8-2022

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Citation

HUANG, Allen; LIN, An-Ping; and ZANG, Amy Y.. Cross-industry information sharing among colleagues and analyst research. (2022). *Journal of Accounting and Economics*. 74, (1), 1-20.

Available at: https://ink.library.smu.edu.sg/soa_research/2009

Journal of Accounting and Economics 74 (2022) 101496

Contents lists available at ScienceDirect

Journal of Accounting and Economics

journal homepage: www.journals.elsevier.com/journal-of-accounting-and-economics

Cross-industry information sharing among colleagues and analyst research

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A R T I C L E I N F O

Article history:
Received 12 December 2019
Received in revised form 26 March 2022
Accepted 29 March 2022
Available online 11 April 2022

JEL classification:
D23
G24
G29
L14
M14
M40
M41

Keywords:
Financial analyst
Information sharing
Economically connected industries
Supply chain
Analyst performance
Industry specialization

A B S T R A C T

We identify a specific organizational resource in brokerage houses—information sharing among analyst colleagues who cover economically related industries along a supply chain. After controlling for brokerage selection effects, we show evidence consistent with the benefit of this resource to analyst research performance. Specifically, we find that analysts whose colleagues cover more economically connected industries have better research performance, especially when their colleagues produce higher-quality research. We further show that colleagues' coverage of downstream (upstream) industries is positively related to the accuracy of only analysts' revenue (expense) forecasts and that analysts and their highly connected colleagues tend to issue earnings forecast revisions contemporaneously. Last, we find that analysts with economically connected colleagues tend to have a higher level of industry specialization. Overall, our findings suggest that analysts rely on organizational resources to produce high-quality research. Hence, a portion of their performance and reputation is not transferable across employers.

1. Introduction

Sell-side financial analysts are important information intermediaries in the capital market. An abundance of research has investigated the nature of their skills and decision processes (see reviews by Schipper, 1991; Bradshaw, 2011). Much of this research considers analysts as isolated units of information acquisition and production, viewing their performance and reputation as personal and portable. In contrast, research on the economics of organizations typically treats employee performance as a property of the worker–firm combination (Coase, 1937; Hart, 1989). In reality, analysts do not work in isolation. Rather, they work in brokerage houses alongside other analysts who cover different industries and with whom they share

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https://doi.org/10.1016/j.jacceco.2022.101496

information. Yet, current understanding of information dissemination and collaboration among analyst colleagues within a brokerage remains limited.[1]

The theory of the firm asserts that, to a large extent, organizations exist to solve coordination problems among workers so that they do not need to acquire all of the knowledge necessary to produce (Garicano, 2000). In a knowledge-intensive firm such as a brokerage house, production requires coordination of knowledge acquisition and communication (Bolton and Dewatripont, 1994; Garicano, 2000). That is, when communication is available, analysts can focus on collecting the most relevant information for their industries while accessing the broader knowledge needed to produce high-quality research and services from colleagues. An important implication of this theory is that analysts rely on organizations to produce high-quality research and do not completely “own” their performance. Hence, a portion of their research quality and reputation is not transferable across employers.

To test the notion that a part of analyst performance is attributable to their employers, we focus on a particular organizational resource: access to colleagues who cover economically related industries along a supply chain. We hypothesize that this access improves analyst performance for two reasons. First, analysts can produce higher-quality research for their own industries if they stay alert to news and developments in upstream and downstream industries. Prior research shows that shocks to commodity prices, consumer demand, or technological advancement ripple through layers of the supply chain (Acemoglu et al., 2012). Thus, information about events impacting one industry has value implications for its upstream and downstream industries (Menzly and Ozbas, 2010). Second, if analysts can obtain this relevant information from colleagues, they can afford a more focused research portfolio and take advantage of economies of scale in information acquisition and production due to commonalities across companies in an industry. In this way, they can more easily become industry experts.

Information sharing among colleagues has been observed anecdotally, as in this description of Goldman Sachs (Groysberg, 2010, page 101):

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

Brokerage houses promote colleague collaboration via several organizational mechanisms, such as co-locating colleagues who cover related industries, organizing conferences to bring colleagues in related industries together, and acknowledging collaborative efforts in performance evaluations (Hill and Teppert, 2010). These mechanisms can contribute to a firm's competitive advantage, as noted in the following description (Groysberg, 2010, pages 120 and 57):

> *Balog and other Lehman [Brothers] 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 …*

Information sharing among colleagues likely occurs through various private channels, such as face-to-face discussions, phone calls, and emails, which are unobservable to researchers. Therefore, we infer that such activities occur by showing their varying effects on individual analysts' performance according to different levels of information complementarity with colleagues. We measure information complementarity as the economic connectedness between an analyst's industry and those of her colleagues along a supply chain.[2] We use data from the Benchmark Input−Output Surveys of the Bureau of Economic Analysis (hereafter, BEA) to estimate the level of supply-chain reliance of one industry (A) on another (B) by summing A's input commodities produced by B and A's output commodities used by B, scaled by A's total output commodities.[3] Next, we aggregate the reliance of an analyst's covered industry on those of her colleagues to measure her economic connection with colleagues.[4]

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[1] We refer to analysts working for the same brokerage house as colleagues in this paper.

[2] Throughout the paper, we use the terms “economic connectedness,” “economic connection,” and “industry connection” interchangeably to refer to supply-chain relations between industries and, in turn, connectedness between an analyst and her colleagues.

[3] As an illustration, in 2017, the highest reliance of one industry on another was the reliance of “oil and gas extraction” (BEA industry code 211) on “petroleum and coal products” (BEA code 324). The sum of oil/gas's output used by petroleum/coal and oil/gas's input produced by petroleum/coal amounted to 92.4% of oil/gas's total output (of which 91.2% was oil/gas industry's output used by petroleum/coal, such as crude oil and natural gas condensate). Another 2017 example is the reliance of “food and beverage and tobacco products” (BEA code 311 F T) on “farms” (BEA code 111 C A), which reached 25.9% of food/beverage/tobacco's total output (of which 22.6% was food/beverage/tobacco's input produced by farms, including grains, vegetables, fruits, oils, meat, milk, and eggs). In the same year, the lowest reliance was between “social assistance” (BEA code 624) and “forestry, fishing, and related activities” (BEA code 113FF), which had no input or output activities between them.

[4] We do not measure economic connectedness of analyst coverage based on company-level supply-chain relations (i.e., companies with direct trading relationships) for two reasons. First, companies frequently conceal the identities of major customers, i.e., those that contribute more than 10% of their total revenues, which creates a selection bias in the data (Ellis et al., 2012). Second, major customers are usually much larger than the disclosing companies (Cohen and Frazzini, 2008). Thus, it is difficult to detect the information flow from suppliers to customers (Menzly and Ozbas, 2010). Nonetheless, we conduct sensitivity tests (untabulated) that either control for the analysts' and their colleagues' coverage of direct major suppliers and customers, or exclude colleagues who cover direct major suppliers or customers when we calculate the economic connection between analysts and their colleagues. We find that analyst performance is better when colleagues cover major supplier/customer companies, but our main results hold after controlling for company-level supplier/customer links.

During our sample period of 1982–2017, the average connection between an analyst's and her colleagues' covered industries is economically significant at 69.8% of her industry's total output. That is, on average, an analyst's colleagues cover industries that collectively account for her industry's input and output to the amount of 69.8% of her industry's total output (see Appendix A for an example of the economic connection between a Bear Stearns analyst covering the "paper products" industry and the analyst's colleagues). Furthermore, there are substantial cross-sectional and time-series variations in economic connection with colleagues due to differences and changes in industry pairs' reliance and colleagues' industry coverage, and due to colleague turnovers, which we exploit in our empirical tests.

Using this measure of economic connectedness between an analyst's industry and those of colleagues, we find evidence consistent with information sharing among colleagues improving analyst performance. First, after controlling for other factors that affect research quality, we find that an analyst's earnings forecast accuracy and stock recommendation profitability are positively correlated with the level of economic connectedness between the analyst's industry and those of her colleagues. Next, we measure analyst performance in terms of investor recognition using investor response to analyst earnings forecast revisions and the analyst's *Institutional Investor* (*II*) All-Star ranking (Groysberg et al., 2011). These two measures are arguably more comprehensive measures of performance than forecast accuracy or stock recommendation profitability because investors also value analysts' industry knowledge, written reports, and idea generation (Gleason and Lee, 2003; Institutional Investor, 2011; Huang et al., 2014; Huang et al., 2018). The results show that analysts whose coverage is more economically connected to that of colleagues elicit stronger investor reactions to their forecast revisions and are more likely to be ranked as an *II* All-Star. Our finding is consistent with their research benefiting from information sharing in ways that investors recognize. In addition, we conduct cross-sectional tests and find that the relation between economic connection with colleagues and analyst performance is stronger when colleagues produce higher-quality research, as measured by colleagues' earnings forecast accuracy, stock recommendation profitability, industry experience, and All-Star status. This result is consistent with the intuition that better-quality colleagues share more useful information and constitute a more valuable organizational resource.

Next, we refine the main test by examining whether economic connectedness with colleagues covering upstream and downstream industries have differential impacts on an analyst's performance on expense and revenue forecasts. We make this prediction because, intuitively, colleagues covering upstream industries can inform the analyst about supply shocks and input pricing, both of which affect companies' expenses such as cost of goods sold, and colleagues covering downstream industries can inform the analyst about customer demand, which affects revenues.[5] Empirically, we find results consistent with this intuition. That is, upstream connectedness is positively related to the accuracy of expense forecasts but not revenue forecasts, whereas downstream connectedness is positively related to the accuracy of revenue forecasts but not expense forecasts. These results further support our main hypothesis, because if there is indeed information sharing among colleagues, the type of information shared matters; that is, information benefits analyst performance more when it is more relevant to the task.

One challenge of empirical research of organizational economics is disentangling the treatment effect from the selection effect, or the likelihood that some organizations select higher-quality employees (Allison and Long, 1990; Hwang et al., 2019). In our empirical tests, we use several strategies to exploit variations in the treatment effect of colleague information sharing while controlling for the selection effect. First, we include broker fixed effects in all empirical analyses such that we examine the treatment effect on analysts who work in the same brokerage house. Analysts working in the same brokerage house can have different levels of economic connection with colleagues because the amounts of products and services flowing among different industries vary. Second, we exploit colleague turnovers and test whether analyst performance improves (deteriorates) after a colleague who covers a highly connected industry joins (departs) the brokerage house. This specification controls for analysts' access to other brokerage resources, such as the same research director, quantitative researchers, and macroeconomists (Hugon et al., 2016; Birru et al., 2019; Bradley et al., 2019), as well as other support staff (Mikhail et al., 1997; Clement, 1999; Groysberg et al., 2008; Gao et al., 2021). Last, the empirical tests that separately examine the effects of upstream and downstream connectedness further alleviate the selection effect by exploiting the constructs' different relations with an analyst's forecasts of expenses and revenues, while keeping constant the brokerage house, the period, the analyst, and her coverage.[6]

We perform an additional analysis that corroborates the main findings. In this test, we investigate the timing of analysts' earnings forecast revisions and find that an analyst is more likely to revise earnings forecast when a colleague who covers a highly connected industry does so, compared with a similar analyst covering the same company but without such a colleague.

[5] Take the "paper products" analyst in Appendix A as an example. The analyst's downstream connectedness to colleagues is 41.2%, which is higher than the sample median of 29.0%. Thus, we expect the analyst's revenue forecasts to benefit more from colleagues, compared to the average analyst in our sample. Similarly, the analyst's upstream connectedness of 24.6% is lower than the sample median of 34.7%. Thus, we expect the analyst's expense forecasts to benefit less from colleagues, compared to the average analyst.

[6] In addition to these strategies, we use three alternative research designs to control for the selection effect. First, we replace broker fixed effects with analyst fixed effects to control for the possibility that brokerage houses might assign more capable analysts to better-connected industries. Second, we use a matched sample approach in which we compare two analysts who work for the same brokerage in the same year and who have similar industry experience and number of covered companies in the industry but whose covered industries have different levels of economic connectedness with those of colleagues. Third, we use a change specification. We find results consistent with our main analyses in all three specifications (untabulated).

This result indicates a tendency of connected colleagues to issue forecast revisions contemporaneously, consistent with information sharing among colleagues.

Last, we explore the relation between the level of concentration in an analyst's coverage of industries and her industry connection to colleagues. One explanation for our main findings is that analysts allocate more time and effort to their main industries if they can access information about upstream and downstream industries from colleagues. These analysts take advantage of economies of scale in information acquisition and production due to commonalities across companies in one industry. Such focus benefits analysts' research quality, allowing them to become industry experts more easily (Kini et al., 2009). To provide empirical evidence supporting this explanation, we follow Sonney (2009) and measure an analyst's industry specialization using the Herfindahl–Hirschman Index, calculated as the sum of the squared percentage of coverage share of each industry in the analyst's portfolio. We find that the level of concentration in an analyst's coverage of industries is higher when her main industry is more connected to industries covered by colleagues, which is consistent with such connectedness allowing analysts to become industry specialists.

Our study contributes to several streams of literature. First, we extend the analyst literature by identifying a specific organizational attribute that contributes to analyst performance—access to complementary information about economically relevant industries through colleague collaboration. The extant literature often assumes that analysts work in isolation and that their performance is personal. For example, several prior studies argue that analysts trade off between enjoying economies of scale in information acquisition and production by specializing in an industry and obtaining complementary information through coverage diversification (Kini et al., 2009; Sonney, 2009; Guan et al., 2015; Luo and Nagarajan, 2015).[7] Our research complements these studies by showing that analysts can maintain a focused portfolio and obtain information about economically related industries through collaboration with colleagues.

Second, our study contributes to the literature on information transfer by documenting that analysts can facilitate cross-industry information diffusion through collaboration with colleagues. Prior literature identifies gradual cross-industry information diffusion (Menzly and Ozbas, 2010; Aobdia et al., 2014) and attributes it to friction in information processing (Hou and Moskowitz, 2005; Cohen and Lou, 2012). Some of these studies (e.g., Menzly and Ozbas, 2010; Parsons et al., 2020) suggest that analysts as industry specialists contribute to information segmentation in the market.[8] Our study shows that, contrary to this assertion, analysts can facilitate cross-industry information transfer by collaborating with colleagues.

Third, our study adds to an emerging research area on brokerage knowledge resources. Since Clement (1999) and Jacob et al. (1999), most studies on financial analysts have recognized the importance of brokerage resources. However, most do not delve into their specific content and structure but merely control for them using summarizing proxies, such as broker size and reputation (see the review by Ramnath et al., 2008). Recently, a stream of research finds that analysts benefit from colleagues who are macroeconomists, quantitative researchers, research directors, and debt analysts; who are *II* All-Stars covering the same industry; and who cover the other company in an M&A transaction (Hugon et al., 2016; Birru et al., 2019; Bradley et al., 2019; Hwang et al., 2019; Do and Zhang, 2020: Hugon et al., 2021). We extend this research by documenting a new type of knowledge resource—access to colleagues covering economically related industries along a supply chain.

Last, in demonstrating that analyst performance is an outcome of the analyst–firm combination, our findings have practical implications for brokerage houses and other knowledge-intensive firms. By encouraging colleague information sharing, such firms may create a sustainable competitive advantage that improves employee performance through knowledge dissemination and expertise development and helps to retain talent because employee performance is less portable to other employers (Groysberg et al., 2008).

2. Hypothesis development

Financial analysts are regarded as industry experts. According to *II*'s (2011) annual survey, institutional investors rank industry knowledge as the most desired attribute of analysts. Analysts usually have educational or work experience in the main industry they cover (Bradley et al., 2017) and strive to develop “an encyclopaedic knowledge of a handful of companies” within that industry (Groysberg, 2010, page 266). To produce high-quality research, analysts must stay alert to news and developments in economically connected industries to “connect the dots” across industries and provide “big picture” investment ideas that are valued by institutional investors.

Modern companies and industries are closely interconnected. One important and well-defined connection is their economic links along the supply chain. For example, shocks to commodity prices, consumer demand, or production, as well as technological advancements, ripple through the supply chain (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016), leading to highly correlated fundamentals for companies in closely connected industries (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). Thus, information from one industry has value implications for both its upstream and downstream industries (Menzly and Ozbas, 2010; Aobdia et al., 2014).

[7] Fang and Hope (2021) study analysts leading teams of junior research associates, but such teams are still assumed to be an isolated unit of information acquisition and production.

[8] For example, Menzly and Ozbas (2010) argue that cross-predictability in stock returns in a limited-information model requires the assumption that informed investors specialize. They address this assumption by presenting evidence for the specialization of equity analysts and money managers. Similarly, Parsons et al. (2020) use analyst industry specialization to explain the geographic lead–lag effect in companies' returns.

Several studies propose that analysts understand the importance of accessing complementary information from related industries and thus also cover companies in those industries by themselves (Kini et al., 2009; Sonney, 2009; Guan et al., 2015; Luo and Nagarajan, 2015). However, these studies implicitly assume that analysts work in isolation. For example, Kini et al. (2009) argue that analysts face "the tradeoff between the economies of scale in information acquisition and production an analyst can exploit by focusing her portfolio on a particular country or sector and the benefits of exposure to complementary information when she diversifies her portfolio to include companies in other countries or sectors." We propose an alternative to this tradeoff, that is, an analyst can obtain relevant information from colleagues who cover upstream and downstream industries.

The research department of a brokerage house coordinates its knowledge assets, namely analysts. Communication and collaboration among these analysts can improve their performance for two reasons. First, colleagues covering upstream and downstream industries provide a broad set of high-quality and timely information. Second, analysts can focus on their main industries without the risk of becoming less informed about other related industries. Such a focus allows them to enjoy the economies of scale in information acquisition and production because companies in one industry share similarities such as business models, products and competitive landscape. As a result, analysts become industry experts more easily.[9]

Brokerage houses recognize the benefits of knowledge sharing among colleagues and facilitate it through both formal and informal mechanisms (Tsai, 2002; Inkpen and Tsang, 2005). For example, they co-locate analysts who conduct related research (Hill and Teppert, 2010), host conferences for analysts and companies in related industries (Bushee et al., 2011), acknowledge collaboration in analyst performance evaluations (Hill and Teppert, 2010), organize corporate retreats and other social bonding events, and sometimes even push analysts who cover related industries along a supply chain to co-publish in-depth reports (Groysberg, 2010). Not all analysts have incentives to collaborate, however, particularly if they compete for promotions to positions such as research executive or director of research (Wu and Zang, 2009; Bradley et al., 2019). These intra-firm tournament incentives can impede knowledge sharing and even lead to sabotage (Harbring and Irlenbusch, 2011; Charness et al., 2014).

Given the relevance of colleagues' knowledge and the intense competition from other brokerages' analysts covering the same industry, we expect that the incentives to collaborate with colleagues will dominate and that information sharing among colleagues will result in a greater improvement in an analyst's performance when colleagues' knowledge has a higher level of complementarity, which can be captured by the supply-chain connectedness between the analyst's industry and those of her colleagues. We propose our hypothesis as follows:

H1. *An analyst's performance benefits more from information sharing with her colleagues when those colleagues cover industries that are more economically connected to the industry covered by the analyst.*

3. Empirical measures

3.1. Empirical measures and descriptive statistics of industry interdependence and economic connectedness with colleagues

We measure the level of information complementarity of colleagues' knowledge as the economic connectedness between an analyst's industry and her colleagues' industries, based on the Benchmark Input−Output Accounts prepared by the BEA (Fan and Goyal, 2006; Menzly and Ozbas, 2010; Ahern, 2012).[10] These accounts comprise Make and Use tables showing the dollar values of respective production and consumption of commodities, including goods and services, by each industry in each year. These data show how much an industry's production relies on other industries' outputs and summarize supply chains across the US economy.

To construct our measure of an analyst's information complementarity with colleagues, we begin by measuring the interdependence between two industries. Specifically, the importance of industry j to industry i is the ratio of the sum of i's input commodities produced by j (i.e., j's importance to i as its upstream industry) and i's output commodities used by j (i.e., j's importance to i as its downstream industry) to industry i's total output. That is, the importance of industry j to industry i depends on j's role as both a supplier and a customer (Acemoglu et al., 2012; Baqaee, 2018). Formally, we have the following:

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

[9] This conjecture is consistent with how economists conceptualize the firm as a coordinated network of specialized workers that is greater than the sum of its parts (Klein, 1988; Hart, 1989).

[10] To accurately measure total commodity production and use by industry, the Benchmark Input-Output accounts include both publicly traded and private firms (Horowitz and Planting, 2009). The inclusion of private firms in the accounts should not introduce biases to our study because we gauge the importance of upstream and downstream information based on industry exposure. We are not aware of any prior research showing that supply chain reliance differs by firms' listing status.

where $Importance_{i,j,t}$ indicates the importance of industry j to industry i in year t. During our sample period, BEA uses 61 industries during 1982–1996 and 65 industries during 1997–2017.[11] We measure *Importance* for each industry pair annually, resulting in 144,540 observations ($61 \times 61 \times 15 + 65 \times 65 \times 21 = 144{,}540$) for *Importance*.

The descriptive statistics of *Importance* (reported in Table 2, Panel A) show that the mean (median) value of *Importance* is 1.5% (0.4%).[12] The average value of cross-sectional standard deviation of *Importance* in a year is 4.8% (untabulated), which suggests wide variation in the economic interdependence of industries in the US economy. This interdependence also changes over time. The average value of time-series standard deviation is 0.6% for an industry pair (untabulated), larger than the median value of *Importance* (0.4%). Some industry pairs experience large temporal changes. For example, the *Importance* of Warehousing and Storage (BEA industry code 493) to Primary Metals (BEA industry code 331) increased from 0% in 1982 to 1.66% in 2017.

Next, we measure the economic connection between analyst l, who covers industry i, and her colleagues in year t ($Ind\_Connect_{l,i,t}$) as the sum of the *Importance* of all industries covered by her colleagues for industry i during that year.[13, 14] In our example in Appendix A, the Bear Stearns analyst covering the "paper products" industry enjoys an *Ind_Connect* of 65.9%, which equals the sum of *Importance* of the 26 unique industries covered by the analyst's colleagues to the "paper products" industry in 1991.

Our sample comprises data on all analysts who cover US companies included in I/B/E/S from 1982 to 2017 and for whom we have data to measure our required variables (see Table 1 for sample selection details).[15] Based on this condition, we have 221,328 analyst–industry–year observations from 19,399 unique analysts. The mean value of *Ind_Connect* in Table 2, Panel A, indicates that, on average, for an analyst's industry, the sum of its input produced by her colleagues' industries and its output used by her colleagues' industries amounts to 69.8% of its total output, which is economically significant. There are substantial variations in analysts' industry connections to colleagues: the analyst in the third quartile of *Ind_Connect* has colleagues covering industries that account for 95.2% of her industry's outputs, whereas colleagues of the analyst in the first quartile cover only 38.5%. These variations arise from two sources: the number of industries covered by colleagues and the economic interdependence between the analyst's industry and those of her colleagues.[16]

3.2. Empirical measures of analyst performance

We measure analyst performance in several ways. We use earnings forecast accuracy and stock recommendation profitability, both of which are considered analysts' most important and visible quantitative outputs. We also use market reaction to earnings forecast revisions and *II* All-Star rankings to capture investors' recognition of analyst research quality.

We follow previous studies (e.g., Hong et al., 2000) to calculate the relative earnings forecast accuracy of analysts. First, we calculate the normalized rankings of the absolute forecast error of all analysts following a company in a year, based on the last annual earnings forecasts issued at least one month prior to the fiscal year end, such that the most (least) accurate analyst receives a normalized rank of 100 (0).[17] Next, we average the normalized ranks across all companies analyst l covers in industry i in year t ($Accuracy_{l,i,t}$), which measures the analyst's relative forecast accuracy compared to that of her peers who follow the same industry in the same year.

We measure stock recommendation profitability in a similar manner. First, we calculate the market-adjusted buy-and-hold return obtained from following an analyst's recommendation for a company in a year. We assume a long position for buy and strong buy recommendations and a short position for hold, sell, and strong sell recommendations (e.g., Loh and Mian, 2006). The investment horizon of analyst recommendations is usually 12 months (Bradshaw, 2004; Barber et al., 2006; Kadan et al., 2012, 2020), so we specify an investment window starting two days after an analyst's recommendation announcement date and ending either 364 days after the recommendation announcement date or two days before the

[11] Most BEA industries are defined based on three-digit NAICS codes (49 out of 61 BEA industries during 1982–1996, and 54 out of 65 BEA industries during 1997–2017), with the remaining ones based on two-digit (7 out of 61, and 6 out of 65, respectively) and four-digit NAICS codes (5 out of 61, and 5 out of 65, respectively). We do not include BEA industries without corresponding NAICS codes. We assign the company–year observations to the corresponding BEA industries based on the companies' historical NAICS codes (or current NAICS codes if historical ones are not available) obtained from Compustat.

[12] The literature considers any input/output relationship of at least 1% or 5% to be sufficiently important to identify targets of vertical mergers (Fan and Goyal, 2006). We find that during our sample period, around 32% of industry pairs have an *Importance* value greater than 1% and around 7% of industry pairs have an *Importance* value greater than 5%.

[13] If multiple colleagues cover the same industry, we count the *Importance* of that industry only once when measuring *Ind_Connect*.

[14] In a sensitivity test, we include industries covered by analyst *l* but not by her colleagues in measuring *Ind_Connect* and find qualitatively similar results (untabulated).

[15] We focus on US companies in our study because the BEA's Input–Output accounts include industry-level goods and services produced for US domestic industries only and combine import/export data for all other countries. Thus, we cannot calculate the economic interdependence between two industries from different countries, such as US car manufacturing and Canadian metal production. Nonetheless, we conduct a sensitivity analysis using an all I/B/E/S analyst sample and assume that the economic interdependence among industries in other countries is the same as in the US. We repeat our main analyses using this sample and find similar results (untabulated).

[16] The average value of cross-sectional standard deviation of *Ind_Connect* within a broker–year is 14.0% (untabulated). This statistic indicates that analysts in the same brokerage in the same year have vastly different levels of economic connection with colleagues, which is driven solely by varying degrees of the industries' economic interdependence.

[17] In an untabulated sensitivity test, we use the first annual earnings forecast after the prior fiscal year results are reported to measure earnings forecast accuracy and find results similar to those of our main analyses.

Table 1
Sample Selection.
This table presents the sample construction procedure for the analyst earnings forecast accuracy test.

Sample selection criteria	# of analyst—company—years	# of analyst—industry—years	# of analysts
Analyst—company—years with earnings forecasts, 1982—2017	1,352,841		27,071
Retain: companies with GVKEY	652,466		20,357
Aggregate to analyst—industry—years through averaging analyst—company—years, by BEA industries		237,635	20,357
Retain: at least one covered company 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 company has actual earnings announcement date to calculate average forecast horizon		230,209	20,015
Retain: at least one covered company has financial information to calculate control variables		221,484	19,483
Retain: brokerage houses and industry—years with multiple observations		221,328	19,399
Final earnings forecast accuracy test sample		221,328	19,399

analyst's next recommendation announcement date, whichever is earlier.[18] Next, we rank all analysts following a company in a year and normalize their rankings such that the most (least) profitable analyst receives a rank of 100 (0). Finally, we take the average of normalized ranks across all companies that analyst l covers in industry i in year t to obtain her relative stock recommendation profitability for the industry—year ($Rec\_Profit_{l,i,t}$).

Investor recognition reflects an overall assessment of analyst research quality beyond their quantitative research outputs. To measure investor recognition, we first follow the literature by using the market reaction to earnings forecast revisions (Gleason and Lee, 2003; Bonner et al., 2007). In particular, we take the average of absolute cumulative three-day market-adjusted return centered on the revision date across all earnings forecast revisions issued by analyst l for companies in industry i in year t ($CAR_{l,i,t}$). For our second measure of investor recognition, we use the *II* All-Star Ranking list. We identify an analyst as an All-Star ($Star_{l,t}$) if she is ranked among the first, second, or third team, or listed as a runner-up by *II* in year t. In each year, *II* surveys thousands of institutional investors and asks them to vote for analysts based on a wide range of attributes, including industry knowledge, integrity, accessibility, management access, special services, written reports, financial models, useful and timely calls and visits, idea generation, and research delivery. Thus, the *II* ranking is a comprehensive measure of analyst research quality and performance.

4. Empirical results

4.1. Main tests of information sharing: relation between analyst performance and economic connectedness with colleagues

The descriptive statistics reported in Panel A of Table 2 show that the median analyst in our sample covers five companies, has six years of experience, and works in a brokerage that employs 34 analysts. The unconditional probability of being named an All-Star analyst is 14.4%. In Panel B, we observe that *Ind_Connect* is significantly and positively correlated with all analyst performance measures.

To test the relation between analysts' performance and their economic connectedness with colleagues (i.e., H1) while controlling for other performance determinants, we use the following regression model:

$$Analyst\ Performance = \alpha + \beta \cdot Ind\_Connect + \sum \gamma Control\_Performance + Broker\ FE + Industry\_Year\ FE + \varepsilon, \quad (1)$$

where *Analyst Performance* is *Accuracy*, *Rec_Profit*, *CAR*, or *Star*. We use analyst—industry—year level OLS regressions except when the dependent variable is *Star*, for which we use an analyst—year level probit regression because *II* ranks analysts according to their main industry in the year. We define an analyst's main industry as the one in which the total market cap of her covered companies is the highest among all her covered industries and assume she is best-known for that industry. Our main variable of interest is *Ind_Connect*. From H1, we expect the coefficient on *Ind_Connect* to be positive. That is, a positive coefficient on *Ind_Connect* is consistent with analyst performance benefiting from information sharing more when colleagues cover industries that are more economically connected to the analyst's industry.

As discussed in the introduction, it is essential that we control for the selection effect that larger brokerage houses select higher-quality analysts. To address this endogeneity concern, we include in our estimation broker size (measured as the total number of analysts working for the brokerage house in the year) and broker fixed effects (Stickel, 1995; Clement, 1999; Jacob

[18] In untabulated sensitivity tests, we either exclude all hold recommendations in calculating stock recommendation profitability or use alternative investment windows ending two, three or six calendar months after the recommendation announcement date. We find results similar to those of our main analyses.

Table 2
Descriptive statistics.

Panel A: Summary statistics.
This panel presents the summary statistics for the sample. The sample size for the dependent variable varies across tests. The descriptive statistics for control variables are based on the sample for the earnings forecast accuracy test, except for *NComp_Total*, *Optimism*, and *Bold*, which are based on the sample for the All-Star status test. The variable definitions are in Appendix B.

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
IC_Upstream	221,328	0.336	0.183	0.189	0.347	0.473
IC_Downstream	221,328	0.362	0.330	0.133	0.290	0.490
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
CAR	205,895	0.047	0.035	0.023	0.038	0.062
Star	72,033	0.144	0.351	0.000	0.000	0.000
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
HHI_NComp	57,975	0.710	0.289	0.453	0.722	1.000
HHI_MV	57,975	0.811	0.234	0.615	0.960	1.000
BSize	221,328	48.045	43.754	14.000	34.000	74.000
Expr_Ind	221,328	4.424	3.956	1.000	3.000	6.000
Expr_Gen	221,328	7.961	5.983	3.000	6.000	11.000
NInd	221,328	3.486	2.340	2.000	3.000	5.000
NComp_Ind	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
Loss	221,328	0.175	0.328	0.000	0.000	0.200
NComp_Total	72,033	6.162	5.324	2.000	5.000	9.000
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

Panel B: Pearson correlation table.
This panel presents the Pearson correlation table for the sample. Bold face indicates significance at the 5% level. The variable definitions are in Appendix B.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) *Ind_Connect*	1												
(2) *Accuracy*	**0.02**	1											
(3) *Rec_Profit*	**0.01**	**0.02**	1										
(4) *CAR*	**0.11**	**0.02**	−0.00	1									
(5) *BSize*	**0.56**	**0.02**	**0.01**	**0.05**	1								
(6) *Expr_Ind*	**0.08**	**0.02**	**0.01**	−0.00	**0.06**	1							
(7) *NInd*	**0.07**	**0.02**	0.01	**0.02**	**−0.06**	**0.09**	1						
(8) *NComp_Ind*	**0.08**	**0.03**	**0.02**	**−0.01**	**0.09**	**0.39**	**−0.16**	1					
(9) *Freq*	**0.13**	**0.18**	**0.04**	**0.05**	**0.14**	**0.20**	**0.07**	**0.19**	1				
(10) *Horizon*	**−0.06**	**−0.37**	**−0.04**	**−0.02**	**−0.05**	**−0.07**	**−0.08**	**−0.10**	**−0.50**	1			
(11) *MV*	**0.14**	**−0.01**	**0.03**	**−0.18**	**0.21**	**0.26**	**−0.08**	**0.27**	**0.19**	**−0.10**	1		
(12) *MTB*	**0.05**	**0.01**	−0.00	**0.06**	**0.02**	**0.02**	0.00	**0.01**	**−0.02**	**−0.02**	**0.20**	1	
(13) *ROA*	**−0.05**	**0.03**	**0.02**	**−0.25**	**0.01**	**0.00**	**0.06**	**−0.08**	**−0.01**	**−0.03**	**0.23**	**0.05**	1
(14) *Loss*	**0.05**	**−0.03**	**−0.02**	**0.29**	**−0.02**	**−0.02**	**−0.04**	**0.03**	**0.02**	**0.02**	**−0.22**	−0.00	**−0.71**

et al., 1999). Thus, we compare analysts within a brokerage and determine whether analysts who cover industries that are more economically connected with those of colleagues perform better than other analysts in the same brokerage.

In addition to controlling for brokerage characteristics, we follow the literature (e.g., Mikhail et al., 1997; Clement, 1999; Jacob et al., 1999; Hong and Kubik, 2003; Clement and Tse, 2005) and control for a number of analyst characteristics that might be correlated with performance, such as industry experience (*Expr_Ind*), number of industries followed (*NInd*), number of companies followed in the industry (*NComp_Ind*), average number of earnings forecasts issued per covered company in the industry (*Freq*), and average earnings forecast horizon (*Horizon*). Finally, we control for company characteristics that reflect an analyst's coverage selection and might affect performance: company size (*MV*), market-to-book ratio (*MTB*), and profitability (*ROA* and *Loss*). For the regression in which *Star* is the dependent variable, we further control for earnings forecast accuracy (*Accuracy*), optimism (*Optimism*), and boldness (*Bold*). Appendix B provides variable definitions. We winsorize all continuous variables that are not based on normalized ranks at the top and bottom 1%. In all regressions, we include industry−year fixed effects to control for time-varying industry-specific differences. Standard errors are estimated by two-way clustering at the analyst and industry−year levels (Petersen, 2009).

Table 3 reports the empirical results. Column 1 presents the results for analyst forecast accuracy (*Accuracy*). The coefficient on *Ind_Connect* is positive and significant (at the 0.01 level), which supports our prediction that information sharing with colleagues who cover related industries improves analysts' earnings forecast accuracy. In terms of economic magnitude, a one standard deviation increase in *Ind_Connect* (0.439) increases *Accuracy* by 0.736 (= 0.439 × 1.6770). Based on the estimated coefficient of *Horizon* (−0.1396), this increase is equivalent to the benefit of issuing forecasts five days closer to the earnings announcement date (0.736/0.1396 = 5.27). Consistent with prior studies (e.g., Drake et al., 2020; Fang and Hope, 2021), forecast accuracy is positively correlated with the number of forecasts issued per company in the industry (*Freq*), which captures analyst effort, and negatively correlated with broker size (*BSize*) and forecast horizon (*Horizon*).[19] The results also show that forecast accuracy is positively correlated with the number of industries followed (*NInd*) and the number of companies covered in the industry (*NComp_Ind*).[20, 21]

Column 2 reports the results for stock recommendation profitability (*Rec_Profit*). The coefficient on *Ind_Connect* is positive and significant (at the 0.10 level), consistent with our hypothesis that information sharing with colleagues who cover economically connected industries enables the analyst to provide more profitable recommendations. In terms of economic magnitude, a one standard deviation increase in *Ind_Connect* (0.435) increases *Rec_Profit* by 0.528 (= 0.435 × 1.2131). Throughout the paper, we use in-sample standard deviations to calculate economic magnitudes. Similar to our results for forecast accuracy, we find positive and significant correlations for *NInd*, *NComp_Ind*, and *Freq*.

We next examine the market's response to an analyst's forecast revisions (*CAR*). In Column 3, we find that the coefficient on *Ind_Connect* is positive and significant (at the 0.01 level), which supports our prediction that information sharing with colleagues who cover related industries increases the analyst's market impact. In terms of economic magnitude, a one standard deviation increase in *Ind_Connect* (0.434) is associated with an 11 basis-point (= 0.434 × 0.0025) increase in market response. We find *BSize*, *NComp_Ind*, *Freq*, and *Horizon* to be positively correlated with market response.

In terms of whether analysts with colleagues who cover more economically connected industries are more likely to receive *II* All-Star status (*Star*), we see from the results in Column 4 that the coefficient on *Ind_Connect* is positive and significant (at the 0.01 level). This finding is consistent with information sharing improving the qualitative aspects of analyst performance that institutional investors value, such as industry knowledge, written reports, and idea generation. This result is also economically significant: the marginal effect from the probit regression suggests that a one standard deviation increase in *Ind_Connect* (0.381) increases the odds of being ranked as an All-Star by 11.8% (1.7% compared to the unconditional probability of 14.4%). Taken together, the results in Table 3 are consistent with H1—that is, analyst performance benefits more from information sharing when the colleagues cover industries that are more economically connected to the analyst's industry.

4.2. Cross-sectional tests of information sharing

Next, we explore whether the benefits of information sharing increase when colleagues produce higher-quality research. Intuitively, analysts are more likely to seek information from higher-quality colleagues, and the information acquired from such colleagues will be timelier and more useful. Indeed, Bradley et al. (2019) and Do and Zhang (2020) find that compared to lower-quality mentors and research directors, higher-quality ones have larger beneficial effects on analyst performance. However, more competent colleagues also have higher opportunity costs in terms of their time and lower expectations in terms of the benefits of reciprocal relations, so they might be less willing to share information (Hardin, 1982; Levine and Prietula, 2012).

To empirically test this prediction, we measure colleagues' research quality using their forecast accuracy, recommendation profitability, industry experience, and *II* All-Star status. Specifically, we separately calculate the sum of *Importance* of the industries covered by colleagues whose research quality is above and below the sample median (or who are star and non-star) and label them *IC_High_Quality* and *IC_Low_Quality*, respectively. We replace *Ind_Connect* in Eq. (1) with *IC_High_Quality* and *IC_Low_Quality* and predict a larger coefficient on *IC_High_Quality*. That is, the per-unit benefit of information sharing with higher-quality colleagues is larger than that of information sharing with lower-quality colleagues.

Table 4 reports the results. Panel A presents our comparison of the relation between analyst performance and industry connectedness with more accurate colleagues (*IC_High_Accu*) versus that with less accurate colleagues (*IC_Low_Accu*). The

[19] Clement (1999), Jacob et al. (1999) and Jacob et al. (2008) document a positive relation between forecast accuracy and broker size, whereas more recent studies (e.g., Drake et al., 2020; Fang and Hope, 2021) document a negative relation. In untabulated sensitivity tests where we exclude broker fixed effects, the relation between forecast accuracy and broker size is either insignificant (when we include analyst fixed effects) or significantly positive (when we use a change specification).

[20] Clement (1999) documents a negative relation between forecast accuracy and number of industries covered, whereas other studies (e.g., Clement et al., 2007; Clement et al., 2011; Tehranian et al., 2014) find a positive or insignificant relation between the two. We investigate the relation between accuracy and number of industries covered further in sensitivity tests (tabulated in Internet Appendix Table IA1, Panel A) and find that it remains positive when we define industry using two-digit SIC codes (Column 4, as in Clement, 1999) instead of BEA definition. The relation becomes negative and significant (at the 1% level), as in Clement (1999), when we exclude fixed effects (Columns 1 and 3, again following Clement, 1999).

[21] Unlike Clement (1999), who measures portfolio complexity by using the total number of companies covered by an analyst across all industries (*NComp_Total*), we capture an analyst's depth of industry knowledge by using the number of companies covered by the analyst *in the industry*. We do this to attempt to explain the analyst's performance for an industry-year. The correlation coefficient between *NComp_Ind* and *NInd* is −0.16 (Table 2, Panel B), suggesting that analysts tend to cover fewer companies in an industry when they cover more industries. The correlation coefficient between *NComp_Ind* and *NComp_Total* is only 0.23 (untabulated). In sensitivity tests (tabulated in Internet Appendix Table IA1, Panel B), we find that the relation between forecast accuracy and *NComp_Total* is insignificant when fixed effects are included (Column 4) and becomes negative and significant (at the 10% level, Column 3) when we exclude broker fixed effects, consistent with Clement (1999).

Table 3
Information Sharing and Analyst Performance.
This table reports the relation between an analyst's performance in an industry and the economic connectedness to colleagues' covered industries. We estimate the OLS regressions $Accuracy\ (Rec\_Profit, CAR) = f(Ind\_Connect,\ Control\_Analyst,\ Control\_Comp) + \varepsilon$ in columns (1) to (3), and the Probit regression $Star = f(Ind\_Connect,\ Control\_Analyst,\ Control\_Comp, Control\_Star) + \varepsilon$ in column (4). *Control_Analyst* includes *BSize*, *Expr_Ind*, *NInd*, and *NComp_Ind* (or *NComp_Total* in column 4). *Control_Comp* includes *Freq*, *Horizon*, *MV*, *MTB*, *ROA*, and *Loss*. *Control_Star* includes *Accuracy*, *Optimism*, and *Bold*. All of the regressions include broker and industry−year fixed effects. The *t*- and *z*-stats based on standard errors 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. The variable definitions are in Appendix B.

	(1)	(2)	(3)		(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*		Star
Ind_Connect	**1.6770*****	**1.2131***	**0.0025*****	*Ind_Connect*	**0.3299*****
	(4.44)	**(1.88)**	**(4.72)**		**(3.05)**
BSize	−0.0245***	−0.0035	0.0000***	*BSize*	0.0032***
	(-4.72)	(-0.39)	(3.19)		(4.20)
Expr_Ind	0.0306	−0.0040	−0.0001*	*Expr_Ind*	0.1141***
	(1.63)	(-0.15)	(-1.92)		(26.69)
NInd	0.2194***	0.1751**	0.0000	*NInd*	0.0630***
	(5.34)	(2.53)	(0.60)		(4.60)
NComp_Ind	0.0848***	0.0730*	0.0002***	*NComp_Total*	0.0168**
	(3.63)	(1.91)	(3.37)		(2.43)
Freq	0.3492***	0.4688***	0.0008***	*Freq*	0.0133***
	(7.18)	(6.18)	(10.41)		(10.38)
Horizon	−0.1396***	−0.0136***	0.0000**	*Horizon*	−0.0013***
	(-87.64)	(-7.16)	(2.38)		(-7.65)
MV	−0.4046***	0.3142***	−0.0040***	*MV*	0.1459***
	(-7.54)	(3.71)	(-27.56)		(10.04)
MTB	0.0528***	−0.0279	0.0003***	*MTB*	−0.0026
	(3.40)	(-1.27)	(4.97)		(-0.80)
ROA	2.2696**	−0.7972	−0.0178***	*ROA*	−0.0908
	(2.42)	(-0.59)	(-5.86)		(-0.42)
Loss	−1.7073***	−1.3997***	0.0113***	*Loss*	0.1403*
	(-6.23)	(-2.98)	(12.97)		(1.73)
				Accuracy	0.0026***
					(4.82)
				Optimism	−0.0466
					(-1.46)
				Bold	−0.0001
					(-0.24)
Broker FE	Included	Included	Included	*Broker FE*	Included
Industry−Year FE	Included	Included	Included	*Industry−Year FE*	Included
N	221,328	95,168	205,895	*N*	72,033
Adjusted R^2	0.161	0.023	0.340	Pseudo R^2	0.411

magnitudes of the coefficients on *IC_High_Accu* exceed those on *IC_Low_Accu* for forecast accuracy, market reaction to forecast revisions, and *II* All-Star status (F-tests show that the first two differences are significant at the 0.05 and 0.01 levels, respectively). Panel B presents our comparison of the relation between analyst performance and industry connectedness with more profitable colleagues (*IC_High_Profit*) versus that with less profitable colleagues (*IC_Low_Profit*). The coefficients on *IC_High_Profit* are significantly greater than those on *IC_Low_Profit* for recommendation profitability, market reaction to forecast revisions, and *II* All-Star status (at the 0.05, 0.01, and 0.10 levels, respectively). Note that results in Panels A and B are consistent with information sharing from colleagues with more accurate earnings forecasts improving earnings forecast accuracy, and information sharing from colleagues with more profitable recommendations improving recommendation profitability. The findings align with the view that these two types of research outputs involve information of different natures (Bradshaw, 2004; Ertimur et al., 2007; Huang and Zang, 2009).

Panel C shows that the magnitudes of the coefficients on *IC_Long_Expr_Ind* (more experienced colleagues) are larger than those on *IC_Short_Expr_Ind* (less experienced colleagues) for all four analyst performance measures (significant at the 0.01 and 0.10 levels for forecast accuracy and *II* All-Star status, respectively). Finally, Panel D compares the relation between analyst performance and industry connectedness with *II* All-Star versus that with non-All-Star colleagues, using a sample of analysts who work for brokerages that employ both. The evidence is consistent with our prediction that information sharing with *II* All-Star colleagues is more effective in helping the analyst obtain *II* status, compared to sharing with non-All-Star colleagues (significant at the 0.01 level).

In sum, out of 16 specifications, *IC_High_Quality* is positive and statistically significant in 13 and *IC_Low_Quality* only in 6. Their differences are statistically significant in 8, supporting our prediction that information sharing with higher-quality colleagues is more beneficial to analyst performance than sharing with lower-quality colleagues.

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

This table reports the relation between an analyst's performance in an industry and the economic connectedness to colleagues' covered industries, conditional on colleague research quality. We estimate the OLS regressions *Accuracy* (*Rec_Profit*, *CAR*) = *f*(*IC_High_Quality*, *IC_Low_Quality*, *Control_Analyst*, *Control_Comp*) + ε in columns (1) to (3) and the Probit regression *Star* = *f*(*IC_High_Quality*, *IC_Low_Quality*, *Control_Analyst*, *Control_Comp*, *Control_Star*) + ε in column (4). *IC_High_Quality* (*IC_Low_Quality*) are *IC_High_Accu* (*IC_Low_Accu*), *IC_High_Profit* (*IC_Low_Profit*), *IC_Long_Expr_Ind* (*IC_Short_Expr_Ind*), and *IC_Star* (*IC_Non_Star*) in Panels A, B, C, and D, respectively. *Control_Analyst*, *Control_Comp*, and *Control_Star* are defined in Table 3. All regressions include broker and industry−year fixed effects. *t* and *z*-stats based on standard errors 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. The variable definitions are in Appendix B.

Panel A: Colleague earnings forecast accuracy.

	(1)	(2)	(3)	(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*	*Star*
IC_High_Accu	2.4401***	0.7219	0.0037***	0.4021***
	(4.51)	(0.78)	(5.13)	(3.19)
IC_Low_Accu	0.6440	1.3808	0.0008	0.2546**
	(1.12)	(1.48)	(1.09)	(2.07)
Controls, Broker, Industry−Year FE	Included	Included	Included	Included
N	212,547	91,819	198,276	71,090
Adjusted/Pseudo R^2	0.161	0.020	0.343	0.411
F-stats of *IC_High_Accu* = *IC_Low_Accu*	**4.86****	**0.27**	**10.31*****	**1.67**

Panel B: Colleague stock recommendation profitability.

	(1)	(2)	(3)	(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*	*Star*
IC_High_Profit	1.4826***	1.7257**	0.0037***	0.2351**
	(2.72)	(2.15)	(5.14)	(2.05)
IC_Low_Profit	1.6556***	−0.3344	0.0013*	0.0583
	(3.18)	(-0.41)	(1.77)	(0.43)
Controls, Broker, Industry−Year FE	Included	Included	Included	Included
N	167,615	90,617	155,716	51,544
Adjusted/Pseudo R^2	0.168	0.017	0.296	0.429
F-stats of *IC_High_Profit* = *IC_Low_Profit*	**0.08**	**4.20****	**10.04*****	**2.72***

Panel C: Colleague industry experience.

	(1)	(2)	(3)	(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*	*Star*
IC_Long_Expr_Ind	3.0490***	1.0623	0.0028***	0.4492***
	(5.87)	(1.31)	(4.29)	(3.34)
IC_Short_Expr_Ind	0.1731	0.9868	0.0018***	0.2407**
	(0.32)	(0.98)	(2.66)	(2.00)
Controls, Broker, Industry−Year FE	Included	Included	Included	Included
N	217,046	93,500	202,076	71,806
Adjusted/Pseudo R^2	0.161	0.021	0.341	0.411
F-stats of *IC_Long_Expr_Ind* = *IC_Short_Expr_Ind*	**16.02*****	**0.00**	**1.86**	**2.71***

Panel D: Colleague All-Star status.

	(1)	(2)	(3)	(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*	*Star*
IC_Star	5.0195***	0.5457	0.0024**	1.3476***
	(4.91)	(0.29)	(2.03)	(8.57)
IC_Non_Star	3.6517***	1.1453	0.0014	−0.3376**
	(4.32)	(0.70)	(1.51)	(-2.57)
Controls, Broker, Industry−Year FE	Included	Included	Included	Included
N	94,924	39,892	87,187	42,853
Adjusted/Pseudo R^2	0.158	0.041	0.367	0.344
F-stats of *IC_Star* = *IC_Non_Star*	**2.65**	**0.12**	**0.99**	**130.41*****

4.3. Refined tests of information sharing: relation between expense/revenue forecast performance and upstream/downstream connectedness with colleagues

In this section, we refine our main tests and examine whether industry connectedness with colleagues covering upstream (downstream) industries has a more pronounced benefit on analysts' expense (revenue) forecasts. This prediction is based on the intuition that information about suppliers helps an analyst understand supply shocks and predict input costs and that information about customers helps improve understanding of demand shocks and predict revenues. These tests are more stringent tests of information sharing for two reasons. First, they require a relation between a specific type of information shared by colleagues and analyst performance in a task in which that information is most relevant. Second, they impose strict control of the selection effect by keeping constant the brokerage house, the period, the analyst, and her coverage.

To test our prediction, we divide an analyst's economic connection with colleagues (*Ind_Connect*) into the portion from colleagues' coverage of upstream industries (*IC_Upstream*, measured as her industry's total input commodities produced by colleagues' industries, scaled by her industry's total output), and the portion from colleagues' coverage of downstream industries (*IC_Downstream*, measured as her industry's total output commodities used by colleagues' industries, scaled by her industry's total output). We obtain analyst revenue forecast data from I/B/E/S. For expense forecasts, we use the difference between revenue and EBITDA forecasts, as I/B/E/S does not separately record expense forecasts. We measure an analyst's revenue and expense forecast accuracy at the industry−year level (*Accuracy_Rev* and *Accuracy_Exp*) in a similar fashion as we do for earnings forecast accuracy. We estimate a regression model similar to Eq. (1). Given that we infer analysts' expense forecasts from their revenue forecasts, we control for revenue forecast accuracy in our regression of expense forecast accuracy. Due to I/B/E/S data availability, our sample period for the revenue (expense) forecast accuracy analysis is 1996−2017 (2002−2017).

From Table 5, Column 1, we observe that the coefficient on *IC_Downstream* is positive and significant (at the 0.05 level) when the dependent variable is *Accuracy_Rev*, consistent with downstream information sharing facilitating revenue forecasting. In Column 2, the coefficient on *IC_Upstream* is positive and significant (at the 0.10 level) when the dependent variable is *Accuracy_Exp*, consistent with upstream information sharing facilitating expense forecasting. In terms of economic magnitude, a one standard deviation increase in *IC_Downstream* (0.320) and *IC_Upstream* (0.167), respectively, increases *Accuracy_Rev* and *Accuracy_Exp* by 0.598 ($= 0.320 \times 1.8682$) and 0.515 ($= 0.167 \times 3.0845$). Based on the estimated coefficients of *Horizon* in the two regressions (−0.1451 and −0.0458, respectively), these increases are equivalent to the benefit of issuing forecasts 4 and 11 days closer to the earnings announcement date ($0.598/0.1451 = 4.12$; $0.515/0.0458 = 11.24$). Equally important, the coefficient on *IC_Upstream* (*IC_Downstream*) is not significant in the regression with *Accuracy_Rev* (*Accuracy_Exp*) as the dependent variable, consistent with information sharing about upstream (downstream) industries not benefiting revenue (expense) forecasting.[22] In sum, the tests provide further support for H1 because the differential benefits of colleagues' coverage of upstream and downstream industries to the same analyst's expense and revenue forecasts cannot be explained by other brokerage resources or the selection effect.[23]

4.4. Colleague turnover and information sharing

To provide corroborating evidence and further mitigate endogeneity concerns, we exploit a setting in which an analyst experiences the joining or leaving of a colleague who covers a highly connected industry (hereafter, highly connected colleague).[24] For each such analyst, we compare her performance in a given industry in the year when the highly connected colleague is hired (*Post_Hiring* equals one) or in the year after the highly connected colleague departs (*Post_Departure* equals one) with that of the prior year. Table 6, Panel A, shows that the coefficients on *Post_Hiring* are positive and significant (at least at the 0.10 level) for *Accuracy*, *Rec_Profit*, and *CAR*, consistent with analysts benefiting from additional colleagues who cover economically important industries.[25] In Panel B, the coefficients on *Post_Departure* are negative and significant (at the 0.01 level) for *Accuracy* and *Rec_Profit*, consistent with analyst performance declining when these colleagues leave.[26] In sum, the results of colleague turnover analyses further alleviate the concern that endogeneity drives our main results.

4.5. Timing of earnings forecast revisions among highly connected colleagues

Because we cannot observe private communications among colleagues, we provide an alternative research design based on a more direct outcome of information sharing. We predict that when an analyst's highly connected colleague (as defined in

[22] In a sensitivity test, we use the coverage of upstream and downstream industries by All-Star colleagues and find similar results as those in Table 5, but with larger magnitudes for the coefficients, which is consistent with information sharing from higher-quality colleagues having a stronger impact (untabulated).

[23] Compared with the results in Column 1 of Table 3, *NInd*, *NComp_Ind*, *MTB*, and *ROA* become insignificant in Table 5 and *Freq* becomes negative and significant in the expense forecast sample. We investigate the source of the discrepancy with several untabulated tests. First, we re-estimate the *Accuracy* regression using the sample periods with available information to calculate revenue and expense forecast accuracy (1996−2017 and 2002−2017, respectively) and find results largely similar to Table 3, suggesting that the sample period is not the primary reason for the insignificant control variables in Table 5. Next, we re-estimate the *Accuracy* regression using the samples in Table 5 and find insignificant coefficients on *NInd*, *NComp_Ind*, and *Freq*, consistent with sample differences (i.e., all analyst−industry−years in Table 3 versus analyst−industry−years with revenue and expense forecasts in Table 5) accounting for most of the discrepancy. Finally, when we change the dependent variable of Eq. (1) from *Accuracy* to *Accuracy_Rev* and *Accuracy_Exp* and estimate the model using the samples in Table 5, *ROA* becomes insignificant, consistent with the change in *ROA*'s coefficients being driven by changes in the dependent variables.

[24] We define a highly connected industry as one whose level of *Importance* to an analyst's covered industry equals or exceeds the sample median (0.4%). If an analyst has more than one such colleague, we select the one who covers the industry with the highest level of *Importance* to the analyst's industry. In the final sample, the mean (median) of *Importance* of the highly connected industries is 9.4% (6.9%).

[25] The control variables are the same as those in Eq. (1). For brevity, we report only the main variables in Table 6.

[26] In a sensitivity test, we focus on turnovers of highly connected All-Star colleagues and find stronger results than those reported in Table 6 (untabulated), consistent with the greater impact of higher-quality colleagues. For example, *Post_Hiring* becomes significantly positive (at the 5% level) in the *Star* regression.

Table 5
Upstream and Downstream Industry Information Sharing and Forecast Accuracy.
This table reports the relation between an analyst's revenue and expense forecast accuracy in an industry and the upstream and downstream economic connectedness to industries covered by colleagues. We estimate the OLS regressions $Accuracy\_Rev = f(IC\_Upstream, IC\_Downstream, Control\_Analyst, Control\_Comp) + \varepsilon$ in column (1) and $Accuracy\_Exp = f(IC\_Upstream, IC\_Downstream, Control\_Analyst, Control\_Comp, Accuracy\_Rev) + \varepsilon$ in column (2). *Control_Analyst* and *Control_Comp* are defined in Table 3. Both regressions include broker and industry−year fixed effects. The *t*-stats based on standard errors 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. The variable definitions are in Appendix B.

	(1)	(2)
Dependent Variables	*Accuracy_Rev*	*Accuracy_Exp*
IC_Upstream	**−0.3634**	**3.0845***
	(-0.24)	**(1.69)**
IC_Downstream	**1.8682****	**1.4429**
	(2.54)	**(1.06)**
BSize	0.0157	−0.0137
	(0.83)	(-0.71)
Expr_Ind	−0.0219	−0.0268
	(-0.51)	(-0.51)
NInd	−0.0581	0.0457
	(-0.67)	(0.61)
NComp_Ind	−0.0425	0.0221
	(-0.89)	(0.31)
Freq	−0.1865	−0.2415*
	(-1.53)	(-1.82)
Horizon	−0.1451***	−0.0458***
	(-32.08)	(-9.33)
MV	−0.3864***	−0.0394
	(-3.15)	(-0.34)
MTB	−0.0265	−0.0366
	(-0.93)	(-1.60)
ROA	−4.3374	−2.4652
	(-1.55)	(-1.54)
Loss	−0.5055*	−0.1684
	(-1.80)	(-0.24)
Accuracy_Rev		0.4470***
		(16.04)
Broker FE	Included	Included
Industry−Year FE	Included	Included
N	50,180	32,282
Adjusted R^2	0.124	0.202

Section 4.4) issues a forecast revision, presumably due to the arrival of new information, that analyst is more likely to issue a forecast revision around the same time, compared with another analyst who does not have a highly connected colleague. To test this prediction, we match analysts who cover *the same company in the same year*, wherein one analyst has a highly connected colleague (referred to as the connected analyst; *Connected* equals one) and another analyst does not have such a colleague (referred to as the non-connected analyst; *Connected* equals zero).[27] We identify the information events as all earnings forecast revisions issued by the highly connected colleague for this colleague's largest covered company in the year. The dependent variable *Revision* equals one if the connected analyst (or the non-connected analyst used as the control) issues a forecast revision in the $[-1, 1]$ window of the event date (information events are defined as above), and zero otherwise. We use the following pooled OLS regression:

$$Revision = \alpha + \beta \cdot Connected + \sum \gamma Control\_Revision + Broker\ FE + Industry\_Year\ FE + \varepsilon. \quad (2)$$

In addition to *BSize*, *Expr_Ind*, *NInd*, and *NComp_Ind*, we control for the number of earnings forecasts issued by the connected (or non-connected) analyst (*Revision_Freq*) and the number of days between the event date and the earnings announcement date (*Revision_Horizon*) for the company in the year.

In Table 7, Column 1, the results show a significantly positive coefficient on *Connected* (at the 0.01 level). The coefficient's magnitude indicates that around the date that a highly connected colleague issues a forecast revision, the connected analyst is 27.7% more likely to issue a forecast revision than the non-connected analyst (6.68% compared to the unconditional

[27] We focus on each analyst's main industry in the year. To ensure that the connected and non-connected analysts are comparable in other dimensions, any differences in broker size and industry experience must be less than the corresponding medians (four analysts and two years, respectively) and neither analyst covers the industry covered by the highly connected colleague. For multiple non-connected analysts matched to a connected analyst, we select the one most similar to the connected analyst in terms of broker size, industry experience, and total market value of covered companies, in this order.

Table 6
Turnovers of Colleagues Covering Highly Connected Industries and Analyst Performance.

Panel A (B) reports the change in an analyst's performance in an industry from before to after the hiring (departure) of a colleague who covers a highly connected industry not covered by other colleagues (i.e., one with a level of *Importance* greater than or equal to the sample median of 0.4%). If an analyst has more than one such colleague, we select the one who covers the industry with the highest level of *Importance* to her industry. We re-estimate the regressions in Table 3, replacing *Ind_Connect* with *Post_Hiring* (*Post_Departure*) in Panel A (B). In Panel A (B), the sample includes the year of the hiring (departure) of a highly connected colleague and the prior (subsequent) year. All regressions include broker and industry−year fixed effects. The *t*-stats based on standard errors 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. The variable definitions are in Appendix B.

Panel A: Hiring of colleagues covering highly connected industries.

	(1)	(2)	(3)	(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*	*Star*
Post_Hiring	0.6074*	0.5152*	0.0011***	0.0007
	(1.67)	(1.94)	(2.77)	(0.08)
Controls, Broker, Industry−Year FE	Included	Included	Included	Included
N	14,223	7,224	14,026	4,796
Adjusted R^2	0.098	0.033	0.414	0.360

Panel B: Departure of colleagues covering highly connected industries

	(1)	(2)	(3)	(4)
Dependent Variables	*Accuracy*	*Rec_Profit*	*CAR*	*Star*
Post_Departure	−2.0596***	−1.8224***	0.0006	0.0185
	(-6.48)	(-3.28)	(1.00)	(1.47)
Controls, Broker, Industry−Year FE	Included	Included	Included	Included
N	11,818	5,222	11,283	3,941
Adjusted R^2	0.186	0.054	0.415	0.449

probability of 24.1%).[28] This finding provides corroborating evidence consistent with information sharing among connected colleagues.

To mitigate the concern that the results are driven by other differences between the connected and non-connected analysts, such as competence, we conduct two sets of falsification tests using alternative event dates. First, we use 45 days before or after the highly connected colleague's forecast revision date. Second, we use the forecast revision date of the connected analyst's non-colleague (i.e., an analyst who covers the same industry as the highly connected colleague but who works for another brokerage).[29] In Table 7, Columns 2−5, we find insignificant coefficients on *Connected* in all falsification tests, further supporting our prediction that information sharing explains the co-issuance of forecast revisions among connected colleagues.

4.6. Information sharing and analyst industry specialization

One explanation for our main finding of improved performance among analysts whose colleagues cover more economically connected industries is that these analysts can focus on their main industries and rely on colleagues for supplementary and relevant information from economically connected industries. In this section, we empirically test whether an analyst has a higher level of industry specialization in coverage portfolio when her colleagues cover industries that are more economically connected to her main industry.[30] To measure industry specialization in analysts' coverage, we follow Sonney (2009) and use the Herfindahl−Hirschman Index, calculated as the sum of the squared percentage of coverage share of each industry, with coverage share based on either the number of covered companies (*HHI_NComp*) or covered market cap (*HHI_MV*). That is, for analyst *l* in year *t*, $HHI\_NComp_{l,t} = \sum_i \left(\frac{NComp\_Ind_{l,i,t}}{NComp\_Total_{l,t}}\right)^2$ and $HHI\_MV_{l,t} = \sum_i \left(\frac{MV_{l,i,t}}{MV_{l,t}}\right)^2$, where *i* denotes each industry she

[28] An alternative explanation for the result is that the analyst and her highly connected colleague obtain information from attending a private event that excludes analysts from other brokerage houses, such as brokerage-hosted conferences (Green et al., 2014). To rule out this explanation, we exclude forecast revisions issued within one day of any brokerage-hosted conference that the covered company attends (conference dates are obtained from the Compustat Capital IQ Key Development database). Public information events, such as earnings conference calls, are unlikely to drive our results because all analysts have access to such events.

[29] When there are multiple non-colleagues, we select either the one with the longest industry experience and largest market cap coverage in that industry (a lead analyst, reported in Column 4) or the one with the most similar broker size, industry experience, and market cap coverage as the highly connected colleague (a similar analyst, reported in Column 5).

[30] Note that having colleagues covering economically related industries does not preclude the analyst from covering other companies in those industries. In nearly half (48.2%) of our sample of 57,975 analyst−year observations, the analyst covers at least one non-main industry that is also covered by her colleagues. In a sensitivity test, we investigate whether *Ind_Connect* is associated with analyst *l*'s tendency of covering the most important upstream or downstream companies to the companies she covers in her main industry. We define these important companies either as major customers or suppliers of the companies in her main industry or as large companies (above the industry−year mean or in the top decile in terms of market cap) in the most important upstream or downstream industry to her main industry. We do not find any significant association (untabulated).

Table 7
Colleagues Covering Highly Connected Industries and Co-Occurrence of Analyst Forecast Revisions.
This table reports the relation between whether an analyst has a highly connected colleague and her issuing a forecast revision within [-1, +1] of the event date. In column (1), the event date is the day that the analyst's or matched analyst's highly connected colleague issues a forecast revision. Each pair of observations (one for the connected analyst and one for the non-connected analyst) corresponds to an earnings forecast revision issued by the highly connected colleague for this colleague's largest covered company in the year. In columns (2) and (3), the event dates are 45 days before and after the event date in column (1), respectively. In column (4), the event date is the day that the lead non-colleague analyst in the highly connected colleague's industry issues a forecast revision. The lead analyst is the one covering the largest market cap and with the longest experience in the industry. In column (5), the event date is the day that a non-colleague analyst similar to the analyst's highly connected colleague issues a forecast revision. The similar analyst is the one with the closest broker size, industry experience, and total covered market cap. We estimate the OLS regression $Revision = f(Connected, Control\_Revision) + \varepsilon$. *Control_Revision* includes *BSize*, *Expr_Ind*, *NInd*, *NComp_Ind*, *Revision_Freq*, and *Revision_Horizon*. All regressions include broker and industry−year fixed effects. The *t*-stats based on standard errors 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. The variable definitions are in Appendix B.

	Main test:	Falsification tests:			
Event Date=	Connected colleague's revision date	Connected colleague's revision date − 45 days	Connected colleague's revision date +45 days	A non-colleague *lead* analyst's revision date	A non-colleague *similar* analyst's revision date
	(1)	(2)	(3)	(4)	(5)
Dependent Variable			*Revision*		
Connected	**0.0668*****	**−0.0023**	**−0.0073**	**−0.0044**	**0.0039**
	(7.41)	**(-0.44)**	**(-1.26)**	**(-0.76)**	**(0.40)**
BSize	−0.0002	0.0000	0.0002	−0.0004	−0.0002
	(-0.67)	(0.25)	(1.16)	(-1.30)	(-0.37)
Expr_Ind	0.0005	−0.0002	−0.0035***	0.0034**	−0.0019
	(0.36)	(-0.14)	(-2.67)	(2.35)	(-0.91)
NInd	0.0025	0.0001	0.0016	−0.0003	0.0023
	(1.34)	(0.06)	(1.24)	(-0.18)	(0.70)
NComp_Ind	−0.0016	0.0009	0.0016	0.0003	0.0013
	(-1.09)	(0.57)	(1.03)	(0.22)	(0.70)
Revision_Freq	0.0456***	0.0196***	0.0206***	0.0439***	0.0389***
	(25.49)	(14.59)	(12.60)	(21.06)	(10.68)
Revision_Horizon	0.0000	−0.0000***	0.0000***	0.0000	−0.0000
	(0.52)	(-2.90)	(4.86)	(0.61)	(-1.43)
Broker, Industry−Year FE	Included	Included	Included	Included	Included
N	151,330	151,330	151,330	148,908	29,700
Adjusted R^2	0.195	0.211	0.215	0.207	0.258

covers. A higher value of *HHI_NComp* or *HHI_MV* indicates that the analyst is more concentrated (i.e., more specialized) in her industry coverage.

We use the following pooled OLS regression at the analyst−year level:

$$HHI\_NComp(HHI\_MV) = \alpha + \beta \cdot Ind\_Connect + \gamma_1 BSize + \gamma_2 Expr\_Gen + Broker\ FE + Industry\_Year\ FE + \varepsilon. \quad (3)$$

For each analyst−year, we use the *Ind_Connect* of the analyst's main industry from the prior year to allow the analyst to optimize coverage based on colleagues' coverage in the prior year.[31, 32] We expect the coefficient on *Ind_Connect* to be positive. Following the literature (e.g., Kini et al., 2009), we control for factors that might be correlated with the analyst's industry specialization, such as broker size (*BSize*) and general experience (*Expr_Gen*). We also include broker fixed effects to control for other brokerage resources and industry−year fixed effects to control for time-varying industry-specific differences, such as total market cap of the analyst's main industry and level of self-reliance (i.e., how much the industry uses its own outputs as inputs), both of which capture the importance of the industry to the analyst.[33]

In Table 8, Columns 1 and 2, the coefficients on *Ind_Connect* are positive and significant (at the 0.01 and 0.05 levels) for *HHI_NComp* and *HHI_MV*, respectively. These results are consistent with the argument that when analysts have access to information about economically connected industries from colleagues, they maintain a more focused portfolio in terms of industry coverage, which in turn contributes to their improved performance.

[31] In a sensitivity test, we use contemporaneous *Ind_Connect* and find consistent results, that is, industry specialization is significantly and positively associated with information sharing with colleagues (untabulated).

[32] It is possible that analysts select which industries to cover based on potential information sharing from colleagues, which introduces a sample selection bias to our main analyses in Table 3. To mitigate this potential endogeneity, we use the two-stage Heckman procedure in a sensitivity test. In the first stage, we estimate a probit regression model to model whether an analyst covers an industry during the year. We then re-estimate Eq. (1), incorporating the inverse Mills ratio from the first stage. The results are similar to those of our main regressions (untabulated).

[33] We do not include control variables (e.g., market cap, profitability, market-to-book) associated with analysts' covered companies or those measuring analysts' research outputs (e.g., forecast frequency and horizon) because analysts likely make these decisions after their industry coverage decision.

Table 8
Information Sharing and Analyst Industry Specialization.
This table reports the relation between an analyst's industry specialization and the economic connectedness among her main industry and the industries covered by colleagues. We estimate the OLS regressions $HHI\_NComp(HHI\_MV) = f(Ind\_Connect,\ BSize, Expr\_Gen) + \varepsilon$ in columns (1) and (2). All independent variables are based on lagged values. Both regressions include broker and industry−year fixed effects. The *t*-stats based on standard errors 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. The variable definitions are in Appendix B.

	(1)	(2)
Dependent Variables	*HHI_NComp*	*HHI_MV*
Ind_Connect	**0.0282***	**0.0153**
	(2.98)	**(2.03)**
BSize	0.0002*	0.0002*
	(1.72)	(1.90)
Expr_Gen	−0.0073***	−0.0052***
	(-16.82)	(-14.06)
Broker FE	Included	Included
Industry−Year FE	Included	Included
N	57,975	57,975
Adjusted R^2	0.363	0.340

5. Conclusion

Most studies on financial analysts consider them as isolated units of information acquisition and production and view their performance and reputation as personal and portable. In contrast, research in the economics of organizations typically treats employee performance as a property of the worker−firm combination. We address this disparity by providing evidence that organizational resources contribute to analyst performance. Specifically, we examine a knowledge asset in brokerage houses: information sharing among analyst colleagues who cover economically related industries along a supply chain.

We predict that the value of this knowledge asset to individual analysts depends on the level of their information complementarity. We measure this complementarity as the economic connectedness between the industry covered by an analyst and those covered by her colleagues, measured using BEA Benchmark Input−Output data. After controlling for broker fixed effects and other determinants of analyst performance, we find that analysts issue more accurate earnings forecasts, provide more profitable stock recommendations, trigger greater investor reaction with earnings forecast revisions, and are more likely to be ranked as an *II* All-Star when the economic connectedness between their covered industries and those of colleagues is stronger. Cross-sectionally, we show that the positive relation between analyst performance and economic connection with colleagues is stronger when colleagues are of higher-quality.

To reinforce the main finding, we separate economic connection with colleagues into upstream and downstream connectedness and find evidence consistent with analysts' revenue (expense) forecasts benefiting from downstream (upstream) connectedness with colleagues. This test provides more stringent controls for the selection effect of the brokerage by holding constant the brokerage house, the period, the analyst, and her coverage. Exploiting a setting of colleague turnover, we find that analyst performance improves (deteriorates) after a colleague who covers a highly connected industry joins (departs) the brokerage house, which further alleviates endogeneity concerns.

Last, we perform two analyses to provide additional insights. The first one shows that an analyst is more likely to revise earnings forecasts when a highly connected colleague does so, compared to another analyst who does not have such a colleague, which is consistent with a more direct outcome of information sharing, thus corroborating our main findings. The second one shows that an analyst has a higher level of industry specialization when her colleagues cover industries that are more economically connected to her main industry, consistent with the intuition that having access to complementary information of related industries through colleagues helps analysts focus on their main industries.

Our study extends the literature by identifying a specific organizational resource that contributes to analyst performance. It also broadens understanding of analysts' role as an information intermediary by revealing that as industry specialists, analysts can facilitate information flows across industries by collaborating with colleagues. Our findings have pragmatic implications for brokerage houses and other knowledge-intensive firms. By encouraging information sharing among employees, such firms can create competitive advantages that benefit employee performance and help firms retain talent because their employee performance and reputation will be less portable to other employers.

Acknowledgment

We thank Robert Holthausen (editor), Mark Bradshaw (referee), Kun-Chih Chen, Peter Chen, Shuping Chen, Peter Joos, Lin Lin, Shuli Ren, Jenny Tucker, Mohan Venkatachalam, Jin Xie, Haifeng You, and Tianyu Zhang; workshop participants at the CUHK Shenzhen, HKUST, National Tsing Hua University, Zhongnan University of Economics and Law, and University of Southampton; and attendees of the AAA Annual Meeting and Taiwan Accounting Association Annual Meeting for their comments. Any errors are our own. Allen Huang gratefully acknowledges financial support from a grant from the Research

Grants Council of the HKSAR, China (Project No., HKUST 16504115). An earlier version of this paper was titled, “Cross-Industry Information Sharing and Analyst Performance.”

Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jacceco.2022.101496.

Appendix A

Illustration of Industry Connectedness Between an Analyst Covering the “Paper Products” Industry and the Analyst's Colleagues.

This appendix provides an example of the measurement of industry connection (Ind_Connect) between a Bear Stearns analyst covering the “paper products” industry in 1991 and 33 colleagues covering 26 unique industries in the same year. The analyst's Ind_Connect (0.659) is the sum of Importance of colleagues' 26 industries to the “paper products” industry in 1991 (column (3)). The upstream and downstream industry connections between the analyst and colleagues (IC_Upstream of 0.246 and IC_Downstream of 0.412) are the sum of Upstream_Importance (column (1)) and Downstream_Importance (column (2)), respectively, of the 26 industries covered by colleagues to the “paper products” industry in 1991. Industry definitions are from Bureau of Economic Analysis. Appendix B provides variable definitions.

Colleagues' Covered Industries	(1) *Upstream Importance*	(2) *Downstream Importance*	(3) *Importance*
Chemical products	0.071	0.045	0.116
Food and beverage and tobacco products	0.005	0.106	0.111
Wholesale trade	0.050	0.037	0.087
Publishing industries, except internet (includes software)	0.001	0.055	0.056
Plastics and rubber products	0.027	0.020	0.047
Retail trade	0.008	0.037	0.045
Utilities	0.027	0.001	0.029
Administrative and support services	0.006	0.013	0.019
Food services and drinking places	0.002	0.014	0.016
Fabricated metal products	0.007	0.009	0.016
Nonmetallic mineral products	0.002	0.013	0.015
Federal Reserve banks, credit intermediation, related activities	0.009	0.005	0.014
Miscellaneous manufacturing	0.001	0.013	0.014
Machinery	0.006	0.007	0.013
Farms	0.003	0.009	0.012
Computer and electronic products	0.001	0.011	0.012
Petroleum and coal products	0.009	0.002	0.011
Furniture and related products	0.000	0.007	0.007
Primary metals	0.004	0.001	0.005
Insurance carriers and related activities	0.002	0.001	0.004
Broadcasting and telecommunications	0.002	0.002	0.004
Air transportation	0.003	0.000	0.003
Amusements, gambling, recreation industries	0.000	0.001	0.001
Data processing, internet publishing, other information services	0.000	0.001	0.001
Other transportation equipment	0.000	0.001	0.001
Oil and gas extraction	0.000	0.000	0.000
	IC_Uptream	*IC_Downstream*	*Ind_Connect*
Total	**0.246**	**0.412**	**0.659**

Appendix B

Variable Definitions.

Industry—pair—year level variables:	
$Importance_{i,j,t}$	The importance of industry j to industry i in year t, calculated as the ratio of the sum of i's input commodities produced by j and i's output commodities used by j to i's total output. That is, $Importance_{i,j,t} = \frac{\sum_k \left(\begin{array}{c} \text{Commodity k used by i} \times \% \text{ of Commodity k produced by j} + \\ \text{Commodity k used by j} \times \% \text{ of Commodity k produced by i} \end{array} \right)}{\text{Total output of i}}$
$Upstream\_Importance_{i,i,t}$	The upstream importance of industry j to industry i in year t, calculated as the ratio of the sum of i's input commodities produced by j to i's total output. That is, $Upstream\_Importance_{i,j,t} = \frac{\sum_k (\text{Commodity k used by i} \times \% \text{ of Commodity k produced by j})}{\text{Total output of i}}$
$Downstream\_Importance_{i,i,t}$	The downstream importance of industry j to industry i in year t, calculated as the ratio of the sum of i's output commodities used by j to i's total output. That is, $Downstream\_Importance_{i,j,t} = \frac{\sum_k (\text{Commodity k used by j} \times \% \text{ of Commodity k produced by i})}{\text{Total output of i}}$

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*.
$IC\_Upstream_{l,i,t}$	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*.
$IC\_Downstream_{l,i,t}$	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*.
$Accuracy_{l,i,t}$	The average relative earnings forecast accuracy of analyst *l* in industry *i* in year *t*. First, earnings forecast error is calculated as the absolute value of the difference between the last forecasted earnings per share issued at least one month prior to the fiscal year end and the actual earnings per share; next, forecast errors of all analysts following the same company are ranked and normalized such that the most (least) accurate analyst receives a normalized rank of 100 (0) (i.e., $100-\left[\frac{Rank\_FE-1}{Number\ of\ Analysts-1}\right]\times 100$, where *Number of Analysts* is the number of analysts who issue earnings forecasts for the company in the year and *Rank_FE* is the ranking of the earnings forecast error); last, we take the average of analyst *l*'s normalized ranks across all companies covered in industry *i* in 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) recommendation, where the return window is [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 and normalized such that the most (least) profitable analyst receives a normalized rank of 100 (0); last, we take the average of analyst *l*'s normalized ranks across all covered companies in industry *i* in year *t*.
$CAR_{l,i,t}$	The average market reaction to the earnings forecast revisions issued by analyst *l* for companies in industry *i* in year *t*. The market reaction to each forecast revision is measured as the absolute cumulative three-day market-adjusted return centered on the analyst's earnings forecast revision date.
$Accuracy\_Rev_{l,i,t}$	The average relative revenue forecast accuracy of analyst *l* in industry *i* in year *t*. First, revenue forecast error is calculated as the absolute value of the difference between the last forecasted revenue issued at least one month prior to the fiscal year end and the actual revenue; then, we follow the same normalization process as for $Accuracy_{l,i,t}$ and take the average of analyst *l*'s normalized ranks across all covered companies in industry *i* in year *t*.
$Accuracy\_\mathrm{Exp}_{l,i,t}$	The average relative expense forecast accuracy of analyst *l* in industry *i* in year *t*. First, we infer analyst *l*'s expense forecast by last revenue forecast minus EBITDA forecast (both issued at least one month prior to the fiscal year end) and then calculate expense forecast error by comparing with actual revenue minus actual EBITDA; then, we follow the same normalization process as for $Accuracy_{l,i,t}$ and take the average of her normalized ranks across all of the companies she covers in industry *i* in year *t*.
$IC\_High\ \_Accu_{l,i,t}$ $IC\_High\_Profit_{l,i,t}$ $IC\_Long\_Expr\_Ind_{l,i,t}$	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*, or (3) *Expr_Ind*, respectively.
$IC\_Low\_Accu_{l,i,t}$ $IC\_Low\_Profit_{l,i,t}$ $IC\_Short\_Expr\_Ind_{l,i,t}$	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*, or (3) *Expr_Ind*, respectively.
$IC\_Star_{l,i,t}$ $IC\_Non\_Star_{l,i,t}$	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 are (or are not) *Institutional Investor* All-Stars in year *t*, respectively.
$Post\_Hiring_{l,i,t}$	An indicator variable that equals one for the year of hiring a colleague who covers a highly connected industry that was not covered by any colleague of analyst *l* in the previous year. A highly connected industry is one with an above median *Importance* (0.4%) to the industry covered by analyst *l*.
$Post\_Departure_{l,i,t}$	An indicator variable that equals one for the year following the departure of a colleague who covered a highly connected industry that was not covered by any other colleague of analyst *l*. A highly connected industry is one with an above median *Importance* (0.4%) to the industry covered by analyst *l*.
$Expr\_Ind_{l,i,t}$	The number of years of following industry *i* for analyst *l* in year *t*.
$NComp\_Ind_{l,i,t}$	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.
$Loss_{l,i,t}$	The percentage of companies followed by analyst *l* in industry *i* that report a loss (i.e., negative income before extraordinary items) in year *t*.

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 first, second, or third team, or a runner-up in year *t* and zero otherwise.
$Post\_Hiring_{l,t}$	An indicator variable that equals one for the year of hiring a colleague who covers a highly connected industry that was not covered by any colleague of analyst *l* in the previous year. A highly connected industry is one with an above median *Importance* (0.4%) to the industry with the largest market cap covered by analyst *l*.
$Post\_Departure_{l,t}$	An indicator variable that equals one for the year following the departure of a colleague who covered a highly connected industry that was not covered by any other colleague of analyst *l*. A highly connected industry is one with an above median *Importance* (0.4%) to the industry with the largest market cap covered by analyst *l*.
$HHI\_NComp_{l,t}$	The Herfindahl-Hirschman Index calculated as the sum of the squared percentage, where the percentage is the number of companies followed in an industry over the total number of companies followed by analyst *l* in year *t*.

$HHI\_MV_{l,t}$	The Herfindahl-Hirschman Index calculated as the sum of the squared percentage, where the percentage is the market cap of companies followed in an industry over the total market cap of companies followed by analyst *l* in year *t*.
$BSize_{l,t}$	The number of analysts working at analyst *l*'s brokerage house in year *t*.
$Expr\_Ind_{l,t}$	The value of $Expr\_Ind_{l,i,t}$ where industry *i* is the industry with the largest market cap covered by analyst *l* in year *t*.
$Expr\_Gen_{l,t}$	The number of years since analyst *l* first issued an earnings forecast in I/B/E/S.
$NInd_{l,t}$	The number of industries followed by analyst *l* in year *t*.
$NComp\_Total_{l,t}$	The total number of companies followed by analyst *l* in year *t*.
$Freq_{l,t}$	The total 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*.
$Loss_{l,t}$	The percentage of companies followed by analyst *l* that report a loss (i.e., negative income before extraordinary items) in year *t*.
$Accuracy_{l,t}$	The average relative earnings forecast accuracy of analyst *l* in year *t*. Similar to $Accuracy_{l,i,t}$, the forecast errors of all analysts following the same company are calculated, ranked and normalized; then, we take the average of analyst *l*'s normalized ranks across all covered companies in year *t*.
$Optimism_{l,t}$	The average company-level optimism dummy variable for analyst *l* in year *t*. First, the optimism dummy variable equals one when analyst *l*'s last earnings forecast for the company is greater than the consensus forecast of all other analysts following the same company and zero otherwise; next, we take the average of the optimism dummies across all companies analyst *l* covers in year *t*.
$Bold_{l,t}$	The average of the normalized ranks of the forecast deviation for analyst *l* in year *t*. 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 and normalized such that the boldest analyst receives a normalized rank of 100 and the least bold analyst receives a rank of 0; last, we take the average of analyst *l*'s normalized ranks across all covered companies in year *t*.
Variables used in the earnings forecast revision co-occurrence test:	
$Connected_{l,t}$	An indicator variable that equals one if analyst *l* has a colleague who covers a highly connected industry in year *t* and zero otherwise. A highly connected industry is one with an above median *Importance* (0.4%) to the industry with the largest market cap covered by analyst *l*.
Revision	An indicator variable that equals one if the analyst issues an earnings forecast for the common covered company in the [-1, 1] window of the event date and zero otherwise. Common covered companies are ones covered by both connected and non-connected analysts. The event date is the day that the analyst's or matched analyst's highly connected colleague issues a forecast revision.
$Revision\_Freq_{l,t}$	The number of earnings forecasts issued by analyst *l* for the common covered company in year *t*.
Revision_Horizon	The number of days between the event date and the earnings announcement date for the common covered company.

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