Do analysts with close ties improve the firms' information environment? Evidence from a relationship-based economy

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Abstract

This paper examines the information role of social and business ties between financial analysts and firm managers in a relationship-based economy like China's, where relational contracts create challenges to a firm's public disclosures. We find that social and business ties can facilitate the private transfer of information and create positive externalities that improve the firm's information environment. Specifically, we find that forecasts of analysts connected through social and business ties are more accurate and timely than those of unconnected analysts. Similarly, firms with more connected analysts following have more accurate consensus forecasts and lower forecast dispersion. These results are not simply the aggregation of the effects of individual analysts, but rather are due to a spillover effect that impacts the forecast accuracy of both the unconnected analysts and the firm's information environment as a whole. This spillover effect is stronger for firms that are politically connected or that have a concentrated number of customers and suppliers whose contracts are more relationship-based. In additional tests, we find that these results are present using a difference-in-difference analysis of a subsample of analysts that have left the financial analyst industry.

1. Introduction

China's listed firms rely heavily on relationship-based contracting because the country's capital market and legal institutions are not well developed (Rajan and Zingales, 1998; Hung et al., 2014). These relational contracts, due to their implicit nature, create a challenge for public disclosure because the information is often imprecise and hard to verify. In addition, public reporting may reveal sensitive information about network ties (e.g., political connections or strategic partnerships), which can jeopardize the firms' competitiveness and even destabilize the connection itself. Thus, when firm managers determine their disclosure strategy, they need to balance between the political and proprietary costs of disclosing information associated with relationship-based contracts and the high cost of financing as a result of information opacity.

In this paper, we study whether financial analysts with social ties to a firm manager can be credible channels of information dissemination in China. Although prior research has already documented that network ties can facilitate the transfer of private information in the U.S. (Cohen et al., 2008, 2010), we argue that the nature of the information being transferred and the relative importance of this information channel are different in the two markets. As discussed earlier, economic activities in China are dominated by relational contracts, which create challenges to a firms' public information disclosure. The trust established through close network ties can overcome these challenges by credibly converting the soft information (e.g., relational contracts) into hard information (e.g., earnings forecasts) while protecting the propriety of the information. Rather than communicating through public disclosures, transfer of information via private networks of trusted analysts can be an important and effective channel for the managers to credibly convey information about the relational contracts. This contrasts with the U.S. where firms typically communicate about their arms-length contracts through public channels.[1]

The reliance on social connections for information transfer is further reinforced by the social structures of Chinese society, in which strong trust is developed within closely, knitted social groups (Jacobs, 1979; Gold, 1985; Guthrie, 1998; Peng, 2004). Because of the prevalence of relationship-based contracts, the trust developed through Chinese social structures, and the ability of social ties in resolving the information disclosure difficulties of these contracts, we expect network ties to play a much more significant role in information transfer in China. Thus, our first research question examines whether financial analysts with close ties to the firms have more accurate, informative, and timely forecasts than those without close ties.

When a manager aims to communicate to the market via connected analysts, her goal is not limited to simply enhancing the knowledge of the analysts within the private network. The network transfer should produce positive externality so that the information will eventually be transmitted to *other* analysts following the same firm, thus improving the firm's information environment as a whole. However, the literature is not clear about whether network transfer of private information produces positive externalities (Allen and Babus, 2009). If such network only gives connected analysts an information advantage and increases the asymmetry among analysts, it may drive out other competent but unconnected analysts and lead to even lower consensus forecasts by reducing

[1] While private communication channels are also considered an important information channel for the U.S. firms, such channels are often used to supplement public disclosures (Solomon and Soltes, 2014; Soltes 2014) and may even considered to be illegal if it leads to selective disclosure to certain connected parties (because of Regulation Fair Disclosure [Reg FD]).

the competition among analysts (Hong and Kacperczyk, 2010). Such outcome will not be considered an effective communication strategy for the firm.

Thus, our second research question examines whether the information transfer between the connected analysts and the firm manager, which occurs between two nodes in a network, has a spillover effect by improving the consensus forecast accuracy of analysts unconnected with the firm. Finding a positive spillover effect on the forecast accuracy of the unconnected analysts will show that the private information transfer produces a positive externality and improves the information environment of the firm. It also confirms the earlier arguments that the social structures of the ties are strong enough to ensure credible information exchanges and to overcome the communication challenges associated with relational contracts.

In our final research question, we test whether the spillover effect is stronger among firms with more relationship-based contracts. Documenting a stronger spillover effect for firms with more relational contracts will highlight the role of network ties in transmitting private information and its positive externality. Furthermore, finding affirmative results for these two research questions will support the conjecture that firm managers successfully use their network ties to connected analysts to communicate with the capital market, especially when firms face more challenges in communicating about their relational contracts.

We begin by identifying analysts that share close ties with firm managers. We use three measures of close ties. The first is school ties, based on the analysts and managers of the investee firms' education networks. We consider an analyst to share close ties with a firm if the analyst went to the same university as any of the senior managers in a firm's management team. We construct a second proxy of close ties using geographic proximity and consider an analyst to be connected when the analyst and the firm are located in the same city (Coval and Moskowitz, 2001). In addition to social networks, close ties can emerge through business interactions (Jacobs, 1979). Our final measure of close ties is based on the investment banking relationship between the firm and the analyst's brokerage firm. We consider an analyst to be closely connected to a firm if they share any of the three tie measures discussed above.

We conduct our analysis both at the analyst and the firm levels. The analyst-level test allows us to directly compare the properties of the forecasts of individual analysts. We confirm that the earnings forecasts of connected analysts are more accurate and also timelier. The estimates suggest that the forecasts of connected analysts are 8.35% (6.35%) more accurate (timelier) than those of unconnected analysts. Also, the forecasts of connected analysts are more likely to trigger revisions from unconnected analysts. Following the issuance of the connected analysts' forecasts, the revisions of other analysts are more likely to show a reduction in their forecast errors. This reduction suggests that the forecasts of connected analysts are more likely to provide new, relevant information to the market.

Next, the firm-level tests examine how the forecasting activity of connected analysts affects the accuracy of consensus forecasts. We find that the activity of connected analysts leads to lower consensus forecast errors and lower dispersion among all analysts. As more connected analysts cover a firm, the consensus forecast (as well as the consensus forecasts of *unconnected* analysts) becomes more accurate. More specifically, a one standard deviation increase in the number of forecasts issued by connected analysts reduces the consensus forecast errors by 13.3% relative to the sample mean. Greater activity by connected analysts reduces the dispersion of forecasts among all analysts (as well as the forecast dispersion of all *unconnected* analysts). We also find that analysts' forecasts get impounded into prices faster as the activity of connected analysts increases. Taken together, the findings suggest that the greater forecasting activity of connected analysts increases the precision of the analysts' forecasts (as a group). The increased performance is achieved through two channels: (i) the direct aggregation effect of individual analysts' forecasts and (ii) the indirect spillover effect on the forecasts of other, unconnected analysts.

In further cross-sectional tests, we show that the activity of connected analysts have a greater spillover effect on firms that are politically connected or that have a concentrated number of customers and suppliers. We expect private information transfers to play a relatively more important role in these firms, whose contracts are more relationship-based and harder to be verified by a third party. The findings suggest that the benefit of connected analysts' activity, measured in terms of consensus forecast accuracy and forecast dispersion, is greater when the firm's economic activity relies heavily on relational contracts. This cross-sectional test lends more support to the mechanism through which the benefits of connected analysts occur.

Nonetheless, the difficulty in empirically identifying the effect of connected analysts is that the followings of connected analysts and their accuracies are endogenously determined. The decision to cover a firm is not randomly assigned and how intensively an analyst follows that firm is determined by factors such as skill and the analyst's relative information advantage. Hence, our inferences may be limited by the fact that analysts make their coverage decisions endogenously, and these decisions may lead to an association between the performance of an individual analyst and her connections even in the absence of private information transfers. We address this concern by additionally investigating firms that experience a decrease in the coverage of connected analysts for relatively exogenous reasons. That is, we exploit analysts' departures that result from a career change and/or a brokerage closure or merger.[2]

We find that following the departure of a connected analyst, the accuracy of consensus forecasts show a significant reduction. In contrast, when we examine firms with departing *unconnected* analysts, we find no changes in consensus forecasts' accuracy following the departure event. Empirical tests show that following the departure of a connected analyst, the increase in the forecast errors of the consensus forecasts is 23% greater than the benchmark sample (the increase following the departure of an unconnected analyst). Also, the effect a connected analyst's departure has on the firm's information environment is greater when the departing analyst plays a pivotal role, i.e., when the departing analyst was the only connected analyst following a firm. The results confirm our earlier findings that the greater forecasting activity of a connected analyst has the effect of increasing the performance of other analysts' forecasts. Using analyst departures, we find that the departure of a connected analyst has a perverse effect on the quality of analyst forecasts.

This paper contributes to the literature in two ways. First, we provide new insights into the literature on the sources of financial analysts' information advantage and its impact on the firms' information environment. In addition to the finding in Cohen et al. (2010) that social ties can reduce the cost of private information acquisition and improve analysts' stock recommendations, we show that connected financial analysts produce more accurate and timely forecasts. More importantly, our evidence shows that the increase in connected analyst forecast accuracy leads to a spillover effect on the firm's information environment as a whole. This illustrates that information transfers via network

[2] This approach was first developed by Kelly and Ljungqvist (2012) and Hong and Kacperczyk (2010) and has been used to determine causality in numerous subsequent analyst studies.

ties do not simply increase the private information of the two nodes within a link, but that there is a spillover effect on nodes outside the link, producing a positive externality.

Second, we contribute to the research on the role of networks in private information transfer in emerging markets. Firms often face challenges in credibly disclosing information because much of the revenue sources are based on implicit contracts. Private information transfer through networks can achieve the objective of credible information dissemination while protecting the propriety of sensitive information associated with the contracts. We demonstrate that connected analysts can serve as a channel that enables firms to transmit private information via network ties, and that this effect is stronger among firms that are more relationship-based. One implication of our findings is that in such markets, where public disclosure cannot credibly communicate soft information and too much public disclosure may expose firms' stakeholders to significant proprietary costs, policies that prohibit private communication through selective disclosure to financial analysts such as Reg FD may lead to an unintended consequence: they can reduce financial analysts' informational role. In emerging markets, analysts with close ties can improve their firm's information environment by verifying and disseminating soft information that would otherwise be difficult to credibly communicate.

The remainder of the paper is organized as follows. Section 2 describes the prior literature and the hypotheses. In Section 3, we discuss the sample and present descriptive statistics. Section 4 presents our empirical tests, which examine the role of the connected analyst on various forecasting outcomes. Section 5 discusses additional analyses and Section 6 concludes.

2. Prior literature and hypotheses development

Prior research documents that analysts provide information to the market through two channels: the analysis of public information (Bhushan, 1989; Lang and Lundholm, 1996) and the acquisition of private information (Chen et al., 2010).[3] Access to private information can be obtained through direct contact with firm managers (Ke and Yu, 2006; Soltes 2014) or other non-public information sources such as connections with large institutional investors or other analysts (Jennings et al., 2014).

We expect analysts' private information acquisition through network connections to be more important in China. In fact, this network transfer of information is an important communication channel between the firms and the market. Like other emerging economies, China's legal and market institutions are not well developed, and social structures in Chinese society encourage trust building through social ties (Jacobs, 1979; Gold, 1985; Guthrie, 1998; Peng, 2004). Also, firms rely more on relationships rather than arms-length mechanisms to enforce contracts (Rajan and Zingales, 1998; Hung et al., 2014). Many key terms and contingencies of contracts are not formally specified and are difficult for a third party to verify. Also, the implicit nature of these contracts gives rise to the disclosure of mostly soft, rather than hard, information, which makes public disclosure about the contracts difficult.[4]

[3] The two channels are not mutually exclusive; analysts can use pieces of private information to better analyze public information.

[4] Many of these contracts are implicit and involve specific investments in the form of social, political and business relationships (Klein, Crawford, and Alchian, 1978). Due to the specificity of these investments (i.e. each relationship is specific and different), it is hard for outsiders to evaluate the risks and payouts, which impact firm value.

This contracting environment leads to a concentration of ownership and control of firms (Fan and Wong, 2002) and an insider-based accounting system (Ball et al., 2000, 2003). That is, accounting is less transparent and there is much less firm-specific information available in the markets (Fan and Wong, 2002; Piotroski and Wong, 2012; Gul et al., 2010). Instead of public reporting and disclosure, firm managers can engage in private, direct communication with large shareholders, trade partners, and creditors with whom they have relationship-based contracts and with the government, with which these firms have established strong ties. Nonetheless, these firm managers will face a tradeoff as their demand for external financing in the equity markets increases. They will need to balance between protecting proprietary and sensitive information and reducing information asymmetry through communication with the capital market.

One way for the firm managers to balance these opposing forces and maintain control over the communication process is via private networks. We propose that in China, firm-specific information can be transferred from a firm to the market via credible information intermediaries such as financial analysts that have close ties with the firm. The prior literature shows ample evidence suggesting that social ties can facilitate the transfer of private information (Uzzi and Gillespie, 2002; Granovetter, 2005; Cohen et al., 2008, 2010; Gao et al., 2014). Close ties can ensure that the information being released by the firms to the analysts is credible and that the analysts will protect the propriety of the information and can convert soft information (i.e., relational contracts) into hard information (i.e., earnings forecasts). By having an intermediary, a financial analyst, publicly issue an earnings forecast, the firm can expect the hard forecast to convey a soft signal that may be too sensitive to disclose publicly, and make use of the analyst's credibility and reputation to increase the market's faith in the released information. The analyst's timely public releases of forecasts can also serve as a monitoring device for the firms to ensure that their soft information is being conveyed to the market.

Further, the informational role of the forecasts is not restricted to the link between analysts and firm managers. The connected analysts can credibly disseminate the information to institutional investors within their social and business networks. Firm managers can thus communicate with a vast network of outside investors to which they would not otherwise have access.

Thus, we expect China's analysts, relative to their U.S. counterparts, to focus more on establishing close ties with firms for the purpose of securing private information than on building expertise in analyzing and interpreting the publicly available information. Of course, these private information channels are also likely to be present in developed economies such as the U.S. For example, O'Brien and Tan (2014) find that the geographical proximity of analysts increases analyst coverage for IPO firms.[5] Nevertheless, due to the nature and prevalence of relationship contracts in China, private information transfer through social and business ties is likely to be an important communication channel, which can transmit information to the market when the public disclosure channels fail.

However, it is possible that the social structure governing the relationship between analysts and firm managers is too weak to secure the information transfer. Also, strong incentives to make an individual profit may induce the analysts to delay releasing private information or to fail to release it at all. On the firm's side, firms with relationship-based contracting may have strong incentives to not disclose the information publicly, even via connected analysts. More accurate and timely forecasts, although not accompanied by sensitive or proprietary information, could increase the chances of

[5] However the authors find that the role of geographic proximity is greater when a firm's operations are less complex, suggesting that the role of nearby analysts is limited when a firm's economic activities are inherently complicated.

public scrutiny, which could jeopardize their connections and competitiveness. Thus, whether the connected analysts serve as conduits for information transmission through their social and business networks remains an empirical question. This leads to our first hypothesis, which is as follows.

H1: Ceteris paribus, connected analysts are more likely than unconnected analysts to issue more accurate and timely earnings forecasts.

Finding evidence that the forecasts of the connected analysts are more accurate and timely is consistent with the notion that private networks are used as an information channel to the market. Although we cannot directly test whether firms take the initiative to release private information to connected analysts, the results are consistent with the notion that the firms are, at least, allowing private information to be transferred to the connected analysts. That is, if a firm dislikes having its private information leaked via network ties, it will distant itself from the connected analysts or shut them out. However, if firm managers do intend to engage connected analysts as a means of transferring private information, then these analysts are expected to publish accurate and timely forecasts as a credible assurance that they have promptly communicated the information to investors.

Our next research question addresses whether the transfer of private information is limited within the networks, or it is transmitted to the rest of the market, increasing the information environment of the firms. Finding such a positive externality will further demonstrate that Chinese firms can use the private networks of analysts to communicate with the market. Prior literature has found that in a developed market like the U.S., social ties do facilitate the transfer of private information in various contexts (Ivkovic and Weisbenner, 2007; Cohen et al., 2008, 2010; O'Brien and Tan, 2014). Our first hypothesis will shed light on whether network ties can facilitate private information transfer between firms and financial analysts in an emerging market. Although prior research has shown that social ties can be an important mechanism that channels information, it is less clear about whether there are network externalities (Allen and Babus, 2009). Our next hypothesis addresses this gap in the literature.

One important aspect of network externalities in our context is whether the connections between firm managers and financial analysts actually increase or decrease the firms' overall information environment, as captured by the consensus forecasts of the *unconnected* analysts. Here, we want to test if the network transfer of private information will have a spillover effect by raising the forecast accuracy and informativeness, and by lowering the forecast dispersion of unconnected analysts, leading to a positive externality. However, the network transfer can create entry barriers that drive away capable but unconnected analysts and that reduce the firms' overall (consensus) forecast accuracy, resulting in a negative externality.

We conjecture that unconnected analysts are unlikely to leave the market because even when a connected analyst has an information advantage over them with regard to a particular firm, this dynamic is unlikely to hold for all the firms in the unconnected analysts' portfolios. This is because the same unconnected analyst can be connected to another firm, one for which the original connected analyst has little information advantage.[6] Further, information could be shared between connected analysts and unconnected analysts. Recent theoretical studies show that communication among competing participants can be beneficial (Stein, 2008) because, through the exchange of opinions,

[6] Unconnected analysts will not only stay in the market, they may have incentives to follow firms for which they have an information disadvantage to better serve their own clients (e.g., institutional investors). When a connected analyst receives private information about a soft signal, she will not directly disclose it to the public. Instead, she will use this soft information to make an earnings forecast that conveys the soft signal without revealing too much sensitive information. In these circumstances, unconnected analysts can provide value to their clients by interpreting the connected analysts' forecasts. Institutional investors that do not have direct access to the firm or the connected analyst will instead look to an unconnected analyst to interpret the earnings forecast the connected analyst issued and update their own belief.

analysts can also collect new pieces of information and learn about other analysts' views, which in turn helps to validate their own opinions. In sum, if connected analysts' forecasts are indeed more accurate and timely (our hypothesis 1) and their presence does not push out the unconnected analysts, and information is shared between the two analyst groups, the externality can be positive. Our second hypothesis is as follows.

H2: Greater activity on the part of connected analysts will increase the accuracy and timeliness of the consensus forecasts of other (unconnected) analysts.

Finally, we predict that the spillover effect of connected to unconnected analysts is likely to be stronger in firms that are more relationship-based. When firms engage in more relational contracts, we expect connected analysts to play a more important role in transmitting private information. They are thus likely to have a larger effect on the accuracy, informativeness, and dispersion of the forecasts of unconnected analysts. To test this prediction, we exploit the cross-sectional variation in the listed firms' levels of relationship-based contracting. We identify firms as being more or less relationship-based by using information about whether they have strong vs. weak political connections or concentrated vs. non-concentrated suppliers and customers. Thus, our third hypothesis is as follows.

H3: Ceteris paribus, the spillover effect of connected analysts onto unconnected analysts is greater among firms that are more relationship based, as opposed to less relationship based.

3. Sample and empirical measures

3.1 Sample

Our analyst sample starts in 2005, the year the financial analyst industry experienced significant growth in China, and ends in 2013. The rapid growth of the financial analyst industry was triggered by the government's decision to deregulate IPO pricing in 2004.

To collect analyst earnings forecasts, we compile our data using 10 different data vendors.[7] While many research papers use a subset of these data sources, we find that no single vendor provides comprehensive coverage of analyst followings in China. For example, the coverage in CSMAR (RESSET), which is one of the most widely used databases in prior studies on Chinese analysts (e.g., Gu et al., 2013), includes only 14% (58%) of our earnings forecast sample. The number of brokerage firms included in the CSMAR (RESSET) sample is 130 (119) compared to the 185 in our merged sample. Also, Thomson I/B/E/S, another database widely used in cross-country studies (Bae et al., 2008), only includes a portion of our sample.[8] The coverage in I/B/E/S is biased towards larger firms and the forecasts included in I/B/E/S tend be more pessimistic compared to the forecasts in our entire sample. Hence, our study highlights the importance of using a comprehensive sample when conducting analyst research in emerging markets or cross-country studies.

We download all the earnings (EPS) forecasts from these 10 databases. We only include firm-level earnings and exclude industry-level forecasts. We ensure that all the earnings forecasts are for annual earnings and are made within the year prior to the earnings announcement. We start out with the CSMAR analyst forecast database because it is one of the most widely used databases for China's analyst research; we obtain all the firm financial variables from CSMAR. We then add new forecasts from the different data vendors. To ensure accuracy, for a new forecast to be included in

[7] The 10 vendors are the following: CSMAR (http://www.gtadata.cn), RESSET (http://www1.resset.cn:8080/product), WIND (http://www.wind.com.cn), IFIND (http://www.10jqka.com.cn) , Choice (http://choice.eastmoney.com/Product/index.html), CCXE (http://data.ccxe.com.cn/user/toLogin.action) , VSAT (http://www.vsatsh.com.cn), JY (http://www.gildata.com.cn), SUNTIME (http://www.go-goal.com/), and QMX (http://www.shenguang.com/qmx/qmx2/10down.html).

[8] The coverage in I/B/E/S is particularly spare in earlier years. In the earlier years of our sample period (from 2005 to 2008), we find that I/B/E/S includes only 43% of our sample observations. The coverage improves post 2010.

our sample, we require that the observation is recorded in at least two of the other nine databases. For a brokerage firm to be included in our sample for that year, we require that it has at least 20 or more distinct earnings forecasts. Otherwise, the brokerage firm is considered inactive and we remove all its forecasts from the sample for that year.

We match the analyst sample with the firm sample in CSMAR. We include all firms that issue A-shares traded on the Shanghai and Shenzhen Stock Exchanges. We include only firms that have at least one analyst following throughout the sample period. The final sample includes 2,372 firms and 4,516 analysts. The average (median) number of analysts following a given firm is 15(9) in our sample period.[9]

3.2 Empirical measures of close ties

We employ three measures of close ties. The first two measures capture the social ties between an analyst and a firm manager. For the first measure of social ties, we use school ties between an analyst and the managers of a firm the analyst follows. Extant studies show that education networks can function as a channel of information transfer for financial analysts (Cohen et al., 2010). Following this literature, we exploit school ties, namely attendance at the same academic institutions, to identify analysts with close ties to a firm. The management team's educational backgrounds are collected from the CSMAR corporate governance research database, which contains biographical information about the C-suite executives of each firm. The educational backgrounds of the analysts are hand collected from individual resumes obtained from the following sources: the 2014 star

[9] The unit of analysis is the brokerage team. In other words, we consider forecasts issued by a team as an individual forecast.

analysts report sponsored by *New Fortune* magazine, manual searches of professional networking sites (*WeiBo*), individual analyst reports, and/or brokerage firm websites.

Second, we use the geographic proximity between the analyst and the firm headquarters (Hong et al., 2004). O'Brien and Tan (2014) show that nearby analysts are more likely to cover a firm, especially when the firm is smaller and less visible. Also, Malloy (2005) shows that local analysts provide more accurate forecasts and generate greater price responses than do more distant analysts. He argues that analysts located close to a firm may have better access to management established through more frequent face-to-face interactions. Following this line of research, we use geographic proximity as our second measure of social ties. We consider an analyst to have close geographic ties with a firm manager when the analyst's brokerage firm is located in the same city where the firm is headquartered.

The third measure captures the business ties between the firm and the analyst's brokerage firm formed via prior investment banking relationships. An extensive literature shows that underwriting relationships play a substantial role in analyst activities (see O'Brien et al., 2005; James and Karceski, 2006; Ljungqvist et al., 2006; Clarke et al., 2007). O'Brien et al. (2005) show that affiliated analysts show biased forecasts at the time of the IPO. But while a conflict of interest may lead to biased forecasts *at the time of the IPO*, our interest is in capturing the close relationship that form *following the IPO*. We argue that ties established through prior banking relationships (and the subsequent favors exchanged between the two parties) are likely to sustain and build subsequent ties between the two parties. Empirically, we consider an analyst to have business ties with a firm manager if the analyst's brokerage firm served as the firm's lead underwriter for share issuance (IPOs and SEOs) within the last five years. Information on initial public offerings and secondary equity offerings (i.e., the offering data and the name of the lead underwriter) is obtained from CSMAR. We match the IPO and SEO sample with the analyst sample and identify whether the earnings forecast issued was for a firm that had an underwriting relationship with the analyst's brokerage house within the last five years.

Social ties emerge through multiple channels. Jacobs (1979) argues that in Chinese society these channels of network ties (termed *guanxi bases* in his paper) mainly arise from ties among kin, local residents, co-workers, classmates, and business associates. In our empirical tests, we consider an analyst to have close ties to the firm if she shares school, geographic, or investment banking ties with the firm. Table 1, Panel A shows the distribution of analyst followings that are considered to be closely tied to the firms in our sample. The most common sources of ties between a firm and a financial analyst are geographic ties and investment banking ties, followed by school ties. 27% (15%) of the firm-years show a following from at least one analyst with geographic ties (investment banking ties). School ties are less frequent: 15% of firm-years have at least one analyst connected through school ties. Empirically, we consider an analyst to be connected if she shares at least one of the three measures of close ties. Panel A shows that 44% of firm-years have at least one connected analyst following the firm. The percentage of firm-years with two connected analysts are significantly lower, i.e., 7.89%.

4. Empirical analyses

4.1 Analyst-level analysis

4.1.1 Test design

Our first analysis runs cross-sectional regressions using analyst-firm-year pairs as the unit of analysis. We regress the accuracy of individual analyst forecasts on various firm and analyst characteristics to test the notion that analysts with close ties possess an information advantage. We run the following regression model:

$$\text{Abs. forecast error (Timeliness, Convergence)}_{a,i,t} = \beta \times \text{D\_connected}_{a,i,t} + \gamma \times \text{Controls} + \text{FE} + \varepsilon_{a,i,t.} \quad (1)$$

The unit of analysis is analyst (*a*) – firm (*i*) – year (*t*). $D\_connected_{a,i,t}$ is our main variable of interest; it takes a value of one when Analyst *a* shares close ties with firm *i* at the beginning of year *t*. We include industry fixed effects and year fixed effects to control for unobservable factors that affect the predictability of firm earnings in different industries and years.[10]

We infer the performance of the analyst by examining three different properties of earnings forecasts. First, we examine forecast accuracy measured using absolute forecast error. $\textit{Abs. forecast error}_{i,t,\,a}$ is defined as the absolute value of Analyst *a*'s latest forecasts minus the actual EPS of firm *i*, scaled by the stock price at the beginning of the fiscal year *t*. We include only the latest forecast issued by each analyst to ensure that the forecast performance is not affected by its age (Clement 1999).

The other performance measures capture the level of influence the forecast had on the activities of other analysts. The *Timeliness* measure is based on the intuition that the more time it takes for a forecast event to trigger forecast issuances from other analysts, the less timely is the forecast. The underlying assumption is that more influential analysts will tend to lead the information release of other analysts and trigger more prompt forecast issuances (Cooper et al., 2001). Following Cooper et

[10] In additional analysis, we also include firm-year fixed effects (Malloy, 2005) to control for factors that make a particular firm's earnings easier (or harder) to predict in some years than others (e.g., voluntary management disclosures, mergers, management turnover, etc.). All our results remain intact with reduced economic significance.

al. (2001), we measure *Timeliness* as the cumulative number of days required to generate N earnings forecasts from other analysts preceding the forecast issuance (=T0) divided by the number of days required to generate N forecasts following the issuance (=T1) (Cooper et al., 2001; Shroff et al., 2014).[11]

The final performance measure, *Convergence*, captures the forecast's influence by examining the effect it had on other analysts' forecast accuracy after its issuance. Empirically, we define *Convergence* as (FE0 – FE1)/FE0, where FE0 (FE1) is the average absolute forecast error for the two forecasts from T0 (T1) of the timeliness measure. The measure takes a higher value if there is a relatively greater reduction in forecasts errors following the forecast issuance.

We control for several factors that previous research has identified as affecting analyst accuracy. Clement (1999) stresses the need to control for the age of the forecasts when comparing their accuracy. We include the number of days (*Horizon*) between Analyst *a*'s forecast for firm *i* and the firm's fiscal year end. Following Clement (1999), we also include controls for analyst's experience level and available resources. We measure the individual analyst's overall experience (*Experience*) as the number of days between the analyst's first forecast (in the database) and the day of the current forecast. We also measure analysts' firm-specific experience (*Experience_firm*) using the number of days between an analyst's first forecast for a firm and the day of the current forecast for that firm. We measure available resources by calculating the size of Analyst *a*'s brokerage firm (*Broker_size*), computed as the total number of analysts hired by the analyst's brokerage firm for the same year. We

[11] We impose N to equal 2 throughout our empirical tests. While increasing the Ns in the measurement period would allow us to capture the longer term effect, doing so would mean dropping the firms with a small number of analysts following. Thus, our sample in the timeliness tests includes only firms that are followed by at least five analysts. (=2 in pre-period + 2 in post-period+1).

control for analyst reputation by computing dummy variables that are equal to 1 if Analyst *a* is a star analyst (*Star*).

Finally, we control for various firm characteristics, including firm size (Bhushan 1989), trading volume (*volume*), and institutional holdings (*institutions_share*) to control for firm visibility. We include the book-to-market ratio (*BM*) and returns volatility (*Stdret*) to account for the riskiness of the firm that may make forecasting a more difficult exercise. Following Alford and Berger (1999), we include analyst followings (*following_all*) to control for the fact that more analysts following is associated with greater accuracy. We winsorize the extreme 1% observations for each dependent variable and all control variables. Detailed definitions of each measure are provided in the appendix.

4.1.2 Full sample regression results

Table 2 shows the estimated results of the pooled regression. The estimated coefficients show that forecast accuracy is greater for analysts with close ties to the firm. In column (1), using *abs. forecast error* as the dependent variable, the estimated coefficient on the *D_connected* indicator is negative and significant (β= -0.079, p-val <0.001). This suggests that the forecasts of connected analysts show greater absolute forecast errors by 0.079, on average. Considering the sample mean of the forecast errors (= 0.945, Table 1, Panel B), the estimate suggests that the forecasts of connected analysts are 8.35% more accurate than those of unconnected analysts.

Many of the control variables load in the expected direction. Perhaps the most important is the horizon, which captures the age of the forecasts. *Horizon* is positively related to the forecasts errors (γ = 0.004, p-val <0.001), which suggests that the later forecasts are more accurate. The economic magnitude is comparable to the estimates of Clement (1999) who reports that the relative absolute forecast errors increase at the rate of 0.35% per day, and who stresses the need for careful controls for age when comparing forecasts. The results show that forecast errors are positively associated with returns volatility (*Stdret*) and trading volume (*Volume*), and negatively associated with the number of analysts following the firm (*Following_all*). We find no evidence of an analyst's prior experience affecting forecast accuracy: an analyst's firm-specific experience shows no significant relation with forecast accuracy while we find that an analyst's individual experience is negatively associated with forecast accuracy.

While we control for the age of the forecasts, it is still possible that the greater accuracy of connected analysts is partially driven by delayed issuances of the forecasts which the *Horizon* control variable fails to measure. In column (2), we therefore directly test whether the forecasts of connected analysts are more/less timely relative to that of the unconnected analysts. Using the *Timeliness* variable defined earlier as the dependent variable, we find that connected analysts issue more timely forecasts than do unconnected analysts. The estimated coefficient on the *D_connected* indicator is positive and significant (β = 0.060, p-val =0.005). The estimated coefficient suggests that the forecasts of connected analysts are, on average, 6.35% timelier than those of unconnected analysts (= 0.06/0.945, where 0.945 is the sample mean from Table 1, Panel B). The finding supports the view that the greater accuracy of connected analysts shown in column (1) cannot be explained by delayed issuance of forecasts. The forecasts of connected analysts are timelier than those of unconnected analysts.

In column (3), we use *Convergence* as the dependent variable to examine the impact the forecasts of connected analysts have on other analysts' forecast accuracy. The estimated coefficients are positive and significant, suggesting that the forecasts of connected analysts are more likely to increase the forecast accuracy of other analysts. The improvement in the forecast accuracy of other analysts is 2.65% greater for connected analysts than it is for the unconnected analysts (= 0.025/0.945, where 0.945 is the sample mean from Table 1, Panel B). In sum, the findings in Table 2 indicate that the performance of the connected analyst's forecasts is superior to that of the unconnected analysts: they are more accurate, timelier, and informative.

4.2 Firm-level analysis

4.2.1 Test design

Having shown that the individual forecasts of connected analysts have greater information content, i.e., greater accuracy and timeliness, we now examine how connected analysts affect the forecast properties at the firm level. Examining forecasts at the firm level allows us to test how the greater activity of connected analysts affects the forecast of the analysts as a group. In contrast to individual analysts' forecasts, we now use the properties of analyst forecasts at the firm level, e.g., consensus forecasts. We use the regression model in equation (2).

$$\text{Consensus forecast errors (Dispersion)}_{i,t} = \text{Following\_connected}_{i,t} + \text{Controls} + \text{FE} + \varepsilon_{i.t.} \quad (2)$$

The unit of analysis is firm (*i*)-year (*t*). The dependent variable $\textit{Consensus forecast errors}_{i,t}$ is the average absolute forecast error of the latest earnings forecast issued by each analyst for firm *i* in fiscal year *t*. The absolute forecast error of individual analysts is defined as the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year. *Dispersion* is the standard deviation of the latest earnings forecast issued by each brokerage firm.

$\textit{Following\_connected}_{i,t}$ is our main variable of interest; it measures the number of the latest earnings forecasts issued by a connected analyst. As previously, the estimation includes industry fixed effects and year fixed effects. We continue to include all control variables used in the individual analyst-level analysis in equation (1). For the analyst-level controls (i.e., *Horizon*, *Experience*, *Experience_firm, Broker_size*, and *Star*), we use the average value of all analysts following during the firm-year. Detailed definitions of each measure are provided in the appendix.

In addition to the two dependent variables above, we also evaluate the benefits of having connected analysts by examining the aggregate informativeness of the analysts' forecasts. Following Frankel et al. (2006) and Lehavy et al. (2011), we examine the informativeness of analyst forecasts (*informativeness_forecasts*) by calculating the sum of the absolute one-day size-adjusted returns for all forecast revisions in a given year, scaled by the sum of the absolute size-adjusted daily returns for all trading days in that year. We expect connected analyst forecasts to be more informative than are unconnected analyst forecasts.

Merkley et al. (2014) argue that analyst reports and companies' earnings announcements represent two potentially competing sources of information. If analysts play a greater role in the information discovery process during the period leading up to an earnings announcement, the increased information content released through analysts' reports can lead to less reliance on the earnings announcement news (Chen et al., 2010). That is, if a connected analyst's activity increases (decreases) the average informativeness of all analysts, this will lead to a reduction (rise) in the informativeness of earnings announcements. We therefore examine the informativeness of the earnings announcement as another way to examine the benefit of having connected analysts. The informativeness of an earnings announcement (*informativeness_earnings*) is calculated as the sum of the 3-day absolute cumulative size-adjusted abnormal returns around the dates of quarterly and annual earnings announcements for each firm, scaled by the sum of the absolute size-adjusted daily returns for all trading days in that year.

4.2.2 Main empirical results

Before proceeding with the regression results, we present a univariate comparison of the characteristics of firms with at least one connected analyst following vs. those with none. Table 1, Panel C shows the results. We find that the firms with more connected analysts following show a lower mean consensus forecasts error (1.037 vs. 1.598) and a smaller forecast dispersion (0.668 vs. 0.794). Not surprisingly, firms followed by connected analysts tend to be larger and with fewer institutional investors, returns volatility, and trading volume.

Table 3 shows the estimated results of equation (2). We find that firms with greater activity by connected analysts show more accurate consensus forecasts and less dispersion in the individual forecasts. Column (1) shows the estimated results using the consensus forecasts errors as the dependent variable. The estimated coefficient on the *Following _connected* variable is negative and significant (β = -0.084, p-val <0.001), indicating that a one standard deviation increase in the number of forecasts issued by connected analysts (=2.142 from Table 2, Panel C) reduces the consensus forecast errors by 0.169, i.e., a 13.3% reduction from the sample mean (=1.351).

While the findings point to connected analyst activity being associated with more accurate consensus forecasts, the observed association can simply be a result of the aggregation of individual analysts' effects. As a matter of fact, we have shown earlier that the individual forecasts of connected analysts are more accurate than those of unconnected analysts (see Table 2). When constructing our dependent variables, we thus repeat our analysis using the latest forecasts of *the unconnected analysts only*. This provides direct evidence on the spillover effect connected analysts have on unconnected analysts.

Column (3) shows the results of the regression analyses. Here again, we find that the number of forecasts issued by connected analysts has a positive effect on the accuracy of the consensus forecasts of *unconnected* analysts (β = -0.061, p-val =0.011), suggesting a strong spillover effect. The estimates show that a one standard deviation increase in the number of forecasts issued by connected analysts (=2.142) reduces the consensus forecast errors of unconnected analysts by 0.130, i.e., a 9.7% reduction from the sample mean (=1.351).

Columns (2) and (4) present the coefficient estimates using dispersion as the dependent variable. We find robust evidence that the number of forecasts issued by connected analysts is associated with lower forecast dispersion. In column (2), using the latest forecasts of all analysts to compute the dispersion variable, we find that the coefficient on the *Following_connected* variable is negative and significant, suggesting that more forecasting activity on the part of a connected analyst is associated with less dispersion of analysts' forecasts (β = -0.062, p-val <0.001). Also, in column (4), which uses the latest forecasts of only the unconnected analysts to compute dispersion, we continue to find a negative association between connected analysts' number of forecasts and forecast dispersion (β = -0.079, p-val <0.001).

In Table 4, we show the estimated results of equation (2) using the informativeness of analysts' forecasts/earnings announcements as the dependent variable. The coefficient estimates in columns (1) and (2) show that the greater forecasting activity of connected analysts is (i) positively associated with the informativeness of analysts' forecasts made during the same period (β column (1) = 0.475, p-val <0.001) and (ii) negatively associated with the informativeness of the earnings announcement (β column (2) = -0.063, p-val =0.005). The estimated coefficient indicates that a one standard deviation increase in the number of forecasts issued by connected analysts (=0.714) increases the informativeness of forecasts by other analysts by 0.339 (=0.475*0.714), i.e., a 4.8% increase relative to the sample mean of the informativeness of all forecasts (=7.028, unreported). Similarly, a one standard deviation increase in the number of forecasts issued by connected analysts (=0.714) reduces the informativeness of the earnings announcement by 0.045 (=-0.063*0.714), i.e., a 1.5% decrease relative to the sample mean of all earnings forecasts (=2.961, unreported). Columns (3) and (4) repeat the estimation using volume-based measures of informativeness. The volume-based measures use trading volume instead of stock returns to calculate each informativeness measures. The findings mirror the earlier findings in columns (1) and (2) with marginally increased economic significance.

In sum, the results in Tables 3 and 4 suggest that connected analysts' greater forecasting activity has the effect of increasing the performance of all analysts' forecasts, i.e., a lower consensus forecast and dispersion. The results are robust to using only the forecasts of unconnected analysts to compute the consensus variable. We conclude that the increased performance is achieved not only through the direct aggregation effect of individual analysts' forecasts but more importantly through an indirect spillover effect on the forecasts of other, unconnected analysts.

4.2.3 Cross-sectional results

Prior studies find that complex firms are more difficult to analyze (Bhushan and Cho, 1996). Economic transactions in China can also be difficult to assess, not necessarily due to the complexity of the transactions per se, but because they often involve relationships that are intricate or difficult to verify. Judging the validity and economic values of a contract requires knowledge of the relationship between the counterparties of the contract. Information about the relationships is strategic and highly secretive, and can only be shared within closely knit social groups. If connected analysts bring benefits to firms by successfully conveying inside information that is otherwise difficult to verify and which the firm does not wish to report through public channels, it is possible that such analysts' private information access matters more for firms whose operations rely more relationship contracts, i.e., insider-based.[12]

We thus expand the estimation in equation (2) and examine the marginal benefit of having a connected analyst when firms are more insider-based. In particular, we run a modified version of equation (2) using the following regression model:

$$\text{Consensus forecast errors (Dispersion)}_{i,t} = \beta \times \text{Following\_connected}_{i,t} \times \text{Insider-based}_{i,t} + \mu \times \text{Following\_connected}_{i,t} + \lambda \times \text{Insider-based}_{i,t} + \gamma \times \text{Controls} + \text{FE} + \varepsilon_{i.t.} \quad (3)$$

$Following\_connected_{i,t} \times Insider\_based_{i,t}$ is our main variable of interest, which estimates the marginal effect of the *Following_connected* variable for insider-based firms. $Insider\text{-}based_{i,t}$ is an indicator variable that takes the value of one if a firm is insider-based, zero otherwise. We consider a firm to be insider-based if (i) its total related party transactions are more than 50% of total sales; (ii) purchases from (sales to) the top five suppliers (customer) exceed 50% of total purchases (sales); or (iii) the majority of firm shares are controlled by the government, the Chairman/CEO is an ex-government official, a representative in the National People's Congress or the People's Political Consultative Conference, or the firm receives subsidies (larger than 5% of total sales) in the given year.[13]

[12] Using a U.S. sample, O'Brien and Tan (2014) show that nearby analysts play a more important role when the firm's operations are less complex. The authors interpret these findings as local analysts facing greater difficulties in gaining an information advantage on a firm with complex, dispersed operations. In contrast, we argue that in China the social ties that give analysts the knowledge advantage are significantly more important because of the complex relationships in the contracting.

[13] Data sources of the insider-based firm measures are as follows. The related party transaction information is from CSMAR. The information on the concentration of customers and suppliers is hand collected from the company's annual reports. The subsidy information is from the Juyuan database. Finally, we use CSMAR to identity if a firm has a large shareholder.

Table 5 shows the estimated results. Using consensus forecast errors as the dependent variable in column (1), we find that the main effect of the insider-based indicator is positive and significant (λ column (1) = 0.198, p-val =0.001), suggesting that insider-based firms are more difficult to forecast. The main effect on the number of followings of connected analysts ($Following\_connected_{i,t}$) is negative but not significant. More importantly, the interaction effect of the *Following_connected* variable for insider-based firms ($Following\_connected_{i,t} \times Insider\_based_{i,t}$) is negative and significant (β column (1) = -0.127, p-val =0.001), indicating that the negative effect of the number of forecast activities of connected analysts on the consensus forecasts are driven by the insider-based firm sample. Column (3) repeats the analysis using only the forecasts of unconnected analysts to construct the consensus forecasts. Our findings are very similar to those in column (1), with marginally greater economic significance.

Using dispersion as the dependent variable also depicts a similar picture. The estimated coefficients in column (2) show that the main effect of insider-based firms on forecast dispersion is positive and significant, suggesting that the forecasts of insider-based firms show greater disagreement among analysts. The main effect of the number of the latest forecasts issued by connected analysts is negative and significant. Importantly, the marginal effect of the *Following_connected* variable ($Following\_connected_{i,t} \times Insider\text{-}based_{i,t}$) is greater for insider-based firms, indicating that the benefit of having a greater number of connected analyst followings increases when the firm is insider-based. In column (4), we find qualitatively similar results using only the forecasts of unconnected analysts to construct the dispersion measure.

Taken together, the findings suggest that the benefit of connected analysts' activity, measured in terms of the accuracy of the consensus forecast and dispersion, is greater when the firm's economic activity relies heavily on relationship contracts, and hence are difficult to be verified by a third party. While these tests permit more confidence in the mechanism through which the benefits of connected analysts are conferred, it is still possible that the cross-sectional tests are confounded by unobserved factors that may simultaneously determine the analyst's performance and the subsequent decisions of connected analysts to follow a firm. To better identify the effect of connected analysts, we next turn to a changes analysis that uses analyst departures due to relatively exogenous reasons.

4.3 Changes analysis: Analyst departures

4.3.1 Empirical test design of analysts departures

Analyst followings are not randomly determined; analysts are not randomly assigned to firms and how intensively an analyst follows the firm is determined by many different factors in addition to the analyst's relative information advantage. Our earlier findings may be affected by the fact that analysts make their coverage decisions endogenously, and these decisions may lead to an association between performance and an individual's connections, even in the absence of an information advantage. We address this concern by investigating firms that experience a decrease in the coverage of connected analysts for relatively exogenous reasons. We conduct a changes analysis where analysts drop coverage of a firm for relatively exogenous factors: their departures due to brokerage closures or mergers and/or their own career changes.

The sample of brokerage house closures is hand collected using various sources for each individual brokerage house (e.g., industry reports, company website, and internet search engine). In China, there were 63 brokerage firms that experienced M&As or closure during our sample period. 48 of the mergers occurred during the first half of our sample period (i.e., 2004 to 2007); 15 occurred following the 2008 financial crisis period. Additionally, we collect a sample of analyst departures due to career changes. We consider an analyst to have changed careers if a particular analyst disappears from the analyst database (indefinitely), even when other analysts belonging to the same brokerage firm continue to issue their forecasts.

To be included in our departure sample, we require the departing analyst to have at least one forecast for that firm within 360 days prior to the departure date. This allows us to capture only the departure of analysts who had a relatively meaningful role in the firm. Also, to ensure that the departure events are not affected by other confounding events, we require firms to have no other departing analysts 360 days prior to this event.

Using the departure sample, we compare the effect that the departure of a connected analyst had on the forecast properties following her departure, relative to the departure of an unconnected analyst. The test is akin to a difference-in-difference model where we use the departure of unconnected analysts to control for unobserved factors that may confound the departing sample. The departure of connected analysts is the treatment group. Equation (4) shows the regression model for the departure test:

$$\text{Consensus forecast errors (Dispersion)}_{d,t} = \beta\times\text{D\_connected\_departure}_{d}\times\text{Post\_departure}_{d,t} + \delta\times\text{D\_connected\_departure}_{d} + \mu\times\text{Post\_departure}_{d,t} + \gamma\times\text{Controls} + \text{FE} + \varepsilon_{d.t.} \quad (4)$$

The unit of analysis is firms with departing analysts (*d*)- pre/post (*t*). We include only firms with departing analysts, both connected and unconnected. A firm is considered to have a departing analyst if a departing analyst issued an earnings forecast for the firm within 2 months prior to her departure. We limit the pre- (post-) departure observations included in the regression to analyst forecasts made within 180 days prior to (following) the event date. We define a departure event date as 30 days after the final forecast was issued by the departing analyst.[14]

D_connected_departure$_d$ is an indicator variable that takes a value 1 if the departure event *d* involves a connected analysts, and zero otherwise. *Post_departure*$_{d,t}$ is an indicator variable that takes a value 1 for observations following the departure event *d*, and zero otherwise. Thus, the *Post departure*$_{d,t}$ variable captures the mean changes in a firm's consensus forecast errors following the departure of an analyst, i.e., 180 days following the departure event. The interaction term *D_connected_departure*$_d$ ×*Post_departure*$_{d,t}$ is our main variable of interest; it captures the incremental effect of an analyst's departure when the departure event involved a connected analyst. We predict that the increase in consensus forecast errors following the departure of a connected analyst will be greater than they would be after the departure of an unconnected analyst.

As before, consensus forecast error (*Consensus_FE*) is defined as the average absolute forecast error of the earnings forecasts issued by each analyst closest to the departure date. That is, we include all forecasts made within the 180 days before/after the departure date, using only the forecasts closest to the departure event for each individual analyst. To be more precise, for the pre-departure period we use the last forecast of each analyst within the 180 days prior to the departure event. For the post-departure period, we use the first forecast of each analyst within the 180 days after the departure of the analyst. Similarly, we define *Dispersion* as the standard deviation of the earnings forecast issued by each brokerage firm closest to the departure date. As before, we include

[14] Allowing a sufficient period of time (i.e., 30 days) to mark the departure date allows us to ensure that (i) the departing analyst has indeed left and (ii) that the post-period forecast made by the non-departing analysts are less influenced by the final forecast made by the connected analyst. In untabulated results, we use a shorted (15-day) cutoff and find qualitatively similar results.

the year fixed effect (based on the departure event year) and the industry fixed effect in the estimation. We include all control variables as defined in the appendix.

4.3.2 Empirical results of the analyst departure test

Figure 1 graphically shows the changes in consensus forecasts following the departure of a connected vs. an unconnected analyst. Panel A plots the changes in the mean consensus forecast errors following the departure of a connected analyst as opposed to an unconnected one. The x-axis is the number of months before and after the departure event. The y-axis presents the consensus forecast errors defined as the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year × 100%.

Panel A shows that following the departure of a connected analyst, consensus forecast errors increase from 0.85 (2 months before the departure event) to 1.18 (2 months after the departure event). In contrast, the consensus forecast errors before and after the departure of an unconnected analyst show a very modest increase, from 1.14 before the departure vs. 1.16 after the departure. Interestingly, the level of forecast errors for the two types of firms (those with connected departing analysts and unconnected departing analysts), which used to show significant differences prior to the departure event (0.85 vs. 1.14), converge following the departure event (1.18 vs 1.16).

In Panel B, we repeat the plot for the two groups of firms using only the consensus forecasts of unconnected analysts. The plotting appears to be similar to that in Panel A, with slightly greater changes following departure of a connected analyst. While the patterns shown in Figure 1 are informative, we next turn to the regression analysis to explicitly control for other factors that may affect the changes in consensus forecasts following an analyst departure.

Table 6 shows the estimated results of the departure test in equation (4). Using consensus forecasts as the dependent variable in column (1), we find that the increase in consensus forecast errors following the departure of a connected analyst is greater than the increase after the departure of an unconnected analyst. The estimated coefficient on β is positive and significant (β column (1) = 0.208, p-val =0.032), suggesting an incremental increase in forecast errors when a connected analyst leaves, relative to an unconnected analyst's departure ($D\_connected\_departure_d \times Post\_departure_{d,t}$). The estimated coefficient suggests that following the departure of a connected analyst, the incremental increase in the forecast errors is 23% higher than the benchmark (the departure of an unconnected analyst).[15] The $Post\_departure_{d,t}$ variable, which captures the mean changes in the consensus forecast errors following the departure of an analyst, is negative but not significant. We find similar results when we use only the forecasts of unconnected analysts to compute the consensus forecast errors (column (3)).

Using dispersion in columns (2) and (4), we find similar patterns. Column (2) shows that following an analyst's departure (both connected and unconnected), there is a decrease in the dispersion of analyst forecasts. That is, the estimated coefficient on the $Post\_departure_{d,t}$ variable is negative and significant (μ column (2) = -0.121, p-val =0.001). However, the incremental effect of the connected analyst's departure is positive and significant (β column (2) = 0.239, p-val =0.010), suggesting that unlike that of unconnected analysts, the departure of a connected analyst leads to an increase in forecast dispersion (i.e., β + μ in column (2) = 0.118). Overall, the findings in Table 6

[15] The figure is obtained by multiplying the coefficient 0.208 by the average of the consensus forecasts included in the estimation (=0.208*1.1158).

show a greater reduction in the performance of the forecasts of analysts as a group (i.e., less accuracy and greater dispersion) after the departure of a connected analyst relative to an unconnected analyst.

In Table 7, we present the estimated results of equation (4) using the informativeness measures as the dependent variable. The dependent variable *M_Informativeness_forecasts* is the mean 3-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast each analyst made within the 180-day period before (after) the departure event. The estimated coefficients in column (1) show that the departure of a connected analyst is negatively associated with the informativeness of the analyst forecasts (β column (1) = -0.004, p-val =0.059). In column (2), we repeat the analysis for an alternative measure of informativeness, *M_Informativeness_forecasts2*, defined as *M_Informativeness_forecasts* divided by the mean unsigned daily absolute abnormal returns of the corresponding 180-day period before (after) the departure event. We find that the coefficient on the interaction term $D\_connected\ departure_d \times Post\_departure_{d,t}$ is again negative and significant, suggesting a significant drop in the informativeness of analysts' forecasts following the departure of a connected analyst. Columns (3) and (4) repeat the estimation while using the forecasts of only the unconnected analysts to measure informativeness. The findings mirror the earlier findings in columns (1) and (2) with marginally increased economic significance.

In sum, the results in Tables 6 and 7 confirm the earlier findings in Tables 3 and 4 showing that the greater forecasting activity of a connected analyst has the effect of increasing the performance of all analysts' forecasts. Using relatively exogenous analyst departures, we find that the departure of a connected analyst has a perverse effect on the quality of the analyst's forecasts. Using a difference-in-difference specification, we find that following the departure of a connected analyst there is an increase in forecast errors, forecast dispersion, and a decrease in the forecasts' informativeness.

5. Additional Analysis: The centrality of connected analysts

Network theory suggests that the importance of the individual depends on the structure of the network (Burt, 1992; Granovetter, 2005). We provide cross-sectional evidence of the departure tests to show that the effect a connected analyst's departure has on the firm's information environment is greater when the departing analysts played a pivotal role in the network. We identify critical departures as those when the departing analyst was the only connected analyst following the firm. The idea is that the departure of a connected analyst will lead to a greater void when no other connected analysts remain in the network.

We partition the earlier departure sample in Table 6 into critical departures and less critical departures. We predict that the reduction in the accuracy of the consensus forecasts following the departure of a connected analyst is driven by the critical departure subsample, i.e., where the departing analyst is the only connected analyst. We test this prediction using a regression model that includes an indicator variable for the post-departure years. We compare the coefficient on the indicator variable across the two partitions: critical departures vs. less critical departures.

We present the estimated results in Table 8. Column (1) shows the changes in the consensus forecasts for the critical departure subsample. We find that the increase in consensus forecast errors following the departure of a connected analyst is positive and significant. The estimated coefficient on the $Post\_departure_{d,t}$ variable is positively significant (coeff= 0.510, p-val =0.074), suggesting an increase in forecast errors after critical departures. In the sample of less critical departures (column (2)), however, we find the coefficient to be positive yet insignificant (coeff = 0.107, p-val =0.312). The F-test comparing the coefficients on the *Post_departure*$_{d,t}$ variable across the two samples is positive and statistically significant, indicating that there is a greater increase in consensus forecast errors for the critical departure sample relative to the non-critical departure sample. In columns (3) and (4), we find similar results when we compute the consensus forecast errors using only the forecasts of unconnected analysts. We find a greater increase in the consensus forecast errors in the sample of critical departures (column (3)) compared to the sample of non-critical departures (column (4)).

6. Conclusion

We test whether greater activity by connected analysts will increase the accuracy and timeliness of the consensus forecasts of other (unconnected) analysts. Our results show that connected analysts provide the capital market with more accurate and timely information. We also find that there is positive externality in the network transfer of private information. We document a positive spillover effect on the unconnected analysts, which indicates that connected analysts improve the overall information environment of their firms. In addition, the results are stronger for firms that are politically connected or that have a concentrated number of customers and suppliers.

These results suggest that in China, close ties between analysts and firm managers serve as a mechanism that allows firms to release private information to the market and to improve the firms' overall information environment, even though public reporting and disclosure is found to be significantly less transparent than it is in developed markets.

One important implication of our results is that in emerging markets where contracts are implicit and the public reporting and disclosure of contracts may jeopardize firms' competitiveness and strategic connections, alternative channels such as network information transfer may serve the firms well. These findings are in stark contrast to the practices and regulations in developed markets, where full and fair disclosure such as Reg FD are found to improve firms' information environments (Heflin et al., 2003; Bailey et al., 2003). Our results are consistent with the notion that in emerging markets where economic activities are implicit and thereby challenging to credibly disclose, selective disclosure through networks can also lead to an improvement in the information environment by increasing the aggregate amount of disclosed information.

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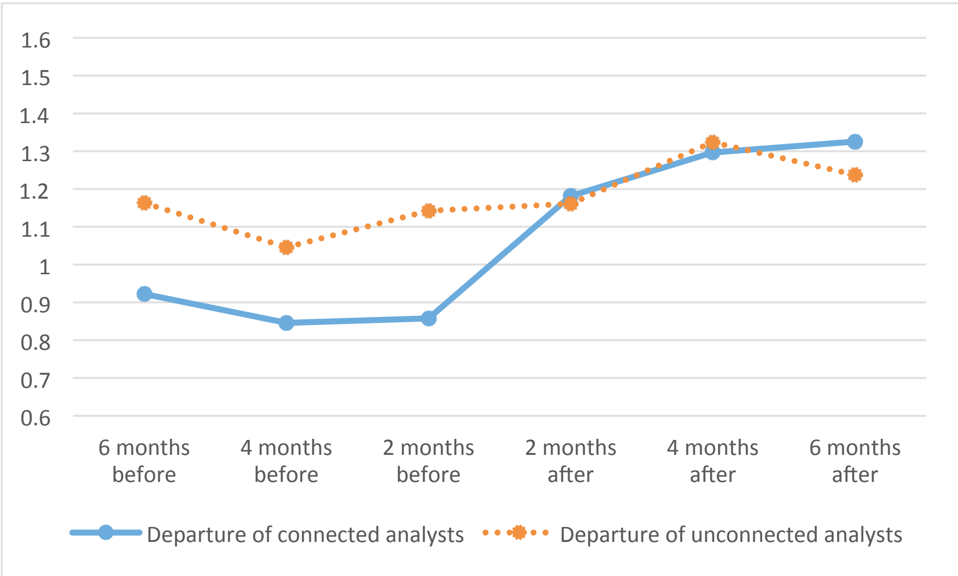
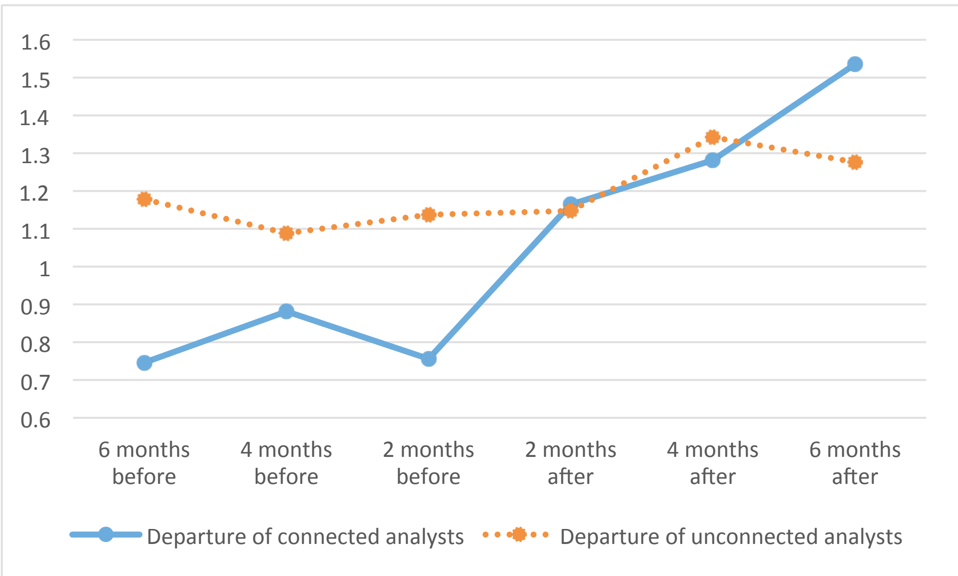
Figure 1 Consensus forecast errors before and after analysts' departures

Figure 1 plots the changes in consensus forecast errors following the departure of a connected analyst. Panel A plots the changes in consensus forecast errors (absolute earnings forecast errors) following the departure of a connected analyst vs. an unconnected analyst; Panel B repeats the plot for the two groups of firms using the consensus forecasts of only unconnected analysts. Each unit on the x-axis is the number of months before and after the departure event. To compute the consensus, we use the latest (earliest) forecast made by each analyst during the two-month period before (after) the departure. Y-axis is the consensus forecast errors defined as the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year × 100%.

Panel A: Changes in the consensus forecast errors of all analysts



Panel B: Changes in the consensus forecast errors of unconnected analysts



Appendix- Variable Definitions

Variable	Definition
Analyst-forecast-level measures	
Abs. forecast error	The absolute value of the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year. We include only the latest earnings forecast issued by each analyst.
Timeliness	The cumulative number of days required to generate N earnings forecasts from other analysts preceding the forecast issuance (=T0) divided by the number of days required to generate N forecasts following the issuance (=T1) (Cooper et al., 2001; Shroff et al., 2014). The more time it takes for the forecast event to trigger issuances of forecast updates from other analysts (i.e., a higher T1), the less influential the forecast is (i.e., a lower T0/T1). The measure is based on the assumption that more influential analysts will tend to lead the information release of other analysts and trigger more prompt forecast issuances. We set the number of required forecasts (=N) at two, i.e. two distinct forecasts by two different analysts. If fewer than two forecasts are issued before/after the forecasts events, we set the number of days at 360 when there is one other forecast, and 360×2 when there are no other forecasts. We then rank T0/T1 and set the timeliness variable to one if the measure is T0/T1 > 1 and ranks above top 50%, and zero otherwise. We require a firm to have at least five distinct analysts following for the year.
Convergence	Convergence is defined as 1 - FE1/FE0, where FE0 (FE1) is the average absolute forecast error for the two forecasts from T0 (T1) of the timeliness measure. The measure takes a higher value if there was a relatively greater reduction in forecasts errors following the forecast issuance.
D_connected	Indicator variable that takes a value of one if the forecasts are from a connected analyst. An analyst is considered to be connected to the firm if at least one of the following conditions is met: (i) the analyst shares school ties with a C-suite manager in the firm, (ii) the headquarters of both the analyst's brokerage and the firm are located in the same city, and (iii) the analyst's brokerage firm served as the firm's lead underwriter for share issuance (IPOs and SEOs) within the last five years.
Horizon	Days between forecast date and the year-end (Dec 31) date.
Firm-level measures	
Consensus_FE	The average absolute forecast error of the latest earnings forecast issued by each analyst. Absolute forecast error is defined as the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year.
Dispersion	The standard deviation of the latest earnings forecast issued by each brokerage firm.
Informativeness _forecast (_vol)	The aggregate informativeness of analyst forecasts defined as the sum of the absolute one-day size-adjusted returns (trading volume) for all forecast revisions in a given year, scaled by the sum of the absolute size-adjusted daily returns (trading volume) for all trading days in that year (Merkley et al., 2014).

Informativeness _earnings (_vol)	The informativeness of earnings announcements defined as the sum of the 3-day absolute cumulative size-adjusted abnormal returns (volume) around the dates of quarterly and annual earnings announcements for each firm, scaled by the sum of the absolute size-adjusted daily returns (trading volume) for all trading days in that year (Merkley et al., 2014).
M_Informativeness _forecasts	The mean 3-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast of each analyst made within the 180-day period before (after) the departure event.
M_Informativeness _forecasts2	M_Informativeness_forecasts divided by the mean daily unsigned cumulative abnormal returns of the corresponding180-day period.
Following_connected	Log (1 + number of connected analysts following for the year).
Following_all	Log (1 + number of all analysts following for the year).
Size	Log (firm total market value at the beginning of the year).
BM	Book-to-market ratio measured in the beginning of the year.
Institutions_share	Share ownership percentage (average of four end-of-quarter balances) of the top 10 shareholders that are institutional investors (e.g., mutual funds, foreign institutional investors, brokerage firms, insurance companies, pension funds, investment trusts, and banks).
Stdret	Standard deviation of daily returns for the calendar year.
Volume	Log (annual trading volume in thousands of RMB).
Insider-based	Indicator variable that takes the value of one if the firm engages in insider-based transactions and zero otherwise. We consider a firm to be insider based if (i) its total related party transactions are more than 50% of total sales; (ii) purchases from (sales to) the top five suppliers (customers) exceed 50% of the total purchases (sales); or (iii) the majority of firm shares are controlled by the government, the Chairman/CEO is an ex-government official, a representative in the National People's Congress or the People's Political Consultative Conference, or the firm receives subsidies (larger than 5% of total sales) for the year.
Analyst-level measures	
Brokersize	Total number of analysts hired by the analyst's brokerage firm for the year.
Experience	Number of days between the analyst's first forecast of any firm in the database and the day of the current forecast.
Experience_firm	Number of days between the analyst's first forecast for the same firm and the day of the current forecast.
Star	Indicator variable that takes the value of one if the analyst is awarded a star analyst rating by *New Fortune Magazine* in the prior year, and zero otherwise.

Table 1: Descriptive statistics

Panel A: The distribution of the number of connected analysts at the firm-year level

# of connected analysts	Composite measure	School ties	Geographic ties	Investment banking ties	Composite measure	School ties	Geographic ties	Investment banking ties
	# of firm-years				%			
>=5	798	182	538	16	7.20	1.64	4.86	0.14
4	352	110	238	33	3.18	0.99	2.15	0.30
3	512	182	345	83	4.62	1.64	3.11	0.75
2	874	356	485	241	7.89	3.21	4.38	2.18
1	2,302	796	1,343	1,835	20.78	7.18	12.12	16.56
>=1	4,878	1,626	2,949	2,208	44	15	27	20
0	6,201	9,453	8,130	8,871	56	85	73	80
Total	11,079	11,079	11,079	11,079	100	100	100	100

Panel B Descriptive statistics of the forecast characteristics at the individual-analyst level

Variable	# of observations	Mean	Median	Std	q1	Q3
Abs. Forecast errors	96,777	0.945	0.437	1.409	0.149	1.110
Timeliness	90,404	0.444	0.000	0.497	0.000	1.000
Convergence	69,055	-0.131	0.125	1.278	-0.200	0.446
D_connected	96,777	0.138	0.000	0.345	0.000	0.000

Panel C: Firm-characteristics of firms with vs. without connected analysts following

Variables		mean		median		std	q1	q3	n
Consensus_FE	all	1.351		0.693		2.142	0.331	1.425	11079
	unconnected	1.598		0.789		2.492	0.358	1.691	6201
	connected	1.037		0.598		1.533	0.305	1.182	4878
	difference	0.561	***	0.191	***	0.959	0.054	0.509	
Dispersion	all	0.723		0.429		0.994	0.127	0.918	11079
	unconnected	0.668		0.327		1.029	0.000	0.855	6201
	connected	0.794		0.517		0.942	0.260	0.972	4878
	difference	-0.125	***	-0.189	**	0.087	-0.260	-0.117	
Size	all	15.256		15.092		1.115	14.470	15.860	11079
	unconnected	14.946		14.858		0.930	14.294	15.509	6201
	connected	15.651		15.499		1.203	14.776	16.322	4878
	difference	-0.705	***	-0.641	***	-0.272	-0.482	-0.813	
BM	all	0.434		0.369		0.280	0.224	0.574	11079
	unconnected	0.444		0.381		0.285	0.230	0.590	6201
	connected	0.420		0.351		0.272	0.217	0.554	4878
	difference	0.025	***	0.030	***	0.013	0.013	0.036	
Institutions_ share	all	7.735		4.515		10.733	1.550	9.344	11079
	unconnected	6.457		3.361		9.666	1.000	7.765	6201

	connected	9.359		6.161		11.754	2.635	11.050	4878
	difference	-2.902	***	-2.800	***	-2.088	-1.635	-3.285	
Stdret	all	0.030		0.029		0.008	0.024	0.035	11079
	unconnected	0.030		0.029		0.008	0.024	0.035	6201
	connected	0.029		0.028		0.008	0.023	0.034	4878
	difference	0.001	***	0.001	***	0.000	0.001	0.001	
Volume	all	23.252		23.257		1.071	22.568	23.948	11079
	unconnected	23.086		23.137		1.020	22.441	23.764	6201
	connected	23.464		23.437		1.097	22.740	24.201	4878
	difference	-0.378	***	-0.300	***	-0.077	-0.299	-0.437	

Notes: This table presents the descriptive statistics of the variables include in our tests. Panel A shows the distribution of the number of connected analysts across different firm-years. An analyst is considered to be connected to a firm if at least one of the following conditions is met: (i) the analyst shares school ties with a C-suite manager of the firm (*school ties*), (ii) the headquarters of both the analyst's brokerage and the firm are located in the same city(*geographic ties*), and (iii) the analyst's brokerage firm served as the firm's lead underwriter for share issuance (IPOs and SEOs) within the last five years (*business ties*). Refer to Section 3.2 for a detailed definition of each tie measure. Panel B shows the descriptive statistics of various forecast characteristics of individual analysts. Panel C shows a univariate comparison of firm-level characteristics of firms with connected analysts and those without connected analysts. All other variables are defined in the appendix.

Table 2 Forecast characteristics of connected analysts, from 2005 to 2013

Dependent VARIABLES	(1) Abs. forecast errors	(2) Timeliness	(3) Convergence
D_connected	-0.079***	0.060***	0.025**
	(0.000)	(0.005)	(0.042)
Following_all	-0.241***	-0.100***	-0.110***
	(0.000)	(0.002)	(0.000)
Size	-0.036	-0.009	0.020*
	(0.143)	(0.482)	(0.071)
BM	1.030***	0.028	-0.026
	(0.000)	(0.342)	(0.456)
Institutions_share	0.000	-0.000	-0.001
	(0.766)	(0.424)	(0.327)
Stdret	14.318***	1.519	5.459***
	(0.000)	(0.364)	(0.000)
Volume	0.163***	0.029**	-0.025**
	(0.000)	(0.039)	(0.040)
Experience_firm	0.002	0.005	0.012***
	(0.440)	(0.281)	(0.000)
Experience	0.009*	0.002	-0.019***
	(0.069)	(0.801)	(0.000)
Star	0.021	-0.015	-0.005
	(0.123)	(0.594)	(0.769)
Horizon	0.004***	0.006***	-0.000**
	(0.000)	(0.000)	(0.012)
Brokersize	0.009	-0.058**	0.035***
	(0.373)	(0.029)	(0.004)
Constant	-2.442***	-0.653**	0.261
	(0.000)	(0.011)	(0.199)
# of observations	96,777	90,404	69,055
R-square	0.191	0.040	0.006
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
SE clustering	Firm, Analyst	Firm, Analyst	Firm, Analyst

Notes: This table presents the firm-analysts-level regressions using various forecast properties as the dependent variable. *D_connected* is the main variable of interest, an indicator variable for the forecasts of analysts who share close ties with the firm. Abs. forecast errors is the absolute value of the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year. We include only the latest earnings forecast issued by each analyst. *Timeliness* is the cumulative number of days required to generate N earnings forecasts from other analysts preceding the forecast issuance (=T0) divided by the number of days required to generate N forecasts following the issuance (=T1) (Cooper et al., 2001; Shroff et al., 2014). The more time it takes for a forecast event to trigger issuances of updated forecast from other analysts (i.e., a higher T1), the less influential the forecast is (i.e., a lower T0/T1). The measure is based on the assumption that more influential analysts will tend to lead the information release of other analysts and trigger more prompt forecast issuances. *Convergence* is defined as (FE0 – FE1)/FE0, where FE0 (FE1) is the average absolute forecast error for the two forecasts from T0 (T1) of the timeliness measure. The measure takes a higher value if there was a relatively greater reduction in forecasts errors following the forecast issuance. All other variables are defined in the appendix.

Table 3 The effect of a connected analyst on the accuracy and dispersion of consensus forecasts, firm level

	Forecasts of all analyst		Forecasts of unconnected analyst only	
	(1)	(2)	(3)	(4)
VARIABLES	Consensus_FE	Dispersion	Consensus_FE	Dispersion
Following_connected	-0.084***	-0.062***	-0.061**	-0.079***
	(0.001)	(0.000)	(0.011)	(0.000)
Following_all	-0.262***	0.002	-0.280***	0.023
	(0.000)	(0.915)	(0.000)	(0.210)
Size	-0.002	0.002	0.009	-0.008
	(0.963)	(0.939)	(0.832)	(0.748)
BM	1.331***	0.977***	1.271***	0.885***
	(0.000)	(0.000)	(0.000)	(0.000)
Institutions_share	0.002	-0.000	0.002	-0.000
	(0.444)	(0.915)	(0.492)	(0.813)
Stdret	25.907***	17.161***	26.102***	16.231***
	(0.000)	(0.000)	(0.000)	(0.000)
Volume	0.037	0.098***	0.042	0.099***
	(0.395)	(0.000)	(0.334)	(0.000)
Experience_firm	0.005	-0.006	0.001	-0.009
	(0.734)	(0.555)	(0.943)	(0.384)
Experience	0.046	0.085***	0.054	0.090***
	(0.329)	(0.002)	(0.255)	(0.001)
Star	0.246	0.128	0.269*	0.044
	(0.111)	(0.128)	(0.094)	(0.602)
Horizon	0.005***	0.002***	0.005***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Brokersize	0.110	0.034	0.137	0.059
	(0.187)	(0.453)	(0.102)	(0.216)
Constant	-1.043	-2.958***	-1.355*	-2.935***
	(0.192)	(0.000)	(0.092)	(0.000)
# of observations	11,079	9,092	10,799	8,718
Adjusted R-square	0.132	0.161	0.136	0.157
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm

Notes: This table presents the firm-level regressions using various firm-level forecast characteristics as the dependent variable. *Following_connected* is the main variable of interest, which is the log of one plus the number of connected analysts following the firm for the year. *Consensus_FE* is defined as the average absolute forecast error for the latest earnings forecast issued by each analyst. Absolute forecast error is the difference between the forecast and the actual EPS, scaled by the stock price at the beginning of the year. *Dispersion* is the standard deviation of the latest earnings forecast issued by each brokerage firm. All other variables are defined in the appendix.

Table 4 The effects of connected analysts following on the forecasts' informativeness

	Returns-based measures		Trading-volume-based measures	
	(1)	(2)	(3)	(4)
VARIABLES	Informativeness _forecasts	Informativeness _earnings	Informativeness _forecasts _vol	Informativeness _earnings _vol
Following_connected	0.475***	-0.063***	0.477***	-0.092***
	(0.000)	(0.005)	(0.000)	(0.000)
Following_all	5.008***	-0.482***	4.834***	-0.753***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.680***	0.090**	0.237*	0.031
	(0.000)	(0.010)	(0.052)	(0.362)
BM	-1.140***	0.014	-1.511***	-0.125*
	(0.001)	(0.851)	(0.000)	(0.093)
Institutions_share	-0.000	-0.002	-0.003	0.002
	(0.958)	(0.102)	(0.557)	(0.143)
Stdret	97.706***	29.761***	-14.827	1.307
	(0.000)	(0.000)	(0.394)	(0.791)
Volume	0.217	-0.288***	0.634***	-0.318***
	(0.201)	(0.000)	(0.000)	(0.000)
Experience_firm	-0.042	0.005	-0.034	-0.036***
	(0.145)	(0.671)	(0.171)	(0.002)
Experience	0.185**	-0.022	0.203***	0.010
	(0.011)	(0.524)	(0.003)	(0.756)
Star	0.150	-0.061	0.063	-0.056
	(0.548)	(0.483)	(0.772)	(0.538)
Horizon	-0.007***	0.001*	-0.007***	0.001***
	(0.000)	(0.078)	(0.000)	(0.001)
Brokersize	0.072	-0.042	0.148	-0.029
	(0.574)	(0.480)	(0.189)	(0.616)
Constant	-14.976***	9.442***	-14.326***	14.000***
	(0.000)	(0.000)	(0.000)	(0.000)
# of observations	11,065	11,065	11,065	11,065
Adjusted R-square	0.619	0.185	0.656	0.354
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm

Notes: This table presents the firm-level regressions using various firm-level measures of the informativeness of the analyst forecasts (earnings) as the dependent variable. *Following_connected* is the main variable of interest, which is the log of one plus the number of connected analysts following the firm for the year. *Informativeness_forecast(_vol)* is defined as the sum of the absolute one-day size-adjusted returns (trading volume) for all forecast revisions in a given year, scaled by the sum of the absolute size-adjusted daily returns (trading volume) for all trading days in that year (Merkley et al., 2014). *Informativeness_earnings(_vol)* is defined as the sum of the 3-day absolute cumulative size-adjusted abnormal returns (volume) around the dates of quarterly and annual earnings announcements for each firm, scaled by the sum of the absolute size-adjusted daily returns (trading volume) for all trading days in that year (Merkley et al., 2014). All other variables are defined in the appendix.

Table 5 The effects of connections for insider-based vs. outsider-based firms

	Forecasts of all analysts		Forecasts of unconnected analysts	
	(1)	(2)	(3)	(4)
VARIABLES	Consensus_FE	Dispersion	Consensus_FE	Dispersion
Insider-based ×Following_connected	-0.127***	-0.045**	-0.133***	-0.045**
	(0.001)	(0.045)	(0.000)	(0.041)
Following_connected	-0.015	-0.037**	0.010	-0.055***
	(0.608)	(0.037)	(0.733)	(0.002)
Insider-based	0.198***	0.060*	0.200***	0.065**
	(0.001)	(0.067)	(0.001)	(0.043)
Following_all	-0.256***	0.003	-0.274***	0.025
	(0.000)	(0.875)	(0.000)	(0.184)
Size	-0.004	0.002	0.007	-0.008
	(0.930)	(0.936)	(0.859)	(0.744)
BM	1.346***	0.980***	1.286***	0.888***
	(0.000)	(0.000)	(0.000)	(0.000)
Insitutions_share	0.002	-0.000	0.002	-0.000
	(0.473)	(0.894)	(0.524)	(0.790)
Stdret	25.591***	17.070***	25.800***	16.107***
	(0.000)	(0.000)	(0.000)	(0.000)
Volume	0.037	0.098***	0.041	0.100***
	(0.400)	(0.000)	(0.340)	(0.000)
Experience_firm	0.006	-0.005	0.002	-0.008
	(0.686)	(0.576)	(0.894)	(0.402)
Experience	0.045	0.085***	0.053	0.090***
	(0.336)	(0.002)	(0.260)	(0.001)
Star	0.238	0.125	0.260	0.040
	(0.120)	(0.138)	(0.104)	(0.632)
Horizon	0.005***	0.002***	0.005***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Brokersize	0.112	0.034	0.140*	0.058
	(0.178)	(0.459)	(0.095)	(0.219)
Constant	-1.127	-2.990***	-1.444*	-2.969***
	(0.160)	(0.000)	(0.073)	(0.000)
# of observations	11,079	9,092	10,799	8,718
Adjusted R-square	0.133	0.162	0.137	0.157
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm

Notes: This table presents the firm-level regressions of the effect of connected analysts' followings on various forecast characteristics of insider-based firms. *Insider-based × Following_connected* is the main variable of interest, which captures to marginal effect of connected analyst for insider-based firms. *Insider-based* is an indicator variable that takes the value of one if the firm engages in insider-based transactions, i.e., (i) the total related party transactions are more than 50% of total sales, (ii) the purchases (sales) from the top five suppliers (customers) exceed 50% of total purchases (sales), or (iii) the firm is politically connected. We define a firm as politically connected if (i) a majority of the firm's shares is controlled by the government, (ii) the Chairman/CEO is an ex-government official or a representative in the National People's Congress or the People's Political Consultative Conference, or (iii) the firm receives government subsidies (larger than 5% of total sales) for the year. *Following_connected* is the log of one plus the number of connected analysts following the firm for the year. All other variables are defined in the appendix.

Table 6 Effect of the departure of connected analysts on firm-level analysts forecasts, from 2005 to 2013

	Forecasts of all analysts		Forecasts of unconnected analysts	
	(1)	(2)	(3)	(4)
VARIABLES	Consensus_FE	Dispersion	Consensus_FE	Dispersion
D_connected_departure	0.208**	0.239**	0.273***	0.190**
× Post departure	(0.032)	(0.010)	(0.006)	(0.048)
Post departure	-0.031	-0.121***	-0.040	-0.126***
	(0.368)	(0.001)	(0.251)	(0.001)
D_connected_departure	-0.193**	-0.186***	-0.230***	-0.148**
	(0.016)	(0.005)	(0.002)	(0.032)
Following_all	-0.243***	-0.012	-0.272***	0.033
	(0.000)	(0.787)	(0.000)	(0.388)
Size	0.008	0.002	0.003	-0.001
	(0.836)	(0.950)	(0.943)	(0.978)
BM	1.241***	0.904***	1.249***	0.898***
	(0.000)	(0.000)	(0.000)	(0.000)
Institutions_share	-0.004**	-0.001	-0.004*	-0.003
	(0.041)	(0.439)	(0.058)	(0.108)
Stdret	29.401***	14.882***	27.368***	13.732***
	(0.000)	(0.002)	(0.000)	(0.002)
Volume	0.000*	-0.000	0.000*	0.000
	(0.098)	(0.786)	(0.089)	(0.795)
Experience_firm	0.029	0.023	0.041*	0.009
	(0.220)	(0.256)	(0.074)	(0.595)
Experience	0.082	0.022	0.047	0.042
	(0.174)	(0.717)	(0.409)	(0.419)
Star	0.436**	0.242	0.374**	0.284*
	(0.032)	(0.150)	(0.038)	(0.052)
Horizon	0.004***	0.002***	0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Brokersize	-0.133	0.209**	-0.085	0.130
	(0.244)	(0.036)	(0.431)	(0.132)
Constant	-0.119	-1.134*	0.123	-1.102
	(0.874)	(0.099)	(0.868)	(0.102)
# of observations	2,594	2,488	2,546	2,425
Adjusted R-square	0.179	0.171	0.181	0.170
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm

Notes: This table presents the changes in the firm-level forecast characteristics following the departure of a connected analyst relative to the departure of an unconnected analyst. We include departures that are due to analysts' career changes and/or brokerage closures or mergers (see Section 4.3 for details). We define a departure event as 30 days after the final forecast was issued by the departing analyst. The pre- (post-) departure period includes the 180 days prior to (following) the event date. We include in our estimation all firms followed by the departing analysts issued within 2 months prior to his/her departure. *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by each analyst. To calculate the consensus forecasts, we include all forecasts made within 180 days before/after the departure date, using only the forecasts closest to the departure event for each individual analyst. That is, for the pre-departure period, we use the last forecast of each analyst within 180 days prior to the departure event. For the post-departure period, we use the first forecast of each analyst within 180 days after the departure of the analyst. *Dispersion* is the standard deviation of the latest earnings forecast issued by each brokerage firm. All other variables are defined in the appendix.

Table 7 Effect of the departure of a connected analyst on the firm-level informativeness of analyst forecasts

	Forecasts of all analysts		Forecasts of unconnected analysts	
	(1)	(2)	(3)	(4)
VARIABLES	M_Informative-ness_forecasts	M_Informativen-ness_forecasts2	M_Informative-ness_forecasts	M_Informative-ness_forecast2
D_connected_departure × Post_departure	-0.004*	-0.276**	-0.005**	-0.323**
	(0.059)	(0.024)	(0.044)	(0.016)
Post_departure	-0.001	-0.090**	-0.001	-0.096**
	(0.194)	(0.045)	(0.209)	(0.039)
D_connected_departure	0.001	0.054	0.002	0.122
	(0.525)	(0.572)	(0.218)	(0.236)
Following_all	0.000	-0.058	0.000	-0.085*
	(0.637)	(0.235)	(0.982)	(0.098)
Size	-0.001	-0.006	-0.001	-0.003
	(0.492)	(0.880)	(0.550)	(0.934)
BM	-0.004**	-0.037	-0.003*	0.028
	(0.027)	(0.689)	(0.057)	(0.758)
Institutions_share	0.000	-0.002	0.000	0.000
	(0.470)	(0.363)	(0.285)	(0.978)
Stdret	1.090***	10.649**	1.095***	11.306**
	(0.000)	(0.039)	(0.000)	(0.040)
Volume	0.001	0.009	0.001	0.013
	(0.467)	(0.830)	(0.453)	(0.752)
Experience_firm	-0.000	-0.011	0.000	0.006
	(0.355)	(0.565)	(0.861)	(0.761)
Experience	-0.001	-0.090*	-0.001	-0.084
	(0.249)	(0.098)	(0.333)	(0.110)
Star	0.003	0.098	0.007**	0.288*
	(0.197)	(0.496)	(0.015)	(0.055)
Horizon	0.000	0.000	0.000	0.000
	(0.105)	(0.626)	(0.132)	(0.492)
Brokersize	0.003	0.120	0.003	0.121
	(0.128)	(0.247)	(0.143)	(0.224)
Constant	-0.008	1.744**	-0.011	1.465*
	(0.564)	(0.021)	(0.440)	(0.059)
# of observations	2,488	2,488	2,428	2,428
Adjusted R-square	0.167	0.019	0.158	0.019
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm

Notes: This table presents the changes in the informativeness of analyst forecasts following the departure of a connected analyst relative to the departure of an unconnected analyst. We include departures that are due to analysts' career changes and/or brokerage closures or mergers (see Section 4.3 for details). *D_connected departure* is an indicator variable that takes a value of one if the departing analyst is a connected analyst. *Post departure* is an indicator variable that takes a value of one for firm-years following the departure date. We define the departure date as 30 days after the final forecast was issued by the departing analyst. The pre- (post-) departure period includes the 180 days prior to (following) the event date. *D_connected departure* × *Post departure* is our main variable of interest capturing the incremental changes in the informativeness of earnings announcements following the departure of a connected analyst relative to the departure of an unconnected analyst. The dependent variable *M_Informativeness_forecasts* is the mean 3-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast of each analyst made within the 180-day period before (after) the departure event. *M_Informativeness_forecasts2* is *M_Informativeness_forecasts* divided by the mean daily unsigned cumulative abnormal returns around the analyst forecasts of the corresponding 180-day period. All other variables are defined in the appendix.

Table 8 The importance of the departing connected analysts

Dependent variable: Consensus forecast errors

	(1)	(2)	(3)	(4)
	All analysts		Unconnected analysts	
VARIABLES	Firms where the departing analyst is the only connected analyst	Firms with other connected analysts that remain	Firms where the departing analyst is the only connected analyst	Firms with other connected analysts that remain
Post departure	0.510*	0.107	0.517*	0.135
	(0.074)	(0.312)	(0.073)	(0.193)
Following_all	-0.665	-0.021	-0.678	0.062
	(0.218)	(0.918)	(0.211)	(0.763)
Size	-0.210	0.005	-0.211	0.035
	(0.564)	(0.967)	(0.560)	(0.754)
BM	1.230	1.282***	1.260	1.202***
	(0.237)	(0.003)	(0.227)	(0.007)
Institutions_share	-0.057**	-0.011*	-0.057**	-0.012
	(0.044)	(0.055)	(0.043)	(0.102)
Stdret	7.440	31.939*	7.278	27.837*
	(0.882)	(0.071)	(0.884)	(0.078)
Volume	0.000	-0.000	0.000	-0.000
	(0.477)	(0.126)	(0.462)	(0.121)
Experience_firm	0.047	0.101	0.042	0.110*
	(0.592)	(0.183)	(0.632)	(0.099)
Experience	0.298	-0.227	0.308	-0.327**
	(0.220)	(0.259)	(0.192)	(0.028)
Star	0.097	0.361	0.069	-0.494
	(0.877)	(0.499)	(0.914)	(0.287)
Horizon	0.006*	0.004***	0.006*	0.004***
	(0.073)	(0.000)	(0.071)	(0.000)
Brokersize	-0.218	-0.015	-0.197	0.736*
	(0.724)	(0.973)	(0.747)	(0.055)
Constant	3.813	0.024	3.733	-2.407
	(0.592)	(0.992)	(0.599)	(0.394)
F test:	H: (1) event= (2) event		H: (3) event= (4) event	
	chi2(1) =3.09 Prob > chi2 =0.0789		chi2(1) = 2.75 Prob > chi2 = 0.0970	
# of observations	78	274	78	262
Adj. R-square	0.335	0.202	0.339	0.217
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm

Notes: Panel A presents the changes in the consensus forecast errors for departure events when the connected analyst is the only connected analyst following the firm (columns (1) and (3) vs. when there are other connected analysts that stay and follow the firm (columns (2) and (4)). We include analyst departures that are due to the analyst's career changes and/or brokerage closures or mergers (see Section 4.3 for details). We define a departure event as the 30 days after the final forecast was issued by the departing analyst. The pre- (post-) departure period includes the 180 days prior to (following) the event date. The dependent variable *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by all analysts. Columns (1) and (2) use forecasts of all analysts while columns (3) and (4) use only the forecasts of all unconnected analysts.