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Peer-Level Analyst Transitions

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ABSTRACT

This study examines the effect of peer-level analyst transitions (i.e., switching between brokerage houses) on associated *regular incumbent analysts'* forecasting performance. We employ a difference-in-differences research design with *analyst fixed effects* and compare incumbent analysts of different groups within the *same broker* and *same time* periods. We find that incumbents who cover at least one common industry as the transiting analyst (i.e., affected incumbents) issue more accurate and timely forecasts after a transiting analyst arrives than incumbents who cover different industries (i.e., unaffected incumbents). Further, affected incumbents issue less accurate forecasts after a transiting analyst leaves than do unaffected incumbents. We also examine potential mechanisms of knowledge spillover and find some evidence that the effect is more salient when the transiting analyst switches from a larger brokerage house, has greater industry scope, or covers geographically linked firms.

Keywords: Peer-level analyst transitions; Peer Effects; Lateral knowledge sharing; Within-firm research design

Peer-Level Analyst Transitions

1. Introduction

Relying on peer-effects theory in the labor economics and management literatures, we examine whether peer effects exist among regular (non-star) sell-side financial analysts, who represent the majority of employees in the sell-side industry (Mas and Moretti 2009; Chan, Li, and Pierce 2014). Research in organizational behavior and applied psychology research suggests that *lateral relationships* are linked to important individual employee outcomes (e.g., Chiaburu and Harrison 2008; Kim and Yun 2015). Individual peer-based learning is a foundation of both organizational learning curves and knowledge spillovers across firms. In addition, as shown by Haesebrouck, Cools, and Van den Abbeele (2018), individual incentives can motivate knowledge sharing among equal-status groups but cannot overcome the negative effects that arise with status differences. The contributions of higher-status individuals are often given too much weight while those of lower-status individuals are often overlooked. Similarly, the all-star analyst is recognized as having a superior social status in the sell-side analyst labor market. To address the issues of status differences among analysts, in this study we focus on the effect of non-star analyst transitions on their equal-status counterparties – non-star incumbent analysts.

Furthermore, it is perhaps not surprising that incumbents will be significantly influenced by all-star analyst transitions because all-star analysts act as their role models. In contrast, knowledge spillover between regular analysts remains an empirical question. It is also interesting to examine whether regular transiting analysts possess valuable information to their peers – regular incumbent analysts. First, a transiting analyst may only exert a trivial impact on incumbents if she is not a "star." Second, regular transiting analysts may not necessarily share knowledge with incumbents due to competition concerns. Research shows that analysts involve in intra-firm tournaments, where analysts employed by the same brokerage house may compete for internal promotion opportunities (Yin and Zhang 2014).

As pointed out by Hasan and Koning (2019), an essential driver of peer effects identified in the literature is spatial proximity to coworkers and peers who may possess diverse knowledge or skills. While the magnitude of these effects differs across contexts, proximate peers rather than distant ones are more likely to shape performance. Consistent with this argument, we make use of the fact that analysts are industry experts to measure proximity among regular analysts. Knowledge sharing is more likely to occur if two analysts share common industry coverage. Intuitively, an analyst covering the technology industry is more likely to gain relevant industry knowledge from a colleague who covers the same industry than from a colleague who covers a completely different industry.

Different from all-star analysts who may impact a larger group of incumbents in the brokerage, regular analysts are more likely to influence a smaller group of coworkers who interact with them. Accordingly, we compare the performance of incumbent analysts who cover at least one of the same industries as the transiting analyst (hereafter, "affected incumbent analysts") with the performance of those who have no overlapping industry coverage as the transiting analyst (hereafter, "unaffected incumbent analysts"). By comparing the incumbents of different groups *within the same broker* (and for the *same time periods*), we mitigate the possibility that structural or cultural changes at the broker level lead to general performance differences in incumbents employed at different brokers. We define an analyst transition as the case where the transiting analyst leaves employment at one brokerage house and finds employment at another brokerage house. This requirement addresses the issue that the transiting analyst could be a rookie analyst without sell-side industry experience, or that the turnover decision is involuntary.[1] Additionally, this definition ensures that a transiting analyst comes from the sell-side industry rather than a different industry (e.g. corporate firms, credit-rating agencies, or banks), which satisfies our "transitions within sell-side industry" requirement.

Focusing on regular analysts offers us a clear distinction from Do and Zhang (2020) who examine the turnover of *all-star* analysts. They compare the performance of incumbents in brokers that experience the turnover of all-star analysts with that of incumbents in brokers that do not experience all-star turnovers. However, it is challenging to distinguish the peer effects by all-star analysts from performance differences among incumbents from different brokers. All-star analysts' transitions usually cluster in larger brokerage houses. In contrast, we focus on regular analysts who transit between brokers across different sizes. We document that regular analyst transitions do *not* have a significant impact on *unaffected* incumbents. We also complement their empirical methodology by using a DiD research design that holds the *brokerage house constant*, to directly mitigate the possibility that *unobservable broker-level characteristics* may cause performance differences in analysts from different brokers. Extending their study, we show that affected incumbent analysts can learn from non-star analysts, enhancing the generalizability of peer effects among analysts.

To make it clear, we focus on *incumbent analysts* who remain in the same brokerage house but experience changes in their peers, which arguably is an exogenous shock to their current knowledge base. As a result, the effect of a peer change can be inferred from the different performance patterns of *incumbents* before and after an analyst transition. Research on analyst turnover focuses on the antecedents and consequences of analyst transitions (e.g., Mikhail et al. 1999; Hong and Kubik 2003; Clarke, Khorana, Patel, and Rau 2007), showing

[1] Mohammad and Nathan (2008) define voluntary (involuntary) turnover when analysts leave their employment at one broker and find (do not find) employment at another broker. They find that job performance is positively (negatively) related to voluntary (involuntary) turnover.

that analysts with higher accuracy are more likely to experience favorable job turnovers. Instead of examining transiting analysts, we focus on the *transition effects on incumbent analysts who do not change employer*s. It is challenging to draw causal inferences between analyst turnover and performance from transiting analysts' perspectives because transition decisions are endogenous. Better performance may offer transiting analysts promising career changes, while job-hopping opportunities can also affect their incentives to improve performance. In other words, the transition decisions by transiting analysts are unlikely to be exogenous. Additionally, unlike studies that investigate analysts who exit the sell-side industry to covered firms (e.g., Horton, Serafeim, and Wu 2017; Lourie 2018), to the buy-side industry (e.g., Cen, Ornthanalai, and Schiller 2017; Guan, Li, Lu, and Wong 2019) or to investor relations (Hope, Huang, and Moldovan 2021), we focus on the *analyst transitions within the sell-side industry* (i.e., switches between brokers). Different types of labor markets possess various components and features, which contribute to contrasting incentives for workers. For instance, Groysberg, Healy, and Chapman (2008) show that buy-side analysts issue more optimistic and less accurate forecasts than their sell-side counterparts. One of the potential reasons for this performance difference is buy-side firms' greater retention of poorly performing analysts. Focusing on analysts who remain in the same labor market mitigates the need to control for unobservable features of labor market differences.

Incumbents can benefit from peer effects through knowledge spillover and peer pressure, between which we do not attempt to distinguish.[2] They can learn from peers even when they are not all-star analysts. Furthermore, they may feel less stressed when consulting with their peers who are more accessible as well. That is, analysts interact and communicate with their coworkers via different channels such as email communications, phone conversations, and meetings. For example, in weekly research update meetings, analysts

[2] In the economics literature, distinguishing between knowledge spillover and peer pressure is still unresolved.

covering the same sector may exchange their own opinions on relevant industry updates. Utilizing analyst transitions to examine knowledge sharing among regular analysts is consistent with the argument by Simon (1991) that an organization improves its knowledge base either by learning from its members or by ingesting new members who have knowledge the organization did not previously have. Absorbing new talents is a potential mechanism for the employer to improve knowledge sharing among employees. When a transiting analyst joins the brokerage house, she may share relevant information resources or techniques that were neglected by incumbent analysts. For example, some analysts may utilize advanced web-scraping techniques to extract sales-related statistics from on-line platforms for their covered firms in the retail industry. Incumbent analysts can benefit from lower information-acquisition costs and improve their performance when they can directly seek advice from colleagues who master the techniques better. On the flip side, incumbent analysts lose the direct learning contacts after the departure of a transiting analyst.

When a transiting analyst joins a particular broker, incumbent analysts can access knowledge that is complementary to their existing practices. Because analysts assume essential roles in collating and disseminating information, they have strong incentives to obtain knowledge from all possible resources. Coming from a different brokerage house, a transiting analyst can extend incumbents' industry knowledge by sharing valuable experience and practices in her prior employer. Furthermore, when a transiting analyst joins a new broker, she brings her own information sets to incumbents in this new broker, potentially supplementing the knowledge-sharing practices among analysts. When a transiting analyst leaves a broker, her colleagues in the old broker lose the opportunities to directly interact with her. Based on these arguments, we hypothesize that incumbent analysts will increase (decrease) performance after a transiting analyst arrives (departs).

To construct our sample, we start with quarterly earnings forecasts for U.S. firms from the I/B/E/S database over the period 1994 to 2018. To ensure that the sample is restricted to analysts with more similar statuses, we exclude all-star analysts from the sample. Incumbent analysts who do not change brokers are defined as those who remain in the same brokerage house in the current year, prior year, and the following year. We identify an analyst transition when we observe a change in the broker identifier that the analyst is associated with. We pair each transiting analyst with incumbent analysts by their current employed broker and employed year. We employ two *standardized* measures of analyst forecasting performance: accuracy and timeliness (e.g., Clement 1999; Cooper et al. 2001; Brown and Hugon 2009). If knowledge spillover between analysts directly affects their information productivity, then it is natural to examine the forecasting performance as an outcome. In other words, we employ forecasting accuracy and timeliness to determine whether analysts accumulate and analyze information to benefit information users.

Our results show that regular analyst transitions do not have a statistically significant impact on *all* analysts in a particular broker on average.[3] Instead, transiting analysts affect incumbents of *different groups in the same broker* in different ways. Specifically, we find that *affected* incumbents issue more accurate and timely forecasts than unaffected incumbents after a transiting analyst arrives. Similarly, affected incumbent analysts issue less accurate but not less timely forecasts than unaffected incumbents after an analyst departs.[4] The findings indicate that affected incumbent analysts in the new broker obtain valuable knowledge from the transiting analyst and produce information more accurately and quickly. In other words, the

[3] This finding is different from the results in Do and Zhang (2020) who find that the arrival of an all-star analyst impacts all the analysts.

[4] One possible explanation for the different results from Do and Zhang (2020) is the significant status difference between regular analysts and all-star analysts. Incumbent analysts can continue to utilize the knowledge acquired from a role model even after a star analyst leaves. However, incumbent analysts may lose the opportunities for day-to-day interactions with their peers after a regular analyst departs. Given the differences in sample criteria and research setting, caution should be taken in making direct comparisons of the results of these two studies.

transiting analyst provides affected incumbents with incrementally new information and extends these incumbents' knowledge base. The conclusions are unaltered after controlling for available resources (broker size) and workload (number of industries and firms covered).

By focusing on regular analysts, we ensure the coworkers in the same brokerage house possess a similar social status. Motivated by prior studies on horizontal knowledge sharing, we next examine potential channels of knowledge spillover (Wang and Noe 2010). We find that when a transiting analyst switches from a larger broker to a smaller broker, she can exert a more significant impact on the affected incumbents' performance in the new broker. This finding suggests that transiting analysts possibly share their practice and experience from the larger broker to incumbents in the new broker. Moreover, we show that the knowledge spillover effect is more pronounced when transiting analysts cover multiple industries. Larger industry scope creates more knowledge-sharing opportunities for affected incumbents. For example, when a transiting analyst covers three industries, two of which share common coverage with incumbents, then incumbents can obtain knowledge about two industries rather than one industry if the transiting analyst only covers one industry. Finally, we find that the knowledge-spillover effect is more salient when transiting analysts cover geographically-linked firms as incumbents, indicating that transiting analysts may also spillover local economic knowledge to incumbents. Our inferences are robust to using *paired transiting analysts and incumbent analyst fixed effects*, which control for potential sorting mechanisms between transiting analysts and incumbent analysts. Finally, we utilize a placebo test to provide additional control for any residual endogeneity issues.

Our study offers implications for academics, practitioners, and investors. First, the paper adds to the growing literature that examines how colleagues' quality can affect analyst forecasting accuracy (e.g., Gao, Ji, and Rozenbaum 2019; Phua, Tham, and Wei 2020; Neururer and Sun 2021). Instead of relying on unidentified connections between analysts, we utilize a setting where incumbent analysts' peers change with analyst transitions. Additionally, the transition effect on incumbents' subsequent performance can be directly identified. We add to this line of literature by showing that the transition of regular analysts can impact incumbent analysts' performance.

Next, we provide a potential explanation for high turnovers in the sell-side equity analyst industry. The analyst labor market is a knowledge-intensive market, where analysts collect industry-related and firm-specific information to produce research output. While practitioners suggest that industry knowledge is perhaps the most important quality an analyst can possess and is critical to an analyst's job, there is little systematic evidence on how industry knowledge affects analyst performance, possibly because industry knowledge is inherently difficult to measure. We shed light on how analysts can transfer their industry knowledge into value-added information to peers. Affected incumbent analysts in the new (old) broker benefit (suffer) from the portable and transferrable information sets owned by the transiting analyst. There are also possible implications for brokerage-house hiring decisions. For example, brokers will potentially enjoy more benefits if they absorb new analysts who cover firms or industries related to the coverage portfolios of their incumbent analysts.

Moreover, our study extends research on the consequences of analyst job changes. Most prior studies focus on the subsequent performance of transiting analysts whose turnover decisions are endogenous (e.g., Hong and Kubik 2003; Clarke et al. 2007). It is challenging to establish a causal relation between an analyst's turnover and her subsequent performance changes. To mitigate this inherent endogeneity, later studies use broker closures or mergers to examine the impact of analyst job changes on forecasting performance (e.g., Wu and Zang 2009). However, mergers and closures of brokerage houses are rare events, while analyst transitions happen regularly. Focusing on incumbent analysts (and employing analyst, broker, and quarter fixed effects) alleviates endogeneity because the incumbents' subsequent performance is more likely to be influenced by an analyst transition instead of the other way around.

2. Related Literature and Testable Hypotheses

2.1 The Effect of Peer-Level Analyst Transitions

Marshall (1890) is among the first to recognize that social interactions among workers create learning opportunities that can enhance productivity. Since then, a line of literature has built on this idea and proposed theoretical models where human-capital externalities in the form of learning spillover are engines of economic growth (e.g., Jovanovic and Rob 1989; Glaeser 1999; Moretti 2004). In many production processes, the output is a function of the combined effort of many workers instead of a single worker. Kandel and Lazear (1992) show theoretically that the presence of peer effects mitigates the free-riding problem. Consistent with this theory, empirical studies find evidence of productivity spillovers at workplaces (e.g., Mas and Moretti 2009; Falk and Ichino 2006; Cornelissen, Dustmann, and Schonberg 2017).[5]

Peer effects are a subject of increasing attention. A growing literature examines corporate actions as a potential domain of peer effects, such as corporate financial policy (Leary and Roberts 2014), investment (Beatty, Liao, and Yu 2013), voluntary disclosures (Lin, Mao, and Wang 2017), tax-paying (Bird, Edwards, and Ruchti 2018), and restatements (Gleason, Jenkins, and Johnson 2008). Sell-side equity analysts, as sophisticated information intermediaries in the capital market, can take advantage of information commonalities by covering multiple firms in the same industry or multiple industries (Chan and Hameed 2006; Kini, Mian, Rebello, and Venkateswaran 2009). Consistent with this information efficiency,

[5] Mas and Moretti (2009) find evidence of productivity spillover in businesses. Falk and Ichino (2006) use experiments to show that peer effects raise productivity. Cornelissen, Dustmann, and Schonberg (2017) show that communication and social interaction between coworkers necessarily occur in a general workplace setting across different sectors.

research documents that analysts can facilitate information transfer between economically linked firms (Hilary and Shen 2013; Guan, Wong, and Zhang 2015).[6]

Moreover, the sell-side analyst labor market provides a unique opportunity to study peer effects and knowledge spillover. First, the analyst industry is a knowledge-intensive market where analysts collect industry-related and firm-specific information to produce research reports to investors. Second, analysts' production output can be easily quantified and is homogeneous. These attributes allow researchers to better examine the effect of peer groups on an individual analyst's behavior and performance. For example, Phua, Tham, and Wei (2020) examine whether equity analysts learn from their colleagues by identifying connections among brokerage analysts. They find that analysts who are more likely to exchange information with their in-house colleagues exhibit better forecasting performance, especially for hard-to-value stocks. Similarly, Neururer, and Sun (2021) document that spillover effects from peer analysts are large, positive, and statistically significant across economic sectors by using a model that relates mean peer-group ability along with the analyst's own innate ability to an analyst's forecast accuracy.

Social exchange theory (SET) is among the most impactful conceptual paradigms for understanding workplace behavior (Cropanzano and Mitchell 2005). Many of the important topics in organizational behavior have been examined based on SET (e.g., Cropanzano, Anthony, Daniels, and Hall 2017). SET suggests that resources are exchanged through a process of reciprocity where one party tends to repay the good or sometimes bad deeds of another party (Gouldner 1960). The social exchange process begins when an actor treats a target individual in a positive or negative fashion (Riggle, Edmondson, and Hansen 2009). Generally,

[6] Hilary and Shen (2013) find that when a firm issues a management forecast, analysts who have observed more forecasts from this firm subsequently improve their accuracy more and provide timelier earnings forecasts for other non-issuing firms in the same industry. Guan, Wong, and Zhang (2015) find that analysts who follow a covered firm's customer provide more accurate earnings forecasts for the supplier firm than analysts who do not.

a series of successful reciprocal exchanges may transform an economic exchange relationship into a high-quality social exchange relationship. Equity analysts assume essential roles in collating and disseminating information. They further have strong incentives to exchange both explicit and tacit knowledge, especially in the same brokerage house, to enhance overall information productivity. On one hand, when an actor analyst initiates a positive action or shares knowledge with a target analyst, the target analyst may tend to reply in kind by engaging in more positive reciprocating responses. For example, peer analysts can learn analytical skillsets and stock-picking techniques more quickly when they have access to peer analysts. In other words, a brokerage house can be viewed as an assembly of analysts who transmit and collect value-relevant knowledge. Moreover, mentorship programs or mandatory training sessions offer platforms for newcomers to interact with incumbents.

On the other hand, as Cropanzano, Anthony, Daniels, and Hall (2017) point out, reciprocal exchanges can occur in a negative manner. For instance, competition for annual bonuses or internal promotion opportunities among analysts within the same brokerage house may hinder knowledge sharing practices among analysts. However, the analyst-transition setting helps to alleviate this possibility. As studies suggest, employees pay special attention to coworkers' past development in relation to their own (e.g., Schaubroeck and Lam 2004; Reh, Troster, and Van Quaquebeke 2018). Transiting analysts may have lower incentives to compete with incumbent analysts when they have no prior working relationships. In other words, it is more likely than not that knowledge spillover occurs when a new analyst joins the broker. Based on these arguments, we hypothesize that incumbent analysts in the new broker learn from the transiting analyst (knowledge-spillover gain), while incumbents in the old broker lose the opportunities to learn from the transiting analyst (knowledge-spillover loss).

Next, according to studies in psychology such as Chiaburu and Harrison (2008), lateral coworkers can provide work-related resources by sharing task-relevant skills as well as knowledge, leading to improved performance of focal employees. Employees have interactions with leaders and coworkers and there is more likely to be more discretion in lateral than in vertical exchanges. Specifically, vertical relationships are governed by authority ranking as opposed to equality matching (Fiske 1992) while coworker exchanges are based on reciprocation (Gouldner 1960). Further, because of coworkers' greater presence relative to leaders in almost any organization, employees are more likely to interact more frequently with their coworkers (Ferris and Mitchell 1987). This argument is also consistent with role-sending and receiving theories, which suggest that lateral social influences on an individual's role perceptions are central (Katz and Kahn 1978). In the analyst setting, regular analysts are more likely to treat each other as lateral relationships compared with all-star analysts who often assume supervisor or leadership roles. These arguments support the idea that we focus on regular analysts as the subjects of this study.

The underlying assumption of this knowledge-sharing process is that the transiting analyst shares value-added information with incumbents. Hasan and Koning (2019) show that an essential driver of peer effects identified in the literature is spatial proximity to coworkers and peers who may possess diverse knowledge or skills. Similarly, As Brown et al. (2015) point out, industry knowledge is recognized as the most useful input to analysts' earnings forecasts and ranked as the most valued capabilities by institutional investors (see also Bradley, Gokkaya, and Liu 2017). As shown by Mas and Moretti (2009), workers respond more to the presence of coworkers with whom they frequently interact. While the magnitude of these effects differs across contexts, proximate peers rather than distant ones are more likely to shape performance. Analysts are usually grouped by industries or sectors in each brokerage house. It is not only more economically relevant to discuss and solicit feedback from colleagues covering the same industry but also more natural to interact if they share the same backend resources (e.g., research databases, support staff, and research assistants). Therefore, we argue that the exchange of ideas and information is more feasible and valuable among analysts who cover overlapping industries. If an incumbent analyst covers at least one of the same industries as the transiting analyst, she is more likely to be affected by the analyst transitions (affected analyst) compared to an incumbent analyst who has no overlapping industry coverage (unaffected analyst).

When knowledge spillover occurs between transiting analysts and incumbents, incumbent analysts will gain deeper insights about the covered firms, and their performance may improve. Therefore, our first hypothesis is:[7]

***H1**: Incumbent analysts in the new (old) broker will improve (decrease) performance via knowledge spillover after a transiting analyst joins (leaves) the broker.*

2.2 Channels of Knowledge Spillover Among Analysts

As Hayek (1945) points out, each individual can acquire knowledge about a relatively narrow range of problems. A critical economic problem in society is to use the available knowledge optimally. Over the decades, economists have examined the knowledge-based theory of the firm from different aspects. Aoki (1986) compares the horizontal with the vertical information structure of firms, describing stylized contrasts between Japanese firms and U.S. firms. As shown in his model, the aspects of hierarchical control and those of horizontal coordination may coexist in any single firm. The resource-based view of the firm by Barney (1986) recognizes the transferability of a firm's resources and capabilities as a critical determinant of its capacity to confer sustainable competitive advantage. Accordingly, Grant (1996) further shows that horizontal and team-based structures of organizational forms correspond to the knowledge-based approach of firm operations. Along with the knowledge-

[7] The hypotheses are stated in the alternative.

based view of firms, researchers examine the knowledge flows within multinational corporation networks (Cui, Griffith, and Cavusgil 2005; Noorderhaven and Harzing 2009; Michailova and Minbaeva 2012). As proposed by Crespo, Griffith, and Lages (2014), not only can vertical knowledge outflows from parent to subsidiaries but also horizontal knowledge outflows between subsidiaries help the corporation to increase its performance.

In addition, ample empirical evidence highlights the existence of lateral knowledge transfers among coworkers within the same organization. Wang and Noe (2010) review prior studies on knowledge sharing from different disciplines including psychology, organizational behavior, strategic management, and information systems. They suggest that organizations should create opportunities for employee interactions to occur and employees' ranks, positions in the organizational hierarchy, and seniority should be deemphasized to facilitate knowledge sharing. They also call for more research on knowledge sharing through different types of relational ties such as horizontal versus vertical ties. Dimmock, Gerken, and Graham (2018) show that coworkers influence an individual's propensity to commit financial misconduct by financial advisors. Ouimet and Tate (2019) find that the choices of coworkers in the firm's employee stock-purchase plans exert a significant influence on employees' own decisions to participate and trade. Finally, Duh, Knechel, and Lin (2019) conclude that knowledge sharing among audit professionals within an audit firm is positively associated with audit quality and efficiency.

In a knowledge-based economy, using the available knowledge optimally is essential to production efficiency. Vera-Munoz, Ho, and Chow (2006) argue that auditors need to share with members of the audit team their knowledge and expertise about industry-specific trends as well as accounting, auditing, and regulatory issues to enhance audit efficiency. Similar to other professional-services organizations, sell-side equity analysts are in a knowledge-based industry. Regular analysts are those who have equal (or similar) social status. Prior studies show rich evidence that status differences can affect knowledge sharing. For example, as shown by Bunderson and Reagans (2011), status differences generally have negative effects on knowledge sharing. The contributions of higher-status individuals are often given too much weight while those of lower-status individuals are often overlooked. Similarly, Haesebrouck et al. (2018) show that individual incentives can induce knowledge sharing among equal-status groups while they cannot overcome the negative interactions that arise under status differences. Focusing on regular analysts with similar status enables us to examine the horizontal knowledge transfer within the same brokerage house.

To further analyze potential channels of knowledge spillover from transiting analysts to incumbent analysts, we explore cross-sectional variations resulting from different analyst characteristics. First, we analyze the effect of broker size of transiting analysts. As indicated by Hwang, Liberti, and Sturgess (2019), individuals owe much of their success to the organizations that employ them. Besides experience, research also reveals a positive correlation between broker size and analyst forecasting performance. Stickel (1995) documents that larger brokerage houses have more advanced distribution networks for the dissemination of their analysts' recommendations in capital markets. In a similar vein, Clement (1999) shows that large brokers provide superior resources that contribute to the better forecast accuracy of their analysts. Based on these studies, we argue that transiting analysts can spillover their experience and practices accumulated in old brokers to incumbent analysts in the new broker if they switch from larger brokers.

The key principle of knowledge sharing is the social interactions among group members (Phillips, Mannix, Neale, and Gruenfeld 2004; Thomas-Hunt, Ogden, and Neale 2003). Team members with a diversified knowledge base will be more likely to participate in knowledge sharing activities to facilitate decision-making. Consistent with prior studies, analysts who cover multiple industries enjoy information commonalities among firms (Hilary and Shen

2013; Guan, Wong, and Zhang 2015). Hwang et al. (2019) find that analysts issue more accurate forecasts for the acquirer whose target is also covered by in-house colleagues. Covering multiple industries creates more opportunities for transiting analysts to interact with incumbents.[8] Transiting analysts can also share general macroeconomic knowledge or cross-industry information with incumbents when they have larger industry scope. Accordingly, we examine whether the knowledge-spillover effect is stronger when the transiting analysts cover more than one industry in their portfolio.

Finally, we examine whether transiting analysts share other types of knowledge besides industry-specific knowledge with incumbent analysts. Parsons, Sabbatucci, and Titman (2020) highlight the importance of geographic location. Ali and Hirshleifer (2020) show that analysts benefit from information commonalities by covering geographically-linked stocks. More generally, incumbents are more likely to learn from a transiting analyst if they have more overlapping interactions. When covered firms of analysts are in the same geographic location, analysts can share local economic updates with others. For example, certain regulations and government policies only apply to particular states and firms located in these areas are simultaneously affected. Likewise, O'Brien and Tan (2015) show that analysts are more likely to cover local firms than non-local firms, potentially suggesting that geographic information is an important input for analyst forecasting. Therefore, our second hypothesis is:

H2*: The knowledge-spillover effect is more pronounced when the transiting analyst switches from a larger broker, has greater industry scope, or covers geographically-linked firms.*

[8] For example, a transiting analyst covers three industries in her portfolio, two of which share common coverage with incumbents. She will interact with incumbents about these two industries (case 1). But when a transiting analyst covers only one industry, she can interact with incumbents only about this one industry (case 2). As a result, a transiting analyst potentially has more opportunities to interact with incumbents in case 1 than in case 2.

3. Data and Research Design

3.1 Sample Selection

Table 1 summarizes the sample-selection process. We start with all analysts with at least one quarterly earnings forecast over the 1994 to 2018 period. Consistent with prior literature (e.g., Hilary and Hsu 2013; Do and Zhang 2020), we start the sample in 1994 because forecasts were delivered to I/B/E/S in batches before 1994, making the announcement dates of forecasts less inaccurate. We then merge the full sample with COMPUSTAT to obtain industry identification information.[9]

Given that each earnings forecast is tagged with the date and unique identifiers that identify the issuing analyst (analyst ID) and the brokerage house (broker ID), we reconstruct the employment histories of all sell-side analysts in the I/B/E/S database from 1994 to 2018. We identify an analyst transiting between brokers when we observe a change in the broker ID that the analyst is associated with. For the convenience of presentation, we define the "in-date" of a transiting analyst as her first forecast-announcement date in the new broker, whereas the "out-date" is defined as her last forecast-announcement date in the old broker.[10] Then we obtain the sample of transiting analysts with their transition records. We conduct several filtering processes to ensure our observations capture real analyst transitions. We exclude brokers with too many outliers.[11] Requiring a transiting analyst to stay for at least one year ensures that incumbent analysts have sufficient working interactions with the transiting analyst.

[9] We exclude financial firms (SIC codes 6000-6999), regulated utilities (SIC codes 4900-4999), and institutions in public administration (SIC codes above 9000).

[10] "In-date" refers to the date when a transiting analyst moves to a new broker. "Out-date" refers to the date when a transiting analyst leaves the old broker.

[11] Outliers refer to the analysts who make multiple transitions in a year, stay in the broker for less than one year, have a long hiatus between the in-date and out-date, perform abnormally, or make transitions in the same quarter as other analysts to alleviate the possibility that firm-wide events such as mergers and acquisitions result in organizational changes and high turnover rates. For example, a brokerage house may experience mergers and acquisitions and its employees are reassigned to the acquirer. As shown in our sample, some analysts may switch between brokers from day to day. This abnormal phenomenon is due to mergers of two brokers, which is not a real transition by our definition. We confirm this phenomenon with the I/B/E/S database support teams.

Consistent with Clement and Tse (2005), we retain the most recent forecast issued within a horizon between 30 to 360 days for each quarter.[12] The main sample is restricted to incumbent analysts who have *not changed* brokers in the *current* year, *prior* year, and the *following* year. In contrast, Do and Zhang (2020) define incumbent analysts as those who stay at the same broker in the current and prior year. However, if an incumbent analyst plans to join a new broker in the following year, her performance can be confounded by the job-hopping incentive rather than the transition effect of another analyst.[13] Moreover, if the incumbent analyst tends to exit the sell-side industry to the buy-side or corporates, this career decision may impair her independence, which can affect forecasting performance (Lourie 2018).[14] The extended periods help us to examine the impact of transition on the incumbents' performance more cleanly and consistently.

Finally, we pair each transiting analyst with an incumbent analyst by their current employed broker and employed year. The same year-level matching ensures that incumbents have a current working relationship with the transiting analysts. Further, the same broker-level matching ensures that transiting analysts are paired with incumbents in the old broker and new broker, respectively. We only retain the forecasts issued within the 4th quarter to the 3rd quarter prior to an analyst transition plus the 3rd quarter to the 4th quarter after an analyst transition and exclude forecasts issued in between to eliminate the noisy periods around transitions. In practice, a transiting analyst may stay at the old broker for some time after she issues the last forecast, and it takes time for her to issue the first forecast after moving to the new broker. To

[12] Horizon is the number of days between the forecast issuance date and the announcement date of the actual earnings announcement date.

[13] For example, when the incumbent analyst plans to seek another employment in the coming year, she will have strong incentive to maintain or even improve performance.

[14] Lourie (2019) shows that when analysts plan to join the firm they cover, they may bias EPS forecasts to gain favor from prospective employers.

capture this hiatus of transition, we shift the "in-date" backward with 90 days and "out-date" forward with the same windows.[15] See Figure 1 for an illustration.

3.2 Measures of Forecasting Performance

One of the most extensively studied areas in the analyst literature is analysts' earnings forecasting performance. Studies have revealed the importance of forecast accuracy as one of the key measures of analyst performance (e.g., Mikhail, Walther, and Willis 1999). Numerous studies show that variation in forecast accuracy depends on a number of elements, including the number of industries and firms followed (Clement 1999), sector and country specialization (e.g., Sonney 2009; Kini, Mian, Rebello, and Venkateswaran 2009), and experience (e.g., Mikhail et al. 1997; Clement 1999; Jacob et al. 1999). Besides accuracy, timeliness is another important measure of analyst forecasting performance. According to Cooper, Day, and Lewis (2001), performance rankings based on timeliness are more informative than those based on trading volume and accuracy, suggesting that the market values timely forecasts. Brown and Hugon (2009) also use timeliness as an alternative dimension of forecasting performance to examine analyst-team performance. In summary, knowledge spillover between transiting analysts and incumbent analysts can be manifested by the subsequent information productivity of incumbents, proxied by forecast accuracy and timeliness.

3.3 Empirical Design

To control for the possibility that incumbent analysts change their forecasting performance due to some unobservable broker-level reasons, we conduct difference-in-differences (DiD) tests. If the improved performance of incumbents in the new broker is due

[15] In practice, a newly hired analyst often takes one to two months for onboarding training before she starts the regular work. Similarly, when an analyst submits the resignation, she usually spends another month to hand over tasks.

to increasing funds, corporate-culture changes, or strategic decisions, then all incumbent analysts in the new broker should, on average, improve their performance. Otherwise, any variation in performance among different groups of incumbent analysts in the same broker after an analyst transition demonstrates that performance changes are attributed to some additional factor other than broker-level changes. Analysts in each brokerage house are grouped by industries, and they care more about the industry updates related to their coverage portfolios, highlighting the necessity to consider analysts as different groups of industry experts when examining the knowledge spillover between analysts. If an incumbent analyst covers at least one of the *same industries* as the transiting analyst, then she is included in the *treated* group. Otherwise, if an incumbent covers completely different industries than the transiting analyst, she is included in the control group. Specifically, it is implausible for an analyst covering the fashion industry to share knowledge with one who covers the energy industry. Figure 2 presents a visualization of the research design. The regression model for our primary test is:

$$Dep\ variable = \beta_0 + \beta_1 \times PostIn + \beta_2 \times PostOut + \beta_3 \times Affected +$$
$$\beta_4 \times Affected \times PostIn + \beta_5 \times Affected \times PostOut + Controls +$$
$$Analyst\ Fixed\ Effects + Broker\ Fixed\ Effects + Quarter\ Fixed\ Effects + \varepsilon$$

(1)

For our primary analyses, the dependent variable is specified as one of the two forecast performance measures, *Accuracy* and *Timeliness*. AFE (absolute forecast error) is defined as the absolute difference between the forecasted value and the actual value of firm's EPS in the quarter. Timeliness (raw values) is measured by using the ratio T_0/T_1, where T_0 (T_1) is the cumulative number of days the N preceding (subsequent) forecasts lead (lag) the forecast of interest (Brown and Hugon 2009).[16] Next, to control for systematic differences across firm-years, we *standardize* each of the performance measures and continuous control variables to range from 0 to 1, following Clement and Tse (2003).[17] Among all of the incumbent analysts providing a forecast for the firm in the quarter, each variable is transformed to be the distance relative to the minimum value and then divided by the range of that variable. Specifically, *Accuracy*, *Timeliness* and control variables used in the main regression are calculated using the following formula:

$$Accuracy = \frac{MaxAFE - AFE}{\text{MaxAFE} - \text{MinAFE}}$$

$$Timeliness = \frac{Timeliness - MinTimeliness}{\text{MaxTimeliness} - \text{MinTimeliness}}$$

$$Control\ Variable = \frac{Control\ Variable - MinControl\ Variable}{\text{MaxControl Variable} - \text{MinControl Variable}}$$

Importantly, we employ incumbent analyst fixed effects, broker fixed effects, and quarter fixed effects to control for the potential time-invariant analyst, broker and time effects. All continuous variables are winsorized at the top and bottom 1%.[18] We cluster standard errors at the broker level.

PostIn (PostOut) takes the value 1 when the forecast is issued after a transiting analyst joins (leaves) the broker (i.e., post-transition), and 0 before (i.e., pre-transition). *Affected* equals 1 if the incumbent analyst covers at least one same industry (i.e., SIC 2-digit codes) as the transiting analyst, and 0 otherwise. The main variables of interest are the two interaction terms. β_4 (β_5) captures the subsequent performance of affected analysts relative to control analysts in the same broker after an analyst joins (leaves) the broker. We expect that the coefficient for

[16] If a relatively long period absent of earnings forecasts is followed by analyst i's forecast, which in turn is followed shortly thereafter y analyst h's forecast, analyst i's forecast will be considered relatively timely. Sample size will decrease when using timeliness as performance measure due to the data availability for T0 and T1.
[17] Note that such standardization obviates the need to control for firm characteristics (or industry effects).
[18] Inferences are not affected if we do not winsorize.

Affected×PostIn (β_4) will be positive, while the coefficient for *Affected×PostOut* (β_5) will be negative.

We control for a number of analyst characteristics that relate to analysts' performance according to prior literature. *Firm Experience* is the number of quarters that the analyst has provided annual forecasts for the specific firm. *General Experience* equals the number of quarters that the analyst appears in I/B/E/S. *Horizon* refers to the number of days between the forecast issuance date and the announcement date of the actual earnings. *Firm Number* is the number of firms covered by the analyst, and *Industry Number* is the number of industries (i.e., SIC 2-digit codes) covered by the analyst in a given quarter. *Days Elapsed* is the number of days between the forecast and the most recent forecast issued by any analyst for the specific firm in the quarter. *Specialization* is the percentage of a specific industry of all industries covered by the analyst.[19] *Broker Size* indicates the number of analysts employed by the broker in the quarter. *Bundle* is an indicator variable that equals 1 if the analyst issues more than one forecast on the same day.

To test the second hypothesis on the channels of knowledge spillover, we partition the sample by analyst characteristics. First, we expect that the knowledge-spillover effect is more salient when the transiting analysts switch from a larger broker to a smaller broker. We use the number of analysts employed by the broker to proxy for the broker size. If the transiting analyst switches from a larger (smaller) broker to a smaller (larger) broker, we include them into *Big-to-Small (Small-to-Big)* case.

Next, we split the sample by whether transiting analysts cover more than one SIC 2-digit industry in their portfolio. Comparing the transiting analysts covering only one industry, those who cover more industries potentially can share additional knowledge with incumbents.

[19] Jacob, Lys, and Neale (1999) and Dunn and Nathan (1998) find that industry specialization by analysts is associated with increased earnings forecast accuracy.

In other words, their overlapping and interactions can be more intense.[20] *One industry* represents the situation when the transiting analysts cover only one industry. *Multiple industries* refer to the case when the transiting analysts cover more than one industry.

Finally, we divide the sample by whether the geographic locations of the covered firms by transiting analysts are the same as those covered by incumbent analysts. Geographic location refers to the state of the headquarters of the firms. If the transiting analyst covers geographically-linked firms, then they are included in the *Same Location* sample. Otherwise, they are included in the *Different Location* sample.

3.4 Summary Statistics

Table 2 presents summary statistics for the variables used in the main regression model, industry distribution, and year distribution. As shown in Panel A, the mean raw values of *Accuracy* and *Timeliness* are -0.08 and 1.38, respectively. Specifically, 23% of the forecasts are issued after a leaving analyst departs, while 27% of the forecasts are announced after a transiting analyst arrives. 37% of the incumbent analysts cover at least one common industry as the transiting analyst. On average, an analyst in the sample has 14.47 quarters (3.6 years) of firm-specific experience, 28.31 quarters (7.1 years) of general experience, and covers 14.59 firms and 3.2 industries. The mean value of *Horizon* is 79.45 days and the mean value of *Days Elapsed* is 5.39 days. 36% of the forecasts are defined as *Bundle*, and mean analyst *Specialization* is 0.58. The broker employs 48 analysts, on average. Panel B further shows the standardized measures of variables used in the regressions.

Panel C shows that the analyst transitions cluster in manufacturing industries and services industries, consistent with the clustering of publicly listed firms in these two industries.

[20] For example, when a transiting analyst covers three industries, two of which share common coverage with incumbents, the incumbent analysts will gain knowledge about two industries instead of one.

Panel D reveals that analyst transitions happen regularly, further motivating the need to examine the effect of analyst transitions on incumbent analysts. Finally and importantly, Panel E indicates that the transiting analysts have similar characteristics as incumbent analysts.

4. Empirical Results and Discussion

4.1 Main Results for H1

Table 3 presents the results for H1 and includes forecasts issued within the 4th to 3rd quarter before the analyst transition and the 3rd to 4th quarter following the transition. We find that the coefficients on *Affected×PostIn* for both *Accuracy* and *Timeliness* are positive and statistically significant, suggesting that affected incumbent analysts are more likely to improve their forecasting accuracy and timeliness after a new analyst joins the broker than unaffected incumbent analysts in the same broker (and for the same time period). Specifically, as shown in Column (1), the coefficient on *Affected×PostIn* for *Accuracy* is 0.023, and the coefficient on *Affected×PostOut* is -0.024, statistically significant at the 10% level and 5% level (using two-sided tests), respectively.[21] This result suggests that the forecasting accuracy of affected incumbents will be affected by around 2% in terms of the relative performance among all the analysts who issue forecasts for a firm.[22] Furthermore, in Column (2), the coefficient on *Affected×PostIn* for *Timeliness* is positive (0.083) and significant at the 5% level while the coefficient on *Affected×PostOut* is insignificant. The insignificant effect for *Timeliness* after an analyst leaves suggests that incumbent analysts may not issue less timely forecasts after their colleagues depart from the broker. One potential explanation is that it is easier for an analyst to maintain timely forecasts compared to their ability to maintain the quality of forecasts after a

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[21] The similar-magnitude coefficients on *Affected×PostIn* and *Affected×PostOut* reveal that incumbents' performance is symmetrically affected by the arrival and departure of transiting analysts.

[22] Do and Zhang (2020) report the coefficient as 0.019 for the same dependent variable for the arrival of all-star analysts in their Table 5. If we instead were to use raw (or unstandardized) values of forecasting performance, the estimated improvement in forecasting accuracy is 6.3%.

peer leaves. The newcomer provides valuable knowledge to incumbents, enabling them to produce information in a timelier way and to offer more accurate research output. In addition, after an analyst leaves the broker, affected incumbents issue less accurate forecasts relative to unaffected incumbents, suggesting that incumbents in the old broker lose the knowledge spillover opportunities offered by the leaving analyst.[23]

In summary, the results in Table 3 generally support the idea that affected incumbent analysts in the new broker improve their performance (i.e., accuracy and timeliness) after an analyst arrives due to knowledge-spillover benefits. In addition, affected incumbents' performance (i.e., accuracy) in the old broker deteriorate after an analyst departs because of knowledge-spillover losses.

4.2 Results for H2

As discussed in Section 4.3, we operationalize the channels of knowledge spillover from transiting analysts by their characteristics –broker size, industry expertise, and geographic location of covered firms. Research reveals a positive correlation between broker size and analyst forecasting performance (Stickel 1995; Clement 1999). First, coming from a large brokerage house represents an analyst's capabilities to some extent because large brokers generally attract talented analysts in the labor market. Second, transiting analysts covering multiple industries potentially have more intense interactions between them and affected incumbent analysts. Finally, transiting analysts can share incremental knowledge related to the local economy if their covered firms are in the same state as those covered by incumbent analysts. Based on these arguments, we argue that an analyst who switches from a larger broker,

[23] Potential alternative explanations for incumbents' improved performance could be lower workloads (higher capacity) or more resources after a new analyst arrives. To address these possibilities, the model includes broker size, the number of firms covered, and the number of industries covered. Inferences remain unchanged if we further control for the team size (i.e., proxied by the number of analysts in the same industry in the same broker) and the number of other analysts covering the focal firm.

has greater industry coverage scope, and covers geographically-linked firms will spillover relevant knowledge to incumbent analysts.

4.2.1 Partition Based on Broker Size

In Table 4, we partition the sample based on whether the transiting analyst's prior experience comes from a larger broker or a smaller broker. We define *Big-to-Small* as the case when a transiting analyst moves from a larger broker to a smaller or equal broker and *Small-to-Big* as the other way around. As evidenced in Table 4, consistent with our prediction, the transiting analyst can exert a more significant impact on the incumbents in the new broker under the *Big-to-Small* case. The coefficients on *Affected×PostIn* for both *Accuracy* and *Timeliness* are positive and significant at the 10% and 5% levels, respectively. Intuitively, incumbent analysts in a smaller brokerage house are likely to be more willing to learn from a transiting analyst from a larger broker. For example, a transiting analyst from a larger brokerage house can share knowledge about their successful practices with incumbents in the new smaller broker.

The coefficients on *Affected×PostOut* are insignificant but their signs are aligned with the predicted directions. When a transiting analyst leaves from a larger brokerage house to a smaller brokerage house, incumbent analysts in the large broker may not suffer as much because they have alternative support.[24]

4.2.2 Partition Based on Industry Scope

In Table 5, we partition the sample based on whether the transiting analysts have greater industry scope. If the transiting analyst covers more than one industry in her portfolio, it is

[24] This result is also consistent with the findings in Do and Zhang (2020). They find that the departure of all-star analyst does not have a significant impact on incumbent analysts.

possible that affected incumbents will have more overlapping industry coverage with the transiting analysts and benefit from more interactions. This can partially proxy for the strength of their relationship. *One Industry* represents the situation when the transiting analysts cover only one industry. *Multiple Industries* refer to the case when the transiting analysts cover more than one industry. We find that the transiting analyst exerts a more significant impact on the incumbents when she covers multiple industries. The coefficients on *Affected×PostIn* and *Affected×PostOut* for *Accuracy* are significant at the 5% level when the transiting analysts cover more than one industry.

These findings suggest transiting analysts potentially share more knowledge with incumbents since they have more interactions (have more overlapped industries), which enriches the information sets of the affected incumbents. Additionally, the information commonalities between industries may benefit the production quality of analysts (i.e. higher forecasting accuracy).

4.2.3 Partition Based on Geographic Location

In Table 6, we partition the sample based on whether the transiting analysts cover geographically-linked firms with incumbent analysts. The location of the firms is determined by the state of headquarters. If two firms' headquarters are in the same state, we treat them as geographically linked ones.[25] *Same Location* refers to the situation where the states of covered firms by incumbents are in the same states of covered firms by transiting analysts. *Different Location* refers to the situation where the locations of covered firms by incumbents are in the different states of covered firms by transiting analysts. The results in Table 6 show that the transiting analyst has a greater impact on the incumbents when she covers geographically-

[25] "Two firms" refer to the firm covered by transiting analysts and the other firm covered by incumbent analysts.

linked firms. Specifically, the coefficients on *Affected×PostIn* and *Affected×PostOut* for *Accuracy* are significant at the 10% level and 5%, respectively, suggesting that transiting analysts can share information related to the local economic conditions to affected incumbents as well.

5. Additional Analyses

5.1 Paired Transiting Analyst-Incumbent Analyst Fixed Effects

It is possible that the transiting and incumbent analysts may have unobservable connections. For example, they could join the same fitness gym and interact with each other during their leisure time. This type of social bonding may create a sorting mechanism between them, potentially driving the decision of the transiting analyst to join the broker and influencing the subsequent performance changes of incumbents. To mitigate this alternative explanation, we use *paired transiting analyst and incumbent analyst fixed effects* (transiting analyst FE × incumbent analyst FE) instead of incumbent analyst fixed effects. As shown in Table 7, the inferences are unaltered, with similar economic significance and magnitudes of coefficients.

5.2 Placebo Analysis

To further mitigate the possibility that the analyst transition decisions are endogenous, we use a placebo test, where the transition has not actually happened. The pseudo-transition date is defined as one year before the transition date. In other words, the analyst transition has *not* happened yet. If, as we predict, the analyst transition causally leads to changes in incumbent analysts' performance, then an earlier transition date should not show any impact on the incumbent analysts' performance. Consistent with our prediction, the coefficients on *Affected×PostIn* and *Affected×PostOut* are not significant in Table 8, providing further validity to H1. An earlier analyst transition does not lead to any changes in incumbent analysts' performance. In other words, incumbent analysts' performance does not have significant patterns (increase or decrease) before analyst transitions.

5.3 Transiting Analysts

The focus of this study is to examine the effect of analyst transitions on incumbent analysts. That focus also allows us to employ a strong econometric design that importantly controls for broker-level unobservables. In particular, we control for analyst, broker, and time fixed effects and employ within-brokerage analyses. To shed more light on the effect of analyst transitions on transiting analysts, we further examine the effects on the transiting analysts. Note that such analyses do *not* allow for our strong research design.

First, we examine the coverage portfolio compositions of transiting analysts. *SameFirm* equals 1 if the firm is in the coverage portfolios both before and after the transitions, and zero otherwise. Among all the firms that are covered by the transiting analysts before and after the transitions, only 37% of firms appear in the prior coverage portfolios and post coverage portfolios. In addition, *%SameFirm* represents the percentage of firms in the new portfolios for each transiting analyst, which are also covered by the transiting analyst before the transition. In other words, it shows the percentage of coverage portfolios that remain unchanged after the transitions. As shown in Panel A of Table 9, around 36% of firms in the new coverage portfolio are covered by transiting analysts before the transition. In other words, transiting analysts change around two-thirds of their coverage portfolios after transitions (which limits the power of these tests).

Next, we run the regressions by explaining the forecasting accuracy with the transition indicator variable *Post*. We only include the forecasts issued by the transiting analysts for the same firms before and after the transition. *Post* equals 1 if the forecast is issued after the transition and 0 if the forecast is issued before the transition. We use the raw values of dependent variables and control variables and then take the average of these variables across all the forecasts issued by a transiting analyst in a broker. We find that after the transitions, transiting analysts generally issue more timely forecasts than before the transitions. Although we find that the forecast accuracy after the transition is higher than that before the transition (i.e., *Post* is positive), we do not find statistical significance for this effect.

5.4 Sorting Incumbents based on the Industry of Star Analysts

Finally, we examine whether non-star transitions will matter to all-star incumbents. Specifically, we include *all* analysts (both regular and star analysts) in the sample and sort the incumbents based on the industry of the star analysts by utilizing our research design. Briefly, we find that regular analyst transitions only exert an impact on regular (non-star) incumbents but not all-star incumbents (untabulated). These findings also support our focus on regular incumbents to analyze the effect of regular analyst transitions.

6. Conclusions

In this paper, we use a setting where a non-star transiting analyst switches from a brokerage firm to a new broker to study the peer effects among "regular" (or non-all-star) financial analysts. We examine the subsequent performance of incumbent analysts after a transiting analyst arrives or departs. We hypothesize that incumbent analysts will improve (decrease) their performance after an analyst joins (leaves) the broker due to knowledge-spillover benefits (losses). To control for the possibility that broker-level changes lead to analyst transitions and incumbents' performance changes, we compare the performance of two groups of incumbents in the *same broker* (and for the same time periods). Affected incumbent analysts cover at least one common industry as the transiting analyst, while unaffected incumbent analysts cover different industries. The empirical results show that affected incumbent analysts issue more accurate and timely forecasts after an analyst arrives than unaffected incumbents. Further, affected incumbent analysts issue less accurate forecasts after an analyst leaves than unaffected incumbents.

To further examine potential channels of knowledge-spillover effect, we examine how transiting analysts spillover knowledge to affected incumbents. We find some evidence that the transiting analyst is more likely to share knowledge to incumbents when she comes from a larger brokerage house, has a greater industry scope, or covers geographically-linked firms. These results support the idea that regular analyst transitions can also affect their related peers.

REFERENCES

Ali, U., & Hirshleifer, D. (2020). Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics,* 136(3), 649-675.

Aoki, M. (1986). Horizontal vs. vertical information structure of the firm. *The American Economic Review,* 76(5), 971-983.

Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *The Review of Economic Studies*, 29(3), 155-173.

Arthur, J. B., & Huntley, C. L. (2005). Ramping up the organizational learning curve: Assessing the impact of deliberate learning on organizational performance under gainsharing. *Academy of Management Journal*, *48*(6), 1159-1170.

Barney, J. B. (1986). Strategic factor markets: Expectations, luck, and business strategy. *Management Science*, *32*(10), 1231-1241.

Beatty, A., Liao, S., & Yu, J. J. (2013). The spillover effect of fraudulent financial reporting on peer firms' investments. *Journal of Accounting and Economics*, 55(2-3), 183-205.

Bird, A., Edwards, A., & Ruchti, T. G. (2018). Taxes and peer effects. *The Accounting Review*, 93(5), 97-117.

Bradley, D., Gokkaya, S., & Liu, X. (2017). Before an analyst becomes an analyst: Does industry experience matter? *The Journal of Finance*, 72(2), 751-792.

Brown, L. D., & Hugon, A. (2009). Team earnings forecasting. *Review of Accounting Studies*, 14(4), 587-607.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research*, 53(1), 1-47.

Bunderson, J. S., & Reagans, R. E. (2011). Power, status, and learning in organizations. *Organization Science*, *22*(5), 1182-1194.

Cen, L., Ornthanalai, C., & Schiller, C. M. (2017). Navigating Wall Street: Career Concerns and Analyst Transitions from Sell-Side to Buy-Side. Working paper, University of Toronto.

Chan, K., & Hameed, A. (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics*, 80(1), 115-147.

Chan, T. Y., Li, J., & Pierce, L. (2014). Compensation and peer effects in competing sales teams. *Management Science*, 60(8), 1965-1984.

Chan, T. Y., Li, J., & Pierce, L. (2014). Learning from peers: Knowledge transfer and sales force productivity growth. *Marketing Science*, 33(4), 463-484.

Chiaburu, D. S., & Harrison, D. A. (2008). Do peers make the place? Conceptual synthesis and meta-analysis of coworker effects on perceptions, attitudes, OCBs, and performance. *Journal of Applied Psychology*, 93(5), 1082.

Clarke, J., Khorana, A., Patel, A., & Rau, P. R. (2007). The impact of all-star analyst job changes on their coverage choices and investment banking deal flow. *Journal of Financial Economics*, 84(3), 713-737.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27(3), 285-303.

Clement, M. B., & Tse, S. Y. (2003). Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters? *The Accounting Review*, 78(1), 227-249.

Clement, M. B., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance*, 60(1), 307-341.

Collins, C. J., & Smith, K. G. (2006). Knowledge exchange and combination: The role of human resource practices in the performance of high-technology firms. *Academy of Management Journal*, *49*(3), 544-560.

Cooper, R. A., Day, T. E., & Lewis, C. M. (2001). Following the leader: A study of individual analysts' earnings forecasts. *Journal of Financial Economics*, 61(3), 383-416.

Cornelissen, T., Dustmann, C., & Schönberg, U. (2017). Peer effects in the workplace. *American Economic Review*, 107(2), 425-56.

Crespo, C. F., Griffith, D. A., & Lages, L. F. (2014). The performance effects of vertical and horizontal subsidiary knowledge outflows in multinational corporations. *International Business*

Review, *23*(5), 993-1007.
Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. *Journal of Management*, 31(6), 874-900.
Cropanzano, R., Anthony, E. L., Daniels, S. R., & Hall, A. V. (2017). Social exchange theory: A critical review with theoretical remedies. *Academy of Management Annals*, 11(1), 479-516.
Cui, A. S., Griffith, D. A., & Cavusgil, S. T. (2005). The influence of competitive intensity and market dynamism on knowledge management capabilities of multinational corporation subsidiaries. *Journal of International Marketing*, *13*(3), 32-53.
Dimmock, S.G., W.C. Gerken, & N.P. Graham. (2018). Is Fraud Contagious? Coworker Influence on Misconduct by Financial Advisors. *The Journal of Finance*, 73(3), 1417-1450.
Do. T., and H. Zhang (2020). Peer effects among financial analysts. *Contemporary Accounting Research* 37 (1), 358-391.
Drake, M., Joos, P., Pacelli, J., & Twedt, B. (2020). Analyst forecast bundling. *Management Science*, 66(9), 4024-4046.
Duh, R. R., Knechel, W. R., & Lin, C. C. (2019). The Effects of Audit Firms' Knowledge Sharing on Audit Quality and Efficiency. *Auditing: A Journal of Practice and Theory*.
Dunn, K., & Nathan, S. (1998). The effect of industry diversification on consensus and individual analysts' earnings forecasts. *Available at SSRN 102908*.
Falk, A., & Ichino, A. (2006). Clean evidence on peer effects. *Journal of Labor economics*, 24(1), 39-57.
Fang, B., & Hope, O.-K. (2021). Analyst teams. Forthcoming, *Review of Accounting Studies*.
Ferris, G. R., & Mitchell, T. R. (1987). The components of social influence and their importance for human resources research. *Research in personnel and human resources management*, 5, 103-128.
Fiske, A. P. (1992). Four elementary forms of sociality: Framework for a unified theory of social relations. *Psychological Review*, 99, 689 –723.
Gao, M., Ji, Y., & Rozenbaum, O. (2019). When Do Associate Analysts Matter? Working paper, George Washington University.
Glaeser, E. L. (1999). Learning in cities. *Journal of Urban Economics*, 46(2), 254-277.
Gleason, C. A., Jenkins, N. T., & Johnson, W. B. (2008). The contagion effects of accounting restatements. *The Accounting Review*, 83(1), 83-110.
Gouldner, A. (1960). The norm of reciprocity, *American Sociological Review*.
Grant, R. M. (1996). Toward a knowledge‐based theory of the firm. *Strategic Management Journal*, *17*(S2), 109-122.
Groysberg, B., Lee, L. E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science*, 54(7), 1213-1230.
Guan, Y., Wong, M. F., & Zhang, Y. (2015). Analyst following along the supply chain. *Review of Accounting Studies*, 20(1), 210-241.
Guan, Y., Li, C., Lu, H., & Wong, M. F. (2019). Regulations and brain drain: Evidence from Wall Street star analysts' career choices. *Management Science*.
Haesebrouck, K., Cools, M., & Van den Abbeele, A. (2018). Status differences and knowledge transfer: The effect of incentives. *The Accounting Review*, 93(1), 213-234.
Hansen, M. T. (2002). Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science*, *13*(3), 232-248.
Hasan, S., & Koning, R. (2019). Prior ties and the limits of peer effects on startup team performance. *Strategic Management Journal*, 40(9), 1394-1416.
Hayek, F. A. (1945). The use of knowledge in society. *The American Economic Review*, 35(4), 519-530.
Hilary, G., & Shen, R. (2013). The role of analysts in intra-industry information transfer. *The Accounting Review*, 88(4), 1265-1287.
Herbst, D., & Mas, A. (2015). Peer effects on worker output in the laboratory generalize to the field. *Science*, 350(6260), 545-549.
Herrmann, D., & Thomas, W. B. (2005). Rounding of analyst forecasts. *The Accounting Review*, 80(3), 805-823.

Hong, H., & Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, 58(1), 313-351.
Hope, O.-K., Huang, Z. & Moldovan, R. (2021). Wall Street Analysts as Investor Relations Officers. Forthcoming, *Journal of Corporate Finance*.
Horton, J., Serafeim, G., & Wu, S. (2017). Career concerns of banking analysts. *Journal of Accounting and Economics*, 63(2-3), 231-252.
Hwang, B.-H., Liberti, J.M., & Sturgess, J. (2019). Information Sharing and Spillovers: Evidence from Financial Analysts. *Management Science*, 65(8), 3624-3636.
Jacob, J., Lys, T. Z., & Neale, M. A. (1999). Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, 28(1), 51-82.
Jovanovic, B., & Rob, R. (1989). The growth and diffusion of knowledge. *The Review of Economic Studies*, 56(4), 569-582.
Kandel, E., & Lazear, E. P. (1992). Peer pressure and partnerships. *Journal of Political Economy*, 100(4), 801-817.
Katz, D., & Kahn, R. L. (1978). *The Social Psychology of Organizations* (Vol. 2, p. 528). New York: Wiley.
Kim, S. L., & Yun, S. (2015). The effect of coworker knowledge sharing on performance and its boundary conditions: An interactional perspective. *Journal of Applied Psychology*, 100(2), 575.
Kini, O., Mian, S., Rebello, M., & Venkateswaran, A. (2009). On the structure of analyst research portfolios and forecast accuracy. *Journal of Accounting Research*, 47(4), 867-909.
Leary, M. T., & Roberts, M. R. (2014). Do peer firms affect corporate financial policy? *The Journal of Finance*, 69(1), 139-178.
Lin, Y., Mao, Y., & Wang, Z. (2017). Institutional ownership, peer pressure, and voluntary disclosures. *The Accounting Review*, 93(4), 283-308.
Lourie, B. (2018). The revolving door of sell-side analysts. *The Accounting Review*, 94(1), 249-270.
Marshall, A. (1890). Principles of Economics, 8th ed. (1920). *London, McMillan*.
Mas, A., & Moretti, E. (2009). Peers at work. *American Economic Review*, 99(1), 112-45.
Mesmer-Magnus, J. R., & DeChurch, L. A. (2009). Information sharing and team performance: A meta-analysis. *Journal of Applied Psychology*, *94*(2), 535.
Michailova, S., & Minbaeva, D. B. (2012). Organizational values and knowledge sharing in multinational corporations: The Danisco case. *International Business Review*, *21*(1), 59-70.
Mikhail, M. B., Walther, B. R., & Willis, R. H. (1997). Do security analysts improve their performance with experience? *Journal of Accounting Research*, 35, 131-157.
Mikhail, M. B., Walther, B. R., & Willis, R. H. (1999). Does forecast accuracy matter to security analysts? *The Accounting Review*, 74(2), 185-200.
Mohammad, E., & Nathan, S. (2008). Antecedents and consequences of financial analyst turnover. *Review of Accounting and Finance*, 7(4), 355-371.
Moretti, E. (2004). Workers' education, spillovers, and productivity: evidence from plant-level production functions. *American Economic Review*, 94(3), 656-690.
Neururer, T., & Sun, E. (2021). Quantifying the Effect of Information and Ability Spillovers on Analyst Earnings Forecast Accuracy. Working paper, University of Akron and Boston University.
Noorderhaven, N., & Harzing, A. W. (2009). Knowledge-sharing and social interaction within MNEs. *Journal of International Business Studies*, *40*(5), 719-741.
O'Brien, P. C., & Tan, H. (2015). Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics*, *59*(1), 41-59.
Ouimet, P., & Tate, G. (2019). Learning from coworkers: Peer effects on individual investment decisions. *The Journal of Finance*.
Parsons, C. A., Sabbatucci, R., & Titman, S. (2020). Geographic lead-lag effects. *Review of Financial Studies*, 33(10), 4721-4770.
Phillips, K. W., Mannix, E. A., Neale, M. A., & Gruenfeld, D. H. (2004). Diverse groups and information sharing: The effects of congruent ties. *Journal of Experimental Social Psychology*, *40*(4), 497-510.
Phua, J. K., Tham, T. M., & Wei, C. (2020). Do equity analysts learn from their colleagues? Working paper, NTU.

Reh, S., Tröster, C., & Van Quaquebeke, N. (2018). Keeping (future) rivals down: Temporal social comparison predicts coworker social undermining via future status threat and envy. *Journal of Applied Psychology*, *103*(4), 399.

Riggle, R. J., Edmondson, D. R., & Hansen, J. D. (2009). A meta-analysis of the relationship between perceived organizational support and job outcomes: 20 years of research. *Journal of Business Research*, 62(10), 1027-1030.

Schaubroeck, J., & Lam, S. S. (2004). Comparing lots before and after: Promotion rejectees' invidious reactions to promotees. *Organizational Behavior and Human Decision Processes*, *94*(1), 33-47.

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science*, *2*(1), 125-134.

Sonney, F. (2009). Financial analysts' performance: Sector versus country specialization. The *Review of Financial Studies*, 22(5), 2087-2131.

Stickel, S. E. (1995). The anatomy of the performance of buy and sell recommendations. *Financial Analysts Journal*, 51(5), 25-39.

Thomas-Hunt, M. C., Ogden, T. Y., & Neale, M. A. (2003). Who's really sharing? Effects of social and expert status on knowledge exchange within groups. *Management Science*, *49*(4), 464-477.

Vera-Munoz, S. C., Ho, J. L., & Chow, C. W. (2006). Enhancing knowledge sharing in public accounting firms. *Accounting Horizons*, *20*(2), 133-155.

Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, *20*(2), 115-131.

Wu, J. S., & Zang, A. Y. (2009). What determine financial analysts' career outcomes during mergers? *Journal of Accounting and Economics*, 47(1-2), 59-86.

Wu, Y. (2015). Organizational structure and product choice in knowledge-intensive firms. *Management Science*, 61(8), 1830-1848.

Yin, H., & Zhang, H. (2014). Tournaments of financial analysts. *Review of Accounting Studies*, *19*(2), 573-605.

APPENDIX: Variable Definitions

Dependent Variables	**Definition**
Accuracy	The scaled value of the accuracy, which is the absolute value of the forecast error (the difference between the forecasted EPS and the actual EPS), and then multiplied by -1.
Timeliness	The scaled value of timeliness, which is the ratio T_0/T_1, where T_0 (T_1) is the cumulative number of days the N preceding (subsequent) forecasts lead (lag) the forecast of interest
Test Variables	**Definition**
PostIn	*PostIn* takes value 1 when the forecast is issued in the 3rd and 4th quarter after a transiting analyst joins the broker (i.e., post-transition), and 0 before (i.e., pre-transition).
PostOut	*PostOut* takes value 1 when the forecast is issued the 3rd and 4th quarter after a transiting analyst leaves the broker (i.e., post-transition), and 0 before (i.e., pre-transition).
Affected	Indicator variable is one if the incumbent analyst covers at least one same industry (i.e., SIC 2-digit codes) as the transiting analyst, and 0 otherwise.
Control Variables	**Definition**
Bundle	Indicator variable is one if the analyst issues more than one forecasts on the same day, and 0 otherwise.
Lag Performance	The scaled value of the lagged value of Accuracy and Timeliness in the prior quarter
Days Elapsed	The scaled value of days elapsed, which is the number of days since the forecast issued by any analyst covering the same firm in the quarter (T0).
Specialization	The scaled value of specialization, which is the percentage of a specific industry in all industries covered by the analyst.
Horizon	The scaled value of horizon, which is the number of days between the forecast issuance date and the announcement date of the actual earnings
Broker size	The scaled number of analysts employed by the broker in the quarter
Firm Number	The scaled number of firms covered by the analyst in the quarter
Industry Number	The scaled number of industries (i.e., SIC 2-digit codes) covered by the analyst
Firm Experience	The scaled number of quarters that the analyst has provided annual forecasts for the specific firm.
General Experience	The scaled number of quarters that the analyst appears in I/B/E/S

Figure 1: Visualization of the Definition of a Transition Date

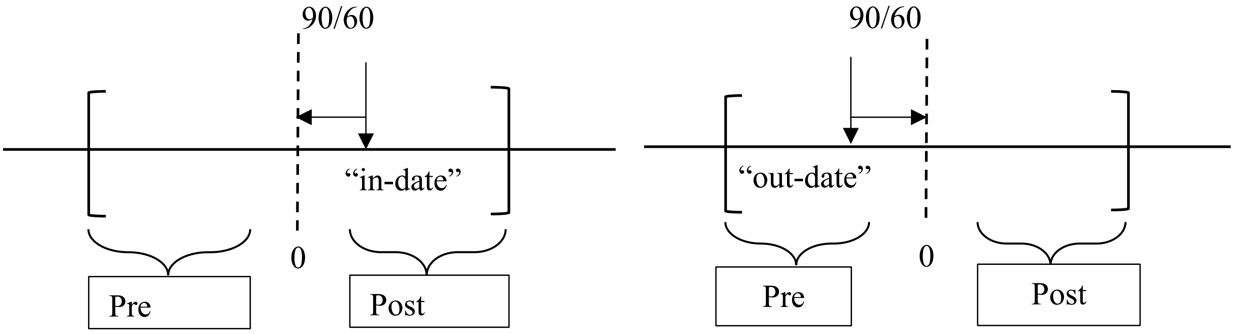

Figure 2: Visualization of the Research Question – DiD Design

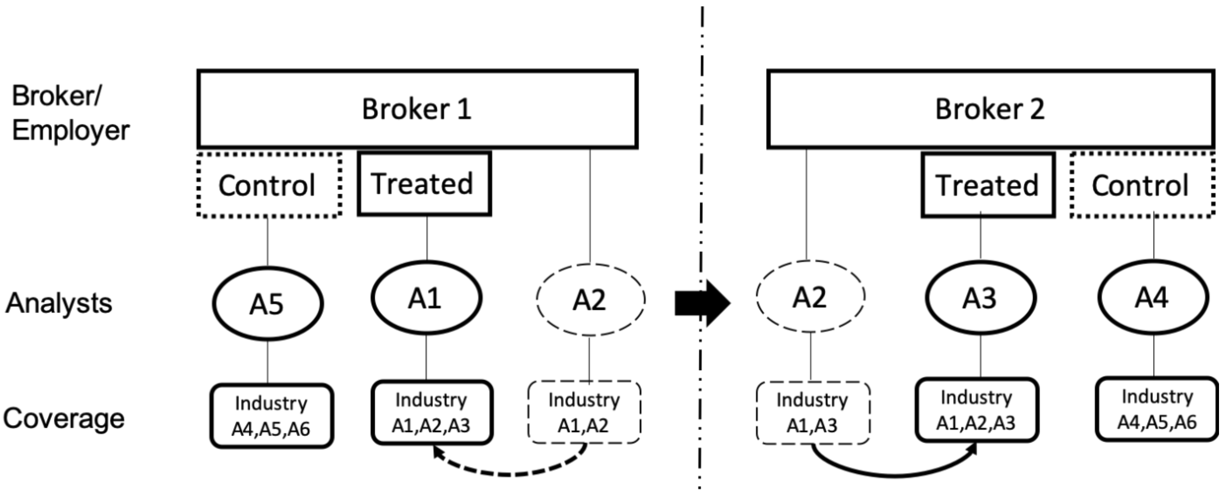

Table 1: Sample Selection

Step 1: Original forecast sample	Observations	Unit
Full list of quarterly EPS forecasts from 1994-2018	3,190,643	analyst-firm-quarter
Delete all-star analysts from the sample	2,845,927	analyst-firm-quarter
Merge with COMPUSTAT (excluded Finance, Public administration, and Utility firms)	1,769,280	analyst-firm-quarter
Step 2: Transiting analyst sample		
Full list of transiting analysts from 1994-2018	17,635	analyst-quarter
Delete transitions with high hiatus, multiple transitions per year, mergers and closures and stay for less than one year	6,512	analyst-quarter
Merge with COMPUSTAT for industry classification	89,859	analyst-firm-quarter
Corresponding to	1,351	transiting analyst
Step 3: Incumbent analyst sample		
Identify incumbent analysts	760,671	analyst-firm-quarter
Corresponding to	5,465	incumbent analyst
Step 4: Merge transiting analyst with incumbent analyst		
Merge transiting analyst with incumbent analyst based on the same broker-year	682,724	analyst-firm-quarter
Corresponding to	298	broker
	1,351	transiting analyst
	5,465	incumbent analyst
	7,661	firms
Step 5: Keep pre- and post-transition sample		
Keep the forecasts issued within pre and post 3, 4 quarters	92,217	analyst-firm-quarter
Ensure each firm has at least one pre-observation and one post-observation	42,611	analyst-firm-quarter

Table 2: Summary Statistics

Summary statistics for variables used in the main regression

Panel A: ***Raw values***

Variable	Mean	p25	p50	p75
accuracy	-0.08	-0.09	-0.04	-0.01
timeliness	1.38	0.00	0.04	0.83
PostIn	0.27	0.00	0.00	1.00
PostOut	0.23	0.00	0.00	0.00
Affected	0.37	0.00	0.00	1.00
bundle	0.36	0.00	0.00	1.00
days elapsed	5.39	0.00	0.00	3.00
specialization	0.58	0.27	0.60	0.92
horizon	79.45	67.00	87.00	91.00
broker size	47.79	19.00	42.00	74.00
firm number	14.59	10.00	14.00	18.00
industry number	3.20	2.00	3.00	4.00
firm experience	14.47	7.00	11.00	19.00
general experience	28.31	13.00	23.00	41.00

Panel B: ***Standardized values (Range from 0 to 1)***

Variable	Mean	p25	p50	p75
Accuracy	0.55	0.18	0.60	0.99
Timeliness	0.34	0.00	0.04	1.00
Days Elapsed	0.23	0.00	0.00	0.26
Specialization	0.56	0.17	0.59	1.00
Horizon	0.65	0.08	0.95	1.00
Broker size	0.46	0.09	0.42	0.80
Firm Number	0.48	0.17	0.46	0.80
Industry Number	0.40	0.00	0.33	0.75
Firm Experience	0.50	0.16	0.45	0.94
General Experience	0.47	0.11	0.41	0.86

Panel C: Descriptive statistics for the industry of analyst transitions

SIC 1-digit	# of transition in	# of transition out	%
3	456	373	30.9%
7	312	236	20.4%
2	253	218	17.6%
5	174	131	11.4%
1	120	98	8.1%
4	107	72	6.7%
8	71	54	4.7%
0	4	4	0.3%

Panel D: Descriptive statistics for year of analyst transitions

Year	# of transition in	# of transition out	%
1994	16	35	1.9%
1995	46	64	4.1%
1996	45	47	3.4%
1997	48	61	4.1%
1998	73	58	4.9%
1999	57	67	4.6%
2000	51	43	3.5%
2001	33	36	2.6%
2002	48	35	3.1%
2003	86	45	4.9%
2004	78	65	5.3%
2005	79	51	4.8%
2006	66	51	4.4%
2007	89	69	5.9%
2008	68	39	4.0%
2009	66	43	4.1%
2010	87	50	5.1%
2011	65	65	4.8%
2012	65	38	3.8%
2013	57	47	3.9%
2014	64	42	4.0%
2015	63	43	4.0%
2016	49	38	3.2%
2017	49	33	3.1%
2018	49	21	2.6%

Panel E: Raw values of transiting analyst characteristics

Variable	Mean	p25	p50	p75
Bundle	0.36	0.00	0.00	1.00
Specialization	0.66	0.35	0.75	1.00
Horizon	76.85	58.00	83.00	91.00
Broker size	19.90	6.00	12.00	24.00
Firm Number	10.59	6.00	10.00	14.00
Industry Number	2.47	1.00	2.00	3.00
Firm Experience	9.56	1.00	5.00	13.00
General Experience	25.35	9.00	20.00	37.00

Table 3: Affected Incumbents' Performance vs. Unaffected Incumbents' Performance

This table presents the results from estimating the OLS regression of Equation (1) and corresponds to DiD in Figure 1. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. *Timeliness* is measured by using the ratio T0/T1, where T0 (T1) is the cumulative number of days the N preceding (subsequent) forecasts lead (lag) the forecast of interest. All continuous variables are standardized at the firm-quarter level, ranging from 0 to 1. *PostIn (PostOut)* takes value 1 when the forecast is issued after a transiting analyst joins (leaves) the broker (i.e., post-transition), and 0 before (i.e., pre-transition). *Affected* equals 1 if the incumbent analyst covers at least one same industry (i.e., SIC 2-digit codes) as the transiting analyst, and 0 otherwise. Column (1) to (2) presents the forecasts issued within 3rd to 4th quarter (both are inclusive) pre transition and 4th to 3rd (both are inclusive) quarter post transition. Quarter fixed effects, broker fixed effects, and analyst fixed effects are included in all specifications. All remaining variables are defined in the Appendix. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Accuracy	Timeliness
Affected×PostIn	0.023*	0.083**
	(1.93)	(2.28)
Affected×PostOut	-0.024**	0.021
	(-2.26)	(0.43)
PostIn	-0.014	-0.120
	(-0.46)	(-1.07)
PostOut	-0.002	-0.112
	(-0.07)	(-1.03)
Bundle	-0.003	0.007
	(-0.56)	(0.48)
Days Elapsed	-0.022***	0.777***
	(-2.99)	(34.52)
Specialization	-0.002	0.011
	(-0.19)	(0.28)
Lag Performance	0.042***	0.002
	(5.02)	(0.13)
Horizon	-0.043***	-0.031
	(-5.07)	(-1.28)
Broker size	-0.014	-0.057
	(-0.79)	(-0.53)
Firm number	-0.012	0.044
	(-1.00)	(1.00)
Industry number	-0.002	-0.070
	(-0.25)	(-1.63)
General experience	0.011	-0.119
	(0.48)	(-1.33)
Firm experience	-0.013	0.006

	(-1.63)	(0.21)
Quarter FE	Yes	Yes
Analyst FE	Yes	Yes
Broker FE	Yes	Yes
Constant	0.979***	0.548
	(6.29)	(1.13)
Observations	27,100	2,743
Adj. R2	0.029	0.437

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 4: Broker Size of the Transiting Analyst

This table presents the results by partition the treatment sample based on the broker size of transiting analysts. *Big-to-Small* refers to the situation when the transiting analyst switches from a larger broker to a smaller broker. *Small-to-Big* occurs when the transiting analyst moves from a smaller or equal broker to a larger broker. Quarter fixed effects, broker fixed effects, and analyst fixed effects are included in all specifications. *Affected* is subsumed by the analyst fixed effect. All remaining variables are defined in the Appendix. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Small-to-Big		**Big-to-Small**	
	Accuracy	Timeliness	Accuracy	Timeliness
Affected×PostIn	0.010	0.051	0.034**	0.076
	(0.60)	(1.27)	(2.15)	(1.61)
Affected×PostOut	-0.030	0.076	-0.021**	-0.015
	(-1.63)	(0.99)	(-2.02)	(-0.27)
PostIn	-0.011	-0.056	0.023	-0.195
	(-0.23)	(-0.33)	(0.64)	(-1.19)
PostOut	-0.012	-0.031	0.044	-0.180
	(-0.25)	(-0.18)	(1.20)	(-1.06)
Bundle	-0.007	0.012	0.000	0.010
	(-0.87)	(0.55)	(0.02)	(0.44)
Days Elapsed	-0.028**	0.738***	-0.016*	0.756***
	(-2.42)	(22.54)	(-1.85)	(27.12)
Specialization	-0.002	0.050	-0.003	0.010
	(-0.14)	(0.97)	(-0.25)	(0.24)
Lag Performance	0.048***	0.018	0.035***	-0.006
	(4.81)	(0.57)	(3.82)	(-0.24)
Horizon	-0.048***	-0.046	-0.040***	-0.044
	(-4.19)	(-1.24)	(-4.18)	(-1.34)
Broker size	-0.008	-0.201	-0.015	0.016
	(-0.38)	(-1.62)	(-0.61)	(0.12)
Firm number	0.001	-0.005	-0.025	0.066
	(0.05)	(-0.08)	(-1.62)	(1.09)
Industry number	-0.003	-0.027	-0.002	-0.074
	(-0.26)	(-0.67)	(-0.17)	(-1.19)
General experience	0.042	-0.086	-0.012	-0.113
	(1.31)	(-0.72)	(-0.39)	(-0.96)
Firm experience	-0.016	0.064	-0.009	-0.023
	(-1.43)	(1.64)	(-0.89)	(-0.59)
Quarter FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes

Broker FE	Yes	Yes	Yes	Yes
Constant	1.003***	0.229	0.257	0.826
	(4.10)	(0.27)	(1.55)	(1.25)
Observations	14,479	1,319	16,757	1,765
Adj. R^2	0.025	0.414	0.026	0.433

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 5: Industry Scope of the Transiting Analyst

This table presents the results by partition the sample based on the industry scope of the transiting analysts. *One Industry* represents the situation when the transiting analysts cover only one industry (SIC 2-digit code). *Multiple Industries* refer to the case when the transiting analysts cover more than one industry (SIC 2-digit code). Quarter fixed effects, broker fixed effects, and analyst fixed effects are included in all specifications. *Affected* is subsumed by the analyst fixed effect in some specifications. All remaining variables are defined in the Appendix. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	One Industry		**Multiple Industries**	
	Accuracy	Timeliness	Accuracy	Timeliness
Affected×PostIn	0.004	0.063	0.034**	0.051
	(0.21)	(0.95)	(2.08)	(0.94)
Affected×PostOut	-0.006	0.035	-0.036**	-0.013
	(-0.36)	(0.44)	(-2.32)	(-0.21)
PostIn	0.040	-0.158	0.014	-0.186
	(0.99)	(-0.72)	(0.35)	(-1.26)
PostOut	0.035	-0.168	0.024	-0.180
	(0.88)	(-0.75)	(0.58)	(-1.14)
Bundle	-0.006	-0.011	0.000	0.030
	(-0.64)	(-0.41)	(0.05)	(1.48)
Days Elapsed	-0.013	0.783***	-0.029**	0.764***
	(-1.24)	(15.87)	(-2.48)	(27.42)
Specialization	0.014	0.025	-0.015	-0.026
	(0.88)	(0.56)	(-1.11)	(-0.45)
Lag Performance	0.044***	0.016	0.040***	-0.025
	(4.48)	(0.63)	(3.49)	(-0.90)
Horizon	-0.034**	0.001	-0.050***	-0.063*
	(-2.36)	(0.02)	(-4.49)	(-1.71)
Broker size	0.013	-0.077	-0.037	-0.015
	(0.50)	(-0.72)	(-1.43)	(-0.09)
Firm number	0.004	0.071	-0.023	0.008
	(0.22)	(0.91)	(-1.42)	(0.15)
Industry number	-0.018	0.010	0.011	-0.126**
	(-1.28)	(0.17)	(0.80)	(-2.25)
Firm experience	-0.007	0.032	-0.016	-0.027
	(-0.57)	(0.78)	(-1.37)	(-0.69)
General experience	0.028	-0.038	-0.008	-0.219*
	(0.96)	(-0.30)	(-0.23)	(-1.87)
Quarter FE	YES	YES	YES	YES

Analyst FE	YES	YES	YES	YES
Broker FE	YES	YES	YES	YES
Constant	0.557*	1.030	0.903***	0.775
	(1.85)	(0.94)	(4.75)	(1.12)
Observations	12,396	1,259	14,697	1,482
Adj. R^2	0.028	0.428	0.023	0.420

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 6: Geographic Location of Covered Firms

This table presents the results by partition the treatment sample based on the geographic location of covered firms by incumbents and transiting analysts. Location of the firms are based on the state-level classification. *Same Location* refers to the situation where the location of covered firms by incumbents are in the same location of covered firms by transiting analysts. *Different Location* refers to the situation where the location of covered firms by incumbents are in the different location of covered firms by transiting analysts. Quarter fixed effects, broker fixed effects and analyst fixed effects are included in all specifications. *Affected* is subsumed by the analyst fixed effect. All remaining variables are defined in the Appendix. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Same Location		**Different Location**	
	Accuracy	Timeliness	Accuracy	Timeliness
Affected×PostIn	0.022*	0.086**	0.061	0.024
	(1.84)	(2.26)	(1.27)	(0.24)
Affected×PostOut	-0.026**	0.030	-0.020	-0.130
	(-2.47)	(0.59)	(-0.44)	(-0.71)
PostIn	-0.015	-0.134	-0.026	-0.212
	(-0.48)	(-1.13)	(-0.74)	(-1.40)
PostOut	-0.003	-0.124	-0.015	-0.194
	(-0.09)	(-1.09)	(-0.44)	(-1.32)
Bundle	-0.004	0.004	-0.010	0.005
	(-0.63)	(0.30)	(-1.15)	(0.28)
Days Elapsed	-0.021***	0.778***	-0.020**	0.802***
	(-2.76)	(33.79)	(-2.05)	(30.37)
Specialization	-0.002	0.007	-0.012	0.016
	(-0.25)	(0.18)	(-0.90)	(0.36)
Lag Performance	0.042***	0.008	0.041***	0.016
	(4.73)	(0.43)	(3.88)	(0.75)
Horizon	-0.041***	-0.036	-0.044***	-0.034
	(-4.86)	(-1.45)	(-4.83)	(-1.04)
Broker size	-0.013	-0.052	-0.002	-0.040
	(-0.72)	(-0.47)	(-0.08)	(-0.31)
Firm number	-0.010	0.043	-0.011	0.071
	(-0.83)	(0.97)	(-0.68)	(1.18)
Industry number	-0.003	-0.079*	-0.008	-0.122**
	(-0.31)	(-1.78)	(-0.65)	(-2.33)
General experience	0.010	-0.119	0.020	-0.118
	(0.41)	(-1.34)	(0.72)	(-1.22)
Firm experience	-0.014*	0.010	-0.006	-0.029
	(-1.77)	(0.35)	(-0.60)	(-0.79)

Quarter FE	YES	YES	YES	YES
Broker FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Constant	0.983***	0.611	0.883***	0.948
	(6.23)	(1.21)	(2.80)	(1.37)
Observations	26,625	2,697	17,790	1,798
Adj. R^2	0.029	0.438	0.030	0.447

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 7: Paired Transiting-Incumbent Analyst Fixed Effects

This table presents the results from using paired transiting analyst-incumbent analyst fixed effects. The variable *Affected* is subsumed by the paired analyst fixed effects. All remaining variables are defined in the Appendix. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Accuracy	Timeliness
Affected×PostIn	0.023*	0.083**
	(1.91)	(2.14)
Affected×PostOut	-0.024**	0.021
	(-2.21)	(0.40)
PostIn	0.003	-0.120
	(0.16)	(-1.00)
PostOut	0.014	-0.112
	(0.70)	(-0.96)
Bundle	-0.003	0.007
	(-0.56)	(0.45)
Days Elapsed	-0.022***	0.777***
	(-2.99)	(32.32)
Specialization	-0.002	0.011
	(-0.17)	(0.27)
Lag Performance	0.042***	0.002
	(5.01)	(0.12)
Horizon	-0.043***	-0.031
	(-5.05)	(-1.19)
Broker size	-0.014	-0.057
	(-0.78)	(-0.49)
Firm number	-0.012	0.044
	(-1.03)	(0.93)
Industry number	-0.002	-0.070
	(-0.26)	(-1.53)
General experience	0.011	-0.119
	(0.48)	(-1.25)
Firm experience	-0.013	0.006
	(-1.62)	(0.20)
Quarter FE	Yes	Yes
Paired analyst FE	Yes	Yes
Constant	0.896***	0.563
	(8.80)	(1.04)
Observations	27,235	3,127

Adj. R^2	0.036	0.467

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 8: Placebo Analyses

This table presents the results by conducting a placebo test where the transition date is moved forward for one year ahead. All variables remain unaltered as those used in Table 3. Quarter fixed effects, broker fixed effects, and analyst fixed effects are included in the main regressions. All remaining variables are defined in the Appendix. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Accuracy	Timeliness
Affected×PostIn	0.015	-0.005
	(1.11)	(-0.11)
Affected×PostOut	0.019	-0.042
	(1.05)	(-1.02)
PostIn	0.015	0.122
	(1.39)	(1.00)
PostOut	0.008	0.119
	(0.60)	(1.03)
Affected	0.098**	0.571**
	(2.51)	(2.23)
Bundle	-0.007*	0.001
	(-1.84)	(0.08)
Days Elapsed	-0.039***	0.732***
	(-3.82)	(34.50)
Specialization	-0.006	-0.012
	(-0.63)	(-0.36)
Lag Performance	0.043***	-0.023
	(5.61)	(-0.98)
Horizon	-0.058***	-0.107***
	(-7.42)	(-5.14)
Broker size	0.020	-0.094
	(1.17)	(-1.18)
Firm number	0.011	0.022
	(0.88)	(0.53)
Industry number	0.003	-0.043
	(0.29)	(-1.07)
General experience	0.007	0.055
	(0.43)	(0.66)
Firm experience	-0.002	-0.006
	(-0.22)	(-0.19)
Quarter FE	Yes	Yes
Analyst FE	Yes	Yes

Broker FE	Yes	Yes
Constant	0.100*	-0.631
	(1.72)	(-1.03)
Observations	27,437	2,704
Adj. R^2	0.029	0.430

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 9: Additional Analyses on Transiting Analysts

Panel A: Summary Statistics for Coverage Portfolios of Transiting Analysts

This table presents the summary statistics for coverage portfolios of transiting analysts. The sample includes all the firms that are covered by the transiting analysts before and after transitions. *SameFirm* equals 1 if the firm is in the coverage portfolios both before AND after the transitions, and zero otherwise. *%SameFirm* shows the percentage of firms in the new portfolios for each transiting analyst, which are also covered by the transiting analysts before the transitions. In other words, it shows the percentage of coverage portfolios that remain unchanged after the transitions.

Variable	Mean	p25	p50	p75
SameFirm	0.37	0.00	0.29	1.00
%SameFirm	0.36	0.06	0.30	0.58

Panel B: Performance of Transiting Analysts

This table presents the results from regressions explaining forecast accuracy with a transition indicator variable. *Post* equals 1 if the forecast is issued after a transition for the same firm. The observations consist of the forecasts issued within two quarters before a transition and forecasts issued within 3rd and 4th quarter after a transition for the same firm. The regression includes analyst fixed effects. Dependent variables Accuracy_t and Timeliness_t are the average RAW values of each performance. Specifically, we take the average accuracy and average timeliness of a transiting analyst's all forecasts in a broker. All control variables are taken as the average across all forecasts issued within the same broker. t-statistics (in parentheses) are adjusted for the broker clustering. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Accuracy_t	Timeliness_t
Post	0.011	1.662**
	(0.24)	(2.16)
Lag Performance_t	0.060*	0.719***
	(1.83)	(2.63)
Bundle_t	-0.079	-0.438
	(-0.72)	(-0.17)
Days Elapsed_t	-0.016*	0.652*
	(-1.94)	(1.94)
Specialization_t	0.229	-4.095
	(0.70)	(-1.01)
Horizon_t	-0.004	-0.011
	(-1.23)	(-0.30)
Broker Size_t	-0.001	0.036*
	(-0.50)	(1.84)
Firm Number_t	-0.009	0.114
	(-1.13)	(1.28)

Industry Number_t	0.020	-0.588
	(0.35)	(-1.08)
General Experience_t	0.009	0.093
	(1.53)	(1.03)
Firm Experience_t	-0.012	-0.165
	(-1.48)	(-1.38)
Size_t	-0.038	-1.677
	(-0.65)	(-1.07)
ROA_t	2.508**	14.964
	(2.44)	(0.94)
BTM_t	-0.157**	-0.162
	(-2.41)	(-0.25)
Constant	-0.053	12.114
	(-0.09)	(1.05)
Analyst FE	Yes	Yes
Observations	620	430
Adj. R^2	0.23	0.47

Robust t-statistics in parentheses
***p<0.01, **p<0.05, *p<0.1