Cross-Industry Information Sharing and Analyst Performance

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Abstract:

Our paper identifies a new channel through which analysts collect information, namely information sharing among colleagues covering economically connected industries. Measuring the potential benefit of information sharing as the interdependence between an analyst's industry and her colleagues' industries, we show that it explains her research performance, including earnings forecast accuracy, stock recommendation profitability, and research productivity in terms of coverage breadth and forecast frequency, after controlling for other determinants. To mitigate endogeneity concerns, we control for brokerage resources by including brokerage and analyst fixed effects, by using a change specification, by using a sample matched on broker, year and experience, by detecting the benefits to revenue and expense forecasts from sharing information with colleagues covering downstream and upstream industries respectively, and by exploiting colleague turnovers. To provide more insight into how information sharing benefits analyst research, we show that the benefit is stronger when the analyst's colleagues have higher research quality measured with their earnings forecast accuracy, recommendation profitability, and industry experience; the benefit is also more salient when the analyst and colleagues have stronger ties, measured as the situations where they have been working at the same brokerage house for a longer period, where they work in the same location, or where they graduated from the same university. Finally, we find that investors recognize the benefit of information sharing to analysts' research: they react more strongly to research reports issued by analysts who enjoy a greater economic connection with their colleagues, and they are more likely to vote such analysts as All-stars.

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

JEL Code: M14, M40, M41

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Cross-Industry Information Sharing and Analyst Performance

1. Introduction

We identify a new channel through which analysts collect information, namely information sharing among colleagues covering economically related industries, and examine its implications for analysts' research quality and productivity, and investors recognition.[1] We document evidence that an analyst's research quality, including forecast accuracy and recommendation profitability, and productivity are positively correlated with the level of economic connection between her industry and the industries covered by her colleagues working for the same brokerage house, suggesting that information sharing with colleagues is beneficial to analyst research performance. Prior literature mostly focuses on analysts' role as industry specialists and concludes that they produce highly specialized information concerning the industry they cover (Boni and Womack 2006; Kadan, Madureira, Wang and Zach 2012; Parsons, Sabbatucci and Titman 2019). We argue that cross-industry information sharing among colleagues is an important analyst activity underexplored by the extant literature. Investigating it not only extends our understanding of analysts' sources of information, but also sheds light on how information diffuses in the market.[2] That is, although analysts specialize in their own covered industries, they facilitate information flow across economically related industries by sharing information with their colleagues.

There is anecdotal evidence that analysts at the same brokerage covering related industries share information. The following example describes such activity at 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

[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 related industries".

impacted," Einhorn [head of Goldman Sachs global research] explained. "And that provided a bond between various analysts."

The following example highlights how Lehman Brothers promotes such collaboration, which, in turn, helps their analysts' All-Star rankings (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...

We argue that there are several forces driving information sharing among colleagues covering economically connected industries. The first force is the economic connection between industries we examine in this study – the connection between supplier industries and customer industries. Because shocks to commodity prices, consumer demand, and technological advancement would ripple through the layers along the supply chain (Acemoglu et al. 2012; Barrot and Sauvagnat 2016), information from one industry has value implications for firms in its upstream and downstream industries (Menzly and Ozbas 2010). The second force is analysts' industry specialization. Analysts face intense competition in discovering and interpreting new information and providing industry knowledge, and specialization is necessary for them to exploit commonalities within firms in the same industries and study them in greater depth (Kini et al. 2009; Parsons, Sabbatucci and Titman 2019). Knowing that she has colleagues specializing in the related upstream and downstream industries, an analyst likely considers it more efficient to obtain relevant information about related industries from her colleagues than to collect it on her own.

Last, besides extrinsic motivations, employees also have intrinsic motivations, such as the feeling of competence or self-efficacy and enjoyment in helping others, to collaborate and share information (Osterloh and Frey 2000; Lin 2007). Recognizing the benefit of knowledge sharing, organizations often put in place informal mechanisms, such as social interactions, and formal structures to encourage such activities (Tsai 2002; Inkpen and Tsang 2005). Anecdotally, brokerage houses often place the offices of analysts covering related industries within close proximity to one another, organize conferences that involve analysts in related industries, and incorporate analysts' collaborative efforts into their performance evaluation (Hill and Teppert 2010).

However, analysts may not collaborate with their colleagues, especially with those regarded as their peers, for several reasons. First, analysts in the same brokerage house share the year-end bonus pool and have incentives to outperform each other (Groysberg, Healy and Maber 2011; Yin and Zhang 2014).[3] They also compete on internal promotion and might view each other as competitors, for instance, to become research executives (Wu and Zang 2009; Bradley, Gokkaya and Liu 2019). Prior research shows that such intrafirm tournament incentives can impede knowledge sharing and may even lead to sabotage (Bonner, Hastie, Sprinkle and Young 2000; Brown and Heywood 2009; Harbring and Irlenbusch 2011). Furthermore, employees are more likely to compare themselves to people in closer proximity and with more interactions (Festinger 1954; Kulik and Ambrose 1992; Kilduff, Elfenbein and Staw 2010). These social comparisons can lead to envy and jealousy, which also result in actions that reduce peers' output and rewards, such as behaving noncooperatively or directly sabotaging others' efforts (Nickerson and Zenger 2008; Tai, Narayanan and McAllister 2012; Charness, Masclet and Villeval 2014).

A few recent studies investigate the interaction between analysts and their colleagues. They find evidence that analysts learn from colleagues that they likely do not view as competitors, such as the directors of research, macroeconomists, quantitative analysts and debt analysts (Hugon, Kumar and Lin 2016; Birru, Gokkaya and Liu 2019; Hugon, Lin and

[3] This is because the annual star ranking by Institutional Investor, which plays an important role in determining analysts' compensation, reputation and career outcomes, ranks analysts by industry (Stickel 1992; Groysberg et al. 2011).

Markov 2019; Do and Zhang 2019; Bradley et al. 2019), and colleagues when their covered firms have a specific and important transaction such as an M&A (Hwang, Liberti and Sturgess 2019). We differ from these studies because we examine information sharing between an analyst and her peers whom she likely deems as competitors. For the reasons discussed above, whether such information sharing takes place remains an empirical question.

We predict that analysts' performance benefits from sharing industry-related information with colleagues. However, we cannot observe the private action of information sharing among analysts directly, such as face-to-face meetings, phone calls, text messages and email exchanges. To detect such an activity, we utilize the extent to which an analyst's industry is economically connected to the industries covered by her colleagues , and test whether it is positively correlated with an analyst's research performance. If information sharing does take place, it benefits an analyst's research performance more when there is a higher level of economic connection between her industry and her colleagues' industries. On the other hand, if information does not take place, we should not expect an analyst's research performance to be explained by how much her colleagues' industries connect to hers.

We measure the economic connection between industries with the level of reliance between them as suppliers and customers (i.e., their relation as upstream and downstream industries) using data from Benchmark Input-Output Surveys of the Bureau of Economic Analysis (hereafter, BEA). For each analyst, we sum up the economic connection between each pair of her industries and those of her colleagues, and refer to it as her industry connection to her colleagues (denoted as $Ind\_Connect$). During our sample period of 1982 to 2017, average $Ind\_Connect$ is 69.8%, that is, an analyst on average has her colleagues covering industries with a combined quantity of input and output commodities that amount to 69.8% of her industries' total output, which is economically significant.

Our findings suggest that information sharing among colleagues improves analyst performance. Specifically, we show that, first, analysts' earnings forecast accuracy and stock recommendation profitability are positively correlated with their industry connection with colleagues, after controlling for other factors that prior literature has shown to explain research quality. This finding suggest that information sharing among colleagues is taking place, and that the information obtained from colleagues covering economically-connected industries is useful in producing information relevant to their own industries. Moreover, the incremental effect of information sharing on analyst performance is economically significant: a one standard deviation increase in industry connection is equivalent to an improvement of 0.74% and 0.54% in forecast accuracy and recommendation profitability respectively. Second, analysts with a higher level of industry connection with their colleagues are able to cover larger firms in the industry and issue more frequent earnings forecasts. This finding suggests that information sharing with colleagues lowers an analyst's information acquisition costs and increases her productivity.

It is important for our study to address the potential endogeneity concern, namely, our measure of industry connection tends to be higher for analysts working for larger brokerages because they might employ more colleagues and provide analysts with more resources such as better access to management and more capable supporting staffs (Mikhail, Walther and Willis 1997; Clement 1999; Gao, Ji and Rozenbaum 2019).[4] We conduct a battery of empirical tests to address the concern. First, we control for other broker resources in the main analyses by including broker size and broker fixed effects. Thus, our findings indicate that for the same broker, analysts with more industry connection outperforms those with less industry connection in research quality and productivity. Second, we replace broker fixed effects with

[4] Arguably, having colleagues who economically connected industries can also be classified as a form of broker resource. However, throughout this paper, we use "broker resource" to refer to other types of supports brokers provide to analysts, and distinguish it from information sharing.

analyst fixed effects, and separately use a change specification and continue to find similar results. Results based on these tests suggest that the performance of a given analyst is better when she has more industry connection with her colleagues. Third, we replicate our empirical analyses using a sample that matches each analyst-industry-year observation with a high level of industry connection to an observation with a low level of industry connection but of similar levels of analyst experience and breadth of coverage from the same broker-year. Results based on this sample indicate that analysts who work for the same broker in the same year and with similar experience and coverage perform better when their colleagues' coverage are more economically connected to theirs. Fourth, we examine the effect of having colleagues covering economically important upstream and downstream industries separately and find that the former is only associated with expense forecast accuracy and the latter only revenue forecast accuracy. This confirms that the level of economic connection with colleagues does not merely capture general brokerage resources. Last, we exploit turnovers in colleagues, which is arguably more exogenous changes in information sharing. We find that analyst performance improves after her broker hires an analyst who covers an industry that is especially important to hers, and deteriorates when such a colleague leaves the broker. Taken together, our study document evidence that analysts benefit from information sharing with colleagues covering economically connected industries.

For the cross-sectional effect of information sharing on an analyst's performance, we predict and find that the effect is more salient when colleagues produce better quality research themselves, and when the analyst has a tighter social connection with her colleagues, which implies more frequent informal contacts and smoother collaborations and more willingness to share information. Specifically, industry connection has a stronger effect on analyst research quality and productivity when colleagues' research ability, measured as their forecast accuracy, recommendation profitability and industry experience, is higher, and when the connection between the analyst and her colleagues is closer, measured as the length of time they work in the same brokerage house, whether they work in the same city or graduated from the same university.

Last, we examine whether investors recognize information sharing's benefit to analysts using investors' response to analyst reports and the vote they cast for analysts for *Institutional Investor* (hereafter *II*) All-Stars rankings (Groysberg et al. 2011). We show that, after controlling for analyst research quality and productivity and other economic factors, analysts with higher industry connection to colleagues elicit stronger investor reaction to their research reports, and are more likely to be ranked as *II* All-Stars. The results indicate that information sharing might benefit analysts' overall research quality that goes beyond earnings forecasts, such as industry knowledge, written reports, and idea generation, all of which are desired by institutional investors. Economically, the effect of information sharing on investors' recognition is significant: the marginal effect of information sharing is 1.7%, or 14.4% of the unconditional probability of getting ranked (11.8%) as *II* All-Stars.

Our study has extended the extant literature on financial analysts in several ways. First, prior studies mostly focus on analysts' role as industry specialists (Clement 1999; Jacob, Lys and Neale 1999; Piotroski and Roulstone 2004; Boni and Womack 2006; and Kini et al. 2009). The main conclusion from the literature is that analysts produce information that is highly specialized along industry lines, which leave an impression that analysts might contribute to informational segmentation in the market (Menzly and Ozbas 2010; Parsons, Sabbatucci and Titman 2019).[5] We show that analysts covering economically connected industries share information, and such activities benefit their research quality. This evidence

[5] Menzly and Ozbas (2010) argue that one of the assumptions that are necessary for obtaining cross-predictability in a limited-information model is specialization among informed investors. They address this assumption by presenting evidence on the specialization of equity analysts and money managers. Similarly, Parsons, Sabbatucci and Titman (2019) also use analyst industry specialization to explain the geographic lead-lag effect in firms.

reveals a role analysts play in the gradual diffusion of information in the market: although analysts specialize in their own industries, they facilitate an efficient flow of information across economically-related industries by sharing information with colleagues.

Second, we contribute to a new stream of literature that examines whether and how analysts learn from their colleagues, including Hugon et al. (2016), Birru et al. (2019), Hugon et al. (2019), Do and Zhang (2019), Bradley et al. (2019) and Hwang et al. (2019). They show that an analyst's research benefits from in-house macroeconomists, quantitative researcher, research director and debt analysts, *II* All-Star colleagues covering the *same* industry, and colleagues covering the other company in an M&A transaction she follows. We contribute to this line of research by showing that analysts share supplier and customer industry information with peers who they may regard as competitors. This evidence sheds light into analysts' coverage decisions: the cost of specializing in one industry can be largely mitigated by sharing information with colleagues covering upstream and downstream industries.

Broadly speaking, our paper also contributes to literature by identifying a new determinant of analyst performance and investor recognition (e.g., Mikhail et al. 1997; Clement 1999; Mikhail, Walther and Willis 2004; Givoly, Hayn and Lehavy 2009; Emery and Li 2009; Bradshaw, Brown and Huang 2013). Therefore, it has a practical implication for brokerage houses that providing coverage along the supply chain industries and promoting collaboration among analysts covering economically connected industries can improve analysts' research quality and productivity, as well as enhance their reputation among investors.

2. Hypothesis development

Analysts covering economically connected industries have incentives to share information for several reasons. First, companies in these industries are economically connected. Information from one industry has value implications for its upstream and downstream industries (Menzly and Ozbas 2010; Huang and Kale 2013; Aobdia, Caskey and Ozel 2014) because shocks to commodity prices, consumer demand, productions and technological advancement ripple through the layers along the supply chain (Acemoglu et al. 2012; Barrot and Sauvagnat 2016). Prior research shows that companies in closely connected industries have highly correlated fundamentals (Cohen and Frazzini 2008; Menzly and Ozbas 2010).

Second, industry knowledge is one of the most sought after information by institutional investors (Bradshaw 2011; Brown, Call, Clement and Sharp 2015; Institutional Investor 2017). Analysts face intense competition in discovering and interpreting new information about an industry (Huang et al. 2018). Industry specialization provides the economy and efficiency for analysts to exploit commonalities within their covered firms in the same industry and understand these firms in greater depth (Clement 1999; Gilson et al. 2001). A majority of analysts have previous working experience in the industry they cover (Bradley et al. 2019). Therefore, financial analysts tend to specialize in one industry by covering a few firms in it (Boni and Womack 2006; Kadan et al. 2012).[6] Knowing that she has colleagues specializing in the upstream and downstream industries, she likely relies on her colleagues to obtain information from related industries instead of collecting it on her own. Prior research has shown that analysts rely on colleagues for certain type of information. For example,

[6] Prior studies have also examined analysts who have country specialization (Sonney 2009; Kini et al. 2009). We focus on equity analysts who specialize in industries by only including U.S. firms in this sample. As discussed in Kini et al. (2009), the vast majority of the analysts in I/B/E/S following U.S. firms do not follow firms in other countries.

analysts learn macroeconomic news from in-house economists (Hugon et al. 2016), and common anomaly mispricing signals from in-house quantitative researchers (Birru et al. 2019).

Last, employees have intrinsic motivations to share information with colleagues, such as to feelings of competence, self-efficacy and enjoyment in helping others (Osterloh and Frey 2000; Lin 2005), especially with those with close ties (Reagans and McEvily 2003). Prior research documents that analysts share information with people who are not colleagues but in analysts' external social network (Cohen, Frazzini and Malloy 2010; Green et al. 2014; Fang and Huang 2017; Gu et al. 2019). Such activity can also improve analysts' relationships with friends, and expand their social connections, which lead to better career outcomes (Li, Lu and Lin 2016). Recognizing the benefit of knowledge sharing, organizations put in place formal structures and informal mechanisms to encourage such activities (Tsai 2002; Inkpen and Tsang 2005). For example, anecdotally, brokerage houses often place the offices of analysts covering related industries within close proximity, organize conferences that involve analysts in related industries, and incorporate analysts' collaborative efforts into their performance evaluation (Hill and Teppert 2010). Examples of informal mechanisms include corporate retreat that foster bonding among colleagues and other social events.

However, analysts also have incentives not to share information with colleagues, especially those regarded as their peers because they compete for cash compensation and promotional opportunity. A substantial amount of analyst annual pay is their year-end bonus (Groysberg et al. 2011). Brokerages determine the size of their bonus pool and allocate it among analysts (Yin and Zhang 2014; Brown et al. 2015). Such zero-sum games can foster individualism and reduce coordination (Lazear 1989; Baiman and Rajan 1995; Berger, Harbring and Sliwka 2013; Arnold and Tafkov 2019). Moreover, analysts compete with colleagues for internal promotions to positions such as research executives and director of research (Wu and Zang 2009; Bradley et al. 2019). Last, management research shows that employees are more likely to compare themselves to others in close proximity and with more interactions (Festinger 1954; Kulik and Ambrose 1992). Such social comparison can lead to envy and jealousy that hinder collaboration among colleagues (Nickerson and Zenger 2008; Kilduff, Elfenbein and Staw 2010; Tai et al. 2012). In sum, these intrafirm tournament incentives and sentiments can lead to activities that impede knowledge sharing, or even sabotage among analysts (Bonner et al. 2000; Chen 2003; Brown and Heywood 2009; Harbring and Irlenbusch 2011; Charness, Masclet and Villeval 2014).

Our paper differs from prior studies on analysts' information sharing activities because of the tension discussed above and the type of the information being shared. Several recent studies examine whether analysts learn from directors of research, macroeconomists, quantitative analysts and debt analysts working for the same brokerage house (Hugon, Kumar and Lin 2016; Birru, Gokkaya and Liu 2019; Hugon, Lin and Markov 2019; Do and Zhang 2019; Bradley et al. 2019). But analysts likely do not view these colleagues as competitors for bonus or promotion because they either work in a different functional area from the analysts or have higher status in the brokerage. In contrast, we study analysts' information sharing with peers who work in the same department, have similar status, and with whom the analysts potentially have plenty of interaction due to the economic connection between the industries they cover. In a recent study, Hwang, Liberti and Sturgess (2019) find that analysts learn from colleagues when their covered firms are involved in an M&A. Our study differs from them by focusing on more general situations where the analyst and her colleagues cover economically connected industries.

In sum, it remains an empirical question whether information sharing can take place in a general scenario between analysts and their peers covering economically connected industries. If it takes place, we predict that it results in an improvement in research outputs. We formally state our hypothesis as follows:

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

To provide insight into how information sharing takes place, we explore the potential cross-sectional variations in the effect of information sharing on analyst performance along two dimensions – colleagues' research quality and the quality of the relation between the analyst and her colleagues. First, we examine whether an analyst would benefit more from information sharing if the related industries are covered by colleagues of higher quality. On the one hand, the intuition is straightforward: analysts are more likely to seek information from higher-quality colleagues and the information signals acquired from such colleagues are likely more useful and timely. Consistent with this intuition, Do and Zhang (2019) and Bradley et al. (2019) find that analysts benefit from mentors and directors of research, who likely have higher research ability and are in charge of coaching. However, it is also possible that better quality peers have a higher opportunity cost of their time and lower expectation for a reciprocal relation, and thus, are 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 are of higher quality.

Our second investigation is whether information sharing is more likely to occur when an analyst and her colleagues have a stronger professional, social or educational tie. This is based on a simple intuition that a collaborative relationship takes time to develop and can be cultivated by pre-existing connections between an analyst and her colleagues. In particular, it might be more efficient for colleagues who had pre-exiting working relationship to understand each other's strengths, information needs, communication styles, and work schedules, and to establish a smooth and sustainable way to interact with each other regularly. In addition, analysts who are connected with each other through a school tie, for example, could be more willing to help each other (Cohen, Frazzini and Malloy [2010]). Moreover, the time it takes to develop a collaborative relationship might be substantially reduced among analysts who are geographically close. However, it is possible that analysts are more likely to compare themselves to people in closer proximity or those with more interactions (Festinger 1954; Kulik and Ambrose 1992; Kilduff, Elfenbein and Staw 2010), which can lead to envy and jealousy (Nickerson and Zenger 2008; Tai, Narayanan and McAllister 2012; Charness, Masclet and Villeval 2014). We state our hypothesis as:

H2b: Analyst performance benefits more from information sharing with colleagues covering the economically-connected industries, when they have a stronger pre-existing professional, social or educational tie.

3. Empirical measure and research design

3.1. Empirical measure and descriptive statistics of industry interdependence and the economic connection with colleagues' industries

To construct the economic interdependence between industries, we follow prior studies, such as Fan and Goyal (2006), Menzly and Ozbas (2010), and Ahern (2012), and use the data from the summary Benchmark Input-Output Accounts (hereafter, I-O accounts) prepared by the BEA. The I-O accounts contain supply and use tables, which show the dollar values of the production and consumption of commodities, including goods and services, by each industry in each year, respectively. These tables essentially summarize the full supply chain in the economy by showing how production of each industry relies on inputs from each industry.

First, we measure industry interdependence. For every industry i, the importance of another industry j to it 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 an industry to another depends on its role as a supplier of inputs and as a consumer of outputs (Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi 2012; Baqaee 2018).[7] The measurement can be formally expressed as follows:

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

where $Importance_{i,j,t}$ stands for the importance of industry j to industry i in year t. The I-O accounts are based on 65 industries prior to 1997 and 71 industries for later years, both defined using NAICS codes. We follow the industry definition of BEA and classify firm-year observations into the corresponding BEA industries based on firms' historical NAICS code (or current NAICS code if historical ones are not available), obtained from COMPUSTAT.

Our sample period is from 1982 to 2017 (see the sample selection procedure in Table 1). We calculate the interdependence between each pair of industries in each year ($Importance_{i,j,t}$), and report the descriptive statistics in Panel A of Table 2. The mean and median value of $Importance$ is 1.5% and 0.4%, and nearly all industry pairs have nonzero

[7] In an additional analysis, we examine industry j's importance to industry i as a supplier and as a customer separately, and find that analysts' revenue and expense forecast accuracy benefit from colleagues covering important customer and supplier industries, respectively. See discussion in Section 5.1 for details.

commodity flows. Prior literature has considered a one percent or five percent relationship economically significant enough to identify vertical mergers (e.g., Mc Guckin, Nguyen and Andrews 1991; Matsusaka 1996; Fan and Goyal 2006). We find that around 32% of the industry pairs have $Importance$ of greater than one percent and around 7% of the industry pairs have $Importance$ of greater than five percent. The average cross-sectional standard deviation of $Importance$ is 4.8%. The economic linkage between industries not only varies across industry pairs, but also changes over time for the same industry-pair, with an average time-series standard deviation of 0.6% for $Importance$ of a given industry pair, larger than the median value of $Importance$ (0.4%). Some industry-pairs have 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.

[Insert Table 1 here]

[Insert Table 2 here]

Next, we measure the economic connection between an analyst's industry and those of her colleagues as the sum of the $Importance$ of all industries covered by her colleagues to her industry in the year.[8] We label this variable as $Ind\_Connect_{l,i,t}$, where analyst l covers industry i in year t:

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

[8] An alternative approach is to measure the importance of colleagues' coverage at the company level, i.e., focusing on companies with direct trading relationships. 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, examining information sharing that occurs among analysts covering companies with existing direct trading relationships likely understates the prevalence of information sharing among analysts. Second, since 1997, companies only disclose the identities of their major customers (with greater than 10% of the company's total revenues) voluntarily under SFAS No. 131. The data suffer from a selection bias. Third, the major customers are usually much larger than the disclosing companies (see, for example, Cohen and Frazzini 2008). As discussed by Menzly and Ozbas (2010), detecting information flow from suppliers to customers with these data is unlikely due to their size difference.

where, $J_{l,t}$ are industries covered by analyst l's colleagues in year t and industry j is one of $J_{l,t}$. Intuitively, it measures 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 the analyst l's colleagues.

Our sample contains all analysts in I/B/E/S during 1982 to 2017 for whom we can measure the required variables, which include 72,033 analyst-year observations or 221,328 analyst-industry-year observations. As reported in Panel A of Table 2, 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 followed by her, which is economically large. There are substantial variations in the industry connection to colleagues: the third quartile of $Ind\_Connect$ is 0.952, indicating that an analyst's colleagues cover industries that account for 95.2% of her industry's outputs, and those in the first quartile only 38.5%.

The variations in $Ind\_Connect$ origin from two sources. The first source is the number of industries covered by the analyst's colleagues. An analyst who has colleagues covering more industries, either because she has a greater number of colleagues or her colleagues cover a broader set of industries, has higher $Ind\_Connect$. The second source is the importance of economic linkage between her industry and those of her colleagues. Empirically, we find that both sources contribute to the variations. First, as expected, analysts who work for larger brokers have higher $Ind\_Connect$ (the Pearson correlation between employer size and $Ind\_Connect$ is 0.56, see Table 2, Panel C). Second, there are substantial variation in $Ind\_Connect$ among analysts who work for the same broker in the same year, driven by the level of economic interdependence among industries. We find that, within each broker-year, the average cross-sectional standard deviation of $Ind\_Connect$ is 14.0%, i.e., 20% of the average level of $Ind\_Connect$ (69.8%). This indicates that two analysts with identical colleagues (excluding themselves) can have vastly different potential benefits of information sharing. Last, the $Ind\_Connect$ of an analyst who work for the same broker changes over time because of colleague turnovers or changes in their coverage, or because the economic linkages among industries change over time. The average time-series standard deviation of $Ind\_Connect$ of each analyst-broker pair is 16.1%.[9]

3.2. Empirical measure of analyst performance and research design of H1

We measure analyst performance in two dimensions, research quality and productivity. For research quality, we focus on two of their most important and visible quantitative outputs: earnings forecast accuracy and stock recommendation profitability. For research productivity, we use the market cap of firms they cover and earnings forecast frequency. We measure analyst performance at the industry level.

Research quality: earnings forecast accuracy and stock recommendation profitability

We measure earnings forecast accuracy following prior studies (e.g., Hong, Kubik and Solomon 2000). First, we 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 earnings per share and the 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 (zero). Next, we take the

[9] In Section 5.2, we exploit colleague turnovers, i.e., hiring and departure of a colleague who cover an industry that is economically important and find results consistent with our main analyses. That is, analyst performance improves (deteriorates) after the hiring (departure) of such colleagues.

average of $Accuracy_{l,p,t}$ across all the companies analyst l covers in industry i in year t and denote it as her earnings forecast accuracy for the industry-year ($Accuracy_{l,i,t}$). This specification measures an analyst's relative forecast accuracy compared to her peers following the same industry.

We measure stock recommendation profitability in a similar manner. First, we calculate the return of following analyst l's recommendation for company p in year t. Specifically, we use the market-adjusted buy-and-hold return and assume a long position for buy and strong buy recommendations and a short position for hold, sell, and strong sell recommendations, and an investment window starting from two days after the recommendation announcement date and ending on either 364 days after the recommendation announcement date or two days before the next recommendation announcement date, whichever is earlier. Next, we rank all analysts following company p in year t and normalize the ranking to zero and 100, with the most profitable analyst receiving a $Rec\_Profit_{l,p,t}$ of 100. Last, we calculate the average $Rec\_Profit_{l,p,t}$ of analyst l across all companies analyst l covers in industry i in year t as her relative stock recommendation profitability for the industry-year ($Rec\_Profit_{l,i,t}$).

Research productivity: covered firms' market cap and earnings forecast frequency

In addition to increased research quality, we posit that another likely consequence of analysts' information sharing is increased research productivity. This is because having colleagues as a source of value-relevant information lowers an analyst's overall cost of information acquisition and enables her to increase research outputs without being stretched too thin.

We measure research productivity using total market cap covered in the industry and the number of earnings forecasts issued for firms in the industry. Prior research suggests that an analyst has incentives to increase the market cap covered in her industry because it gains her visibility and generates more trading commissions for the broker (Hong and Kubik 2003). More directly, Groysberg et al. (2011) show that covered companies' market cap is positively related with analysts' compensation. Similar to the measures of research quality, we use the normalized ranking of market cap covered in the industry ($Ind\_MV_{l,i,t}$) to control for task difficulty and the differences in company size across industries, such that the analyst covering the largest total market cap in an industry has an $Ind\_MV_{l,i,t}$ of 100 and the one covering the smallest total market cap has an $Ind\_MV_{l,i,t}$ of zero.

Our second measure of research productivity is the frequency of earnings forecasts issued for firms in an industry ($Ind\_Freq_{l,i,t}$), measured based on the normalized ranking similar to that of $Ind\_MV_{l,i,t}$. An analyst has incentives to increase forecast frequency because it is widely used by brokerage houses as an action-based performance measure to evaluate analysts (Groysberg et al. 2011). Prior research also suggests that more frequent revisions generate more trading commissions and investment banking fees for brokerages (Juergens and Lindsey 2009; Krigman, Shaw and Womack 2001).

Research design for H1

We use the following pooled OLS regression model to test H1:

$$\begin{aligned} Analyst\ Performance & \\ &= \alpha + \beta \cdot Ind\_Connect + \sum_m \gamma_m Control\_Performance_m \\ &+ Broker\ FE + Industry\_Year\ FE + \varepsilon \end{aligned} \tag{1}$$

where $Analyst\ Performance$ includes $Accuracy$, Rec_Profit, Ind_MV, and Ind_Freq. Our main variable of interest is $Ind\_Connect$. From H1, we expect a positive coefficient on $Ind\_Connect$, that is, information sharing from colleagues benefits an analyst's performance more when the colleagues cover industries that are more economically important to her industry.

It is important for us to control for other brokerage resources or characteristics so that we can attribute differences in analyst performance to information sharing activities among colleagues covering related industries. As discussed in Section 3.1, part of the variations in $Ind\_Connect$ comes from the number of colleagues an analyst has. Analysts working for larger brokers tend to have higher $Ind\_Connect$. However, larger brokers also have higher reputation and more resources, such as training programs, quality of the distribution network, relationships with the management of companies, access to databases, and research and administrative support, which benefit analyst research, and may attract analysts of higher quality, leading to a positive correlation between analyst performance and $Ind\_Connect$. To address these concerns, first, we include broker size (measured as the total number of analysts working for the broker of analyst l in year t) to control for other brokerage resources that are positively related to broker size (Stickel 1995; Clement 1999; Jacob et al. 1999).[10] Second, we include broker fixed effects in the regressions.[11] Therefore, our empirical tests examine variations among analysts within a broker—that is, whether an analyst with colleagues covering more economically connected industries performs better compared to another analyst within the same brokerage house but with colleagues covering less economically connected industries. Note that, by including broker size and broker fixed effects, our empirical tests likely underestimate the effect of information sharing and hence, measure the lower bound of its economic significance.[12]

Following prior literature (e.g., Mikhail et al. 1997; Clement 1999; Jacob et al. 1999; Hong and Kubik 2003; Clement and Tse 2005), we control for analyst characteristics that

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[10] Our empirical results remain the same if we use an alternative measure of brokerage size based on the number of industries covered by the brokerage.
[11] In a sensitivity analysis, we control for analyst quality by replacing brokerage fixed effects with analyst fixed effects in regressions and find similar results (tabulated in Internet Appendix Table IA1).
[12] In a sensitivity analysis, we excluding broker fixed effects from regressions and find that $Ind\_Connect$ is significant positive and the economic magnitudes of information sharing's effect are larger (tabulated in Internet Appendix Table IA2).

may explain their performance, including industry experience (Ind_Expr), the number of industries followed ($NInd$), the number of companies followed in the industry ($NFirm$), the average number of earnings forecasts issued per covered company in the industry ($Freq$), and average forecast horizon ($Horizon$). We also include firm characteristics that reflect an analyst's coverage selection and may affect her performance such as 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 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), and industry-year fixed effects to control for industry-wide and time-series variations. Detailed variable definitions are included 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).

4. Empirical results

4.1. Descriptive statistics

Our sample contains all of the analysts in I/B/E/S during 1982 to 2017 for whom we can measure the required variables discussed in the previous sections, that is, 72,033 analyst-year observations or 221,328 analyst-industry-year observations (see the sample selection procedure in Table 1). From the descriptive statistics reported in Panel B of Table 2, we can see that the median analyst covers two industries and five companies, issues 13 earnings forecasts a year, and has 48 colleagues. In Panel C, the Pearson correlation table indicates that $Ind\_Connect$ is positively correlated with all analyst performance measures (significant at the 0.01 level), consistent with our prediction that information sharing benefits analysts.

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

Table 3 reports the empirical results for the relation between analyst performance and the economic connection between the industry covered by the analyst and those by her colleagues. We first report the results based on analysts' earnings forecast accuracy for the industry ($Accuracy$) in column 1. 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 analysts' earnings forecast accuracy. The effect of information sharing across related industries is economically significant as well: a one standard deviation increase in $Ind\_Connect$ (0.439) is associated with a 0.74% increase in average forecast accuracy. Consistent with prior literature (e.g., Clement 1999; Jacob et al. 1999), we find the following factors significant in explaining forecast accuracy: Industry experience (Ind_Expr) is positively correlated with forecast accuracy. The number of industries followed ($NInd$) is positively correlated with forecast accuracy, presumably because if an analyst covers economically related industries, it helps her forecasting performance or because more capable analysts choose to cover more than one industries (Guan et al. 2015). The number of companies covered in the industry ($NFirm$) and the number of forecasts issued per company in the industry ($Freq$) capture an analyst's effort and her breadth of knowledge within the industry, are positively correlated with forecast accuracy. Forecast horizon ($Horizon$), measuring how far the forecasts are from the earnings announcement dates, is negatively correlated with forecast accuracy. The estimated coefficient on broker size ($BSize$) is negative and significant. This seemingly unintuitive result is due to the inclusion of broker fixed effects. When broker fixed effects are not included in the regression, $BSize$ is either not statistically significant (Internet Appendix Table IA1 and IA2) or significantly positive (Internet Appendix Table IA3, which uses a change specification).

[Insert Table 3 here]

Column 2 reports the results based on 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 an analyst to provide more profitable recommendations. In economic terms, a one standard deviation increase in $Ind\_Connect$ is associated with a 0.54% increase in average recommendation profitability. Similar to forecast accuracy, recommendation profitability is positively correlated with $NInd$, suggesting that more profitable analysts tend to cover more industries. In addition, we find that recommendation profitability is positively correlated with $NFirm$ and $Freq$, suggesting that the amount of effort an analyst spends in the industry and the breadth of her coverage within the industry also contribute to recommendation profitability.

Columns 3 and 4 report the results for analysts' research productivity and information sharing from colleagues. We find results consistent with our prediction for both measures of productivity, the market cap covered in the industry (Ind_MV) and the earnings forecast frequency for the industry (Ind_Freq): information sharing is significant (at the 0.10 level) and positively correlated with analyst productivity after controlling for brokerage size, experience, and portfolio complexity. In economic terms, a one standard deviation increase in $Ind\_Connect$ is associated with a 0.38% (0.34%) increase in the market cap covered in the industry (forecast frequency for the industry). These results suggest that having colleagues as a source of information from these industries allows an analyst to focus more on her own industry.

4.3. Cross-sectional tests on the relation between analyst performance and economic importance of colleagues' covered industries

In the previous section, we find evidence consistent with the beneficial effect of information sharing on analyst performance. In this section, we examine the cross-sectional variations in the effect of information sharing on analyst performance predicted in H2.

To test H2a that analyst research benefits more from information sharing when the connected colleagues are of higher quality, we measure colleagues' research quality using their forecast accuracy, recommendation profitability, industry experience, and II star status. Specifically, we calculate $IC\_High\_Quality$ ($IC\_Low\_Quality$) based on the sum of the importance ($Importance_{i,j,t}$) of the industries covered by colleagues with research quality above (below) the sample median or by star (non-star) colleagues. We replace $Ind\_Connect$ in Eq. (1) with $IC\_High\_Quality$ and $IC\_Low\_Quality$ and predict that information sharing from high-quality colleagues to have a larger impact than that from low-quality colleagues. That is, the estimated coefficient on $IC\_High\_Quality$ should be significantly larger than that of $IC\_Low\_Quality$.

[Insert Table 4 here]

Table 4 reports the results for the cross-sectional tests related to the research quality of colleagues. Panel A compares the effects of information sharing from more accurate colleagues (IC_High_Acc) with that from less accurate colleagues (IC_Low_Acc) on the analyst's research quality ($ACCURACY$ and Rec_Profit) and productivity (Ind_MV and Ind_Freq). We find that consistent with analysts benefiting more from information sharing with colleagues of higher forecast accuracy, the coefficients on IC_High_Acc are significantly greater than those on IC_Low_Acc in the regressions of forecast accuracy and forecast frequency in the industry (at the 0.05 and 0.01 levels respectively). Panel B compares the effects of information sharing from more profitable colleagues (IC_High_Profit) with that from less profitable colleagues (IC_Low_Profit) on analyst performance. We find that the coefficients on IC_High_Profit are significantly greater than those on IC_Low_Profit in the regressions of recommendation profitability and forecast frequency in the industry (at the 0.05 and 0.01 levels respectively). Similarly, Panel C compares the effects of information sharing from more experienced colleagues (IC_Long_Expr) with that from less experienced colleagues (IC_Short_Expr) on analyst performance. The result shows that the coefficients on IC_Long_Expr are significantly greater than those on IC_Short_Expr in the regressions of forecast accuracy, market cap covered and forecast frequency in the industry (all at the 0.01 level). Finally, Panel D compares the effects of information sharing from star colleagues (IC_Star) with that from non-star colleagues (IC_Non_Star) on the analyst performance. We find that, while information sharing with both star and non-star colleagues improves analyst forecast accuracy, only information sharing with star colleagues improves recommendation profitability. The difference between their effects are not statistically significant at the conventional level. One potential reason is that information sharing from star colleagues provides benefits in the area other than quantitative research outputs such as analyst report contents or social network (Do and Zhang 2019). Collectively, the proxies of $IC\_High\text{-}\_Quality$ are statistically significant in 10 out of 16 specifications, whereas the proxies for $IC\_Low\_Quality$ are statistically significant in only 5 out of 16 specifications, and the differences between them are statistically significant at 5% level in 7 out of 16 specifications. Taken together, we conclude that an analyst benefits more from information sharing when the related industries are covered by higher quality colleagues.

To test H2b that information sharing is more likely to occur when an analyst and her colleagues have a stronger professional, social or educational tie, we measure the quality of their relationship by the length of their working relationship, their proximity, and educational ties between them. We collect the information regarding analysts' historical work location and educational backgrounds from their LinkedIn profiles. As such, the sample period for the latter two tests are based on a subsample of analysts with LinkedIn profiles with shorter sample period from 2007-2016. Empirically, we classify the analyst's colleagues with the length of their relationship above median (measured with the number of years they have been working for the same broker), those working in the same city, and those with school ties (whether they studied in the same university), as having high quality relationship, and others as having low quality relationship. For each analyst, we separately calculate the level of economic connection between the industries covered by these two groups of colleagues and her industry, and denote them as IC_High_Ties and IC_Low_Ties, respectively. We replace $Ind\_Connect$ in Eq. (1) with IC_High_Ties and IC_Low_Ties and predict that information sharing from high relation quality colleagues should have a larger impact than that from low relation quality colleagues. That is, the estimated coefficients on IC_High_Ties should be larger than those of IC_Low_Ties .

[Insert Table 5 here]

Table 5 reports the results for testing H2b. Panel A compares the effect of information sharing from colleagues with whom the analyst has worked together for the same brokerage house for a longer period ($IC\_Long\_Relation$) with that from colleagues with whom she has worked together for a shorter period ($IC\_Short\_Relation$). Consistent with our prediction that analysts benefit more from information sharing when they have a stronger relation with colleagues, the coefficients on $IC\_Long\_Relation$ are positive and significant (at least at the 0.10 level) in all four regressions, whereas the coefficient on $IC\_Short\_Relation$ is positive and significant only in the regression of forecast accuracy. However, the magnitude of the two coefficients is significantly different only in the regression of forecast frequency in the industry (at the 0.01 level). Panel B compares the effects of information sharing from colleagues in the same city (IC_Same_City) with that from those in different cities (IC_Diff_City). We find that the coefficients on IC_Same_City are significantly greater than those on IC_Diff_City in the regressions of forecast accuracy, and total market cap covered and forecast frequency in the industry (at least at the 0.05 level). Finally, Panel C compares the effects of information sharing from colleagues with school ties (IC_School_Ties) with that from colleagues without school ties ($IC\_No\_School\_Ties$). We find that the coefficients on IC_School_Ties are significantly greater than those on $IC\_No\_School\_Ties$ in the regressions of recommendation profitability and forecast frequency in the industry (at the 0.01 level). Collectively, the proxies for IC_High_Ties are statistically significant in all 12 specifications, whereas the proxies for IC_Low_Ties are statistically significant in only 2 out of 12 specifications, and the differences between them are statistically significant at the 5% level in 6 out of 12 specifications. Therefore, the findings support H2b that an analyst benefits more from information sharing from colleagues with whom she has a stronger professional, social or educational ties.

4.4. Do investors recognize the benefits of analysts' information sharing with colleagues covering economically connected industries?

Earnings forecast accuracy and stock recommendation profitability only measure the quality of analysts' quantitative research outputs, thus they might not capture all the dimensions of analyst research desired by investors. Therefore, we also examine whether investors recognize the benefits of analyst information sharing with colleagues covering economically connected industries.

We measure investor recognition of analysts' overall performance using market reaction to analyst reports, following prior literature (Francis and Soffer 1997; Loh and Stulz 2011; Bradley et al. 2014). In particular, we measure market reaction to analyst report for company p in year t as the cumulative absolute three-day market-adjusted return centered on the earnings forecast revision date; next, for each analyst l, we take the average market reaction of all reports she issues for firms in the industry i in year t ($Report\_CAR_{l,i,t}$) and use it as the first measure of investor recognition of analysts' overall performance.

Our second measure of investor recognition of analysts' overall performance is the annual All-Star Ranking by *Institutional Investor* (hereafter, *II* All-Star Ranking).[13] We identify an analyst as a star ($STAR_{l,t}$) if she is ranked among the first, second or third teams or runners-up by *II* published in year t.[14] According to *II*'s survey, institutional investors 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 estimate, and stock selection. Among these attributes, industry knowledge has been ranked as the most sought-after quality in 13 out of the 14 years during which *II* has surveyed institutional investors (1998-2011). Information sharing from colleagues covering economically related industries could be particularly beneficial to an analyst's industry knowledge because she can be more alert to developments in the related industries, such as trends in input prices, supply and demand shocks, and technological advancement, and because having colleagues as a source of information concerning related industries saves her time and effort that she can spend on her own industry. Moreover, as businesses become more integrated, institutional investors demand more cross-industry knowledge from analysts. Sharing information with colleagues covering related industries helps analysts

[13] By polling a large number of institutional investors (i.e., the directors of research and the chief investment officers of major money management institutions), *II* determines the ranking using the number of votes awarded to each analyst weighted by the size of the institutions responding.

[14] As BEA's industry classification is finer than and different with those in *II*'s (there are 65 or 71 BEA industries but *II* has less than 60 industries), we define this variable at the analyst-year level instead of analyst-industry-year level. For each analyst-year, we use the BEA industry in which she covers the largest market cap to study the relation between *II* ranking and information sharing, based on the assumption that the analyst is ranked in the industry where she has the most influence. That is, we measure independent variables including $Ind\_Connect$ in that industry.

produce research reports that "connect the dots" and contain "big picture" investment ideas valued by institutional investors.

Therefore, we expect to find that analysts with colleagues covering economically connected industries receive more investor recognition, i.e., investors react more strongly to their analyst reports, and they are more likely to be ranked as II All Star analysts. We use the following model in an OLS or a Probit specification:

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

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

Table 6 reports the empirical results for Eq. (2). Column 1 reports the results based on the market response around analyst earnings forecast revision date ($Report\_CAR$). 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 one's market impact. Turning to the control variables, we find that 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 ($Horizon$) are positively correlated with market response around analyst earnings forecast revision dates. In economic terms, a one standard deviation increase in $Ind\_Connect$ is associated with a 11 basis point increase in the market reactions.

[Insert Table 6 here]

Column 2 reports the results based on II All-Star Ranking ($Star$). After controlling for analyst forecast accuracy, we find the coefficient on $Ind\_Connect$ to be positive and significant (at the 0.01 level), suggesting that information sharing from colleagues covering economically related industries improves the qualitative aspects of analyst performance that institutional investors value, such as industry knowledge, written reports, and idea generation. Its marginal effect is economically significant: a one standard deviation increase in $Ind\_Connect$ (0.381) increases the probability of being ranked by 1.7%, or 11.8% of the unconditional probability of 14.4%. Turning to the control variables, we find that broker size ($BSize$) is positively correlated with star status, even after controlling for broker fixed effects; $NInd$, $NFirm$ and $Freq$ are all positively correlated with star status; Ind_Expr and $Horizon$ are negatively correlated with star status.

4.5. Cross-sectional tests on investors' recognition of the effect of information sharing on analysts' overall performance

Based on the discussion and results in the Section 4.3, we examine whether investors' recognition of an analyst's overall performance increases with her colleagues' research quality and the quality of the relationship between her and her colleagues.

Table 7 reports the results based on colleagues' research quality measured as in Section 4.3, which includes forecast accuracy, recommendation profitability, industry experience and

II star status. Panel A compares the effects of information sharing with more accurate colleagues (IC_High_Acc) and that with less accurate colleagues (IC_Low_Acc) on investor recognition ($Report\_CAR$ and $Star$). The coefficient on IC_High_Acc is significantly greater than that on IC_Low_Acc in the regression of market reaction to analyst reports (at the 0.01 level), but not in the regression of All-Star status. Both information sharing from high and low accuracy colleagues are associated with better All-Star analyst ranking. Panel B compares the effects of information sharing from more profitable colleagues (IC_High_Profit) and that with less profitable colleagues (IC_Low_Profit). We find that the coefficients on IC_High_Profit are significantly greater than those on IC_Low_Profit in both regressions (at least at the 0.10 level). Panel C compares the effects of information sharing from more experienced colleagues (IC_Long_Expr) and that with less experience colleagues (IC_Short_Expr). Again, the coefficients on IC_Long_Expr are significantly greater than those on IC_Short_Expr in both regressions (at the 0.10 level). Finally, Panel D compares the effects of information sharing from star colleagues (IC_Star) and that with non-star colleagues (IC_Non_Star). The coefficient on IC_Star is significantly greater than that on IC_Non_Star in the regression of star status (at the 0.01 level), but significantly lower in the regression of market response to analyst reports. Collectively, the proxies for $IC\_High\_Quality$ are statistically significant in 7 out of 8 specifications, whereas the proxies for $IC\_Low\_Quality$ are statistically significant in only 5 out of 8 specifications, and the former significantly larger than the latter in 6 out of 8 specifications. These results reinforce our earlier conclusion that an analyst benefits more from information sharing when the related industries are covered by higher quality colleagues.

[Insert Table 7 here]

In Table 8, we rely on the same measures of relationship between the analyst and her colleagues as in Section 4.3., which include the number of years as colleagues, co-location and school ties. Panel A compares the effects of information sharing from colleagues with whom the analyst has been working together for the same brokerage house for a longer period ($IC\_Long\_Relation$) and that with those with whom the analyst has been working together for a shorter period ($IC\_Short\_Relation$). The coefficients on $IC\_Long\_Relation$ are positive and significant (at the 0.01 level) in both regressions, suggesting that the effect of information sharing on investor recognition increases with the length of the relationship between the analyst and her colleagues. Panel B compares the effects of information sharing from colleagues in the same city (IC_Same_City) and that with those in different cities (IC_Diff_City). While the difference between the coefficients on IC_Same_City and IC_Diff_City is statistically significant in the regression of market response to analyst reports, the coefficient on IC_Same_City itself is not statistically significant. We do not find significant results for star status. Finally, Panel C compares the effects of information sharing from colleagues with school ties (IC_School_Ties) and that from colleagues without school ties ($IC\_No\_School\_Ties$), and we do not find significant results. Overall, we find mixed evidence on the effect of information sharing on investor recognition conditional on the relation quality with colleagues (significant differences in 3 out of 6 specifications), presumably because such relation quality is less observable by investors.

[Insert Table 8 here]

5. Additional analyses

5.1. Information sharing with colleagues covering upstream and downstream industries

Our evidence so far suggests that the benefits of information sharing to an analyst vary with how dependent these industries are as suppliers and customers (upstream and downstream industries respectively). In this section, we seek to provide collaborating evidence to H1 by examining information sharing with colleagues covering upstream and downstream industries separately. Because an industry relies on upstream (downstream) industries as the suppliers (customers), if an analyst does share information with colleagues, we expect that information sharing with colleagues covering upstream (downstream) industries will have a more pronounced effect on her forecasts of expenses (revenue). Specifically, we measure the importance of upstream industries covered by an analyst's colleagues ($IC\_Upstream$) as her industry's total input commodities that are made by her colleagues' industries, scaled by 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.

We obtain analyst revenue forecast from I/B/E/S directly. Since analysts usually do not separately forecast expenses, we infer an analyst's expense forecast from the difference between her revenue and EBITDA forecasts. 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 an analyst's expense forecast is inferred, we control for her revenue forecast accuracy in the regression of expense forecast accuracy. Due to I/B/E/S data coverage, the sample period for this test is shorter, from 1996 to 2017 for the revenue forecast accuracy test and from 2002 to 2017 for the expense forecast accuracy test.

Table 9 reports the results. Column 1 shows the results of the revenue forecast accuracy equation. We find that the coefficient on $IC\_Downstream$ is positive and significant (at the 0.05 level) but the coefficient on $IC\_Upstream$ is insignificant, consistent with information sharing with colleagues covering downstream industries, i.e., customers, facilitating an analyst's revenue forecasting. In contrast, Column 2 reports the results of the expense forecast accuracy equation, and shows that the coefficient on $IC\_Upstream$ is positive and significant (at the 0.01 level) while the coefficient on $IC\_Downstream$ is insignificant, suggesting that information sharing from colleagues covering upstream industries, i.e., suppliers, helps an analyst predict companies' expenses. Collectively, the results provide strong support for H1 because both colleagues covering upstream industries and those covering downstream industries work for the same brokerage house, therefore their different impacts to an analyst's expense and revenue forecast accuracy cannot be explained by the effect of general broker resources.

[Insert Table 9 here]

5.2. Colleague turnover analysis

We exploit turnover of colleagues covering economically important industries to further mitigate endogeneity concerns and ascertain that the correlation between $Ind\_Connect$ and analyst performance and investor recognition reflects benefits of analysts' information sharing activities rather than broker resources. Specifically, for analyst l following industry i in year t, we identify turnovers in her colleagues (joining or leaving analyst l's brokerage house) who cover economically important industries (with $Importance_{i,j,t}$ greater than or equal to the sample median) to industry i while working for analyst l's brokerage house. Next, we compare analyst l's performance and investor recognition in the year of hiring the important colleague ($Post\_Hiring$) with the year before the hiring; similarly, we compare analyst l's performance and investor recognition in the year after the departure of the important colleague with the year of the departure ($Post\_Departure$). We estimate a regression similar to Eq. (1), where we replace $Ind\_Connect$ with the year indicator variable of $Post\_Hiring$ or $Post\_Departure$. We expect analyst l's performance and investor recognition to be higher (lower) in the $Post\_Hiring$ ($Post\_Departure$) period due to an increase (decrease) in the number of colleagues covering economically important industries.

Table 10 reports the results. In 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 and productivity, and market reaction to analyst reports, suggesting that the analyst benefits from an increase in colleagues covering economically important industries. In Panel B, we find that the coefficient on $Post\_Departure$ is negative and significant (at the 0.01 level) in the regressions of research performance and productivity, suggesting that the analyst performance suffers after her colleagues covering economically important industries left the brokerage. However, we do not find significant results for investor recognition. Collectively, across the two Panels, $Post\_Hiring$ and $Post\_Departure$ are statistically significant in 7 out of 8 regressions of analyst performance and in 1 out of 4 regressions of investor recognition. These results suggest that the turnover of important colleagues have an immediate effect on analyst performance but have either no effect or a delayed effect on investor recognition.

[Insert Table 10 here]

5.3. Within broker-year analysis

In our main analysis, we control for broker fixed effects to facilitate a within-broker comparison. In this section, we seek to conduct a within-broker-year analysis using a matched sample. Specifically, for a given analyst-industry-year with $Ind\_Connect$ above the median in the corresponding broker-year, we match it with an analyst-industry-year with $Ind\_Connect$ below the median in the same broker-year and with the closest quintile-ranking of Ind_Expr and $NFirm$. By matching within the same broker-year, we controlled for unobservable, time-varying broker resources. The two analysts in a given pair also have similar industry experience and workload. We estimate Eq. (1) based on this matched sample and tabulate the results in Table 11. We find that the coefficient on $Ind\_Connect$ is positive and significant (at least at the 0.10 level) in all regressions of analyst performance and investor recognition, suggesting that our results are robust to broker-year effects.

[Insert Table 11 here]

6. Conclusion

There is anecdotal evidence that analysts at the same brokerage covering related industries share information and that brokerage houses promote research collaboration among analysts. A recent study by Menzly and Ozbas (2010) shows that stocks in economically related industries have correlated fundamentals and cross-predict each other's returns, and provides a rationale for the activity of cross-industry information sharing. The extant literature, however, usually focuses on analysts' role as industry specialists and often makes an implicit assumption that they work in solitude. So far, little knowledge has been accumulated on analysts' *cross-industry* information sharing with peers. Our study fills a void in the literature by documenting evidence consistent with analysts sharing information with colleagues covering economically connected industries.

We measure the economic interdependence between an analyst's industry and her colleagues' industries using BEA industry inputs and outputs data and use it to proxy for the potential benefit of sharing information with colleagues. Our results suggest that information sharing benefits analysts' research along multiple dimensions. First, an analyst has better research performance and productivity and 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 control for brokerage resources, analyst fixed effects, use a change specification, and exploit colleague turnovers to mitigate endogeneity concerns. The evidence that colleagues covering downstream (upstream) industries are particularly helpful for the analyst's revenue (expense) forecasts also confirms that the level of economic connection with colleagues does not merely capture general brokerage resources. Next, we investigate the cross-sectional variations in the benefit of information sharing. We find that analyst performance improves more when her colleagues have higher research quality or when she has a stronger professional, social or educational tie with her colleagues. Last, we find that investors recognize the benefit of information sharing to analysts' overall research quality by reacting more strongly to reports issued by analysts with higher level of information sharing and by casting more votes of *II* All star to these analysts.

Our study contributes to the literature by identifying a new channel through which analysts collect information and providing new insights into their information acquisition efforts. Analysts' cross-industry information sharing broadens our understanding of their role as industry specialists and explains how they reduce cross-predictability of industry returns. Second, our findings imply that specializing in one industry and forgoing complementary information from a diversified coverage may not put analysts in disadvantage because they can obtain supply-chain information from their colleagues. Finally, our findings have practical implications. For brokerage houses, they suggest that promoting cross-industry collaboration among colleagues improves analyst research. For investors, our findings help them identify analysts with better cross-industry knowledge and 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, $IMPORTANCE_{i,j,t} = \frac{\sum_k \left(\begin{array}{c} Commodity\ k\ used\ by\ industry\ i \times \%\ of\ Commodity\ k\ made\ by\ industry\ j + \\ Commodity\ k\ used\ by\ industry\ j \times \%\ of\ Commodity\ k\ made\ by\ industry\ i \end{array} \right)}{Total\ output\ of\ industry\ i}$
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 earnings forecast 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.
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*.
Ind_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 earnings forecasts 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	An indicator variable that equals to one for the year and the subsequent year of hiring a colleague who covers an important industry that was not previously covered by the broker. An important industry is one with an above average importance to the industry covered by the analyst.
Post_Departure	An indicator variable that equals to one for the subsequent year of the departure of a colleague who covers an important industry. An important industry is one with an above average importance to the industry covered by the analyst.

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*.
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*.
NFirm$_{l,t}$	The number of companies followed by analyst *l* in year *t*.
Freq$_{l,t}$	The number of earnings forecasts 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, 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*.

Table 1
Sample Selection

This table presents the procedures to construct the sample 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, NAICS codes, and the corresponding BEA industries	652,149		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

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 earnings forecast accuracy test. Variable definitions are in 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

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 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

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**

Table 3
Information Sharing and Analyst Performance

This table reports the OLS regression results on the relation between analyst performance in an industry and the economic importance of the industries covered by the analyst's colleague to that industry. We estimate the OLS regression $Accuracy(Rec\_Profit) = f(Ind\_Connection, Control\_Analyst, Control\_Firm) + \varepsilon$ in columns (1) and (2), and estimate the OLS regression $Ind\_MV(Ind\_Freq) = f(Ind\_Connection, Control\_Analyst) + \varepsilon$ in columns (3) and (4). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, 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 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

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

This table reports the OLS regression results on the relation between analyst performance in an industry and the economic importance of the industries covered by the analyst's colleague to that industry, conditional on the research quality of colleagues. Colleagues with high research quality are defined as those with average relative earnings forecast accuracy above or equal to sample median (Panel A), those with average relative stock recommendation profitability above or equal to sample median (Panel B), those with industry experience above or equal to sample median (Panel C), or those with All-Star status (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 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	Included	Included	Included	Included
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	Included	Included	Included	Included
Broker, Industry-Year FE	Included	Included	Included	Included
N	167,615	90,617	167,615	167,615
Adj. R-squared	0.168	0.004	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	Included	Included	Included	Included
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***

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	Included	Included	Included	Included
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

Table 5
Information Sharing and Analyst Performance:
Conditional on Relation Quality with Colleagues

This table reports the OLS regression results on the relation between analyst performance and the economic importance of the industries covered by the analyst's colleague to the analyst's covered industry, conditional on the relation quality with colleagues. Colleagues with high relation quality are defined as those who have been working together at the current brokerage firm for 4 years or longer (Panel A), those who work in the same city (Panel B), or those who have school ties or prior work ties (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 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	Included	Included	Included	Included
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	Included	Included	Included	Included
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	Included	Included	Included	Included
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***

Table 6
Information Sharing and Investor Recognition

This table reports the regression results on the relation between investor recognition of analysts and the economic importance of the industries covered by the analyst's colleague to that industry. We estimate the OLS regression $Report\_CAR = f(Ind\_Connection, Control\_Analyst, Control\_Firm) + \varepsilon$ in column (1). We estimate the probit regression $Star = f(Ind\_Connection, Control\_Analyst, Control\_Firm) + \varepsilon$ in column (2). $Control\_Analyst$ includes $BSize$, Ind_Expr, $NInd$, $NFirm$; $Control\_Firm$ includes $Freq$, $Horizon$, MV, MTB, ROA (in column 1) and $Accuracy$, $Optimism$, $Bold$ (additional controls in column 2). *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 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

Table 7
Information Sharing and Investor Recognition: Conditional on Colleague Research Quality

This table reports the regression results on the relation between analyst recognition by investors in an industry and the economic importance of the industries covered by the analyst's colleague to that industry, conditional on the research quality of colleagues. Colleagues with high research quality are defined as those with average relative earnings forecast accuracy above or equal to sample median (Panel A), those with average relative stock recommendation profitability above or equal to sample median (Panel B), those with industry experience above or equal to sample median (Panel C), or those with All-Star status (Panel D). *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 Appendix.

Panel A: Colleague earnings forecast accuracy

Variable	(1) *Report_CAR*	(2) *Star*
IC_High_Acc	0.0037***	0.4111***
	(5.14)	(3.24)
IC_Low_Acc	0.0007	0.2412**
	(1.00)	(1.96)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	198,276	71,090
Adj./Pseudo R-squared	0.338	0.411
F-statistic from testing $\beta_1 = \beta_2$	10.78***	2.14

Panel B: Colleague recommendation profitability

Variable	(1) *Report_CAR*	(2) *Star*
IC_Hight_Profit	0.0037***	0.2340**
	(5.04)	(2.03)
IC_Low_Profit	0.0013*	0.0575
	(1.67)	(0.42)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	155,716	51,544
Adj./Pseudo R-squared	0.291	0.429
F-statistic from testing $\beta_1 = \beta_2$	10.14***	2.72*

Panel C: Colleague industry experience

Variable	(1) *Report_CAR*	(2) *Star*
IC_Long_Expr	0.0029***	0.4503***
	(4.31)	(3.35)
IC_Short_Expr	0.0017**	0.2407**
	(2.54)	(2.01)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	202,076	71,806
Adj./Pseudo R-squared	0.336	0.411
F-statistic from testing $\beta_1 = \beta_2$	2.89*	2.73*

Table 7 (Cont'd)
Information Sharing and Investor Recognition:
Conditional on Colleague Research Quality

Panel D: Colleague All-Star status

Variable	(1) *Report_CAR*	(2) *Star*
IC_Star	-0.0005	1.3063***
	(-0.47)	(9.20)
IC_Non_Star	0.0028***	-0.2035*
	(5.04)	(-1.87)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	202,076	71,806
Adj./Pseudo R-squared	0.336	0.417
F-statistic from testing $\beta_1 = \beta_2$	11.94***	134.38***

Table 8
Information Sharing and Investor Recognition:
Conditional on Relation Quality with Colleagues

This table reports the regression results on the relation between analyst recognition by investors in an industry and the economic importance of the industries covered by the analyst's colleague to that industry, conditional on the relation quality with colleagues. Colleagues with high relation quality are defined as those who have been working together at the current brokerage firm for 4 years or longer (Panel A), those who work in the same city (Panel B), or those who have school ties or prior work ties (Panel C). *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 Appendix.

Panel A: Relation length

Variable	(1) *Report_CAR*	(2) *Star*
IC_Long_Relation	0.0034***	0.7133***
	(5.54)	(6.55)
IC_Short_Relation	0.0021***	0.1472
	(3.70)	(1.39)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	205,895	72,033
Adj./Pseudo R-squared	0.335	0.415
F-statistic from testing $\beta_1 = \beta_2$	7.96***	135.04***

Panel B: Colleague location

Variable	(1) *Report_CAR*	(2) *Star*
IC_Same_City	0.0006	-0.3204
	(0.46)	(-0.81)
IC_Diff_City	-0.0018*	-0.2999
	(-1.79)	(-0.80)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	64,589	12,897
Adj./Pseudo R-squared	0.294	0.472
F-statistic from testing $\beta_1 = \beta_2$	4.80**	0.01

Panel C: Educational ties

Variable	(1) *Report_CAR*	(2) *Star*
IC_School_Ties	-0.0012	-0.5173
	(-0.77)	(-1.21)
IC_No_School_Ties	0.0003	-0.2373
	(0.26)	(-0.61)
Controls	Included	Included
Broker, Industry-Year FE	Included	Included
N	65,760	13,223
Adj./Pseudo R-squared	0.275	0.472
F-statistic from testing $\beta_1 = \beta_2$	1.08	2.05

Table 9
Upstream and Downstream Industry Information Sharing

This table reports the OLS regression results on the relation between analyst performance in an industry and the upstream and downstream importance of the industries covered by the analyst's colleague to that industry. *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.

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 10
Information Sharing and Analyst Performance:
Turnovers of Colleagues Covering Important Industries

This table reports the OLS regression results on the relation between analyst performance in an industry and turnover of analyst's colleague who covers industries of high economic importance to that industry. The sample consists of the year of the hiring of an important colleague and the year before (Panel A) and the year of the departure of an important colleague and the year after. *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 Appendix.

Panel A: Hiring of Important Colleagues

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 FE	Included	Included	Included	Included	Included	Included
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

Table 10 (Cont'd)
Information Sharing and Analyst Performance:
Turnovers of Colleagues Covering Important Industries

Panel B: Departure of Important Colleagues

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

Table 11
Information Sharing and Analyst Performance: Within Broker-Year Matched Sample Analysis

This table reports the OLS regression results on the relation between analyst performance in an industry and the economic importance of the industries covered by the analyst's colleague to that industry, based on a matched sample constructed as follows. For a given analyst-industry-year with *Ind_Connect* above the median in the corresponding broker-year, we identify an analyst-industry-year with *Ind_Connect* below the median in the same broker-year and closest quintile-ranked *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 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	0.004	0.382	0.426	0.302	0.408

Table IA1
Information Sharing and Analyst Performance:
Controlling for Analyst Fixed Effects

This table reports the OLS regression results on the relation between analyst performance in an industry and the economic importance of the industries covered by the analyst's colleague to that industry, controlling for analyst fixed effects. *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 Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*Accuracy*	*Rec_Profit*	*Ind_MV*	*Ind_Freq*	*Report_CAR*	*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

Table IA2
Information Sharing and Analyst Performance:
Excluding Broker Fixed Effects

This table reports the OLS regression results on the relation between analyst performance in an industry and the economic importance of the industries covered by the analyst's colleague to that industry, without controlling for broker fixed effects. *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 Appendix.

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

Table IA3
Information Sharing and Analyst Performance: Change Specification

This table reports the OLS regression results on the relation between the change in analyst performance in an industry and the change in economic importance of the industries covered by the analyst's colleague to that industry. For analyst *k* covering industry *i*, Δ denotes the change from years *t*-1 to t. *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 Appendix.

Variable	(1) Δ*Accuracy*	(2) Δ*Rec_Profit*	(3) Δ*Ind_MV*	(4) Δ*Ind_Freq*	(5) Δ*Report_CAR*	(6) Δ*Star*
Δ*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)
Δ*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)
Δ*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)
Δ*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)
Δ*Freq*	0.5999***	0.6175***			0.0007***	0.0008***
	(9.90)	(4.63)			(11.53)	(5.91)
Δ*Horizon*	-0.1242***	-0.0001			0.0000***	0.0001***
	(-88.72)	(-0.02)			(6.53)	(4.81)
Δ*MV*	0.1246	-0.0733			-0.0055***	0.0019
	(0.84)	(-0.26)			(-31.01)	(1.08)
Δ*MTB*	0.0187	-0.0040			-0.0000	-0.0000
	(1.15)	(-0.12)			(-0.56)	(-0.02)
Δ*ROA*	3.5046***	2.0494			-0.0229***	-0.0226
	(2.61)	(0.79)			(-12.80)	(-1.31)
Accuracy						0.0000
						(0.19)
Optimism						-0.0021
						(-0.73)
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./Pseudo R-squared	0.093	0.001	0.207	0.214	0.020	0.002