both recommendation profitability and forecast frequency (at the 0.05 and 0.01 levels, respectively). That is, intuitively, information sharing from colleagues with more accurate earnings forecast improves earnings forecast accuracy, and information sharing from more profitable recommendation colleagues improves recommendation profitability, consistent with evidence that the two types of forecasts involve information of different natures (Bradshaw, 2004; Ertimur et al., 2007). Continuing with Table 4, from Panel C, we shows that the coefficients on IC_Long_Expr (more experienced colleagues) are significantly greater than those on IC_Short_Expr (less experienced colleagues) for forecast

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accuracy, market cap covered, and report frequency (all at the 0.01 level). Finally, Panel D shows that although information sharing improves analyst forecast accuracy regardless of star status, only information sharing with star colleagues improves recommendation profitability. However, there is no significant difference between the effects of star and non-star colleagues, which is possibly because information sharing from star colleagues provides benefits beyond quantitative research outputs (Do and Zhang, 2019). Together, the results in Table 4, Panels A-C show that the proxies for $IC\_High\_Quality$ are statistically significant in eight out of 12 specifications, whereas the proxies for $IC\_Low\_Quality$ are statistically significant in only three out of 12 specifications. The differences between the proxies are statistically significant at the 5% level in seven out of 12 specifications. Thus, we conclude that there is evidence supporting H2a that an analyst benefits more from information sharing with higher-quality colleagues, especially when analyst quality is defined by objective measures such as earnings forecast accuracy, stock recommendation profitability, and industry experience.

We next turn to H2b and examine whether the effect of information sharing is more salient when the analyst and her colleagues have stronger professional, social, or educational ties. To measure the relationship between the analyst and her colleagues, we use the length of their working relationship, their work location proximity, and whether they studied in the same school. To obtain information about the analysts' historical work locations and educational backgrounds, we use their LinkedIn profiles. Hence, some tests of H2b are based on the subsample of analysts who have LinkedIn profiles and covers a shorter sample period (2007–2016). Empirically, we classify a colleague as having a stronger tie with the analyst if the length of their relationship (measured by the number of years they have worked together in the current broker) is above the median, if they work in the same city, or if they studied at the same

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university. For each analyst, we separately calculate the level of economic connection between the industries covered by these two groups of colleagues and the analyst's industry, and denote them as IC_Strong_Ties and IC_Weak_Ties, respectively. In our analyses, we replace $Ind\_Connect$ in Eq. (1) with IC_Strong_Ties and IC_Weak_Ties and rerun our analyses. Recall that H2b predicts that information sharing from strongly tied colleagues should have a larger impact than that from weakly tied colleagues. That is, the estimated coefficients on IC_Strong_Ties should be larger than those on IC_Weak_Ties .

[Insert Table 5 here]

From Table 5, Panel A, we see that $IC\_Long\_Relation$ has a significantly positive correlation with all four of the performance measures, whereas the coefficient on $IC\_Short\_Relation$ is positive and significant only in the regression of forecast accuracy. However, the magnitudes of the two sets of coefficients are significantly different only in the regression of report frequency (at the 0.01 level). Panel B shows that the coefficients on IC_Same_City are significantly greater than those on IC_Diff_City in the regressions of forecast accuracy, total market cap covered, and report frequency (at least at the 0.05 level). Finally, Panel C shows that the coefficients on IC_School_Ties are significantly greater than those on $IC\_No\_School\_Ties$ in the regressions of recommendation profitability and report frequency (at the 0.01 level). Overall, we find that our relationship proxies for strong social ties (IC_Strong_Ties) are statistically significant in all 12 specifications, whereas the proxies for IC_Weak_Ties are statistically significant in only two out of 12 specifications. The differences between the proxies are statistically significant at the 5% level in six out of 12 specifications, with all three differences significant at the 1% level when the dependent variable is report frequency. We conclude that the evidence supports H2b that analyst research, especially report

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issuance frequency, benefits more from information sharing from colleagues with whom the analyst has stronger professional, social, or educational ties.

4.4. Investor recognition of benefits of analyst information sharing across economically connected industries

In this section, we examine whether investors recognize the benefits of analyst information sharing among colleagues covering economically connected industries. Investors' recognition reflects their overall assessment of analyst research quality, which can go beyond the analyst quantitative research outputs we examine, that is, earnings forecast accuracy and stock recommendation profitability.

To measure investor recognition of analyst performance, we follow prior literature and use the market reaction to analyst reports (e.g., Francis and Soffer, 1997; Loh and Stulz, 2011; Bradley et al., 2014). In particular, we measure the market reaction to an analyst report for company p in year t as the cumulative absolute three-day market-adjusted return centered on the earnings forecast revision date. We take the average market reaction of all of the reports issued by each analyst l for firms in industry i in year t ($Report\_CAR_{l,i,t}$) to obtain our first measure of investor recognition of analyst performance.

For our second measure of investor recognition of analyst performance, we use the annual All-Star Ranking list published by *Institutional Investor* (hereafter, *II* All-Star Ranking).[17] We identify an analyst as a star ($Star_{l,t}$) if she is ranked among the first, second, or third teams or if she is listed as a runner-up by *II* in year t.[18] To determine analyst rankings, *II* surveys a set of

[17] *II* polls a large number of institutional investors (e.g., the directors of research and the chief investment officers of major money management institutions) and determines its rankings using the number of votes awarded to each analyst weighted by the size of the institution responding.

[18] As *II* ranks the analysts according to their main industry, we assign each analyst-year to the industry in which she covers the largest market cap, based on the assumption that she has the most influence in that industry. We also measure the independent variables, including $Ind\_Connect$, at the analyst-year level using that industry.

institutional investors and asks them to vote for an analyst based on a comprehensive set of attributes, including industry knowledge, integrity, accessibility, management access, special services, written reports, financial models, useful and timely calls and visits, idea generation, research delivery, earnings estimates, and stock selection. Among these attributes, industry knowledge has been ranked as the most desirable quality in 13 out of the 14 years during which *II* has surveyed institutional investors (1998–2011). This is important for our study as we examine the role of information sharing from colleagues covering economically connected industries. Such sharing may be particularly beneficial to an analyst's industry knowledge as it alerts her to pertinent developments, such as trends in input prices, supply and demand shocks, and technological advancements, in these related industries. Obtaining this information from colleagues saves the analyst time and effort that she can spend on researching her own industry. Finally, the sharing of information among colleagues who cover related industries helps analysts produce research reports that "connect the dots" across industries and provide "big picture" investment ideas valued by institutional investors.

In this set of analyses, we predict that the market understands the benefits of information sharing and award more investor recognition to analysts who have colleagues covering economically connected industries. That is, investors react more strongly to the reports of these analysts, who are in turn more likely to be ranked as *II* All-Star analysts. We use the following model in OLS and Probit specifications:

$$\begin{aligned} &Investor\ Recognition \\ &\quad = \alpha + \beta \cdot Ind\_Connect + \sum_m \gamma_m Control\_IR_m + Broker\ FE \\ &\quad + Industry\_Year\ FE + \varepsilon, \end{aligned} \tag{2}$$

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where $Investor\ Recognition$ is either $Report\_CAR$ or $Star$. In this set of regressions, we control for broker, analyst, and firm characteristics that have been shown to affect investor recognition. These characteristics are broker size ($BSize$), industry experience (Ind_Expr), the number of industries covered ($NInd$), the number of firms covered in the industry ($NFirm$), report frequency ($Freq$), earnings forecast horizon ($Horizon$), and market cap (MV), market-to-book ratio (MTB), and profitability (ROA) of the covered firms. For the regression with $Star$ as the dependent variable, we include control variables for earnings forecast accuracy ($Accuracy$), optimism ($Optimism$), and boldness ($Bold$). To the extent that information sharing improves analyst forecast performance in areas such as forecast accuracy and report frequency, the coefficient on $Ind\_Connect$ in Eq. (2) should reflect the impact of information sharing beyond its effect on forecast accuracy and report frequency. In other words, the total impact of information sharing on an analyst's star status is likely larger than what is reflected by the marginal effect of $Ind\_Connect$ in this model.

We examine the market's response around an analyst's report issuance date ($Report\_CAR$, measured with earnings forecast revision date from I/B/E/S). The results in Table 6, Column 1 show that the coefficient on $Ind\_Connect$ is positive and significant (at the 0.01 level), supporting our prediction that information sharing from colleagues covering related industries improves the analyst's market impact. These results are economically significant, with a one standard deviation increase in $Ind\_Connect$ associated with an 11 basis-point increase in market response. We find the following controls to be positively correlated with market response: broker size ($BSize$), the number of companies covered in the industry ($NFirm$), the number of forecasts issued per company in the industry ($Freq$), and forecast horizon ($Horizon$).

[Insert Table 6 here]

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In terms of whether analysts with colleagues covering economically connected industries are more likely to receive star status ($Star$), we see from the results in Column 2 that the coefficient on $Ind\_Connect$ is positive and significant (at the 0.01 level). This finding suggests that information sharing from colleagues improves the qualitative aspects of analyst performance—such as industry knowledge, written reports, and idea generation—that institutional investors value. This result is also economically significant: a one standard deviation increase in $Ind\_Connect$ (0.381) increases the odds of being ranked as a star by 11.8% (1.7% compared to the unconditional probability of 14.4%). Finally, for star status, we find positive correlations with $BSize$, Ind_Expr, $NInd$, $NFirm$, $Freq$, and $Accuracy$, and a negative correlation with $Horizon$, suggesting that the total impact of information sharing on star status, which includes its effects through forecast accuracy and report frequency, is even larger.[19]

5. Additional analyses

5.1. Is an analyst more likely to issue a report when her highly connected colleague issues a report?

Our main result is that information sharing among connected colleagues is beneficial to analyst research performance. Although we cannot observe the private communication among colleagues, in this section, we provide a more direct test of one likely outcome of information sharing activity. When a colleague produces information about her industry and passes the relevant information to the analyst who covers a highly connected industry, the analyst is prompted to issue reports for companies in her own industry. Thus, we predict that an analyst is

[19] Results from untabulated analyses of cross-sectional variations in investor recognition of the benefits of information sharing show that investors recognize that an analyst benefits more from information sharing when her related industries are covered by higher-quality colleagues, and when the length of the relationship between the analyst and her colleagues is longer.

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more likely to issue a report when her highly connected colleague issues a report, compared to a matched analyst who does not have a highly connected colleague.

To test this prediction, we identify pairs of analysts covering *the same company*, wherein one analyst, who we refer to as the connected analyst ($Connected$ equals 1), has a colleague covering a highly connected industry, and the other analyst, referred to as the non-connected analyst ($Connected$ equals 0), does not have such colleagues. Here, we define a highly connected industry as one with a level of $Importance$ to the analyst's covered industry greater than or equal to the sample median (0.4%).[20] We test whether the connected analyst has a greater likelihood of issuing a report for the firm than a non-connected analyst around the report date of the connected analyst's colleague. To ensure that the connected and non-connected analysts are comparable in other dimensions, we require the differences in their brokerage firms' size and industry forecasting experience to be less than the corresponding medians (four analysts and two years, respectively).[21] When there are more than one non-connected analysts matched to a connected analyst, we select the one, in the sequence of, having the closest brokerage size, industry experience, and total market value of covered firms to the connected analyst. We use earnings forecast revisions in I/B/E/S as the analyst report issuance dates. We exclude reports issued within one day of any brokerage-hosted conference that the covered firm attends (conference dates are obtained from the Compustat Capital IQ Key Development database) to eliminate the possibility that the connected analyst and her colleague issue reports

[20] If an analyst has more than one such colleagues, we select the one who covers the industry with the highest level of $Importance$ to her industry. In the final sample, the mean (median) of $Importance$ between the connected analysts are 12.3% (7.1%).
[21] We assign each analyst-year to the industry in which she covers the largest market cap.

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simultaneously because they both attend a conference.[22] We estimate the following OLS regression:

$$Report\_Issuance = \alpha + \beta \cdot Connected + \sum_m \gamma_m Control\_Issuance_m + Broker\ FE + Industry\_Year\ FE + \varepsilon, \quad (3)$$

where $Report\_Issuance$ equals one if the connected or non-connected analyst issues a report in the [-1, 1] window of the date that the connected analyst's colleague issues a report for her largest covered firm, and zero otherwise.[23] We include brokerage size ($BSize$), industry experience (Ind_Expr), the number of industries and firms covered ($NInd$ and $NFirm$), forecast frequency for the firm during the year ($Firm\_Freq$), and the horizon of the colleague's report ($Firm\_Horizon$) to control for other characteristics that influence the likelihood of report issuance.

Table 7 shows a significantly positive coefficient on $Connected$ (at the level of 0.01). This result suggests that around the time an important colleague issues a report, connected analysts have a greater chance of issuing a report than non-connected analysts, consistent with the conjecture that the colleague shares information with the connected analyst. This effect is economically significant, with connected analysts being 25% more likely to issue reports during the event window than non-connected analysts (6.41% increase relative to the unconditional likelihood of 25.66%). The estimated coefficients for brokerage size, industry experience, and

[22] It is unlikely that public informational events affect this analysis because both connected and non-connected analysts have access to such events.

[23] We estimate the model with a Probit regression and find similar results that when colleagues issue reports, connected analysts are more likely to issue reports than non-connected analysts. Our results remain when we replace broker fixed effects with analyst or broker-year fixed effects, or use [-3, +3] and [-5, +5] windows instead of the [-1, +1] window.

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the number of firms covered are insignificant, which indicates the success of our matching procedure. Our prediction also holds after conducting falsification tests, in which we change the event window to 45 days before or after the colleague's report date. We find insignificant coefficients on $Connected$ (reported in Columns 2 and 3 of Table 7, respectively).[24] We can conclude that connected and non-connected analysts differ in their tendency to issue a report only around the report issuance by the connected analyst's colleague, not otherwise. Thus, Table 7 provides more direct evidence of information sharing and supplements our main findings.

[Insert Table 7 here]

5.2. Information sharing with colleagues covering upstream and downstream industries

In this section, we seek further evidence to support H1 by examining information sharing with colleagues covering upstream and downstream industries. We expect that upstream information sharing has a more pronounced benefit on expense forecasts, as upstream industries are an industry's suppliers. We also expect that downstream information sharing benefits revenue forecasts more, as downstream industries are the customers. In this set of tests, we measure the importance of upstream industries covered by an analyst's colleagues ($IC\_Upstream$) as her industry's total input commodities made by her colleagues' industries, scaled by the total output of her industry, and the importance of downstream industries covered by an analyst's colleagues ($IC\_Downstream$) as the proportion of output commodities made by the analyst's industry that are used by her colleagues' industries (see Appendix for detailed variable definitions). Note that the sum of $IC\_Upstream$ and $IC\_Downstream$ of an analyst-industry-year is its $Ind\_Connect$.

[24] Using 30 days before or after the colleague's report date in the falsification tests yield similar insignificant results.

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We obtain our analyst revenue forecast data from I/B/E/S. For the analyst expense forecast measure, we use the difference between her revenue and EBITDA forecasts, as analysts usually do not forecast expenses directly. We measure analyst revenue and expense forecast accuracy at the industry level ($Accuracy\_Rev_{l,i,t}$ and $Accuracy\_Exp_{l,i,t}$) in a similar fashion as earnings forecast accuracy ($Accuracy_{l,i,t}$), and estimate a regression model similar to Eq. (1). Given that we infer an analyst's expense forecast from her revenue forecasts, we control for her revenue forecast accuracy in our regression of expense forecast accuracy. Due to I/B/E/S data availability, our sample period for the revenue (expense) forecast accuracy analysis is 1996–2017 (2002–2017).

From Table 8, Column 1, we find that the coefficient on $IC\_Downstream$ is positive and significant (at the 0.05 level) when the dependent variable is $Accuracy\_Rev$, consistent with the notion that downstream information sharing facilitates revenue forecasting. From Column 2, we see that the coefficient on $IC\_Upstream$ is positive and significant (at the 0.01 level) when the dependent variable is $Accuracy\_Exp$, suggesting that upstream information facilitates expense forecasting. Importantly, we observe that information sharing from upstream (downstream) colleagues does not benefit revenue (expense) forecasting. As both colleagues covering upstream and downstream industries work for the same brokerage house in the same year, their different impacts to the analyst's expense and revenue forecast accuracy cannot be explained by other broker resources. Together, these results alleviate the endogeneity concern and provide support for H1.

[Insert Table 8 here]

5.3. Colleague turnover analysis

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To further reinforce our findings and mitigate endogeneity concerns, we examine the effect of colleague turnover on our results. For each analyst-industry-year, we first identify whether the analyst has highly connected colleagues (as defined in Section 5.1, colleagues who cover an industry with a level of $Importance$ greater than or equal to the sample median of 0.4%) that experience a turnover (joining or leaving the broker) during the year. For each affected analyst, we compare her performance and investor recognition in the year when the highly connected colleague is hired ($Post\_Hiring$) or in the year after the highly-connected colleague's departure ($Post\_Departure$) to her performance and investor recognition of the prior year. We estimate a regression similar to Eq. (1) in which we replace $Ind\_Connect$ with the year indicator variable of $Post\_Hiring$ or $Post\_Departure$. Here, we expect analyst performance and investor recognition to be higher (lower) in the $Post\_Hiring$ ($Post\_Departure$) period due to an increase (decrease) in the sharing of information about economically important industries.

From Table 9, Panel A, we find that the coefficient on $Post\_Hiring$ is positive and significant (at least at the 0.10 level) in the regressions of research performance, research productivity, and market reaction to analyst reports, suggesting that analyst research benefits from an increase in colleagues covering economically important industries. From Panel B, we find that the coefficient on $Post\_Departure$ is negative and significant (at the 0.01 level) in the regressions of research quality and report frequency, suggesting that analyst research performance declines with a decrease in colleagues covering economically important industries. We find insignificant results for investor recognition. The results show that $Post\_Hiring$ and $Post\_Departure$ are statistically significant in seven out of eight regressions of analyst performance and in one out of four regressions of investor recognition. These results suggest that

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the turnover of important colleagues has an immediate effect on analyst performance, but the effect on investor recognition is less clear.

[Insert Table 9 here]

5.4. Within broker-year analysis

In our final subsection, we provide further support for our findings by conducting a within-broker-year analysis using a matched sample. Specifically, we match an analyst with above-median $Ind\_Connect$ with an analyst with below-median $Ind\_Connect$ from the same broker in the same year. While we previously use broker fixed effects to control for average broker characteristics, in this analysis we control for time-varying broker resources. We ensure that the matched analysts have the closest quintile-ranking of Ind_Expr and $NFirm$ so that they have similar industry experience and workload. The results in Table 10 show that the coefficient on $Ind\_Connect$ is positive and significant (at least at the 0.10 level) in all of the regressions of analyst performance and investor recognition, suggesting that our results are robust to the controls for time-varying broker resources.

[Insert Table 10 here]

6. Conclusion

Anecdotally, the practice of sharing information on economically connected industries is readily observable and often encouraged in brokerage houses. Information sharing has numerous potential output benefits. For example, the study by Menzly and Ozbas (2010) shows that stocks in economically connected industries have correlated fundamentals and can cross-predict each other's returns. The literature, however, typically focuses on analysts as industry specialists, implying that they develop their research outputs in a non-collaborative environment. Thus, the *cross-industry* information sharing that occurs among peers is overlooked. Our study addresses

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this gap by providing evidence consistent with analysts sharing information with colleagues who cover economically connected industries.

We measure the economic interdependence between an analyst's industry and her colleagues' industries using BEA industry input and output data to assess whether information sharing across economically connected industries improves analyst performance. Our results suggest that information sharing benefits analysts' research along multiple dimensions. First, after controlling for broker size and broker fixed effects, we find that an analyst exhibits better research performance and productivity and has more investor recognition when the economic connection between her industry and those of her colleagues is stronger, suggesting that sharing information with colleagues benefits her forecast performance. This result remains when we replace broker fixed effects with analyst fixed effects, use a change specification, use a matched sample, and exploit colleague turnover to mitigate endogeneity concerns. The finding that colleagues' downstream (upstream) coverage only improves an analyst's revenue (expense) forecasts confirms that the benefits come from economic connections with colleagues, not merely general brokerage resources. We also investigate the timing of analyst report issuance and find that an analyst tends to issue report immediately surrounding the date that her highly-connected colleagues do so, which provides more direct evidence of information sharing. Our study further explores cross-sectional variations in the observed effect and shows evidence that stronger colleague research quality and social ties both increase the magnitude of the effect. We also find that investors recognize the benefit of information sharing to analysts' overall research quality, as investors react more strongly to reports issued by analysts with higher levels of information sharing and more likely rank these analysts as *II* All-Stars.

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Our study contributes to the literature by identifying a new channel through which analysts collect information and by providing new insights into their information acquisition efforts. The evidence of cross-industry information sharing broadens our understanding of the role of analysts as industry specialists and reveals how they can facilitate information flow across industries. Our results imply that industry specialization does not put analysts at a disadvantage as they are able to obtain relevant upstream and downstream information from their colleagues. Our study provides practical implications for brokerage houses, as our results suggest that promoting cross-industry collaboration among colleagues improves analyst research and enhances analysts' reputation among investors. Our findings can also help investors identify analysts who have better cross-industry knowledge and can deliver superior research quality.

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Appendix: Variable Definitions

Analyst-industry-year level variables:	
$Ind\_Connect_{l,i,t}$	The sum of the importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*. The importance of industry *j* to industry *i* in year *t* is the ratio of the sum of industry *i*'s input commodities made by industry *j* and industry *i*'s output commodities used by industry *j* to industry *i*'s total output. That is, $Importance_{i,j,t} = \frac{\sum_k \begin{pmatrix} Commodity\ k\ used\ by\ industry\ i \times \%\ of\ Commodity\ k\ made\ by\ industry\ j + \\ Commodity\ k\ used\ by\ industry\ j \times \%\ of\ Commodity\ k\ made\ by\ industry\ i \end{pmatrix}}{Total\ output\ of\ industry\ i}$
$Accuracy_{l,i,t}$	The average relative earnings forecast accuracy of analyst *l* in industry *i* in year *t*, following Hong et al. (2000). First, absolute earnings forecast error is calculated as the absolute value of the difference between the analyst's last forecasted earnings per share issued at least one month prior to the fiscal year end and the actual earnings per share; next, the absolute forecast errors of all analysts following the same company are ranked such that the most accurate analyst receives a rank of 100 and the least accurate analyst receives a rank of zero; last, for analyst *l*, we take the average of her ranks across all of the companies she covers in industry *i* during year *t*.
$Rec\_Profit_{l,i,t}$	The average relative stock recommendation profitability of analyst *l* in industry *i* in year *t*. First, stock recommendation profitability is calculated as (negative one times) the market-adjusted buy-and-hold return to the analyst's strong buy or buy (hold, sell, or strong sell) recommendations, where the return window is her [current recommendation announcement date +2, min(current recommendation announcement date +364, next recommendation announcement date -2)]; next, the stock recommendation profitability of all analysts following the same company are ranked such that the most profitable analyst receives a rank of 100 and the least profitable analyst receives a rank of zero; last, for analyst *l*, we take the average of her ranks across all of the companies she covers in industry *i* during year *t*.
$Ind\_MV_{l,i,t}$	The normalized ranking of market cap covered by analyst *l* in industry *i* in year *t*. We rank the total market cap of covered companies of all analysts in industry *i* in year *t* such that the analyst covering the highest total market cap in the industry receives a rank of 100, and the one covering the lowest total market cap receives a rank of zero.
$Ind\_Freq_{l,i,t}$	The normalized ranking of report frequency by analyst *l* in industry *i* in year *t*. We rank the earnings forecast frequency of all analysts in industry *i* in year *t* such that the analyst issuing the most forecasts in the industry receives a rank of 100, and the one issuing the least receives a rank of zero.
$Report\_CAR_{l,i,t}$	The average market reaction to the analyst reports issued by analyst *l* for companies in industry *i* in year *t*. The market reaction to each analyst report is measured as the cumulative absolute three-day market-adjusted return centered on the analyst's earnings forecast revision date; next, we calculate the average market reaction of all analyst reports issued by the analyst for companies in industry *i* in year *t*.
$Accuracy\_Rev_{l,i,t}$	The average relative sales forecast accuracy of analyst *l* in industry *i* in year *t*, following Hong et al. (2000). First, absolute sales forecast error is calculated as the absolute value of the difference between the analyst's last forecasted sales issued at least one month prior to the fiscal year end and the actual sales; then, we follow the same normalization process as for $Accuracy_{l,i,t}$ and take the average of her ranks across all of the companies she covers in industry *i* during year *t*.
$Accuracy\_Exp_{l,i,t}$	The average relative expense forecast accuracy of analyst *l* in industry *i* in year *t*, following Hong et al. (2000). First, we infer analyst *l*'s expense forecast by her last (sales forecast minus EBITDA forecast) and then calculate absolute expense forecast error by comparing with (actual sales minus actual EBITDA); then, we follow the same normalization process as for $Accuracy_{l,i,t}$ and take the average of her ranks across all of the companies she covers in industry *i* during year *t*.
$IC\_High\ \_Acc_{l,i,t}$ $IC\_High\_Profit_{l,i,t}$ $IC\_Long\_Expr_{l,i,t}$ $IC\_Long\_Relation_{l,i,t}$	The sum of the importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*, and have above or equal to sample median of (1) *Accuracy*, (2) *Rec_Profit*, (3) *Ind_Expr*, or (4) number of years working in the same brokerage, respectively.

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IC_Low _Acc$_{l,i,t}$ *IC_Low_Profit*$_{l,i,t}$ *IC_Short_Expr*$_{l,i,t}$ *IC_Short_Relation*$_{l,i,t}$	The sum of the importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*, and have below sample median of (1) *Accuracy*, (2) *Rec_Profit*, (3) *Ind_Expr*, or (4) number of years working in the same brokerage, respectively.
IC_Star$_{l,i,t}$ *IC_Same_City*$_{l,i,t}$ *IC_School_Ties*$_{l,i,t}$	The sum of the importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*, and (1) are awarded the *Institutional Investor* All Star analyst status in year *t*, (2) work in the same city, or (3) graduated from the same institution, respectively.
IC_Non_Star$_{l,i,t}$ *IC_Diff_City*$_{l,i,t}$ *IC_No_School_Ties*$_{l,i,t}$	The sum of the importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*, and (1) are not awarded the *Institutional Investor* All Star analyst status in year *t*, (2) work in different cities, or (3) graduated from different institutions, respectively.
IC_Upstream$_{l,i,t}$	The sum of upstream importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*. The upstream importance of industry *j* to industry *i* in year *t* is the ratio of the sum of industry *i*'s input commodities made by industry *j* to industry *i*'s total output. That is, $Upstream\_Importance_{i,j,t} = \frac{\sum_k(Commodity\ k\ used\ by\ industry\ i \times \%\ of\ Commodity\ k\ made\ by\ industry\ j)}{Total\ output\ of\ industry\ i}$
IC_Downstream$_{l,i,t}$	The sum of downstream importance to industry *i* of all industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*. The downstream importance of industry *j* to industry *i* in year *t* is the ratio of the sum of industry *i*'s output commodities used by industry *j* to industry *i*'s total output. That is, $Downstream\_Importance_{i,j,t} = \frac{\sum_k(Commodity\ k\ used\ by\ industry\ j \times \%\ of\ Commodity\ k\ made\ by\ industry\ i)}{Total\ output\ of\ industry\ i}$
Ind_Expr$_{l,i,t}$	The number of years of following industry *i* for analyst *l* in year *t*.
NFirm$_{l,i,t}$	The number of companies followed by analyst *l* in industry *i* in year *t*.
Freq$_{l,i,t}$	The average number of reports issued per covered company by analyst *l* in industry *i* in year *t*.
Horizon$_{l,i,t}$	The average number of days between analyst *l*'s last earnings forecasts and the earnings announcement dates for all companies she follows in industry *i* in year *t*.
MV$_{l,i,t}$	The average log market cap of companies followed by analyst *l* in industry *i* in year *t*.
MTB$_{l,i,t}$	The average market-to-book ratio of companies followed by analyst *l* in industry *i* in year *t*.
ROA$_{l,i,t}$	The average return on assets of companies followed by analyst *l* in industry *i* in year *t*, where return on assets is calculated as income before extraordinary items divided by total assets of a company.
Post_Hiring$_{l,i,t}$	An indicator variable that equals one for the year of hiring a colleague who covers an important industry that was not previously covered by the broker of analyst *l*. An important industry is one with an above median importance to industry *i* covered by analyst *l*.
Post_Departure$_{l,i,t}$	An indicator variable that equals one for the subsequent year of the departure of a colleague who covers an important industry from the broker of analyst *l*. An important industry is one with an above median importance to industry *i* covered by analyst *l*.

Analyst-year level variables:

Ind_Connect$_{l,t}$	The value of *Ind_Connect*$_{l,i,t}$ where industry *i* is the industry with the largest market cap covered by analyst *l* in year *t*.
Connected$_{l,t}$	An indicator variable that equals one if analyst *l* has a colleague who covers an important industry in year *t* and zero otherwise. An important industry is one with an above median $Importance$ to the industry covered by analyst *l*.
Star$_{l,t}$	An indicator variable that equals one if analyst *l* is voted as an *Institutional Investor* All Star analyst in year *t* and zero otherwise.
BSize$_{l,t}$	The number of analysts working at analyst *l*'s brokerage firm in year *t*.
Ind_Expr$_{l,t}$	The value of *Ind_Expr*$_{l,i,t}$ where industry *i* is the industry with the largest market cap covered by analyst *l* in year *t*.
NInd$_{l,t}$	The number of industries followed by analyst *l* in year *t*.

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$NFirm_{l,t}$	The number of companies followed by analyst *l* in year *t*.
$Freq_{l,t}$	The number of reports issued by analyst *l* in year *t*.
$Horizon_{l,t}$	The average number of days between analyst *l*'s last earnings forecasts and the earnings announcement dates for all of the companies she follows in year *t*.
$MV_{l,t}$	The average log market cap of companies followed by analyst *l* in year *t*.
$MTB_{l,t}$	The average market-to-book ratio of companies followed by analyst *l* in year *t*.
$ROA_{l,t}$	The average return on assets of companies followed by analyst *l* in year *t*.
$Accuracy_{l,t}$	The average relative earnings forecast accuracy of analyst *l* in year *t*, following Hong et al. (2000). Similar to $Accuracy_{l,i,t}$, the absolute forecast errors of all analysts following the same company are calculated and ranked; then, for analyst *l*, we take the average of her ranks across all of the companies she covers during year *t*.
$Optimism_{l,t}$	The average company-level optimism dummy variable for analyst *l* during year *t*, following Hong and Kubik (2003). First, the optimism dummy variable equals one when analyst *l*'s last earnings forecast for the company is greater than the consensus forecast of all other analysts following the same company and zero otherwise; next, we take the average of the optimism dummies across all of the companies analyst *l* covers in year *t*.
$Bold_{l,t}$	The average of the normalized ranking of the forecast deviation for analyst *l* in year *t*, following Hong et al. (2000). First, forecast deviation is defined as the absolute value of the difference between analyst *l*'s last earnings forecast for the company and the consensus of all other analysts; next, the forecast deviation of all analysts following the same company are ranked such that the boldest analyst receives a rank of 100 and the least bold analyst receives a rank of zero; last, we take the average of analyst *l*'s ranks across all of the companies she covers in year *t*.
Analyst-firm-year level variables:	
$Report\_Issuance_{l,p,t}$	An indicator variable that equals one if analyst *l* issues a report for company *p* in year t in [-1, 1] window of the event date. The event dates are the dates that analyst *l*'s colleague (or if analyst *l* is a non-connected analyst, her matched analyst's colleague) who covers an important industry issues a report for her largest covered firm. An important industry is one with an above median $Importance$ to the industry covered by analyst *l*.
$Firm\_Freq_{l,p,t}$	The number of reports issued by analyst *l* for company *p* in year *t*.
$Firm\_Horizon_{l,p,t}$	The number of days between the event date and the earnings announcement date for company *p* in year *t*. The event dates are the dates that analyst *l*'s colleague (or if analyst *l* is a non-connected analyst, her matched analyst's colleague) who covers an important industry issues a report for her largest covered firm. An important industry is one with an above median $Importance$ to the industry covered by analyst *l*.

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Table 1
Sample Selection

This table presents the sample construction procedure for the analyst earnings forecast accuracy test.

Sample selection criteria	Number of analyst firm-years	Number of analyst industry-years	Number of analysts
Analyst-firm-years with EPS forecasts, 1982-2017	1,352,841		27,071
Retain: firms with GVKEY	652,466		20,357
Aggregate to analyst-industry-years through averaging analyst-firm-years by BEA industries		237,635	20,357
Retain: at least one covered firm has actual earnings per share and other analysts following to calculate average relative earnings forecast accuracy		233,771	20,202
Retain: at least one covered firm has actual earnings announcement date to calculate average forecast horizon		230,209	20,015
Retain: at least one covered firm has financial information to calculate control variables		221,484	19,483
Retain: brokerage firms and industry-years with multiple observations		221,328	19,399
Final earnings forecast accuracy sample		221,328	19,399

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Table 2
Descriptive Statistics

Panel A: Sample for analyst-industry-year level analysis

This panel presents the descriptive statistics for the sample used in the analyst-industry-year level analysis (i.e., analyst performance tests). The sample size for dependent variable varies across tests, and the descriptive statistics for control variables are based on the sample for the earnings forecast accuracy test. Variable definitions are in the Appendix.

Variable	N	Mean	Stdev	Q1	Median	Q3
Importance	144,540	0.015	0.029	0.001	0.004	0.014
Ind_Connect	221,328	0.698	0.439	0.385	0.658	0.952
Accuracy	221,328	54.901	29.413	33.333	57.143	76.965
Rec_Profit	95,168	50.346	32.776	27.273	50.000	71.944
Ind_MV	221,328	48.731	28.944	23.810	48.341	73.430
Ind_Freq	221,328	47.645	32.203	19.388	47.645	76.056
Report_CAR	205,895	0.047	0.035	0.023	0.038	0.062
Accuracy_Rev	50,180	48.616	30.932	25.000	50.000	70.977
Accuracy_Exp	32,282	48.804	30.995	25.000	50.000	71.399
BSize	221,328	48.045	43.754	14.000	34.000	74.000
Ind_Expr	221,328	4.424	3.956	1.000	3.000	6.000
NInd	221,328	3.486	2.340	2.000	3.000	5.000
NFirm	221,328	2.711	2.930	1.000	1.000	3.000
Freq	221,328	3.197	1.750	2.000	3.000	4.000
Horizon	221,328	155.395	76.564	101.000	120.200	191.000
MV	221,328	7.754	1.816	6.509	7.780	9.017
MTB	221,328	3.482	4.339	1.641	2.571	4.122
ROA	221,328	0.036	0.104	0.015	0.051	0.086

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Table 2 (Cont'd)
Descriptive Statistics

Panel B: Sample for analyst-year level analysis

This panel presents the descriptive statistics for the sample used in the analyst-year level analysis (i.e., All-Star status test). Variable definitions are in the Appendix.

Variable	N	Mean	Stdev	Q1	Median	Q3
Ind_Connect	72,033	0.748	0.381	0.471	0.731	0.990
Star	72,033	0.144	0.351	0.000	0.000	0.000
BSize	72,033	60.945	45.996	24.000	48.000	92.000
Ind_Expr	72,033	4.836	4.262	2.000	3.000	7.000
NInd	72,033	2.173	1.540	1.000	2.000	3.000
NFirm	72,033	6.162	5.324	2.000	5.000	9.000
Freq	72,033	23.103	25.590	5.000	13.000	32.000
Horizon	72,033	158.013	72.517	105.889	130.600	188.600
MV	72,033	8.253	1.664	7.178	8.339	9.427
MTB	72,033	3.472	3.902	1.746	2.693	4.183
ROA	72,033	0.032	0.098	0.014	0.049	0.081
Accuracy	72,033	55.331	23.180	42.128	57.971	70.455
Optimism	72,033	0.495	0.318	0.286	0.500	0.706
Bold	72,033	45.070	22.693	30.797	42.918	57.689

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Table 2 (Cont'd)
Descriptive Statistics

Panel C: Pearson correlation table

This panel presents the Pearson correlation table based on the sample used in the analyst-industry-year level analysis. Bold face indicates significance at the 5% level.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) *Ind_Connect*	1														
(2) *Accuracy*	**0.02**	1													
(3) *Rec_Profit*	**0.01**	**0.02**	1												
(4) *Ind_MV*	**0.12**	**0.03**	**0.02**	1											
(5) *Ind_Freq*	**0.09**	**0.16**	**0.03**	**0.50**	1										
(6) *Report_CAR*	**0.11**	**0.02**	-0.00	**-0.15**	**0.00**	1									
(7) *Star*	**0.14**	**0.06**	**0.01**	**0.16**	**0.15**	**-0.06**	1								
(8) *BSize*	**0.56**	**0.02**	**0.01**	**0.16**	**0.10**	**0.05**	**0.30**	1							
(9) *Ind_Expr*	**0.08**	**0.02**	**0.01**	**0.29**	**0.33**	-0.00	**0.18**	**0.06**	1						
(10) *NInd*	**0.07**	**0.02**	0.01	**-0.10**	**-0.05**	**0.02**	**0.02**	**-0.06**	**0.09**	1					
(11) *NFirm*	**0.08**	**0.03**	**0.02**	**0.46**	**0.62**	**-0.01**	**0.07**	**0.09**	**0.39**	**-0.16**	1				
(12) *Freq*	**0.13**	**0.18**	**0.04**	**0.14**	**0.61**	**0.05**	**0.12**	**0.14**	**0.20**	**0.07**	**0.19**	1			
(13) *Horizon*	**-0.06**	**-0.37**	**-0.04**	**-0.08**	**-0.36**	**-0.02**	**-0.09**	**-0.05**	**-0.07**	**-0.08**	**-0.10**	**-0.50**	1		
(14) *MV*	**0.14**	**-0.01**	**0.03**	**0.71**	**0.22**	**-0.18**	**0.11**	**0.21**	**0.26**	**-0.08**	**0.27**	**0.19**	**-0.10**	1	
(15) *MTB*	**0.05**	**0.01**	-0.00	**0.13**	**-0.01**	**0.06**	-0.00	**0.02**	**0.02**	0.00	**0.01**	**-0.02**	**-0.02**	**0.20**	1
(16) *ROA*	**-0.05**	**0.03**	**0.02**	**0.18**	**-0.02**	**-0.25**	**0.04**	**0.01**	**0.00**	**0.06**	**-0.08**	**-0.01**	**-0.03**	**0.23**	**0.05**

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Table 3
Information Sharing and Analyst Performance

This table reports the relation between an analyst's performance in an industry and the economic connectedness of the industries covered by her colleague to that industry. We estimate the OLS regressions $Accuracy(Rec\_Profit) = f(Ind\_Connect, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1) and (2), and $Ind\_MV(Ind\_Freq) = f(Ind\_Connect, Control\_Analyst) + \varepsilon$ in columns (3) and (4). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA. t-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
Ind_Connect	**1.6757*** **	**1.2239* **	**0.8727* **	**0.7667* **
	(4.44)	**(1.90)**	**(1.67)**	**(1.66)**
BSize	-0.0246***	-0.0036	0.0062	-0.0270***
	(-4.73)	(-0.40)	(0.67)	(-4.21)
Ind_Expr	0.0323*	-0.0030	1.0323***	0.8056***
	(1.72)	(-0.11)	(19.44)	(26.27)
NInd	0.2221***	0.1793***	-0.3921***	0.9362***
	(5.40)	(2.59)	(-4.93)	(15.06)
NFirm	0.0849***	0.0738*	4.9324***	7.4001***
	(3.64)	(1.93)	(24.53)	(53.77)
Freq	0.3415***	0.4610***		
	(7.02)	(6.08)		
Horizon	-0.1397***	-0.0137***		
	(-87.59)	(-7.22)		
MV	-0.3692***	0.3444***		
	(-6.89)	(4.10)		
MTB	0.0484***	-0.0317		
	(3.10)	(-1.43)		
ROA	5.7983***	1.9187*		
	(7.68)	(1.89)		
Broker FE	Included	Included	Included	Included
Industry-Year FE	Included	Included	Included	Included
N	221,328	95,168	221,328	221,328
Adj. R-squared	0.161	0.023	0.418	0.479

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Table 4
Information Sharing and Analyst Performance: Conditional on Colleague Research Quality

This table reports the relation between an analyst's performance in an industry and the economic connectedness of the industries covered by her colleague to that industry, conditional on colleague research quality. We estimate the OLS regressions $Accuracy(Rec\_Profit) = f(IC\_High\_Quality, IC\_Low\_Quality, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1) and (2), and $Ind\_MV(Ind\_Freq) = f(IC\_Strong\_Ties, IC\_Weak\_Ties, Control\_Analyst) + \varepsilon$ in columns (3) and (4). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA. $IC\_High\_Quality$ and $IC\_Low\_Quality$ are IC_High_Acc and IC_Low_Acc in Panel A, IC_High_Profit and IC_Low_Profit in Panel B, IC_Long_Expr and IC_Short_Expr in Panel C, and IC_Star and $IC\_NonStar$ in Panel D. *t*-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Panel A: Colleague earnings forecast accuracy

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_High_Acc	2.4375***	0.7264	0.3363	5.1189***
	(4.50)	(0.78)	(0.49)	(7.81)
IC_Low_Acc	0.6517	1.4015	1.2035*	-4.6547***
	(1.13)	(1.51)	(1.88)	(-7.14)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	212,547	91,819	212,547	212,547
Adj. R-squared	0.161	0.020	0.414	0.474
F-statistic from testing $\beta_1 = \beta_2$	**4.80****	**0.28**	**1.57**	**131.21*****

Panel B: Colleague recommendation profitability

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_High_Profit	1.4837***	1.7314**	0.6636	2.1567***
	(2.72)	(2.16)	(0.94)	(3.61)
IC_Low_Profit	1.6624***	-0.3247	1.2145*	-1.0769*
	(3.19)	(-0.40)	(1.83)	(-1.66)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	167,615	90,617	167,615	167,615
Adj. R-squared	0.168	0.017	0.417	0.493
F-statistic from testing $\beta_1 = \beta_2$	**0.09**	**4.18****	**0.99**	**27.88*****

Panel C: Colleague industry experience

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_Long_Expr	3.0432***	1.0720	2.3686***	2.1951***
	(5.87)	(1.32)	(3.36)	(3.66)
IC_Short_Expr	0.1822	1.0001	-0.9504	-1.2873**
	(0.34)	(1.00)	(-1.47)	(-2.05)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	217,046	93,500	217,046	217,046
Adj. R-squared	0.161	0.021	0.416	0.477
F-statistic from testing $\beta_1 = \beta_2$	**15.88*****	**0.00**	**17.66*****	**19.57*****

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Table 4 (Cont'd)
Information Sharing and Analyst Performance:
Conditional on Colleague Research Quality

Panel D: Colleague All-Star status

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_Star	1.6175**	2.2416*	-0.0911	-0.1148
	(2.21)	(1.87)	(-0.09)	(-0.13)
IC_Non_Star	1.8309***	0.8524	0.9900*	0.6035
	(4.59)	(1.25)	(1.74)	(1.26)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	217,046	93,500	217,046	217,046
Adj. R-squared	0.161	0.021	0.416	0.477
F-statistic from testing $\beta_1 = \beta_2$	**0.09**	**1.31**	**1.16**	**0.67**

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Table 5
Information Sharing and Analyst Performance: Conditional on Colleague Relation Strength

This table reports the relation between an analyst's performance in an industry and the economic connectedness of the industries covered by her colleague to that industry, conditional on her relation strength with colleagues. We estimate the OLS regressions $Accuracy(Rec\_Profit) = f(IC\_Strong\_Ties, IC\_Weak\_Ties, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1) and (2), and $Ind\_MV(Ind\_Freq) = f(IC\_Strong\_Ties, IC\_Weak\_Ties, Control\_Analyst) + \varepsilon$ in columns (3) and (4). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA. IC_Strong_Ties and IC_Weak_Ties are $IC\_Long\_Relation$ and $IC\_Short\_Relation$ in Panel A, IC_Same_City and IC_Diff_City in Panel B, and IC_School_Ties and $IC\_No\_School\_Ties$ in Panel C. *t*-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Panel A: Relation length

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_Long_Relation	1.5852***	1.6086**	1.2041*	4.0056***
	(3.74)	(2.15)	(1.90)	(7.67)
IC_Short_Relation	1.7300***	1.0543	0.8329	-0.6276
	(4.42)	(1.62)	(1.52)	(-1.33)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	221,328	95,168	221,328	221,328
Adj. R-squared	0.161	0.023	0.418	0.480
F-statistic from testing $\beta_1 = \beta_2$	**0.24**	**1.35**	**0.98**	**174.78*****

Panel B: Colleague location

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_Same_City	2.5324***	3.0193**	3.5677***	3.6362***
	(3.09)	(2.26)	(2.82)	(3.63)
IC_Diff_City	0.3851	1.5390	1.1017	0.4756
	(0.52)	(1.47)	(1.08)	(0.55)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	72,178	37,296	72,178	72,178
Adj. R-squared	0.159	0.026	0.468	0.545
F-statistic from testing $\beta_1 = \beta_2$	**8.01*****	**1.98**	**5.68****	**13.18*****

Panel C: Educational ties

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*
IC_School_Ties	1.8659*	4.7567***	2.5143*	3.7473***
	(1.90)	(3.18)	(1.75)	(3.14)
IC_No_School_Ties	1.1751*	1.0513	1.2431	0.6322
	(1.66)	(0.98)	(1.29)	(0.78)
Controls, Broker, Industry-Year FE	Included	Included	Included	Included
N	73,614	37,945	73,614	73,614
Adj. R-squared	0.158	0.026	0.466	0.545
F-statistic from testing $\beta_1 = \beta_2$	**0.75**	**9.78*****	**1.04**	**9.30*****

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Table 6
Information Sharing and Investor Recognition

This table reports the relation between investor recognition of an analyst and the economic connectedness of the industries covered by her colleague to her industry. We estimate the OLS regression $Report\_CAR = f(Ind\_Connect, Control\_Analyst, Control\_Firm) + \varepsilon$ in column (1). We estimate the Probit regression $Star = f(Ind\_Connect, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (2). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Variable	(1) *Report_CAR*	(2) *Star*
Ind_Connect	**0.0025*****	**0.3301*****
	(4.69)	**(3.05)**
BSize	0.0000***	0.0032***
	(3.29)	(4.20)
Ind_Expr	-0.0001**	0.1140***
	(-2.27)	(26.67)
NInd	0.0000	0.0622***
	(0.27)	(4.54)
NFirm	0.0002***	0.0169**
	(3.27)	(2.43)
Freq	0.0009***	0.0133***
	(10.88)	(10.43)
Horizon	0.0000***	-0.0013***
	(2.75)	(-7.65)
MV	-0.0042***	0.1432***
	(-28.97)	(9.91)
MTB	0.0003***	-0.0022
	(5.54)	(-0.68)
ROA	-0.0411***	-0.3468*
	(-17.00)	(-1.79)
Accuracy		0.0025***
		(4.77)
Optimism		-0.0470
		(-1.47)
Bold		-0.0001
		(-0.22)
Broker FE	Included	Included
Industry-Year FE	Included	Included
N	205,895	72,033
Adj./Pseudo R-squared	0.335	0.411

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Table 7
Information Sharing and Analyst Report Issuance

This table reports the relation between whether an analyst has a highly-connected colleague and her issuing a report for a firm during [-1, +1] of the event date. In column (1), the event date is the day that the analyst's highly-connected colleague (or her matched analyst's highly-connected colleague if she does not have one) issues a report. In columns (2) and (3), the event date is 45 days before and after the day that the analyst's highly-connected colleague (or her matched analyst's highly-connected colleague if she does not have one) issues a report, respectively. *t*-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in Appendix**.**

Event Date =	Main test: Highly-connected colleague's report issuance date	Placebo test: Highly-connected colleague's report issuance date – 45 days	Placebo test: Highly-connected colleague's report issuance date +45 days
	(1)	(2)	(3)
Variable	*Report_Issuance*	*Report_Issuance*	*Report_Issuance*
Connect	**0.0641***	**-0.0024**	**-0.0068**
	(7.36)	**(-0.49)**	**(-1.35)**
BSize	0.0001	0.0003	0.0004*
	(0.35)	(1.34)	(1.77)
Ind_Expr	0.0004	-0.0003	-0.0033***
	(0.33)	(-0.32)	(-3.37)
NInd	0.0018	0.0001	0.0016
	(0.97)	(0.03)	(1.35)
NFirm	-0.0013	0.0001	0.0028**
	(-1.01)	(0.11)	(2.20)
Firm_Freq	0.0474***	0.0237***	0.0238***
	(27.23)	(13.48)	(13.67)
Firm_Horizon	0.0000	-0.0000***	0.0001***
	(0.20)	(-3.86)	(5.87)
Broker FE	Included	Included	Included
Industry-Year FE	Included	Included	Included
N	186,652	186,652	186,652
Adj. R-squared	0.199	0.206	0.216

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Table 8
Upstream and Downstream Industry Information Sharing and Forecast Accuracy

This table reports the relation between an analyst's revenue and expense forecast accuracy in an industry and the upstream and downstream economic connectedness of the industries covered by her colleague to that industry. We estimate the OLS regression $Accuracy\_Rev = f(IC\_Upstream, IC\_Downstream, Control\_Analyst, Control\_Firm) + \varepsilon$ in column (1) and $Accuracy\_Exp = f(IC\_Upstream, IC\_Downstream, Control\_Analyst, Control\_Firm, Accuracy\_Rev) + \varepsilon$ (2). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA. *t*-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Variable	(1) *Accuracy_Rev*	(2) *Accuracy_Exp*
IC_Upstream	**-0.3639**	**3.0804***
	(-0.24)	**(1.68)**
IC_Downstream	**1.8624****	**1.4467**
	(2.53)	**(1.09)**
BSize	0.0156	-0.0137
	(0.83)	(-0.71)
Ind_Expr	-0.0215	-0.0265
	(-0.50)	(-0.49)
NInd	-0.0571	0.0464
	(-0.66)	(0.64)
Ind_NFirm	-0.0420	0.0220
	(-0.88)	(0.31)
Freq	-0.1889	-0.2424*
	(-1.55)	(-1.92)
Horizon	-0.1451***	-0.0458***
	(-32.13)	(-9.43)
MV	-0.3721***	-0.0355
	(-3.08)	(-0.29)
MTB	-0.0273	-0.0369
	(-0.95)	(-1.46)
ROA	-3.3457	-2.1346***
	(-1.38)	(-3.61)
Accuracy_Rev		0.4470***
		(16.07)
Broker FE	Included	Included
Industry-Year FE	Included	Included
N	50,180	32,282
Adj. R-squared	0.124	0.202

Table 9
Information Sharing's Effect on Analyst Performance and Investor Recognition: Turnovers of Colleagues Covering Important Industries

Panel A: Hiring of Important Colleagues

This panel reports the change in an analyst's performance and investor recognition in an industry before and after the hiring of a colleague who covers industries of high economic importance to that industry. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Post\_Hiring, Control\_Analyst,\ Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Post\_Hiring,\ Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Post\_Hiring, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. The sample includes the year of the hiring of an important colleague and the prior year. *t* and *z*-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Post_Hiring	**0.6153***	**0.5090****	**0.4388***	**6.6232*****	**0.0010****	**0.0007**
	(1.71)	**(1.96)**	**(1.72)**	**(16.41)**	**(2.63)**	**(0.08)**
BSize	-0.0434	0.0102	0.0048	-0.0549**	-0.0001***	-0.0000
	(-1.32)	(0.18)	(0.17)	(-2.20)	(-3.15)	(-0.02)
Ind_Expr	-0.0797	-0.0464	0.9093***	0.5940***	-0.0000	0.0085***
	(-1.15)	(-0.26)	(9.45)	(7.82)	(-0.23)	(4.63)
NInd	0.0935	0.2002	-0.4795**	0.1469	0.0001	0.0139**
	(0.83)	(0.68)	(-2.12)	(1.13)	(0.46)	(2.50)
NFirm	0.0109	0.0322	4.5569***	6.3026***	0.0003***	-0.0018
	(0.16)	(0.22)	(19.27)	(21.56)	(3.44)	(-0.58)
Freq	0.3294	0.7165***			0.0009***	0.0016***
	(1.44)	(3.27)			(2.89)	(2.78)
Horizon	-0.0921***	0.0046			0.0000	-0.0002
	(-13.99)	(0.34)			(0.83)	(-1.22)
MV	-0.1954	-0.1448			-0.0050***	0.0118**
	(-0.92)	(-0.26)			(-14.55)	(2.39)
MTB	0.1820**	0.0323			0.0005***	-0.0005
	(2.28)	(0.22)			(3.04)	(-0.33)
ROA	8.9517***	6.8694			-0.0401***	-0.0313
	(3.08)	(1.26)			(-5.86)	(-0.54)
Accuracy						0.0002
						(0.48)
Optimism						0.0097
						(0.56)
Bold						0.0001
						(0.39)
Broker, Industry-Year FE	Included	Included	Included	Included	Included	Included
N	14,223	7,224	14,223	14,223	14,026	4,796
Adj./Pseudo R-squared	0.097	0.033	0.445	0.518	0.409	0.361

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Table 9 (Cont'd)
Information Sharing's Effect on Analyst Performance and Investor Recognition: Turnovers of Colleagues Covering Important Industries

Panel B: Departure of Important Colleagues

This panel reports the change in an analyst's performance and investor recognition in an industry before and after the departure of a colleague who covers industries of high economic importance to that industry. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Post\_Departure, Control\_Analyst,\ Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Post\_Departure,\ Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Post\_Departure, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. The sample includes the year of the departure of an important colleague and the subsequent year. *t* and *z*-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Post_Departure	**-2.0570***	**-1.8190***	**-0.2639**	**-6.1194***	**0.0006**	**0.0179**
	(-6.52)	**(-3.32)**	**(-0.94)**	**(-13.88)**	**(0.93)**	**(1.40)**
BSize	-0.0887***	-0.0008	0.0117	-0.0134	-0.0000	-0.0012
	(-3.11)	(-0.01)	(0.32)	(-0.38)	(-0.55)	(-1.48)
Ind_Expr	-0.0235	0.0057	1.0066***	0.1963**	-0.0003***	0.0202***
	(-0.23)	(0.04)	(9.00)	(2.09)	(-3.74)	(6.15)
NInd	0.3742*	-0.0528	-0.4540	0.5115***	0.0001	0.0144*
	(1.74)	(-0.14)	(-1.68)	(2.97)	(0.76)	(1.72)
NFirm	0.1695	-0.1401	4.3635***	6.2896***	0.0002*	-0.0004
	(1.56)	(-0.75)	(17.32)	(14.92)	(2.00)	(-0.10)
Freq	0.2999	0.8631			-0.0002	0.0031***
	(1.03)	(1.52)			(-0.66)	(3.49)
Horizon	-0.1308***	-0.0050			0.0000	-0.0002
	(-17.04)	(-0.34)			(0.34)	(-1.08)
MV	-0.2170	-0.5457			-0.0043***	0.0125*
	(-0.83)	(-1.07)			(-12.79)	(1.78)
MTB	0.0286	-0.0678			0.0006***	0.0037
	(0.32)	(-0.39)			(3.81)	(1.25)
ROA	12.8468***	-0.3238			-0.0422***	-0.1221
	(3.41)	(-0.04)			(-5.01)	(-1.14)
Accuracy						0.0002
						(0.49)
Optimism						-0.0254
						(-0.87)
Bold						0.0002
						(0.66)
Broker FE	Included	Included	Included	Included	Included	Included
Industry-Year FE	Included	Included	Included	Included	Included	Included
N	11,818	5,222	11,818	11,818	11,283	3,941
Adj./Pseudo R-squared	0.186	0.054	0.523	0.505	0.411	0.448

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Table 10
Information Sharing and Analyst Performance:
Within Broker-Year Matched Sample Analysis

This table reports the relation between an analyst's performance and investor recognition in an industry and the economic connectedness of the industries covered by her colleague to that industry using a matched sample. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Ind\_Connect, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Ind\_Connect,\ Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Ind\_Connect,\ Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. For a given analyst-industry-year with above broker-year median $Ind\_Connect$, we identify an analyst-industry-year with below broker-year median $Ind\_Connect$ in the same broker-year and closest quintile-ranks in Ind_Expr and $NFirm$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Ind_Connect	**0.7438****	**1.1303***	**1.2840****	**1.1404****	**0.0046*****	**0.2410***
	(2.01)	**(1.73)**	**(2.32)**	**(2.28)**	**(6.18)**	**(1.85)**
BSize	-0.0238***	-0.0041	0.0029	-0.0323***	0.0000	0.0026***
	(-4.20)	(-0.42)	(0.40)	(-4.88)	(1.17)	(3.20)
Ind_Expr	0.0441*	0.0156	1.0191***	0.8722***	-0.0001***	0.1256***
	(1.84)	(0.44)	(24.78)	(24.21)	(-2.64)	(26.47)
NInd	0.2509***	0.1412*	-0.3859***	0.9724***	0.0000	0.0611***
	(5.36)	(1.96)	(-5.21)	(14.72)	(0.15)	(3.96)
NFirm	0.0873***	0.0866**	5.4961***	8.0844***	0.0002***	0.0264***
	(2.91)	(2.06)	(38.93)	(47.24)	(3.06)	(3.20)
Freq	0.2725***	0.4512***			0.0008***	0.0139***
	(5.21)	(5.32)			(8.91)	(9.27)
Horizon	-0.1384***	-0.0133***			0.0000*	-0.0015***
	(-81.18)	(-6.03)			(1.68)	(-7.39)
MV	-0.3454***	0.3619***			-0.0043***	0.1530***
	(-5.99)	(4.40)			(-27.80)	(9.44)
MTB	0.0402**	-0.0032			0.0004***	-0.0003
	(2.34)	(-0.14)			(5.91)	(-0.08)
ROA	6.4358***	0.5198			-0.0433***	-0.5681***
	(7.98)	(0.52)			(-15.81)	(-2.67)
Accuracy						0.0027***
						(4.40)
Optimism						-0.0529
						(-1.45)
Bold						0.0001
						(0.13)
Broker FE	Included	Included	Included	Included	Included	Included
Industry-Year FE	Included	Included	Included	Included	Included	Included
N	167,340	68,007	167,340	167,340	155,131	49,058
Adj./Pseudo R-squared	0.156	0.013	0.382	0.426	0.302	0.408

Table IA1
Information Sharing's Effect on Analyst Performance and Investor Recognition: Controlling for Direct Coverage of Supplier and Customer Companies

Panel A: Controlling for the Number of Firms with Direct Suppliers and Customers

This panel reports the relation between an analyst's performance and investor recognition in an industry and the economic connectedness of the industries covered by her colleague to that industry, controlling for the number of firms with direct suppliers and customers covered by the analyst and her colleagues. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Ind\_Connect, DirectSC\_Self, DirectSC\_Colleague, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Ind\_Connect, DirectSC\_Self, DirectSC\_Colleague, Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Ind\_Connect, DirectSC\_Self, DirectSC\_Colleague, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix of the main paper and Table IA5 of the Internet Appendix.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Ind_Connect	**1.6728*** **	**1.2327***	**0.9174***	**0.7708***	**0.0025*** **	**0.3225*** **
	(4.43)	**(1.91)**	**(1.74)**	**(1.69)**	**(4.70)**	**(2.99)**
DirectSC_Self	-0.1698	0.3986**	2.6427***	0.2406	0.0006**	0.0282
	(-1.46)	(2.01)	(10.68)	(0.63)	(2.28)	(1.21)
DirectSC_Colleague	-0.1260	-0.1072	2.1028***	-0.9341***	0.0010***	0.0450***
	(-1.42)	(-0.78)	(7.09)	(-3.76)	(5.02)	(3.24)
BSize	-0.0243***	-0.0033	0.0020	-0.0253***	0.0000***	0.0031***
	(-4.69)	(-0.37)	(0.22)	(-3.92)	(2.94)	(4.08)
Ind_Expr	0.0324*	-0.0044	1.0205***	0.8061***	-0.0001**	0.1136***
	(1.73)	(-0.16)	(19.42)	(26.30)	(-2.25)	(26.55)
NInd	0.2236***	0.1742**	-0.4093***	0.9326***	0.0000	0.0737***
	(5.43)	(2.50)	(-5.32)	(14.97)	(0.26)	(5.35)
NFirm	0.1073***	0.0665*	4.5529***	7.4970***	0.0001	0.0114
	(4.04)	(1.72)	(21.02)	(52.25)	(1.20)	(1.61)
Freq	0.3426***	0.4592***			0.0009***	0.0129***
	(7.04)	(6.06)			(10.80)	(10.09)
Horizon	-0.1397***	-0.0136***			0.0000***	-0.0013***
	(-87.58)	(-7.20)			(2.70)	(-7.81)
MV	-0.3600***	0.3410***			-0.0043***	0.1372***
	(-6.70)	(3.98)			(-29.16)	(9.50)
MTB	0.0480***	-0.0313			0.0003***	-0.0026
	(3.08)	(-1.42)			(5.60)	(-0.82)
ROA	5.7591***	1.9494*			-0.0409***	-0.2788
	(7.63)	(1.92)			(-16.92)	(-1.43)
Accuracy						0.0025***
						(4.77)
Optimism						-0.0492
						(-1.54)
Bold						-0.0001
						(-0.27)
Broker, Industry-Year FE	Included	Included	Included	Included	Included	Included
N	221,328	95,168	221,328	221,328	205,895	72,033
Adj./Pseudo R-squared	0.161	0.023	0.421	0.479	0.335	0.411

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Table IA1 (Cont'd)
Information Sharing's Effect on Analyst Performance and Investor Recognition: Controlling for Direct Coverage of Supplier and Customer Companies

Panel B: Excluding Colleague with Direct Suppliers and Customers

This panel reports the relation between an analyst's performance and investor recognition in an industry and the economic connectedness of the industries covered by her colleague to that industry, excluding colleagues who cover direct suppliers and customers. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Ind\_Connect\_NoDirect, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Ind\_Connect\_NoDirect, Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Ind\_Connect\_NoDirect, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix of the main paper and Table IA5 of the Internet Appendix.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Ind_Connect_NoDirect	**1.6228*** **	**1.1955***	**0.3228**	**0.9014** **	**0.0024*** **	**0.2640*** **
	(4.42)	**(1.91)**	**(0.64)**	**(1.99)**	**(4.59)**	**(2.67)**
BSize	-0.0245***	-0.0035	0.0077	-0.0275***	0.0000***	0.0032***
	(-4.73)	(-0.40)	(0.83)	(-4.27)	(3.31)	(4.31)
Ind_Expr	0.0322*	-0.0029	1.0321***	0.8057***	-0.0001**	0.1141***
	(1.71)	(-0.11)	(19.44)	(26.27)	(-2.27)	(26.67)
NInd	0.2216***	0.1787**	-0.3935***	0.9363***	0.0000	0.0618***
	(5.39)	(2.58)	(-4.96)	(15.07)	(0.26)	(4.52)
NFirm	0.0879***	0.0759**	4.9337***	7.4016***	0.0002***	0.0171**
	(3.77)	(1.99)	(24.57)	(53.78)	(3.33)	(2.46)
Freq	0.3425***	0.4621***			0.0009***	0.0133***
	(7.04)	(6.10)			(10.89)	(10.43)
Horizon	-0.1397***	-0.0136***			0.0000***	-0.0013***
	(-87.57)	(-7.21)			(2.76)	(-7.65)
MV	-0.3684***	0.3453***			-0.0042***	0.1431***
	(-6.87)	(4.11)			(-28.96)	(9.90)
MTB	0.0484***	-0.0317			0.0003***	-0.0022
	(3.10)	(-1.43)			(5.54)	(-0.68)
ROA	5.7958***	1.9163*			-0.0411***	-0.3465*
	(7.68)	(1.89)			(-17.00)	(-1.78)
Accuracy						0.0025***
						(4.78)
Optimism						-0.0469
						(-1.46)
Bold						-0.0001
						(-0.22)
Broker FE	Included	Included	Included	Included	Included	Included
Industry-Year FE	Included	Included	Included	Included	Included	Included
N	221,328	95,168	221,328	221,328	205,895	72,033
Adj./Pseudo R-squared	0.161	0.023	0.418	0.479	0.335	0.411

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Table IA2
Information Sharing's Effect on Analyst Performance and Investor Recognition: Controlling for Analyst Fixed Effects

This table reports the relation between an analyst's performance and investor recognition in an industry and the economic connectedness of the industries covered by her colleague to that industry controlling analyst fixed effects. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Ind\_Connect, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Ind\_Connect, Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Ind\_Connect, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix of the main paper.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Ind_Connect	**1.0591*****	**1.1793***	**1.0781****	**2.2657*****	**0.0030*****	**0.6536*****
	(2.67)	**(1.67)**	**(2.36)**	**(5.60)**	**(5.67)**	**(3.98)**
BSize	-0.0005	-0.0159**	0.0022	0.0131***	0.0000***	0.0086***
	(-0.13)	(-2.58)	(0.53)	(3.12)	(3.44)	(8.88)
Ind_Expr	-0.1100***	-0.0335	1.0271***	0.8037***	-0.0002***	0.0277***
	(-3.91)	(-0.68)	(22.47)	(22.40)	(-4.77)	(2.69)
NInd	0.0606	0.0563	-0.0930	1.5353***	0.0002**	0.0096
	(1.02)	(0.49)	(-1.44)	(21.97)	(2.12)	(0.39)
NFirm	0.1149***	0.0969**	5.4721***	7.8531***	0.0003***	0.0184
	(4.25)	(2.01)	(52.74)	(62.53)	(6.96)	(1.49)
Freq	0.4113***	0.4856***			0.0010***	0.0240***
	(7.87)	(5.80)			(12.43)	(11.27)
Horizon	-0.1384***	-0.0124***			0.0000***	-0.0018***
	(-88.29)	(-6.27)			(4.41)	(-6.32)
MV	-0.3480***	0.4090***			-0.0046***	0.0824***
	(-5.52)	(3.77)			(-33.51)	(3.49)
MTB	0.0246	-0.0518**			0.0002***	0.0020
	(1.64)	(-1.97)			(4.00)	(0.41)
ROA	5.3376***	1.1242			-0.0324***	-0.3528
	(6.57)	(0.87)			(-14.78)	(-1.15)
Accuracy						0.0022**
						(2.31)
Optimism						0.1029*
						(1.96)
Bold						-0.0007
						(-0.79)
Analyst FE	Included	Included	Included	Included	Included	Included
Industry-Year FE	Included	Included	Included	Included	Included	Included
N	217,700	92,790	217,632	217,632	202,809	19,761
Adj./Pseudo R-squared	0.182	0.007	0.557	0.536	0.386	0.395

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Table IA3
Information Sharing's Effect on Analyst Performance and Investor Recognition: Excluding Broker Fixed Effects

This table reports the relation between an analyst's performance and investor recognition in an industry and the economic connectedness of the industries covered by her colleague to that industry excluding broker fixed effects. We estimate the OLS regressions $Accuracy(Rec\_Profit, Report\_CAR) = f(Ind\_Connect, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $Ind\_MV(Ind\_Freq) = f(Ind\_Connect, Control\_Analyst) + \varepsilon$ in columns (3) and (4), and the Probit regression $Star = f(Ind\_Connect, Control\_Analyst, Control\_Firm, Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix of the main paper.

Variable	(1) *Accuracy*	(2) *Rec_Profit*	(3) *Ind_MV*	(4) *Ind_Freq*	(5) *Report_CAR*	(6) *Star*
Ind_Connect	**2.9072*****	**0.7172***	**2.2536*****	**4.4894*****	**0.0040*****	**0.5823*****
	(8.52)	**(1.72)**	**(2.89)**	**(10.16)**	**(7.37)**	**(5.76)**
BSize	-0.0043	-0.0017	0.0741***	0.0208***	0.0000	0.0080***
	(-1.61)	(-0.48)	(10.48)	(5.98)	(0.00)	(18.43)
Ind_Expr	0.1728***	-0.0104	1.0690***	0.9598***	0.0000	0.0974***
	(8.34)	(-0.45)	(15.16)	(29.22)	(1.07)	(23.31)
NInd	0.0730	0.0938	-0.6447***	0.5005***	-0.0002**	0.0104
	(1.64)	(1.62)	(-6.07)	(7.72)	(-2.54)	(0.82)
NFirm	0.0809***	0.0566	4.9680***	7.3794***	0.0003***	-0.0060
	(3.38)	(1.49)	(23.75)	(52.66)	(3.73)	(-0.81)
Freq	0.5222***	0.4608***			0.0011***	0.0152***
	(10.36)	(5.75)			(12.72)	(11.32)
Horizon	-0.1420***	-0.0138***			0.0000*	-0.0015***
	(-88.65)	(-7.31)			(1.75)	(-9.45)
MV	-0.6732***	0.3719***			-0.0047***	0.2195***
	(-12.65)	(5.24)			(-32.11)	(15.28)
MTB	0.0749***	-0.0222			0.0004***	-0.0035
	(4.59)	(-1.19)			(6.41)	(-1.13)
ROA	5.3047***	2.0966**			-0.0441***	-0.3157*
	(6.86)	(2.32)			(-18.36)	(-1.69)
Accuracy						0.0027***
						(5.70)
Optimism						-0.0219
						(-0.75)
Bold						0.0007
						(1.41)
Industry-Year FE	Included	Included	Included	Included	Included	Included
N	221,328	95,315	221,328	221,328	205,925	72,035
Adj./Pseudo R-squared	0.149	0.005	0.309	0.453	0.311	0.274

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Table IA4
Information Sharing's Effect on Analyst Performance and Investor Recognition: Change Specification

This table reports the relation between an analyst's performance and investor recognition in an industry and the economic connectedness of the industries covered by her colleague to that industry using a change specification. We estimate the OLS regressions $\Delta Accuracy(\Delta Rec\_Profit, \Delta Report\_CAR) = f(\Delta Ind\_Connect, \Delta Control\_Analyst, \Delta Control\_Firm) + \varepsilon$ in columns (1), (2) and (5), $\Delta Ind\_MV(\Delta Ind\_Freq) = f(\Delta Ind\_Connect, \Delta Control\_Analyst) + \varepsilon$ in columns (3) and (4), and $\Delta Star = f(\Delta Ind\_Connect, \Delta Control\_Analyst, \Delta Control\_Firm, \Delta Control\_Star) + \varepsilon$ in column (6). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, and $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, and ROA; $Control\_Star$ includes $Accuracy$, $Optimism$, and $Bold$. t and z-stats based on standard errors estimated clustered by analyst and industry-year are reported in parentheses below the coefficients. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are in the Appendix of the main paper.

Variable	(1) $\Delta Accuracy$	(2) ΔRec_Profit	(3) ΔInd_MV	(4) ΔInd_Freq	(5) $\Delta Report\_CAR$	(6) $\Delta Star$
$\Delta Ind\_Connect$	**-0.0205**	**2.6407***	**0.9775*****	**0.9642***	**0.0037*****	**0.0235****
	(-0.03)	**(1.75)**	**(3.32)**	**(1.71)**	**(3.90)**	**(2.02)**
$\Delta BSize$	0.0207*	-0.0351	0.0089**	0.0308***	-0.0000	-0.0004***
	(1.84)	(-1.52)	(1.97)	(3.54)	(-0.25)	(-2.86)
$\Delta NInd$	0.4619***	0.3747	0.4184***	3.0653***	0.0005***	0.0014
	(4.44)	(1.48)	(11.09)	(41.51)	(5.07)	(0.69)
$\Delta NFirm$	0.1936***	-0.0110	5.2869***	9.9257***	0.0006***	-0.0012
	(3.49)	(-0.10)	(132.09)	(161.49)	(8.93)	(-1.38)
$\Delta Freq$	0.5999***	0.6175***			0.0007***	0.0008***
	(9.90)	(4.63)			(11.53)	(5.91)
$\Delta Horizon$	-0.1242***	-0.0001			0.0000***	0.0001***
	(-88.72)	(-0.02)			(6.53)	(4.81)
ΔMV	0.1246	-0.0733			-0.0055***	0.0019
	(0.84)	(-0.26)			(-31.01)	(1.08)
ΔMTB	0.0187	-0.0040			-0.0000	-0.0000
	(1.15)	(-0.12)			(-0.56)	(-0.02)
ΔROA	3.5046***	2.0494			-0.0229***	-0.0226
	(2.61)	(0.79)			(-12.80)	(-1.31)
$\Delta Accuracy$						0.0000
						(0.19)
$\Delta Optimism$						-0.0021
						(-0.73)
$\Delta Bold$						0.0000
						(0.13)
Intercept	-2.3025***	-0.3354	-0.1148***	-1.3005***	0.0008***	-0.0159***
	(-22.06)	(-1.39)	(-3.26)	(-19.03)	(8.24)	(-10.72)
N	139,679	48,242	139,679	139,679	130,281	40,984
Adj. R-squared	0.093	0.001	0.207	0.214	0.020	0.002

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Table IA5: Definition of variables used in the Internet Appendix

This table describes the calculation of variables used only in this internet appendix. The variables used also in the core analysis are described in Appendix of main paper.

Variable	Definition
$DirectSC\_Self_{l,i,t}$	The number of analyst *l*'s covered companies in industry *i* in year *t* that have a direct supplier or customer relationship with other companies covered by analyst *l* in year *t*.
$DirectSC\_Colleague_{l,i,t}$	The number of analyst *l*'s covered companies in industry *i* in year *t* that have a direct supplier or customer relationship with companies covered by analyst *l*'s colleagues in year *t*.
$Ind\_Connect\_NoDirect_{l,i,t}$	The sum of the importance to industry *i* of industries covered by other analysts who work in the same brokerage as analyst *l* in year *t*, except those who cover a firm that is a direct supplier or customer of a firm covered by analyst *l* in year *t* in industry *i*. The importance of industry *j* to industry *i* in year *t* is the ratio of the sum of industry *i*'s input commodities made by industry *j* and industry *i*'s output commodities used by industry *j* to industry *i*'s total output. That is, $Importance_{i,j,t} = \frac{\sum_k \binom{Commodity\ k\ used\ by\ industry\ i \times \%\ of\ Commodity\ k\ made\ by\ industry\ j +}{Commodity\ k\ used\ by\ industry\ j \times \%\ of\ Commodity\ k\ made\ by\ industry\ i}}{Total\ output\ of\ industry\ i}$

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