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Abstract

When emerging market firms raise external capital, they face a tradeoff where greater transparency may lead to a lower cost of capital but at the cost of revealing proprietary information in their relational business practices. We find that firms overcome this challenge by relying on financial analysts within their private networks, who then transmit the information to arm's length analysts outside the network. Specifically, we show that firms with more connected analysts have more accurate consensus forecasts and lower forecast dispersion. When a connected analyst departs and stops covering a firm, there is a decrease in the accuracy and informativeness of the *unconnected* (arm's length) analysts' forecasts, suggesting that the connected analyst's knowledge spills over to those outside the private network. The spillover effect is stronger when firms have plans to access external capital or when the firms possess information that is proprietary or hard to verify (e.g., in times of political uncertainty). The findings suggest that managers' private networks with financial analysts can have positive externalities for firms' information environments.

Keywords: Financial analysts; Disclosure externality: Private networks; Information environment

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1. Introduction

Financial development in the form of accounting and disclosure rules can reduce the cost differential between internal versus external financing and enhance economic growth (Rajan and Zingales, 1998). In the absence of financial development, firms in emerging economies must rely mostly on financing from within their private networks, which limits their growth (Rajan and Zingales, 1998; Allen et al., 2005). Firms that go outside their private networks to raise capital will face arm's length investors who expect better public reporting and disclosure. This poses a risk to the firms, as this kind of disclosure may reveal sensitive information about network ties (e.g., political connections or strategic partnerships), which can jeopardize their competitiveness and even destabilize their networks. This dilemma is particularly acute for emerging market firms because their operations are mostly relationship based. Hence they must find a communication channel that allows them to reduce external financing costs while protecting their proprietary information.

We examine whether firms use their dyadic network ties with financial analysts to overcome the challenge of communicating with external capital providers. We posit that firms exploit network ties between managers and analysts as a channel for information dissemination. Specifically, they first reveal private information to analysts within their network, and these analysts then disseminate the information to other analysts and investors through both private and public channels. The connected analysts can privately communicate to a group of institutional investors, who will then transfer the private information to other analysts within their own networks. The connected analysts will also publicly communicate with the market by issuing earnings forecasts.

Connected analysts act as embedded intermediaries for firms. Managers entrust them with private information and expect them to disseminate it without exposing any proprietary information. The dyadic ties between managers and these analysts not only facilitate the transfer of the private information *within* the social network, as documented by Cohen et al. (2008, 2010), they also ensure that the connected analysts will communicate with those *outside* the network, leading to positive externalities (Coleman, 1998; Granovetter, 1985 and 2005).[1] Such ties are likely to have greater value when managers face challenges in communicating using public disclosure because information is proprietary or hard to verify (e.g., in times of greater political uncertainty).

By communicating through analysts, managers need not bear the costs of committing to a particular forecast (Ajinkya and Gift, 1984). Connected analysts instead disseminate information on their behalf. These analysts enjoy enhanced credibility with arm's length parties because their connections with the managers are publicly known. This credibility is particularly important in emerging markets because the economic transactions that underlie forecasts rely heavily on relational contracts that are often unknown to the market.[2]

We use a comprehensive sample of listed firms and financial analysts from 2005 to 2014 in China to test this possible network externality. We expect network ties to play a significant role in information transfer in China. Historically, Chinese private firms relied solely on social networks to enforce contracts (Faure, 2006). Even contemporary Chinese enterprises heavily use

[1] One may ask why connected analysts would release private information to the market and not exploit their information advantage for their own private benefit. We argue that market rewards induce them to serve as firms' messengers. In practice, connected analysts benefit from issuing more informative forecasts. They receive commissions from institutional investors and enjoy the reputational enhancement of being named a star analyst (Gu et al. 2012, 2014).

[2] Consistent with managers facing difficulties credibly issuing their own forecasts, we find that Chinese managers rarely provide voluntary earnings forecasts to the market (only 1.8% of firms in our sample). In untabulated analyses, we include controls of the management forecasts (both voluntary and mandatory) and find robust results.

relational contracts, as the trust developed within closely knit social groups substitutes for formal contracts (Jacobs 1979; Gold 1985; Guthrie 1998; Peng 2004). Furthermore, the establishment of domestic stock markets in the early 1990s has provided relationship-based firms with new opportunities for raising equity capital and greater incentives to communicate with arm's length investors.

We begin by identifying dyadic ties between firm managers and analysts. We define these ties based on school, geography, and business relationships. We consider an analyst as sharing school ties with a firm if the analyst attended the same university as any of the firm's senior managers. We consider an analyst as connected geographically when the analyst and the firm are located in the same city (Coval and Moskowitz, 2001). And we define an analyst and a firm as connected through business when the analyst's brokerage and the firm have a prior investment banking relationship.[3]

Our main specification is a firm-level regression examining the effect of the forecasts of connected analysts on the accuracy of consensus forecasts. We find that, as more connected analysts cover a firm, the consensus forecast becomes more accurate. Also, the forecasts of individual analysts become less dispersed. Taken together, these findings suggest that more forecasting by connected analysts increases the precision of the forecasts overall. Next, we test whether greater activity by connected analysts leads to information spillovers to arm's length analysts (i.e., unconnected analysts). We find that, when firms have more connected analysts following them, there is an increase in the accuracy of *unconnected* analysts' forecasts and a decrease in their dispersion. These findings suggest that connected analysts' forecasting increases

[3] In the empirical analysis, we consider a dyadic tie to be present if the manager and analyst are connected through any of the three aforementioned measures. Our results are robust to alternative definitions of dyadic ties, where we exclude one of the three ties from our measure. This suggests that our findings are not driven by any particular type of tie included in the measure.

the precision of all analysts' forecasts not only through the direct aggregation of individual forecasts but also through an indirect spillover effect on the forecasts of unconnected analysts.

The difficulty in empirically identifying the effect of connected analysts is that these analysts' coverage decisions and forecast accuracy are endogenous. Their decisions to cover firms are not random, and how intensively an analyst follows that firm is determined by factors such as the analyst's skill, relative information advantage, and the ties with the manager (Brochet et al. 2013). Hence there may be an association between an individual analyst's forecasts and her connections, even absent 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 career changes or brokerage closures and mergers.[4]

Using this method, we find that the departure of a connected analyst has a perverse effect on the forecast quality of other analysts following the same firm. Following a connected analyst's departure, the accuracy of both the consensus and the forecasts of the unconnected analysts show a significant reduction. Also, the reduction in forecast accuracy is greater when the departing analysts was the only connected analysts following the firm. In contrast, when we examine firms with departing unconnected analysts, we find no changes in the consensus forecast. This result further supports our earlier evidence that the connected analysts' activity can increase the forecast accuracy of other analysts following the same firm.

We also find that following the departure of a connected analyst, the informativeness of *unconnected* analysts' forecasts diminishes. The evidence that connected analysts' activity can positively influence the informativeness of unconnected analysts' forecasts points to a spillover

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

effect. Finding a positive effect on the informativeness of unconnected analysts also allows us to distinguish positive spillovers from herding, where unconnected analysts copy the forecasts of connected analysts to signal that they have the same private information (Hong et al., 2000).[5]

We provide three cross sectional test on the role of connected analysts. First, we expect firms to have a stronger incentive to communicate with an arm's length party when they plan to issue new shares in the capital market. Also, the dyadic ties will play a more important role when the firms possess information that is proprietary or hard to verify. Consistent with this, we find that there is greater spillover from connected analysts' forecasts (i) when the firm's activities rely heavily on relationship-based contracts or (ii) when firms face greater political uncertainty.

This paper contributes to the literature in three ways. First, we show that dyadic ties can enable firms to disseminate information outside their private networks while protecting proprietary information. This evidence extends prior research that examines information transfer between managers and analysts via school and geographic ties (Cohen et al. 2010; O'Brien and Tan 2014). Our innovation is that we find that information transfers spill over to arm's length analysts. An implication of our findings is that, in markets where public disclosure cannot credibly communicate soft information and too much disclosure may expose significant proprietary information, firms can use private networks of embedded analysts to disseminate information to the capital markets.

Second, our research complements studies in economic sociology on network externalities. Mapping the path from individual to aggregate social capital (at the societal level) is difficult because the latter incorporates network externalities that are hard to quantify (Glaeser et al., 2002). One stream of research examines a form of externality that involves one dyadic tie (between A

[5] If unconnected analysts were herding, their forecasts (though more accurate) would have no information content and no incremental informativeness.

and B) creating a spillover to another tie (between B and C or from A to C). Uzzi and Gillespie (2002) find that an embedded relation between a firm and a bank can enhance that firm's trade-credit relationship with another creditor. Singh (2005) finds that knowledge can spill from one node to another through a common node with whom each of the other two has a collaborative tie, even if the initial two nodes do not collaborate with each other. The positive externality in our setting derives from an information transfer from managers and connected analysts that spills over to the firm's communication with arm's length analysts and investors outside of the network.

Third, we contribute to the research on how social networks and intermediaries reduce contracting costs by lessening information frictions. Prior research, such as by Fisman and Love (2003) and Allen et al. (2005), shows that, in economies where contracting costs are high, relationship-based contracts can substitute for arm's length contracts. However, relationship-dependent firms contract only within their social networks and face economic frictions when they want to establish contracts with arm's length parties outside those networks. In our context, we show that relationship-dependent firms can exploit their social ties to an embedded intermediary to bridge into the external equity markets, reducing their frictions in contracting with arm's length investors.

2. Prior literature and hypotheses development

In a relationship-based economy, firms rely on social networks rather than arm's length transactions to enforce contracts (Rajan and Zingales 1998; Hung et al. 2014). Unlisted private companies thus rely on informal contacts within their networks to obtain financing (Allen et al. 2005). Even for listed firms, ownership structure is typically concentrated (Fan and Wong 2002; Fan, Wong, and Zhang 2013), and accounting is insider based (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 communicate privately and directly with parties with whom they have strong ties, such as large shareholders, trade partners, creditors, politicians, and regulators.

More importantly, the contracts they obtain from and enforce through private ties are best hidden from competitors' and the public. Many key terms and contingencies of these contracts are not formally specified and are difficult for third parties to verify. The implicit nature of these contracts gives rise to mostly soft information, which complicates, and can even preclude, public disclosure.[6]

Nonetheless, relationship-based firms still want to raise money externally, as this allows them to secure larger sums of capital than they could through their private networks. Also, by tapping into the arm's length equity market, these firms will be less affected by the typical hold-up problem in relational financing (Rajan 1992). Firms therefore face a tradeoff between the need to reduce information asymmetry through communication with the arm's length capital market and the need to overcome the challenge of disclosing information that is proprietary and hard to verify.

This dilemma resembles that of a firm or hedge fund that wants to disclose information about a new product or trading strategy (Arrow 1962; Anton and Yao 2002; Glode and Green 2011; Hochberg et al. 2014). Anton and Yao (2002) argue that market transactions involving intellectual property are hard to contract because the seller must reveal the idea for the potential buyer to assess

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

its value, but the buyer has little incentive to pay for it after disclosure. In the prior literature, the typical solution to this dilemma is a strategy of direct disclosure to the buyer that balances reducing the costs of adverse selection with protecting the seller's property rights.

For relationship-based firms, the challenge in disclosure does not arise from intellectual property but from the confidentiality of relational contracts. Instead of using direct disclosure to investors, a typical solution in an arm's length environment, we posit that firms can use an embedded intermediary—financial analysts in their social networks—to credibly communicate to arm's length analysts and investors.[7] The transfer of information via a private network between a firm and analysts creates a positive spillover, conveying value-relevant information to analysts and investors outside the network while protecting information about the relational contracts.[8]

Connected analysts have a unique advantage in evaluating the future performance of relationship-based firms. Such firms' economic transactions can be difficult for unconnected analysts to assess, not necessarily because of the complexity of the transactions (Bhushan and Cho, 1996) but because they often involve relationships that are difficult to verify. Judging the validity and economic values of a contract requires knowledge of the relationship between the contract's parties. This information is strategic and confidential and can be shared only within close social groups. There is ample evidence in the literature that social ties can facilitate the transfer of such private information (Granovetter 1985, 2005; Cohen et al. 2010; Gao et al. 2014).

Due to the prevalence of relationship contracts in China, information transfer via private networks is likely to be a key communication channel (Jacobs 1979; Gold 1985; Guthrie 1998;

[7] Prior research has shown that, apart from social ties, U.S. analysts' access to private information can be obtained through direct contact with firm managers (Ke and Yu 2006; Soltes 2014) or other nonpublic sources, such as connections with large institutional investors or other analysts (Jennings et al., 2014).

[8] Another reason for relationship-based firms not to adopt a strategy of direct disclosure is this can hurt the firm's other contracts and even the contracts of other firms that are associated with this same relationship.

Peng 2004). China's weak legal and market institutions undermine the credibility of public disclosure, which increases the reliance on social ties for the transfer of information. However, private information transfers, although highly effective in protecting proprietary information, are limited to a small circle of people, restricting idea flows and lessening firms' growth opportunities (Gompers et al. 2016).

A key difference between this paper and the literature is that we examine how the information transferred via private ties improves communication *outside* of the private networks through a positive externality. Informal social ties provide assurance that information is credible and that connected analysts will protect proprietary information. The connected analysts then convert the soft information (i.e., relational contracts) into hard information (i.e., earnings forecasts) and disseminate it to arm's length analysts and investors. The firm can expect the hard forecast to convey soft signals that may be too sensitive to disclose, which allows the firm to parlay the analyst's credibility into an increase in the market's faith in the released information and, potentially, raise more external capital. In this environment, forecasts from an informed intermediary may be better received than those of a firm manager because the intermediary will be seen as having less of a vested interest.

The market is likely to know which analysts have access to a firm's secrets because their social and business ties can be traced and their forecast performance can easily be verified. An analyst's timely public releases of forecasts can also serve as a monitoring device for firms to ensure that their soft information is being conveyed. The connected analysts also can disseminate information to institutional and retail investors within their social and business networks. Firm managers can thus communicate with a vast network of outsiders to whom they would not otherwise have access.

Hence, an important aspect of whether connected analysts can serve as a conduit for transferring information to the market is whether the dyadic ties between firms and analysts can lead to a positive externality for those outside the network, leading to an improvement in the information environment of the firm. In this paper, we examine one channel through which these information spillovers may occur: the consensus forecasts of *unconnected* analysts. Finding information spillovers will demonstrate that firms can use their private networks to communicate with arm's length investors.

We believe that our setting offers sufficient conditions for private information transfer within dyadic ties to occur and to create a positive externality of disseminating information to arm's length investors. Connected analysts have strong incentives to act as firms' messengers. They can reap significant benefits in the form of commissions and reputational enhancement. These incentives are strong enough to discourage them from exploiting their information advantage at the expense of the firm. For the firm's part, its expected reduction in financing costs can more than offset the costs of any increased public scrutiny, which could jeopardize its connections and competitiveness.

We argue that unconnected analysts are unlikely to simply copy connected analysts' forecasts. As long as unconnected analysts contribute by adding their knowledge or interpretations, the connected analysts' information will lead to an incremental increase in the informativeness of unconnected analysts' forecasts. We also do not expect the network transfer to create entry barriers that drive away capable but unconnected analysts and reduce the firms' overall (consensus) forecast accuracy. 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 firms. That is, an analyst unconnected to one firm can be connected to another, one for which the original connected analyst has no special information advantage.[9] Furthermore, information could be shared indirectly between a connected analyst and an unconnected analyst through an institutional investor with whom each has a close tie.

Although we believe that the conditions discussed here are likely to hold, it still remains an empirical question whether we can document information spillovers in China. As additional tests, we will examine how varying two conditions—their incentives to raise equity capital and when the firms possess information that is proprietary or hard to verify—impact the spillover effects.

Finding evidence that connected analysts' activities can increase the accuracy of the consensus forecasts of *all* analysts is consistent with the notion that private networks channel information 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 firms, at least, allow private information to be transferred to the connected analysts. That is, if a firm is averse to having its private information leaked via network ties, it will distance itself from the connected analysts. However, if managers aim to engage connected analysts as a means of transferring private information, then these analysts would be expected to publish accurate and timely forecasts as a credible assurance that they have promptly communicated the information to investors on the firm's behalf. Even if the firm is just condoning the connected analyst's

[9] Unconnected analysts will not only stay in the market but may also have an incentive 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, she will not directly disclose it to the public. Instead, it will serve as the basis of an earnings forecast that conveys a soft signal without revealing too much proprietary information. In these circumstances, unconnected analysts can provide value to their clients by interpreting those forecasts. Institutional investors that do not have direct access to the firm or the connected analyst will look to an unconnected analyst for this kind of insight.

dissemination of the information, our evidence can still be interpreted as the connected analysts bridging the information gap between the firm and the market.

If connected analysts' forecasts are indeed more accurate and timely and their presence does not push out unconnected analysts and if information is shared between the two groups, the externality will be positive. Thus the private information transfer will not only increase the connected analysts' forecast accuracy, it will do the same for the unconnected analysts. Our hypothesis therefore is as follows:

***Hypothesis**: Greater activity on the part of connected analysts will increase the accuracy of the forecasts of all (both connected and unconnected) analysts and of unconnected analysts.*

3. Sample and empirical measures

3.1 Sample

Our analyst sample begins in 2005, the year the financial analyst industry experienced significant growth in China, and runs through 2014. The rapid growth of the 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.[10] While many research papers use a subset of these data sources, we find that no single vendor provides comprehensive coverage of analyst coverage in China. For example, the coverage in CSMAR (RESSET), which is one of the most widely used databases on Chinese analysts (e.g., Gu et al. 2012), includes only 14% (58%) of our earnings forecast sample. The number of

[10] 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).

brokerages 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.[11] The coverage in I/B/E/S is biased toward larger firms and the forecasts included in I/B/E/S tend be more pessimistic than those in our entire sample. 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 before 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 then add new forecasts from the different data vendors. To ensure accuracy, for a new forecast to be included in our sample, we require that the observation be recorded in at least two of the other nine databases. For a brokerage to be included in our sample for that year, we require it to have at least 20 or more distinct earnings forecasts. Otherwise, the brokerage is considered inactive, and all its forecasts are removed 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 (domestic shares) traded on the Shanghai and Shenzhen stock exchanges. We include only firms followed by at least one analyst throughout the sample period. The final sample includes 2,460 firms and 6,099 analysts..The average (median) number of analysts following a given firm is 11(8) in our sample period. We obtain all the firm-level financial variables for our empirical analysis from CSMAR.

[11] The coverage in I/B/E/S is particularly sparse 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. Coverage improves after 2010.

3.2 *Empirical measures of dyadic ties*

We employ three types of dyadic ties. The first two capture the social ties between an analyst and a firm manager. For the first measure, we use school ties between an analyst and the managers of a firm the analyst follows. Studies show that educational networks can function as a channel of information transfer for financial analysts (Cohen et al., 2010). Following this literature, we exploit use attendance at the same colleges and universities 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 biographies of each firm's C-suite executives. Educational backgrounds of the analysts are hand collected from individual résumés obtained from the following sources: the 2014 star analysts report sponsored by *New Fortune* magazine, manual searches of professional networking sites (*WeiBo*), individual analyst reports, brokerage firm websites, or a combination of these.

We then measure the distance between the analyst and the firm headquarters to assess geographic ties (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. Malloy (2005) similarly shows that local analysts provide more accurate forecasts and generate greater price responses than do more distant ones. He argues that analysts located nearby may have better access to management, established through more frequent face-to-face interactions. 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.

Our third measure captures business ties between a firm and an analyst's brokerage formed via prior investment banking relationships. An extensive literature shows that underwriting relationships play a substantial role in analyst activities (James and Karceski 2006; Ljungqvist et al. 2006; Clarke et al. 2007). We argue that the ties established through these relationships (and the subsequent favors exchanged between the parties) are likely to sustain 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 a 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 within the last five years.

Dyadic ties can emerge through multiple channels. Jacobs (1979) argues that, in Chinese society, these channels of network ties, which he terms "guanxi bases," mainly arise from ties among kin, neighbors, classmates, co-workers and business associates. In our empirical tests, we consider an analyst to have close ties to a firm if she shares any of the three dyadic ties with the firm.

Table 1, Panel A, shows the distribution of the number (%) of analysts who share dyadic ties for each firm-year observation in our sample. The most common sources of ties between a firm and an analyst are school ties, followed by geographic ties: 27.08% (25.13%) of the firm-years in our sample show a following from at least one analyst with school ties (geographic ties). Panel A shows that 49.72% of firm-years have at least one connected analyst following the firm. The percentage of firm-years with two connected analysts is significantly lower, at 9.18%.

4. Empirical analyses

4.1 Main empirical tests

Our first analysis examines how connected analysts affect forecasts at the firm level. We regress properties of analysts' forecasts (consensus forecasts errors and forecast dispersion) on the following of connected analysts to test how the greater activity of connected analysts affects the forecasts of the analysts as a group. We run the following regression model:

$$\begin{aligned} &\textit{Consensus forecast errors (Dispersion)}_{i,t} = \\ &\quad \alpha_0 + \beta_1 \times \textit{Following\_connected}_{i,t} + \beta_{2\text{-}7} \times \textit{Firm Controls}_{\,i,t} \\ &\quad + \beta_{8\text{-}12} \times \textit{Analyst Controls}_{\,i,t} + \textit{IndustryFE} + \textit{YearFE} + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

The unit of analysis is firm (i)-year (t). $\textit{Following\_connected}_{i,t}$ is our main variable of interest; it measures the number of the latest earnings forecasts issued by a connected analyst. The variable is measured as the log of one plus the number of connected analysts following firm i in year t. We include industry and year fixed effects to control for unobservable factors that affect the predictability of firm earnings in different industries and years.

We examine two properties of earnings forecasts. First, we examine forecast accuracy using the consensus forecasts. $\textit{Consensus forecast errors}_{i,t}$ is defined as 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 captures uncertainty or disagreement about the underlying future earnings (Diether et al. 2002; Johnson 2004) and is defined as the standard deviation of the latest earnings forecast issued by all analyst following the firm.

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 the analyst's experience and resources. We measure the individual analyst's overall experience (*Experience*) as the number of days between her 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 (*Broker_size*), computed as the total number of analysts hired by the brokerage for the same year. We control for analyst reputation by computing dummy variables equal to 1 if analyst *a* is a star analyst (*Star*). For all 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.

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 firm's riskiness, which may make forecasting more difficult. Following Alford and Berger (1999), we include analyst following (*following_all*) to control for the fact that having 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.

4.2 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 versus those with none. Table 1, Panel B, shows the results. We find that the firms with connected analysts show a lower mean consensus forecast error (0.988 vs. 1.432) but a greater mean forecast dispersion (0.739 vs. 0.634).

Not surprisingly, firms with at least one connected analyst tend to be larger and have greater trading volume and more shares held by institutional investors but also have lower return volatility relative to firms with no connected analysts.

Table 2 shows the estimated results of equation (1). We find that firms with more connected analysts show more accurate consensus forecasts and less dispersion in 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 (coeff = −0.091, p-val <0.001). The estimated coefficient indicates that a 100% change in the number of connected analyst, which is equivalent to 1.38 analysts for an average firm in our sample, is associated with a 0.091 reduction in mean consensus forecast, i.e., a 13.5% percentage reduction from the sample mean (= 0.671, Table 1, Panel B).

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* relates positively to forecast errors (coeff = 0.005, p-val <0.001), which suggests that the later forecasts are more accurate (Clement, 1999). 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 analysts' experience affecting forecast accuracy: the average firm-specific experience of all the analysts following the same firm shows no significant relation with its consensus forecast accuracy, while the average individual experience of the analysts following the same firm is negatively associated with its consensus forecast accuracy.

Column (2) presents 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. We find that the coefficient on *Following_connected* is negative and significant, suggesting that more forecasting on the part of a connected analyst is associated with less dispersion of analysts' forecasts (coeff= −0.070, p-val <0.001).

While the findings point to connected analyst activity being associated with more accurate consensus forecasts, the observed association might simply result from the aggregation of individual analyst effects. That is, the consensus forecast may be more accurate because the individual forecasts of connected analysts are more accurate.[12] We thus repeat our analysis using the latest forecasts of *unconnected analysts only* when constructing our dependent variables. This test provides direct evidence on the spillover effect connected analysts have on unconnected analysts.

Table 3 shows the results of the regression analyses. Here again, we find that the number of forecasts issued by connected analysts enhances the accuracy of the consensus forecasts of *unconnected* analysts (coeff = −0.078, p-val = 0.002), suggesting a positive spillover effect. The estimate indicates that a 100% change in the number of connected analysts (which is 1.38 analysts for an average firm in the sample), is associated with a 0.078 reduction in mean consensus forecast.

Also, in column (2), 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 (coeff = −0.095, p-val <0.001). In sum, the results in Tables 2 and 3 suggest that connected analysts' greater forecasting activity increases the accuracy of all analysts' forecasts, yielding a lower consensus forecast error and less forecast dispersion. The results are robust to using only unconnected analysts' forecasts to compute the consensus variable. That is, the increased performance is achieved not only through the direct aggregation

[12] In untabulated analysis, we find that the individual forecasts of connected analysts are more accurate than those of unconnected analysts. Also, forecasts of connected analysts are less optimistic than those of unconnected analysts.

effect of individual analysts' forecasts but, more importantly, through an indirect spillover effect on the forecasts of unconnected analysts.

4.3 Changes analysis: Analyst departures

4.3.1 Empirical test design of analysts' departures

Analyst coverage is not randomly determined. Also, how intensively an analyst follows a firm is determined by many factors besides 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 absent 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 due to brokerage closures or mergers, their own career changes, or both.

The sample of brokerage closures is hand collected using various sources for each individual brokerage (e.g., industry reports, company website, and internet search engine). In China, 70 brokerages merged or closed during our sample period. Thirty of the mergers occurred during the first half of our sample period (i.e., 2004 to 2007); 10 occurred following the 2008 financial crisis.[13] Additionally, we collect a sample of analyst departures due to career changes. We consider an analyst to have changed careers if the analyst disappears from the analyst database (indefinitely), even when other analysts from the same brokerage continue to issue forecasts.

[13] One can argue that, when an analyst is connected through her brokerage's location or prior underwriting relationships with the listed firm, her departure will not necessarily lead to loss in connections because she can be replaced by another analyst from the same brokerage. We therefore repeat our analysis after dropping the 27 departing analysts that are connected through location or prior underwriting relationships and replaced by other analysts from the same brokerage (untabulated). Our results remain unchanged.

Our departure event sample includes all firms with a departing analyst, either connected or unconnected. To be considered a departure, we require the analyst to have at least one forecast for that firm within the 180 days before the departure date. This allows us to capture only the departure of analysts who had a relatively meaningful relationship with the firm. Also, to ensure that departures are not affected by other confounding events, we require firms to have no other departing analysts 180 days before this event.

Using the departure sample, we compare the effect that the departure of a connected analyst had on post-departure forecast properties, relative to the departure of an unconnected analyst. The test is akin to a difference-in-difference model where we use unconnected analysts' departure to control for unobserved factors that may confound the departing sample. The departure of connected analysts is the treatment group. Equation (2) shows the regression model for the departure test:

$$\begin{aligned}
&\textit{Consensus forecast errors (Dispersion)}_{d,t} = \\
&\quad \alpha_0 + \beta_1 \times \textit{D_connected_departure}_d \times \textit{Post_departure}_{d,t} + \beta_2 \times \textit{D_connected_departure}_d \\
&\quad + \beta_3 \times \textit{Post_departure}_{d,t} + \beta_{4\text{-}9} \times \textit{Firm Controls}_{d,t} + \beta_{10\text{-}14} \times \textit{Analyst Controls}_{d,t} \\
&\quad + \text{IndustryFE} + \text{YearFE} + \textit{DepartingAnalystFE} + \varepsilon_{d,t}.
\end{aligned} \tag{2}$$

The unit of analysis is firms with departing analysts (*d*)- pre-/post-(*t*). We include only firms with a departing analyst. A firm is considered to have a departing analyst if the analyst issued an earnings forecast for the firm within two months before leaving. We limit the pre- (post-) departure observations included in the regression to analyst forecasts made within 180 days before (following) the event date. We define a departure date as 30 days after the departing analyst's last forecast was issued.[14]

[14] Allowing enough 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 forecasts made by the nondeparting analysts are less influenced by the connected analyst's final forecast. In untabulated results, we use a shorter (15-day) cutoff and find similar results.

D_connected_departure$_d$ is an indicator variable that takes a value of 1 if departure event *d* involves a connected analyst and zero otherwise. *Post_departure*$_{d,t}$ is an indicator variable that takes a value of 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. 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 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 if an unconnected analyst left.

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 for each individual analyst. To be more precise, for the pre-departure period, we use each analyst's last forecast within 180 days before the departure. For the post-departure period, we use the first forecast of each analyst made within the 180 days following the departure. Similarly, we define *Dispersion* as the standard deviation of the earnings forecast issued by each analyst's firm closest to the departure date. As before, we include 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.

In addition to the two dependent variables above, we also evaluate the benefits of having connected analysts by examining the informativeness of analysts' forecasts. If the activity of connected analysts had a positive spillover effect on the forecasts of other unconnected analysts, we predict that following their departure, the informativeness of *unconnected* analysts' forecasts will diminish. This result will also suggest that the unconnected analysts are not simply mimicking the connected analysts' forecasts but are providing new information to the market by adding their own knowledge and interpretations to the forecasts.

We examine the informativeness of an analyst's forecast using the mean three-day unsigned cumulative abnormal returns around [-1 day, +1 day] the issuance of an analyst forecast. To compute the aggregate informativeness of the forecasts (*M_Informativeness_forecasts*), we use the mean informativeness of each individual forecasts. Informativeness prior to an analyst's departure is computed using the latest forecast of all analyst that issued an earnings forecast within the 180-days before the departure event. Similarly, informativeness following a departure event is calculated using the earliest forecast of all analyst that issued an earnings forecast within the 180-days after the departure event. We also use a second measure of informativeness (*M_Informativeness_forecasts2*) which scales the informativeness measure by the mean unsigned daily absolute abnormal returns of the corresponding 180 days before/after the departure. The scale allows us to control for other underlying news events that may change the information content in the analyst's forecasts.

4.3.2 Empirical results of the analyst departure test

Table 4 shows the estimated results of the departure test in equation (2). 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 *D_connected_departure* ×*Post_departure* is positive and significant (coeff = 0.213, p-val = 0.021), suggesting an incremental increase in forecast errors when a connected analyst leaves, relative to an unconnected analyst's departure. The estimated coefficient suggests that following the departure of a connected analyst, the incremental increase in forecast errors is 18.6% relative to the sample mean.[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.

In column (2), we report the estimated result using dispersion as the dependent variable. Column (2) shows that the incremental effect of the connected analyst's departure is positive and significant (coeff = 0.269, p-val =0.002), suggesting that the departure of a connected analyst leads to a greater increase in forecast dispersion than that of an unconnected analyst. Overall, the findings in Table 4 show a greater reduction in the performance of the analysts' forecasts as a group (i.e., less accuracy and greater dispersion) after the departure of a connected analyst relative to an unconnected analyst.

In columns (3) and (4), we present the estimated results of equation (2) using two informativeness measures as the dependent variable. The estimated coefficient in column (3) shows that the departure of a connected analyst is negatively associated with the informativeness of the analyst forecasts (coeff = −0.006, p-val = 0.006). In column (4), we repeat the analysis for our second measure of informativeness, *M_Informativeness_forecasts2*. We find that the coefficient on the interaction term *D_connected departure*$_d$ ×*Post_departure*$_{d,t}$ is again negative and significant (coeff= −0.321, p-val = 0.010), suggesting a significant drop in the informativeness of analysts' forecasts following the departure of a connected analyst.

In Table 5, we repeat the analysis in Table 4 using only the forecasts of unconnected analysts to compute the dependent variables. The findings mirror the findings in Table 4 with marginally reduced economic significance. The departure of a connected analyst leads to a greater increase in forecast errors among unconnected analysts (column (1) = 0.201, p-val =0.011) and

[15] The figure is obtained by dividing the coefficient 0.213 by the average consensus forecast in the sample (=0.213/1.145).

forecast dispersion among unconnected analysts (column (2) = 0.253, p-val =0.005), relative to the departure of an unconnected analyst. Columns (3) and (4) repeat the estimation using only the unconnected analysts' forecasts to measure informativeness and show similar results.

In sum, the results in Tables 4 and 5 show that more forecasting by a connected analyst increases the accuracy of all analysts' forecasts. Using relatively exogenous analyst departures in a difference-in-difference specification, we find that the departure of a connected analyst hurts the quality of other analyst's forecasts. Specifically, following the departure of a connected analyst, there is an increase in forecast errors and forecast dispersion and a decrease in forecasts' informativeness.

Next, we examine whether 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. Network theory suggests that the importance of an individual depends on the structure of the network (Granovetter, 2005). We identify critical departures as those when the departing analyst was the only connected analyst following the firm. The departure is then likely to lead to a greater void, as no other connected analysts remain in the network.

We partition the earlier departure sample in Table 4 and 5 into critical departures and less critical ones. 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 by comparing the coefficients on *D_connected_departure×Post_departure* (using equation (2)) for the two subsamples: critical departures vs. less critical ones.

We present the estimated results in Table 8. Columns (1) and (2) show the changes in the consensus forecasts for the critical departure and less critical departure samples, respectively. We find that the increase in consensus forecast errors following the departure of a connected analyst is positive and significant (coeff = 0.423, p-val = 0.002), 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 = 0.110, p-val =0.340). The F-test comparing the coefficients across the two samples is positive and statistically significant (p-value=0.073), indicating that there is a greater increase in consensus forecast errors for the critical departure sample relative to the noncritical departure sample. In column (3), we find that the increase in forecast dispersion following the departure of a connected analyst is positive and significant (coeff = 0.369, p-val = 0.001) for critical departures. For less critical departures in column (4), the coefficient is also positive (coeff = 0.231, p-val = 0.035) suggesting an increase in forecast dispersion following a departure of a less critical analyst. In columns (5) and (6), we find a greater decrease in the informativeness of analysts forecast in the sample of critical departures (coeff = −0.016, p-val = 0.001), compared to the sample of noncritical departures (coeff = −0.002, p-val = 0.283). The F-test suggests that the difference in the two coefficients is statistically significant (p-val = 0.009). In panel B, we compute the properties of forecast errors using only the forecasts of unconnected analysts. We find similar results with marginally reduced statistical significance. The findings suggest that the departure of a connected analyst has a greater effect of increasing forecast errors and forecast dispersion and decreasing in forecast informativeness when the departing analyst was the only connected analyst following the firm.

4.4 Cross-sectional tests

The need to find a credible channel of communication especially arises when firms wish to raise external financing but want to protect their proprietary information. Thus we expect connected analysts to play a greater role (i) when a firm plans to raise external financing and (ii) when the firms possess information that is proprietary or hard to verify (e.g., during times of political uncertainty or when firms' operations rely heavily on relationship-based contracts).

We first examine the effect during equity issuances. We estimate the effect of having a connected analyst following using equation (1) but now partition the sample based on periods when firms are raising equity versus when they have no such plans. We use all firms with equity issuances, including seasoned equity offerings and rights offerings, from 2005 to 2014. The sample includes a total of 2,655 equity issuances. For each equity issuance, the *Around equity issuance announcements* subsample includes periods from the six months before the announcement date to the 24 months following it. The *Non-event period* includes the 24 to six months before the announcement date, without overlapping the *Around equity issuance announcement* period.

Table 7 shows the estimated results of the first cross-sectional test. We examine the effect on the forecasting properties on the consensus forecast errors and forecast dispersion. The dependent variable *Consensus forecast error* is defined as the average annual absolute forecast error of all the analysts (or all unconnected analysts only) during the defined period. *Forecast dispersion* is the annual standard deviation of the earnings forecasts issued by all analysts (unconnected analysts) following the firm during the defined period.

The first four columns (columns (1) to (4)) show the estimated results using *Consensus forecast error* as the dependent variables. *Following_connected* is the main variable of interest, which captures the effect of a connected analyst in each subsample period and is defined as the log of one plus the number of connected analysts following the firm in each year during the defined period. Using all analyst's forecasts, connected and unconnected, to construct the consensus forecast errors in columns (1) and (2), we find that the effect of *Following_connected* is negative and significant only in the *Around equity issuance announcements* subsample (column (2) =

−0.095, p-val = 0.029) but not in the *Non-event period* subsample (column (1) = −0.003, p-val = 0.960), suggesting that the negative effect of the number of forecasts of connected analysts on the consensus forecasts is only found around an equity issuance. The F-test shows that the differences in the coefficients are statistically significant. Columns (3) and (4) repeat the analysis by using only the forecasts of *unconnected* analysts to construct the consensus forecasts. Our findings are very similar to those in columns (1) and (2), with marginally smaller economic significance.

The last four columns show the estimated results using *Forecast dispersion* as the dependent variable. Here again, we find that connected analysts only play a significant role in reducing the forecast dispersion of all analysts (unconnected analysts) around an equity issuance. The coefficient on *Following_connected* is negative and significant (column (6) = −0.058, p-val = 0.015) in the *Around equity issuance announcements* subsample only. Also, connected analysts following leads to a reduction in the forecast dispersion of unconnected analysts only around an equity issuance (column (8) = −0.083, p-val = 0.001); it plays a weaker role in normal periods (column (7) = −0.045, p-val = 0.105).

Next, we examine whether connected analysts will play a more important role when the firms possess information that is proprietary or hard to verify; (i) when the firm's activities rely heavily on relationship-based contracts or (ii) when the firms face greater political uncertainty. We first examine firms that rely on relationships that are not arm's length. We partition the sample by firms with operations that heavily rely on non-arm's length transactions and those that do not. Information about the relationships is strategic and confidential and can be shared only within closely knit social groups. If connected analysts bring benefits to firms by conveying inside information that is difficult to verify and that the firm does not wish to report through public channels, analysts' private access may matter more for firms whose operations rely more on relationship contracts.[16]

We thus repeat the estimation in equation (1) after partitioning the sample based on firms that are more relationship based. We define a firm to be a *Non-arm's length firm* if it satisfies one of the following criteria: (i) total related-party transactions are more than 30% of total sales; (ii) purchases from (sales to) the top five suppliers (customers) exceed 30% of total purchases (sales); (iii) the total balance of related-party borrowing or lending is greater than 30% of total assets; (iv) the chairman/CEO is an ex-government official, military officer or state banker or has served as a representative in the National People's Congress or the People's Political Consultative Conference; (v) the firm receives subsidies from the government (larger than 5% of total sales) in the given year; and (vi) the chairman and the party secretary of the city where the firm is located attended the same university.[17]

Table 8 shows the estimated results using consensus forecast errors and forecast dispersion as the dependent variable. Using consensus forecast errors as the dependent variable in columns (1) and (2), we find that the effect of having more connected analysts following (*Following_connected*) is negative and significant only for *Non-arm's length firms* (column (2) = −0.139, p-val<0.001). For the *All other firms* subsample, the estimated coefficient is negative but

[16] Using a U.S. sample, O'Brien and Tan (2014) show that nearby analysts matter more when the firm's operations are less complex. The authors interpret these findings as suggesting that local analysts face 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 a knowledge advantage are significantly more important because of the complex relationships in the contracting.

[17] Data sources of the insider-based firm measures are as follows. The related-party transaction information is from CSMAR. Information on the background of the chairman and CEO and the concentration of customers and suppliers is hand collected from the company's annual reports. The party secretaries' educational backgrounds are collected from various government yearbooks and websites. The subsidy information is from the Juyuan database.

not significant (column (1) = −0.036, p-val=0.287). The F-tests show that the difference in the two coefficients is statistically significant at conventional levels (p-value = 0.024).

The main effect on the number of the followings of all analysts (*Following_all*), both connected and unconnected, is negative and statistically significant for both the *non-arm's length firms* and the *all other firms* sample. Thus, while greater analyst coverage increases the accuracy of consensus forecasts for all firms, a greater number of *connected* analysts following a firm contributes to the forecast accuracy of all analysts for the *non-arm's length firms* only. Columns (3) and (4) repeat the analysis using only the forecasts of *unconnected analysts* to construct the consensus forecasts. The findings mirror the results in columns (1) and (2).

Using dispersion as the dependent variable paints a similar picture. We find that connected analysts help reduce the forecast dispersion of all analysts (unconnected analysts) for *Non-arm's length firms* only. The coefficient on *Following_connected* is negative and significant (column (6) = −0.111, p-val = 0.001) for *Non-arm's length firms* and negative yet insignificant for the *All other firms* subsample (column (5) = −0.036, p-val = 0.285). Using the forecast dispersion of only the unconnected analysts in columns (7) and (8), we find that the activities of connected analysts play a stronger role for *Non-arm's length firms* (column (8) = − 0.124, p-val <0.001) than for *All other firms* (column (7) = −0.061, p-val =0.008). The F-test comparing the two coefficients shows that the difference is statistically significant (p-value = 0.041). 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 a firm relies heavily on relationship contracts, which are difficult for a third party to verify.

For our third cross-sectional test, we examine the effect of political uncertainty using the appointment of a new politician in the locale where the firm operates. Prior studies show that changes in political parties increase the economic uncertainty of firms (Julio and Yook 2012; An et al. 2016). Durnev (2011) argues that heightened uncertainty during election cycles impairs the information environment of firms, leading to less informative stock prices. We predict that in times when there is high political uncertainty, connected analysts will have a greater role to play in disclosing information to the market.

We partition the sample based on periods when firms face political uncertainty vs. when they do not. We define periods of political uncertainty using appointment of a new mayor or a party secretary in the *city* where the firm is located. The advantage of focusing on regional appointments is that they are staggered over time across multiple regions, providing us with a powerful test to control for region and time effects. There are 815 turnover events that occurred during our sample period, from 2005 to 2014.

Table 9 shows the estimated results of the first cross-sectional test. The sample includes all firms located in a region with a newly appointed mayor or party secretary. We consider the first 18 months immediately following a new appointment to be a *High political uncertainty* period. *Low political uncertainty* period is defined as the subsequent 18 months following the *High political uncertainty* period, which do not overlap with other *High political uncertainty* periods.[18] As in the earlier test, we examine the effect on the two forecasting properties; consensus forecast errors and forecast dispersion.

The first four columns show the estimated results when consensus forecast is the dependent variable. *Following_connected* is the main variable of interest, which captures the effect of a connected analyst in each subsample. Using forecasts of all analysts, connected and unconnected,

[18] We use an 18-month period to ensure that the *Low political uncertainty* period is not affected by the uncertainty from the next incoming mayor. The term of a mayor is 5 years (i.e., 60 month) in China. Therefore, by the end of the *Low political uncertainty* period (i.e., 36 months after an appointment), there are still 24 more months before a new mayor gets appointed.

as the dependent variable in columns (1) and (2), we find that the effect of *Following_connected* is negative and significant only in the *High political uncertainty* period (column (2) = −0.149, p-val < 0.001) but not in the *Low political uncertainty* period (column (1) = −0.061, p-val = 0.119). The F-test shows that the differences in the coefficients are statistically significant (p-val = 0.091). Columns (3) and (4) repeat the analysis by using only the forecasts of *unconnected* analysts to construct the consensus. Our findings are very similar to those in columns (1) and (2). Connected analysts play a greater role in improving the consensus forecast when there is greater political uncertainty.

The last four columns show the estimated results using *Forecast dispersion* as the dependent variable. We find that connected analysts play a significant role in reducing the forecast dispersion of all analysts (unconnected analysts) in times of political uncertainty. The coefficient on *Following connected* is negative and significant (column (6) = −0.106, p-val < 0.001) during the *High political uncertainty* period only. Also, connected analysts following leads to a reduction in the forecast dispersion of unconnected analysts only in the *High political uncertainty* period (column (8) = −0.125, p-val < 0.001); it plays a weaker role in times of low political uncertainty (column (7) = −0.026, p-val = 0.311). These findings confirm that the role of connected analysts is stronger when the firms face greater political uncertainty.

4.5 Additional tests

We next explore whether the informational role of connected analysts is observed in times of both positive and negative news. Managers may reveal only positive news to connected analysts (and withhold bad news from them).[19] If so, the information role of connected analysts will be

[19] Also, connected analysts may obtain both good and bad news from managers but incorporate only the positive news in their forecasts, perhaps to please the managers.

limited to times of good news. More importantly, the asymmetry will undermine the credibility of connected analysts' forecasts because other unconnected analysts may consider the connected analysts' forecast to be biased.[20] We therefore repeat our analysis in Table 3 after partitioning the sample into times of positive versus negative earnings surprises.

Table 10 presents the estimated results. A positive (negative) earnings surprise is defined as firm-years where there was an increase (a decrease) in reported earnings from the prior year. The effect of connected analyst coverage on reducing forecast errors is stronger in times of negative news (= −0.116, p-val = 0.002) than positive news (= −0.039, p-val = 0.150). Similarly, connected analyst coverage reduces the forecast dispersion in times of positive news (= −0.039, p-val = 0.048) but more strongly during negative news (= −0.086, p-value <0.001). These results suggest that the information spillover effect of connected analysts is not limited to times of positive news.

5. Conclusion

We examine connected analysts as a channel of information dissemination for Chinese firms. We find that having more connected analysts leads to greater accuracy in the forecasts of *all* analysts as a group. We document a positive spillover effect of connected analysts' forecasts, which indicates that connected analysts improve the information environment of the firms they follow. In addition, our results are stronger for firms with plans to access external capital and more non-arm's length economic activities.

[20] In additional analysis (untabulated), however, we find that earnings forecasts of connected analysts are more pessimistic than those of other analysts, suggesting that they are more likely to err on the side of conservatism.

These results suggest that close ties between analysts and managers can be a channel of information dissemination to arm's-length capital providers. An important implication of our results is that, in emerging markets, where contracts are often implicit, and public reporting and disclosure are significantly limited as they jeopardize firms' competitiveness and strategic connections, private network information transfer can serve as an alternative disclosure channel and contribute to the aggregate amount of disclosed information.

Another implication is that, in emerging markets, embedded intermediaries like financial analysts can use their social ties to reduce their clients' contracting costs with arm's length investors. Future research might explore how other intermediaries, such as auditors, underwriters, and institutional investors, exploit their social ties and reputations in serving as messengers for firms that seek to bridge the relationship-based and arm's length environments. For example, external auditors' social ties with clients may provide private knowledge about relational contracts, and that knowledge may enable auditors to make more accurate public attestations about financial statements. Also, the mechanisms that produce these positive network externalities might be applied to other markets (e.g., labor or product markets), as the benefits of transforming a relationship-based system to an arm's length one are not limited to capital markets (North et al., 2009; Fukuyama, 2011).

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Appendix- Variable Definitions

Variable	Definition
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 analyst.
M_Informativeness _forecasts	The mean three-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast of each analyst made within the 180 days before (after) the departure event.
M_Informativeness _forecasts2	M_Informativeness_forecasts divided by the mean daily unsigned cumulative abnormal returns of the corresponding 180 days.
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 at 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).
Non-arm’s length firm	Indicator variable that takes the value of one if it satisfies one of the following criteria: (i) total related-party transactions are more than 30% of total sales; (ii) purchases from (sales to) the top five suppliers (customers) exceed 30% of total purchases (sales); (iii) the total balance

	of related-party borrowing or lending is greater than 30% of total assets; (iv) the chairman/CEO is an ex-government official, military officer, or state banker or has served as a representative in the National People's Congress or the People's Political Consultative Conference; (v) the firm receives subsidies from the government (larger than 5% of total sales) in the given year; and (vi) the chairman and the party secretary of the city where the firm is located attended the same university.
Analyst-level measures	
Experience_firm	Number of days between the analyst's first forecast for the same firm and the day of the current forecast.
Experience	Number of days between the analyst's first forecast of any firm in the database and the day of the current forecast.
Star	Indicator variable that takes the value of one if the analyst was awarded a star analyst rating by *New Fortune Magazine* in the previous year and zero otherwise.
Horizon	The number of days (*Horizon*) between an analyst's forecast for a firm and the firm's fiscal year-end.
Brokersize	Total number of analysts hired by the analyst's brokerage for the year.

Table 1: Descriptive statistics

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

# of connected analysts	Dyadic ties	School ties	Geographic ties	Investment banking ties	Dyadic ties	School ties	Geographic ties	Investment banking ties
	# of firm-years				% of firm-years			
>=5	1,203	519	529	60	9.36	4.04	4.11	0.47
4	447	318	217	66	3.48	2.47	1.69	0.51
3	740	381	417	99	5.75	2.96	3.24	0.77
2	1,181	591	647	314	9.18	4.60	5.03	2.44
1	2,823	1,673	1,421	2,205	21.95	13.01	11.05	17.15
>=1	6,394	3,482	3,231	2,744	49.72	27.08	25.13	21.34
0	6,465	9,377	9,628	10,115	50.28	72.92	74.87	78.66
Total	12,859	12,859	12,859	12,859	100.0	100.0	100.0	100.0

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

Variables		mean	median	std	p25	p75	n
Consensus	All firms	1.215	0.671	1.649	0.321	1.383	12,859
_FE	Firms with no connected analysts	1.432	0.783	1.904	0.350	1.650	6,564
	Firms with at least one connected analyst	0.988	0.591	1.294	0.300	1.164	6,295
	Difference	0.444***	0.192***	0.610	0.050	0.486	
Dispersion	All firms	0.685	0.419	0.878	0.129	0.895	12,859
	Firms with no connected analysts	0.634	0.315	0.929	0.000	0.840	6,564
	Firms with at least one connected analyst	0.739	0.492	0.817	0.242	0.940	6,295
	Difference	-0.106***	-0.177***	0.112	-0.242	-0.100	
Size	All firms	15.301	15.149	1.092	14.541	15.888	12,859
	Firms with no connected analysts	14.968	14.893	0.890	14.347	15.512	6,564
	Firms with at least one connected analyst	15.648	15.496	1.173	14.807	16.306	6,295
	Difference	-0.680***	-0.603***	-0.284	-0.461	-0.794	
BM	All firms	0.436	0.371	0.282	0.227	0.573	12,859
	Firms with no connected analysts	0.446	0.387	0.284	0.236	0.586	6,564
	Firms with at least one connected analyst	0.426	0.354	0.280	0.220	0.559	6,295
	Difference	0.021***	0.033***	0.005	0.017	0.027	
Institutions	All firms	7.656	4.423	10.612	1.480	9.320	12,859
share	Firms with no connected analysts	6.155	3.130	9.399	0.870	7.553	6,564
	Firms with at least one connected analyst	9.222	5.951	11.539	2.561	11.030	6,295
	Difference	-3.066***	-2.821***	-2.140	-1.691	-3.477	
	All firms	2.941	2.812	0.796	2.364	3.398	12,859

Stdret	Firms with no connected analysts	2.990	2.843	0.803	2.406	3.433	6,564
	Firms with at least one connected analyst	2.890	2.776	0.785	2.321	3.356	6,295
	Difference	0.099***	0.068***	0.018	0.085	0.077	
Volume	All firms	23.335	23.340	1.056	22.677	24.012	12,859
	Firms with no connected analysts	23.144	23.203	0.995	22.529	23.794	6,564
	Firms with at least one connected analyst	23.533	23.518	1.081	22.835	24.248	6,295
	Difference	-0.389***	-0.315***	-0.087	-0.306	-0.455	

Notes: This table presents the descriptive statistics of the variables included in our tests. Panel A shows the distribution of the number of connected analysts across different firm-years. An analyst is considered to have a dyadic tie with 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 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 a univariate comparison of the firm-level characteristics of firms with and without connected analysts. All other variables are defined in the appendix.

Table 2 The effect of a connected analyst on the properties of forecasts of all analysts

	(1)	(2)
	Consensus_FE	Dispersion
Following_connected	-0.091***	-0.070***
	(<0.001)	(<0.001)
Following_all	-0.225***	0.016
	(0.000)	(0.385)
Size	0.004	-0.012
	(0.897)	(0.536)
BM	1.006***	0.839***
	(0.000)	(0.000)
Institutions_share	0.001	-0.000
	(0.441)	(0.691)
Stdret	0.200***	0.147***
	(0.000)	(0.000)
Volume	0.067**	0.093***
	(0.035)	(0.000)
Experience_firm	-0.010	-0.001
	(0.330)	(0.859)
Experience	0.108***	0.058**
	(0.009)	(0.037)
Star	0.244***	0.134**
	(0.009)	(0.036)
Horizon	0.005***	0.002***
	(0.000)	(0.000)
Brokersize	-0.075	0.031
	(0.173)	(0.446)
Constant	-1.185**	-2.380***
	(0.045)	(0.000)
# of observations	12,859	10,624
Adjusted R-squared	0.131	0.163
Industry FE	Yes	Yes
Year FE	Yes	Yes
SE clustering	Firm	Firm

Notes: This table presents the firm-level regressions using various firm-level properties of analyst earnings forecasts 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 analyst. All other variables are defined in the appendix. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 3 The effect of a connected analyst on the accuracy and dispersion of unconnected analysts' forecasts

	Forecasts of unconnected analysts only	
	(1)	(2)
	Consensus_FE	Dispersion
Following_connected	-0.078***	-0.095***
	(0.002)	(<0.001)
Following_all	-0.239***	0.039**
	(0.000)	(0.046)
Size	0.017	-0.016
	(0.597)	(0.440)
BM	0.986***	0.781***
	(0.000)	(0.000)
Institutions_share	0.001	-0.001
	(0.459)	(0.590)
Stdret	0.212***	0.145***
	(0.000)	(0.000)
Volume	0.061*	0.097***
	(0.061)	(0.000)
Experience_firm	-0.012	-0.004
	(0.268)	(0.604)
Experience	0.112***	0.054*
	(0.009)	(0.064)
Star	0.288***	0.077
	(0.004)	(0.235)
Horizon	0.005***	0.002***
	(0.000)	(0.000)
Brokersize	-0.089	0.065
	(0.127)	(0.126)
Constant	-1.201**	-2.517***
	(0.047)	(0.000)
# of observations	12,464	10,103
Adjusted R-squared	0.131	0.160
Industry FE	Yes	Yes
Year FE	Yes	Yes
SE clustering	Firm	Firm

Notes: This table presents the firm-level regressions using various firm-level properties of analyst earnings forecasts 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 unconnected 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 unconnected analyst. All other variables are defined in the appendix. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 4 Effect of a connected analyst's departure on the forecast properties of all analysts

	(1) Consensus_FE	(2) Dispersion	(3) M_Informative-ness_forecasts	(4) M_Informativen-ness_forecasts2
D_connected_departure × Post departure	0.213**	0.269***	-0.006***	-0.321***
	(0.021)	(0.002)	(0.006)	(0.010)
Post departure	-0.023	0.046	-0.000	-0.077*
	(0.472)	(0.127)	(0.675)	(0.094)
D_connected_departure	-0.079	-0.108**	0.003*	0.175*
	(0.375)	(0.031)	(0.059)	(0.066)
Following_all	-0.257***	-0.039	0.000	-0.058
	(0.000)	(0.380)	(0.639)	(0.293)
Size	0.015	-0.026	-0.000	0.008
	(0.805)	(0.464)	(0.672)	(0.842)
BM	0.951***	0.842***	-0.001	0.145
	(0.000)	(0.000)	(0.510)	(0.124)
Institutions_share	-0.002	0.001	0.000	0.000
	(0.431)	(0.757)	(0.537)	(0.944)
Stdret	0.230***	0.159***	0.010***	0.057
	(0.001)	(0.000)	(0.000)	(0.239)
Volume	0.160***	0.113***	0.000	-0.003
	(0.007)	(0.005)	(0.798)	(0.946)
Experience_firm	0.003	0.036**	-0.000	-0.008
	(0.903)	(0.011)	(0.489)	(0.648)
Experience	0.102	0.071	-0.000	-0.055
	(0.173)	(0.190)	(0.602)	(0.293)
Star	0.419***	0.142	0.001	0.048
	(0.007)	(0.247)	(0.729)	(0.724)
Horizon	0.004***	0.002***	-0.000	-0.000
	(0.000)	(0.000)	(0.318)	(0.428)
Brokersize	-0.191**	-0.004	0.003**	0.133
	(0.049)	(0.964)	(0.047)	(0.141)
Constant	-3.138***	-2.680***	0.007	2.338***
	(0.002)	(0.000)	(0.641)	(0.002)
# of observations	2,933	2,723	2,826	2,826
Adjusted R-squared	0.191	0.196	0.120	0.010
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 departing analyst's final forecast was issued. The pre- (post-) departure period includes the 180 days before (following) the event date. *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 before 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 analyst following the firm. *M_Informativeness_forecasts* is the mean three-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast of each analyst made within the 180 days 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 days. All other variables are defined in the appendix. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 5 Effect of a connected analyst's departure on the forecast properties of unconnected analysts

	Forecasts of unconnected analysts only			
	(1)	(2)	(3)	(4)
	Consensus_FE	Dispersion	M_Informative-ness_forecasts	M_Informativen-ness_forecasts2
D_connected_departure × Post departure	0.201**	0.253***	-0.007***	-0.393***
	(0.011)	(0.005)	(0.002)	(0.003)
Post departure	-0.028	0.029	-0.001	-0.096**
	(0.389)	(0.351)	(0.548)	(0.046)
D_connected_departure	-0.096	-0.127**	0.004**	0.213*
	(0.243)	(0.016)	(0.029)	(0.053)
Following_all	-0.249***	-0.019	0.000	-0.072
	(0.000)	(0.671)	(0.838)	(0.190)
Size	-0.004	-0.038	-0.000	0.022
	(0.952)	(0.282)	(0.993)	(0.588)
BM	0.965***	0.829***	-0.001	0.131
	(0.000)	(0.000)	(0.450)	(0.206)
Institutions_share	-0.001	0.000	0.000	0.001
	(0.711)	(0.780)	(0.305)	(0.590)
Stdret	0.225***	0.156***	0.010***	0.054
	(0.001)	(0.001)	(0.000)	(0.283)
Volume	0.172***	0.132***	0.001	0.027
	(0.005)	(0.001)	(0.451)	(0.513)
Experience_firm	-0.004	0.038***	-0.000	-0.007
	(0.867)	(0.005)	(0.451)	(0.699)
Experience	0.101	0.085*	-0.000	-0.061
	(0.139)	(0.088)	(0.784)	(0.268)
Star	0.242	0.196	0.001	0.044
	(0.104)	(0.123)	(0.703)	(0.755)
Horizon	0.004***	0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.638)	(0.801)
Brokersize	-0.112	-0.039	0.001	0.029
	(0.240)	(0.616)	(0.423)	(0.749)
Constant	-3.310***	-2.920***	0.001	1.967**
	(0.001)	(0.000)	(0.946)	(0.014)
# of observations	2,849	2,605	2,713	2,713
Adjusted R-squared	0.187	0.183	0.109	0.009
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 departing analyst's final forecast was issued. The pre- (post-) departure period includes the 180 days before (following) the event date. *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by all *unconnected* analysts. 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 before 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 *unconnected* analyst following the firm. *M_Informativeness_forecasts* is the mean three-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast of each unconnected analyst made within the 180 days before (after) the departure event. *M_Informativeness_forecasts2* is *M_Informativeness_forecasts* divided by the mean daily unsigned cumulative abnormal returns around the unconnected analyst forecasts of the corresponding 180 days. All other variables are defined in the appendix. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 6 The importance of the departing connected analysts

Panel A Forecasts of all analysts

Dependent variables:	Consensus FE		Dispersion		M_Informativeness _forecasts		M_Informativeness _forecasts2	
	(1) Only connected analyst	(2) Multiple connected analysts	(3) Only connected analyst	(4) Multiple connected analysts	(5) Only connected analyst	(6) Multiple connected analysts	(7) Only connected analyst	(8) Multiple connected analysts
D_connected_departure × Post departure	0.423***	0.110	0.369***	0.231**	-0.016***	-0.002	-0.726***	-0.164
	(0.002)	(0.340)	(0.001)	(0.035)	(0.001)	(0.283)	(0.008)	(0.191)
F-test:	3.22		0.82		6.78		3.72	
[P-value]	[0.0727]		[0.3648]		[0.0092]		[0.0537]	
Post departure	-0.029	-0.023	0.042	0.045	-0.000	-0.000	-0.076*	-0.078*
	(0.366)	(0.480)	(0.165)	(0.138)	(0.688)	(0.651)	(0.097)	(0.089)
D_connected_departure	-0.256	-0.010	-0.188**	-0.076	0.007*	0.002	0.320	0.115
	(0.123)	(0.925)	(0.044)	(0.190)	(0.099)	(0.278)	(0.163)	(0.213)
# of observations	2,671	2,817	2,477	2,633	2,574	2,730	2,574	2,730
Adjusted R-squared	0.189	0.193	0.199	0.196	0.117	0.123	0.014	0.009
Controls in Table 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Notes: Panel A presents the changes in the consensus forecast errors, dispersion, and the changes in the informativeness of analyst forecasts following the departure of a connected analyst relative to the departure of an unconnected analyst. Columns (1), (3), (5), and (7)) include departure events when the connected analyst is the only connected analyst following the firm. Columns (2), (4), (6), and (8) include departure when there are other connected analysts that stay and follow the firm. 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 departing analyst's final forecast was issued. The pre- (post-) departure period includes the 180 days before (following) the event date. *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by all analysts. 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 before 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 analyst following the firm. *M_Informativeness_forecasts* is the mean three-day unsigned cumulative abnormal returns around the analyst forecasts using the latest (earliest) forecast of each analyst made within the 180 days 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 days. All other variables are defined in the appendix. P-values represent significance from a two tailed F-test comparing the difference in the coefficients on the D_connected_departure×Post departure term. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 6 (Continued)

Panel B Forecasts of unconnected analysts only

Dependent variables:	Consensus FE		Dispersion		M_Informativeness _forecasts		M_Informativeness _forecasts2	
	(1) Only connected analyst	(2) Multiple connected analysts	(3) Only connected analyst	(4) Multiple connected analysts	(5) Only connected analyst	(6) Multiple connected analysts	(7) Only connected analyst	(8) Multiple connected analysts
D_connected_departure × Post departure	0.362**	0.115	0.377***	0.208*	-0.015***	-0.004	-0.698**	-0.265*
	(0.011)	(0.208)	(0.002)	(0.061)	(0.002)	(0.108)	(0.013)	(0.060)
F-test:	2.33		1.18		4.32		2.05	
[P-value]	[0.1270]		[0.2770]		[0.0376]		[0.1526]	
Post departure	-0.031	-0.029	0.028	0.028	-0.001	-0.001	-0.099**	-0.098**
	(0.335)	(0.375)	(0.378)	(0.376)	(0.541)	(0.539)	(0.041)	(0.042)
D_connected_departure	-0.250	-0.039	-0.204**	-0.099	0.007	0.003	0.328	0.159
	(0.134)	(0.670)	(0.029)	(0.112)	(0.100)	(0.129)	(0.161)	(0.171)
# of observations	2,601	2,735	2,378	2,518	2,477	2,617	2,477	2,617
Adjusted R-squared	0.183	0.189	0.194	0.183	0.107	0.111	0.012	0.007
Controls in Table 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Notes: Panel B presents the changes in the consensus forecast errors, dispersion, and the changes in the informativeness of all *unconnected* analyst forecasts following the departure of a connected analyst relative to the departure of an unconnected analyst. Columns (1), (3), (5), and (7)) include departure events when the connected analyst is the only connected analyst following the firm. Columns (2), (4), (6), and (8) include departures when there are other connected analysts that stay and follow the firm. 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 departing analyst's final forecast was issued. The pre- (post-) departure period includes the 180 days before (following) the event date. *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by all *unconnected* analysts. 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 before 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 analyst following the firm. *M_Informativeness_forecasts* is the mean three-day unsigned cumulative abnormal returns around the *unconnected* analyst forecasts using the latest (earliest) forecast of each unconnected 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 *unconnected* analyst forecasts of the corresponding 180 days. All other variables are defined in the appendix. P-values represent significance from a two tailed F-test comparing the difference in the coefficients on the D_connected_departure×Post departure term. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 7 Cross-sectional tests on the role of connected analysts when external capital is being raised

	Consensus forecast errors				Forecast dispersion			
	All analysts		Non-connected analysts only		All analysts		Non-connected analysts only	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-event period	Around equity issuance announcements	Non-event period	Around equity issuance announcements	Non-event period	Around equity issuance announcements	Non-event period	Around equity issuance announcements
Following_connected	-0.003	-0.095**	0.027	-0.080*	-0.009	-0.058**	-0.045	-0.083***
	(0.960)	(0.029)	(0.657)	(0.077)	(0.726)	(0.015)	(0.105)	(0.001)
F test [p-value]	3.23	[0.0725]	3.53	[0.0603]	3.33	[0.0681]	1.97	[0.1604]
Following_all	-0.233***	-0.137***	-0.250***	-0.150***	0.114***	0.148***	0.130***	0.165***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
# of observations	3,847	5,977	3,702	5,803	3,233	5,200	3,046	4,988
Adjusted R-squared	0.139	0.131	0.136	0.132	0.155	0.136	0.153	0.135
Controls in Table 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Notes: This table presents firm-level regressions of the effect of connected analysts' followings around an equity issuance vs. no such event. The sample includes all firms with equity issuances, including seasoned equity offerings and rights offerings, from 2005–2014, which leads to 2,655 equity issuance events. Observations in the *Around equity issuance announcements* sample includes periods from six months before the announcement date to the 24 months following it. *Non-event period* includes the 24 to the six months before the announcement date without overlapping with the *Around equity issuance announcement* period. The dependent variable *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by all analysts (or all unconnected analysts). *Dispersion* is the standard deviation of the latest earnings forecast issued by each analyst (unconnected analysts) following the firm. *Following_connected* is the main variable of interest, which captures the effect of a connected analyst in each subsample period and is defined as the log of one plus the number of connected analysts following the firm for the year. All other variables are defined in the appendix. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 8 Cross-sectional tests on the role of connected analysts for firms with economic transactions that are relationship based

	Consensus forecast errors				Forecast dispersion			
	All analysts		Non-connected analysts only		All analysts		Non-connected analysts only	
	(1) All other firms	(2) Non-arm's length firms	(3) All other firms	(4) Non-arm's length firms	(5) All other firms	(6) Non-arm's length firm	(7) All other firms	(8) Non-arm's length firms
Following_connected	-0.036	-0.139***	-0.036	-0.100***	-0.036	-0.111***	-0.061***	-0.124***
	(0.287)	(0.000)	(0.112)	(0.000)	(0.285)	(0.001)	(0.008)	(0.000)
F test [p-value]	5.07	[0.024]	4.71	[0.030]	2.64	[0.104]	4.16	[0.041]
Following_all	-0.202***	-0.245***	0.002	0.028	-0.214***	-0.261***	0.020	0.056**
	(0.000)	(0.000)	(0.933)	(0.271)	(0.000)	(0.000)	(0.434)	(0.037)
# of observations	6,089	6,770	5,064	5,560	5,909	6,555	4,798	5,305
Adjusted R-squared	0.148	0.119	0.173	0.159	0.145	0.120	0.169	0.157
Controls in Table 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm	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. Observations in the *Non-arm's length firm* sample include the following firms: (i) the total related-party transactions are more than 30% of total sales; (ii) purchases from (sales to) the top five suppliers (customers) exceed 30% of total purchases (sales); (iii) the total balance of related-party borrowing or lending is greater than 30% of total assets; (iv) the chairman/CEO is an ex-government official, military officer, or state banker or has served as a representative in the National People's Congress or the People's Political Consultative Conference; (v) the firm receives subsidies from the government (larger than 5% of total sales) in the given year; and (vi) the chairman and the party secretary of the city where the firm is located attended the same university. *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 analyst. *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. P-values represent significance from a two tailed F-test comparing the difference in the coefficients on the *Following_connected* variable. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 9 Cross-sectional tests on the role of connected analysts in times of political uncertainty

	Consensus forecast errors				Forecast dispersion			
	All analysts		Non-connected analysts only		All analysts		Non-connected analysts only	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low political uncertainty	High political uncertainty	Low political uncertainty	High political uncertainty	Low political uncertainty	High political uncertainty	Low political uncertainty	High political uncertainty
Following_connected	-0.061	-0.149***	-0.034	-0.128***	-0.005	-0.106***	-0.026	-0.125***
	(0.119)	(<0.001)	(0.417)	(0.004)	(0.835)	(<0.001)	(0.311)	(<0.001)
F test [p-value]	2.86	[0.091]	2.72	[0.099]	8.43	[0.003]	7.56	[0.006]
Following_all	-0.165***	-0.090***	-0.184***	-0.112***	0.027	0.065**	0.045	0.090**
	(<0.001)	(0.008)	(<0.001)	(0.004)	(0.300)	(0.021)	(0.107)	(0.004)
# of observations	4,536	3,934	3,757	4,355	3,028	3,450	2,835	3,195
Adjusted R-squared	0.155	0.143	0.147	0.150	0.170	0.184	0.165	0.176
Controls in Table 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Notes: This table presents firm-level regressions of the effect of connected analysts' followings in times of high political uncertainty and low political uncertainty. We use new appointment of a mayor or the party secretary in the city where the firm is located as an event that heightens political uncertainty of a firm. There are 815 new appointments that occurred during our sample period, from July 2005 to July 2014. Observations in the *High political uncertainty* sample include periods 18 months immediately following the appointment date. *Low political uncertainty* period is defined as the subsequent 18 months following the *High political uncertainty* period, which do not overlap with other *High political uncertainty* periods. The dependent variable *Consensus_FE* is defined as the average absolute forecast error of the latest earnings forecast issued by all analysts (or all unconnected analysts). *Dispersion* is the standard deviation of the latest earnings forecast issued by each analyst (unconnected analysts) following the firm. *Following_connected* is the main variable of interest, which captures the effect of a connected analyst in each subsample period and is defined as the log of one plus the number of connected analysts following the firm for the year. All other variables are defined in the appendix. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.

Table 10 Differential effect of connected analysts in times of positive vs. negative earnings surprises

Dependent variables:	Consensus_FE		Dispersion	
	(1) Positive	(2) Negative	(3) Positive	(4) Negative
Following_connected	-0.039	-0.116***	-0.039**	-0.086***
	(0.150)	(0.002)	(0.048)	(0.000)
F test [p-value]	3.31 [0.069]		3.45 [0.063]	
Following_all	-0.086***	-0.298***	-0.001	0.061**
	(0.003)	(0.000)	(0.970)	(0.017)
# of observations	6,445	6,409	5,401	5,218
Adjusted R-squared	0.136	0.154	0.189	0.170
Controls in Table 2	Yes	Yes	Yes	Yes
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' in times of positive earnings surprises vs. negative surprises using various firm-level forecast characteristics as the dependent variable. Positive earnings surprise sample are firm-years where there was an increase (a decrease) in reported earnings from the prior year. *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 analyst. All other variables are defined in the appendix. P-values represent significance from a two-tailed F-test comparing the difference in the coefficients on the *Following_connected* variable. We cluster standards errors at the firm level. P-values are reported in parentheses below the regression coefficients. ***, **, and * denote statistical significance at the two tailed 1%, 5%, and 10% levels.