The Effects of Analyst-Auditor Connections on Analysts' Performance

Abstract

Using Chinese data, we find that analysts' earnings forecasts are more accurate and less biased when analysts are socially connected with the company's signatory auditor. We also find that forecast performance improves following mandatory auditor rotations that result in new analyst-auditor connections and declines following mandatory rotations that terminate existing connections. We further find that our results become stronger when the information that auditors possess is likely to be more useful to analysts, that connected analysts have better career outcomes than unconnected analysts, and that investors and other analysts are more responsive to forecast revisions issued by connected analysts. Finally, we find that connected auditors provide higher quality audits to their connected clients and are more likely to retain those clients. Overall, our findings are consistent with connected analysts benefitting from private information obtained from their social connections with auditors by providing better earnings forecasts, and in turn, with auditors benefitting from information they receive from connected analysts by delivering higher quality audits that improve client retention.

Keywords: analyst forecasts; social connections; school ties; auditor-client confidentiality.

JEL codes: G14, G17, M40, M42.

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1. Introduction

Financial analysts play a critical role in securities markets by producing and disseminating earnings forecasts for the companies they follow. While earnings forecasts require analysts to form expectations about future earnings, we know little about how analysts gather information to make their forecasts (Bradshaw et al. 2017). Prior research finds that one channel through which analysts obtain private information is their social connections with company insiders, including top executives and board members (Cohen et al. 2008, 2010; Hwang and Kim 2009). We examine a previously unexplored channel through which analysts acquire private information -- their social connections with the external auditors of companies they follow. As independent gatekeepers, charged with monitoring management, auditors are in a unique position of public trust, and thus are a particularly interesting information channel to investigate.

A large body of literature finds that social connections facilitate information sharing.[1] These studies primarily focus on connections between corporate executives and financial intermediaries, including entrepreneurs, mutual fund managers, analysts, and auditors. However, we are unaware of prior research on social ties between analysts and outside independent auditors. Investigating whether analysts are able to gather private information from auditors is important for several reasons. Auditors, like analysts, play a role in producing company-specific value-relevant information for market participants. Unlike analysts, however, auditors have access to proprietary information about factors that influence future earnings. Auditors are likely to possess both "hard" information, such as information on operations, suppliers, and customers, as well as "soft" information, such as management integrity and financial reporting risks, which is especially difficult for analysts to assess (Liberti and Petersen 2019; Bradshaw et al. 2017). Auditors also have unique insights into their clients' accounting issues and how they are likely to impact the financial

[1] See Lerner and Malmendier (2013); Cohen et al. (2008); Hwang and Kim (2009); Pool et al. (2015); Gao and Huang (2016); Cohen et al. (2010); and Guan et al. (2016).

statements. Thus, auditors are likely to possess private information about their clients that analysts would find useful in forecasting earnings.

Analysts should benefit from acquiring private information about the companies they follow (Bradshaw et al. 2017) because it can increase the quality of their forecasts, thereby improving their career prospects (Hong et al. 2000). This provides analysts with an incentive to leverage their social connections with auditors in order to obtain private information. We define analysts and auditors as connected when they are alumni of the same college or university (Cohen et al. 2008; Guan et al. 2016). We expect that analysts and auditors are more likely to interact and communicate if they graduate from the same college or university. Opportunities for these interactions can arise through a variety of channels, including social media and networking events organized by alumni associations. The shared history experienced by university alums also encourages interactions and communication. We expect analysts' interactions with auditors, and the bonds created by their shared background, to facilitate the exchange of information.

A growing body of research suggests that it is not uncommon for auditors to share confidential information about their clients despite prohibitions against this behavior by auditing standards in both China and the United States. Dhaliwal et al. (2016) and Cai et al. (2016) find evidence that auditors share confidential information about target-company clients with acquirer-company clients; Hope et al. (2023) and Chen et al. (2022) suggest that auditors share information about their clients with mutual fund managers; and Kang et al. (2022) find that clients avoid sharing auditors with their product market rivals due to concerns about informational leakage. Further, U.S. auditors are frequently sanctioned for using confidential client information (e.g., Gaetano 2018; Heller 2017; Cohen 2017; SEC Press release 2014-166). A recent high-profile example is former KPMG senior partner Scott London, who was convicted of providing confidential information about his clients to a friend who used the information to engage in insider trading (Pfeifer 2014). In contrast to insider trading, the absence of a paper trail makes it difficult for enforcement agencies to identify cases in which connected analysts gather client information from auditors. Moreover, breaches of client confidentiality may be more likely in China, where cultural norms are different and public enforcement is relatively weak.

Auditors can communicate information to analysts in a variety of ways. At one end of the spectrum, auditors may be bribed into providing confidential client information in exchange for remuneration or favors such as client referrals. Or, as in the case of KPMG partner Scott London, the auditor may simply wish to help a friend. Analysts who are able to glean private information from auditors will have an informational advantage over other analysts, which should, on average, improve the accuracy of their earnings forecasts. In addition, unlike disclosures provided by management, which tend to be biased towards concealing bad news (Kothari et al. 2009), the information obtained from auditors is less likely to be optimistically biased. Thus, we hypothesize that analysts are likely to provide more accurate and less upwardly biased earnings forecasts when they are connected with the auditors of the companies they follow.

We use China as the setting for our study because China has a long history of publicly disclosing the identities and university affiliations of analysts and signatory auditors (i.e., the independent outside auditors who sign the audit opinion). There is also a rich literature that examines analyst forecasts and the behavior of signatory auditors in China (Lennox and Wu 2022). Analysts' earnings forecasts are particularly important in China because its stock market is heavily dominated by retail investors (CSRC 2008; Gu et al. 2019). For example, at the end of 2019, retail investors accounted for more than 80 per cent of share turnover on the two Chinese stock exchanges located in Shanghai and Shenzhen (Lockett 2021; Ding et al. 2014). Retail investors rely more heavily on analysts' earnings forecasts to guide their trading decisions because they are less sophisticated than institutional investors. Consequently, we expect analysts in China to have strong incentives to report accurate earnings forecasts.

Our sample consists of all 2,399 non-financial companies in the Chinese A-share market with earnings forecasts from 2005 through 2019. Social connections between analysts and auditors are relatively common among the companies in our sample, with 33% having a signatory auditor who is socially connected to at least one of its client's analysts. Further, 34.6% of the analysts in our sample are socially connected with a signatory auditor of a followed company, and 22.4% of the signatory auditors are socially connected with an analyst who follows a company they audit. This suggests that analyst-auditor connections potentially impact a significant proportion of companies and professionals.

Following prior literature, we use relative analyst forecast accuracy and bias to measure analyst performance (Clement 1999; Clement and Tse 2003; Jacob et al. 1999; Kini et al. 2009; Luo and Nagarajan 2015; Sonny 2009).[2] An important feature of these measures is that they evaluate each analyst's performance relative to all other analysts following the same company during the same year, allowing us to control for all time-varying company characteristics that may affect individual analysts' forecast performance, including management characteristics, operating characteristics, and reporting complexity.[3] The use of relative performance measures, along with the inclusion of analyst fixed effects, results in a research design that compares an analyst's performance across connected and unconnected companies by controlling for all time-invariant differences between connected and unconnected analysts, such as differences in their skills and intelligence.

As hypothesized, we find that analysts, on average, issue more accurate and less optimistically biased earnings forecasts when they are connected to the company's auditor. This effect is incremental to, and is of similar magnitude, as the effect of analysts' connections with company management (Cohen et al. 2008). We address the endogeneity of analyst-auditor connections by examining mandatory auditor rotations, which results in a plausibly-exogenous change the auditor-analyst connections. We find that forecast performance improves following mandatory rotations that result in new connections, while forecast performance deteriorates following mandatory rotations that terminate connections.

We also conduct cross-sectional analyses which find that connected analysts issue higher quality forecasts in three settings where auditors are likely to possess more private information about the client: 1) after auditors are likely to have begun their year-end fieldwork; 2) when companies face greater uncertainty in earnings realization; and 3) when companies operate in more opaque information environments, making their earnings more difficult to forecast. We further find that both investors and other analysts react more

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[2] We focus on analyst earnings forecasts rather than stock recommendations because over 90% of stock recommendations in China are either "buy" or "strong buy." As observed in Huyghebaert and Xu (2016), this lack of variation makes it difficult to draw meaningful conclusions from analysts' stock recommendations.

[3] Using these analyst performance measures is equivalent to including a separate fixed effect for each company-year observation in our regression models (Gormley and Matsa 2014).

strongly to forecasts issued by connected analysts, and that connected analysts are more likely to move to larger brokerage houses and become all-star analysts.

We further find that connected auditors also benefit from their social connections with analysts. Specifically, socially connected auditors deliver higher quality audits to connected clients, as evidenced by fewer financial misstatements and lower levels of discretionary accruals. We conjecture that this occurs because communications between analysts and auditors not only result in transferring information from the auditor to the analyst, but also from the analyst to the auditor. An analyst's information set includes extensive knowledge of their followed companies and a deep understanding of general economic trends. Thus, analysts can provide auditors with client-specific information as well as macro-level information about the clients' industry and the economy as a whole. The information provided by analysts should give connected auditors deeper knowledge and a better understanding of their clients, thereby enabling them to deliver higher quality audits to their connected clients. We also find that connected auditors are less likely to be dismissed by their connected clients. This is consistent with connected auditors being more attractive to audit committees, due to their ability to deliver higher quality audits and their enhanced understanding of their clients' business, thereby increasing their ability to retain connected clients.

While we find that analysts issue more accurate and less optimistically biased earnings forecasts when they are connected to the company's auditor, we emphasize that our regression coefficients capture marginal effects. As such they should not be interpreted as suggesting that all or even a majority of connected analysts acquire confidential client information from connected auditors. Rather, our results are consistent with analysts finding it easier, at the margin, to obtain private information about their covered companies when they are socially connected to the company's signatory auditor, as compared to settings in which they are not connected.[4]

[4] In China, audit reports are signed by two auditors: a junior auditor, who is in charge of the audit fieldwork, and a more senior auditor, who reviews the audit work papers. Our results suggest that both auditors provide useful information to connected analysts.

We contribute to the financial analysts' literature by identifying a new channel through which analysts obtain information about the companies they follow. In their literature review, Bradshaw et al. (2017) observe that the source of analysts' private information is under-researched. There is also little research on the interactions between financial analysts and auditors. To our knowledge, we are the first to find that analysts exploit their connections with external auditors in order to obtain private information about the companies they follow. Finding that connected analysts issue less optimistically biased forecasts suggests they are better able to unravel managerial optimism. These findings also contribute to the literature that finds evidence of auditors sharing information about clients with outsiders (Dhaliwal et al. 2016; Cai et al. 2016; Kang et al. 2022; Hope et al. 2023; and Chen et al. 2022).

We also contribute to a literature that examines the usefulness of public disclosures about auditors and analysts. Using data from China, Gul et al. (2013) show that individual auditors affect audit quality. An implication of their study is that public disclosure of auditors' identities and attributes can be useful in helping financial statement users evaluate audit quality. In 2017, the PCAOB also began requiring the public disclosure of auditors' identities, but does not disseminate any biographical information about the auditors. In contrast, the CICPA in China provides detailed biographical information about each signatory auditor, including their age and education. Our study suggests that this biographical information may help market participants identify social connections with auditors that potentially affect analysts' performance.

2. Motivation and hypotheses development

Earnings forecasts from sell-side equity analysts are among the most widely-used forms of accounting information in financial markets and "information is the currency in which analysts trade" (Bradshaw et al. 2017). Analysts engage in a variety of search activities to gather private information, including exploiting social connections. Prior studies find that analysts who are socially connected with company insiders gain private access to company-specific information, providing them with an advantage in predicting the company's future performance (Cohen et al. 2008, 2010). While the majority of the literature focuses on analysts' connections with company insiders, recent studies also examine the effects of analysts' social ties with quasi-insiders. For example, Chen and Martin (2011) find that bank-affiliated analysts within financial conglomerates receive private information about borrowers from their commercial banking divisions, resulting in improved analyst forecast accuracy.

Like lenders, signatory auditors also possess private information about their clients. Auditors acquire this information primarily through their audit fieldwork, which includes extensive interactions with management. While auditors are required to keep client information confidential, a growing literature suggests that auditors sometimes breach client confidentiality by sharing information with outsiders. For example, Dhaliwal et al. (2016) and Cai et al. (2016) find that auditors provide information to acquirer-clients about target-company clients, and the shared information benefits the acquirer-clients at the expense of the target-clients by reducing the size of the acquisition premium. Studies also suggest that the Chinese auditors of mutual funds share client-specific information with mutual fund managers (Hope et al. 2023; Chen et al. 2022). Finally, the evidence in Kang et al. (2022) suggests that audit clients are concerned about potential breaches of client confidentiality from auditors leaking information to their product market rivals.

The SEC sometimes prosecutes CPAs for violating client confidentiality (e.g., Press release 2014-166). A recent high-profile case involves a senior audit partner at KPMG, Scott London, who shared confidential client information with a friend who used the information to engage in insider trading. A notable feature of the Scott London case is the relatively small financial reward (including a Rolex watch and $50,000 cash) that he received in exchange for the inside information, which paled in comparison to his multi-million-dollar annual salary as a senior partner. News reports suggest that London's motivation was not financially motivated, and instead resulted from a desire to help a friend.[5] Additional examples of Big 4 auditors being prosecuted for sharing confidential client information for the purpose of financial gain can be found at the SEC website and are reported in the popular press (e.g., Gaetano 2018; Heller 2017; Cohen 2017; Accounting Today 2008).

[5] See a related news report on the case in the Los Angeles Times at http://beta.latimes.com/business/la-fi-kpmg-london-20140425-story.html.

Earnings forecasts require analysts to exert effort in collecting private information (Bradshaw et al. 2017), and analysts benefit from such information acquisition by issuing more accurate forecasts. For example, analysts who issue superior forecasts have better career outcomes, including an increased ability to advance their career by moving to more prestigious brokerage houses (Hong and Kubik 2003; Hong et al. 2000). We conjecture that auditors possess private information that is likely to help analysts make accurate earnings forecasts, and thus analysts have incentives to obtain this information by leveraging their connections with auditors.

The collection of private information from an auditor does not necessarily rely on the auditor intentionally sharing client information, or on the analyst intentionally putting the auditor in a compromising position. Nonverbal communication between individuals is also common and private information is commonly communicated unintentionally (Buck and VanLear 2002; Darwin, 1872; Ekman 1973; Eibl-Eibesfeldt 1975). Importantly, nonverbal communication can occur unintentionally even in settings where individuals attempt to keep the information confidential (Frank and Solbu 2020). These characteristics of human communication are important in our setting because they suggest that analysts may learn private information about their clients from their interactions with auditors even if auditors try their best to uphold the ethical duty of client confidentiality. Such information should allow analysts to derive valuable insights and build a more accurate information mosaic about companies (Li et al. 2020).

We expect that auditors and analysts are more likely to interact with one another if they attended the same university.[6] For example, university alumni use social media groups to track down old friends, to organize networking events, and to find new job opportunities. Analysts and auditors may also make contact through mutual business acquaintances, such as lawyers, or through industry-related organizations or events. Regardless of the circumstances, once contact is made, it is likely to provide a natural conduit for exchanging information about companies.

[6] In untabulated tests we find that there is no significant difference in analyst performance when connected analysts work in the same city as the connected auditor's office, suggesting geographical proximity may not be a reliable measure of the social interactions between analysts and the auditor.

If analysts are able to extract private information about their followed companies through their connections with auditors, such information should improve the accuracy of their forecasts. In addition, the information obtained from auditors is expected to be less optimistically biased relative to information provided by company management, who tend to disclose good news and withhold bad news (Kothari et al. 2009).[7] These arguments lead to the following hypothesis:

Hypothesis*: Analysts issue more accurate and less upwardly biased earnings forecasts for the companies they follow when they are socially connected with the company's signatory auditor.*

While sharing client information violates auditors' ethical responsibilities, the risk of detection is likely to be low when auditors share information with an analyst. Press reports and SEC disclosures suggest that auditors who breach client confidentiality are usually detected when a friend or relative engages in insider trading. These trading gains leave a clear paper trail that allows enforcement agencies to link the auditor with the person who traded on the information. In our setting, however, the information gathered from the auditor is used to improve analysts' forecasts, which does not leave a paper trail for the enforcement agencies. Therefore, it would be difficult for enforcement agencies to detect analysts' communications with auditors, and even more difficult to ascertain the nature of those communications. This low likelihood of detection reduces the costs imposed on auditors who share information with analysts either intentionally or inadvertently.

3. Research design

We test our hypothesis by estimating the following OLS model:

$$REL\_ACC_{i,j,t}\ (REL\_BIAS_{i,j,t}) = \beta_0 + \beta_1\, CONNECT_{i,j,t} + Control\ variables + Analyst\ fixed\ effects + \varepsilon \qquad (1)$$

where i, j, t denote analyst i for company j in year t, respectively.[8] The unit of analysis is the analyst-

[7] The bias in management disclosures is also evident in management forecast behaviour, where managers are more likely to issue forecasts when they expect earnings growth (Core 2001; Miller 2002) and cease issuing forecasts in anticipation of expected bad news (Chen et al. 2011; Houston et al. 2010).
[8] For expositional convenience we drop the subscripts when discussing our variables in the text.

company-year. The sample includes all annual earnings forecasts for year *t* that are issued between the earnings announcement dates of year *t-1* and year *t*.

We measure analyst forecast accuracy and bias following prior literature (e.g., Clement 1999; Clement and Tse 2003; Jacob et al. 1999; Kini et al. 2009; Luo and Nagarajan 2015; Sonny 2009). We define relative forecast accuracy (*REL_ACC*) as the *negative* of analyst *i'*s absolute forecast error for company *j*'s earnings in year *t*, minus the mean absolute forecast error across all analysts who supplied forecasts for the same company-year, scaled by the stock price at the beginning of year *t*.[9] A positive value of *REL_ACC* indicates above-mean forecast accuracy, while a negative value indicates below-mean forecast accuracy. We define the relative forecast bias (*REL_BIAS*) as analyst *i*'s forecast bias (forecasted earnings – actual earnings) for company *j*'s earnings in year *t* minus the mean forecast bias across all analysts who supplied earnings forecasts for the same company-year, scaled by the stock price at the beginning of year *t*. A positive value of *REL_BIAS* indicates an optimistic forecast bias (above the mean), while a negative value indicates a pessimistic forecast bias (below the mean).[10] Our measures of analyst forecast accuracy and bias control for company-year effects by examining how a given analyst performs relative to other analysts who follow the same company in the same year.

Our independent variable of interest in equation (1) is *CONNECT*, which captures whether analyst *i* has a school tie with one or both of company *j*'s signatory auditors in year *t.* Following prior studies (Cohen et al. 2010; Guan et al. 2016), we define individuals as having school ties when they receive a degree from the same university. Specifically, *CONNECT* equals one if analyst *i* shares a university affiliation with one of company *j's* signing auditors, and zero otherwise. Our hypothesis predicts a positive (negative)

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[9] In a robustness test (untabulated), we re-define *REL_ACC* and *REL_BIAS* using forecast accuracy (bias) relative to the median (rather than mean) company-year forecast. Our results remain statistically equivalent. We also re-calculate the mean forecast performance using: (1) all forecasts in a given company-year before sample attrition; (2) all forecasts by unconnected analysts before sample attrition; and (3) all forecasts by unconnected analysts in the final sample after sample attrition. Our results remain statistically equivalent.

[10] In untabulated analyses, we find that our results are unchanged if we normalize our measures of forecast performance by either the mean forecast error (bias) or use mean assets per share for company *j* at the beginning of year *t* as a scalar, or if we use the percentile rank measures of analyst forecast performance as in Hong et al. (2000) and Hong and Kubik (2003).

coefficient on *CONNECT* using *REL_ACC* (*REL_BIAS*) as the dependent variable, which would indicate that connected analysts produce more accurate and less biased forecasts for company *j* in year *t*, as compared with unconnected analysts who follow the same company in the same year.

We include analyst fixed effects to control for time-invariant differences between analysts, such as differences in skills and intelligence, that affect analyst forecast performance. This fixed effects framework measures how an analyst's forecast performance changes as the analyst moves from a company with a connected auditor to a company with an unconnected auditor.[11] Because companies are followed by multiple analysts who issue multiple forecasts in the same year, we double cluster the standard errors at the analyst and year levels (e.g., Kini et al. 2009; Petersen 2009).[12]

The control variables in Equation (1) include forecast and analyst characteristics that potentially affect analyst forecast performance. These include the analyst's connections with company management, as captured by the analyst's school ties with top management (*M_CONNECT*) (Cohen et al. 2010), and the existence of an investment banking relationship between the analyst's affiliated brokerage firm and the company (*AFFILIATE*) (Lin and McNichols 1998). We expect analysts with social connections or investment banking relationships to acquire more and higher quality information. Therefore, we predict positive (negative) coefficients on *M_CONNECT* and *AFFILIATE* in equation (1). Other control variables include analysts' industry and company-specific forecasting experience (ln*GEXP* and ln*FEXP*, respectively), the complexity of their client portfolios as captured by the number of companies followed (ln*NFIRM*), their forecasting effort (ln*FREQ*), the clustering of analyst forecasts (ln*DAYS_ELAP*), forecast horizon (ln*HORIZON*), and the resources available to analysts through their brokerage houses as measured

[11] For example, if analyst A issues earnings forecasts for companies X and Y, where A is connected with the auditor of company X but not connected with the auditor of company Y, our fixed effects framework tests whether A's forecast performance is better for company X than company Y. At the same time, our performance measures control for cross-sectional differences between companies X and Y, by examining how analyst A's performance for companies X and Y compares to that of the other analysts who also issue forecasts for companies X and Y.

[12] We also re-run our main specifications by clustering the standard errors at the analyst-year level given that our dependent and independent variables are de-meaned in a given firm-year. Our results (untabulated) remain quantitatively unchanged.

by the number of analysts employed (ln*BSIZE*) (O'Brien 1990; Mikhail et al. 1997; Clement 1999; Jacob et al. 1999). We also control for the information sharing that prior research has documented between clients of the same audit firm (Dhaliwal et al. 2016; Cai et al. 2016; Kang et al. 2022; Hope et al. 2023; and Chen et al. 2022). *COMMON* equals one if an analyst's affiliated brokerage firm and the client share a common audit firm, and zero otherwise.

To be consistent with the specification of the dependent variables, which capture an analyst's performance relative to other analysts following the same company in the same year, we adjust the control variables by subtracting their mean values using all forecasts supplied by analysts in the same company-year (e.g., Clement 1999; Jacob et al. 1999; Kini et al. 2009), with a "*DM*" prefix indicating the de-meaned variables. Because these variables control for company-year effects, we do not include company characteristics or company fixed effects in Equation (1).[13] Appendix 1 presents a detailed definition of each variable. We winsorize all continuous variables at the top 99% and bottom 1%.

4. Empirical analyses

4.1 Data and sample

Table 1 reports the sample selection process. We begin with all 726,728 analyst forecasts from 2005 through 2019 in the China Stock Market & Accounting Research (CSMAR) database, a widely used database on analyst research for Chinese companies. We begin in 2005 because it is a year in which China's financial analyst profession started to grow significantly, increasing the number of analyst earnings forecasts.[14]

We use the CSMAR database to identify individual analysts and we manually identify the names of signatory auditors from annual audit reports. Chinese auditing standards require audit reports to disclose the names of the two signatory auditors (Ministry of Finance 1995, hereafter MOF 1995). The more junior

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[13] Instead of adjusting the dependent and independent variables by their company-year means, we could use the raw values of both the dependent and independent variables and include company-year fixed effects. Gormley and Matsa (2014) show that these approaches are equivalent. We use the company-year mean-adjusted variables to be consistent with the analyst literature and to facilitate the interpretation of our univariate tests. In un-tabulated analysis we find that using company-year fixed effects yields virtually identical results to those reported in Table 3.
[14] The financial analyst profession is relatively new in China. The *Securities Analysts Association of China* (SAAC) was established in 2000 and relatively few analyst forecasts are available prior to 2005.

signatory auditor is generally in charge of the fieldwork and is not usually an equity partner. The more senior signatory auditor is primarily responsible for reviewing the engagement team's work upon its completion and is typically an equity partner (Auditing Standards 1121, MOF 2001; Lennox et al. 2020).

We identify the universities of the auditors and analysts from personnel profiles provided by the Chinese Institute of Certified Public Accountants (CICPA) and the Chinese Broker and Financial Analysts System (CBFAS) based on its 2017 version, respectively.[15] Following prior studies (e.g., Clement 1999; Jocob et al. 1999; Kini et al. 2009; Sonney 2009 etc.), we keep forecast observations that (1) have non-missing university information for either the analyst or the signatory auditors, (2) are for companies followed by at least three analysts, and (3) are the last current-year annual earnings forecasts issued by each analyst prior to the earnings announcement.[16] We exclude observations with missing values for the control variables. Our final sample contains 107,806 analyst-company-year observations, from 1,982 unique analysts, with 4,377 unique signatory auditors, and 2,399 unique companies. Due to missing data on the university of the company's management, the inclusion of *M_CONNECT* reduces the number of observations to 90,784 analyst-company-years.

Table 1 indicates that analyst-auditor connections are relatively common in our sample. Specifically, 34.6% of the analysts (685/1,297) are socially connected to an auditor of a followed company and 22.4% of the signatory auditors (979/4,377) are socially connected to an analyst of a company they audit. Further, 33% of companies have signatory auditors who are socially connected to at least one analyst (793/2,399).[17]

Panel A of Table 2 reports the ten most common universities in our sample. The university with the most connected analysts is Shanghai University of Finance and Economics (SUFE), accounting for 10.72% of the 2,472 connected analyst-company-years. This is followed by 6.88% and 6.23% for Renmin

[15] The CICPA only keeps current and active membership information. Thus, audit partners who are no longer active CICPA members at the time we collected the data in 2017 are not included in the CICPA database. CBFAS is now named Chinese Research Data Service Platform (CNRDS), and collects analyst information from the *Securities Analysts Association of China* (SAAC).
[16] We also find that our results are robustness to using all forecasts in the regression.
[17] The proportion of forecasts from connected analysts is smaller than the proportion of connected analysts (2.3% = 2,472/107,806) because connected analysts also cover many unconnected companies.

University and Beijing University, respectively. The university with the most unconnected analysts is Beijing University, accounting for 8.09% of the 105,334 unconnected analyst-company-years. This is followed by 6.91% (Tsinghua University) and 4.81% (Fudan University).[18]

Panel B reports the ten universities with the largest number of financial analysts and signatory auditors. Two salient features emerge from this table. First, signatory auditors are more likely than financial analysts to graduate from specialized colleges and universities in finance and economics. This distribution likely reflects the more specialized training in accounting and auditing for signatory auditors, in contrast with the more general analytical skills that financial analysts require. Second, the educational institutions that Chinese analysts and auditors attended are concentrated in the 10 universities listed in panel B, with these schools graduating 38.92% and 32.55% of the analysts and auditors in our sample.

4.2. Descriptive statistics

Table 3 reports summary statistics for the variables in equation (1). We find that 5.8% of forecasts are issued by analysts who attended the same university as company management (*M_CONNECT*). We also find that 3.1% of forecasts are issued by affiliated analysts (*AFFILIATE*), which is comparable to U.S. data reported in Malmendier and Shanthikumar (2014). Analysts have a mean (median) of 5.5 (5.0) years of experience (*GEXP*) and a mean (median) of 2.3 (1.0) years following the company (*FEXP*); they follow an average (median) of 41.2 (30) companies (*NFIRM*), and issue an average of 2.6 (2) annual forecasts in a year (*FREQ*). Compared with U.S. studies (e.g., Clement 2009), the Chinese analysts in our sample follow more companies and are less experienced. The forecast horizon (*HORIZON*) is long, with a mean (median) of 173.0 (153) days before the annual earnings announcement. The affiliated brokerage firms employ a mean (median) of 33.3 (33) analysts (*BSIZE*).

Table 3 also reports summary statistics for the forecasts issued by connected analysts (*CONNECT* = 1) and unconnected analysts (*CONNECT* = 0). This analysis shows that forecasts by connected analysts comprise 2.29% (2,472/(2,472 + 105,334)) of observations. Consistent with our hypothesis, we find that

[18] The universities in our sample represent approximately 32.3% of the 1,258 universities in China.

forecasts by connected analysts are more accurate (*REL_ACC*) and less optimistically biased (*REL_BIAS*) than forecasts by unconnected analysts. Table 2 also shows that, relative to unconnected analysts, connected analysts are more likely to be connected with client management (*M_CONNECT*), are more experienced (*GEXP* and *FEXP*), and issue forecasts that are more frequent (*FREQ*) and less clustered in time (*DAYS_ELAP*). Connected analysts are also more likely to work for larger brokerage houses (*BSIZE*).

4.3. Hypothesis tests: Analyst-auditor connections and analyst forecast performance.

Table 4 reports the results for our hypothesis tests. Consistent with our prediction, the coefficients on *CONNECT* in the *REL_ACC* (*REL_BIAS*) regressions are positive (negative) and significant at $p < 0.01$ in all four specifications. This indicates that analysts, on average, issue more accurate and less optimistically biased forecasts when they are connected with the company's signatory auditor. Further, columns (2) and (4) of Table 4 show that the inclusion of *M_CONNECT*, which controls for analyst-management connections, does not materially change the magnitudes or significance of the coefficients for analyst-auditor connections (*CONNECT)*.[19]

In terms of economic significance, the coefficient of 0.144 on *CONNECT* in the *REL_ACC* regression (column (2) of Table 3) indicates that, holding the control variables constant, forecasts are 0.144% more accurate when they are issued by connected rather than unconnected analysts (in the same company-year).[20] Thus, the presence of a connection improves the analyst's ranking, in terms of forecast accuracy, by 13 percentile points. Similarly, the coefficient of -0.116 on *CONNECT* in the *REL_BIAS* regression (column (4) of Table 4) indicates that forecasts issued by connected analysts are 0.116% less optimistically biased. This means that that the presence of a connection improves the analyst's ranking, in terms of forecast bias, by 10 percentile points. [21] These magnitudes are comparable to the 16 and 13 percentile point estimates for

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[19] Bradley et al. (2020) find that analysts' professional connections with a company's CEO and board of directors improves analyst forecast performance. In untabulated analysis we repeat our Table 3 analysis after controlling for these connections and find that our results are unchanged.
[20] The coefficients in the regressions are multiplied by 100.
[21] We calculate the economic significance of these effects by fitting the model using the estimated coefficients in column (2) of Table 4 with their observed variable values and comparing the forecast accuracy percentile ranking when analysts are unconnected (by setting *CONNECT* = 0) with the ranking when analysts are connected (by setting

the effect of analyst connections with management, based on the *M_CONNECT* coefficients in columns (2) and (4). Thus, the improvements in forecast accuracy and bias are statistically and economically significant.

The coefficients on the other control variables in Table 4 are generally consistent with prior studies (Mikhail et al. 1997; Lin and McNichols 1998; Clement 1999; Jacob et al. 1999; Kini et al. 2009; Sonney 2009). For example, the coefficients on analysts' firm-specific experience (*DM_*ln*FEXP*) and the size of analysts' portfolios (*DM_*ln*NFIRM*) are negative and significant in the *REL_BIAS* regression, consistent with analysts being less optimistically biased when they are more experienced and follow more companies. The positive and significant coefficients on *DM_*ln*FREQ* in the *REL_ACC* regression indicate that analysts are more accurate when they issue more forecasts. In addition, the coefficient on *DM_*ln*DAYS_ELAP* is positive (negative) in the *REL_ACC* (*REL_BIAS*) regression, consistent with Cooper, Day, and Lewis (2001), who find that forecasts are more accurate (less biased) when they are issued long (shortly) after the preceding forecasts. Forecast horizon (*DM_*ln*HORIZON)* has a significantly negative (positive) effect on *REL_ACC* (*REL_BIAS*), consistent with a longer forecast horizon reducing (increasing) forecast accuracy (forecast optimism).

4.4. Addressing endogeneity

Examining relative analyst performance together with controlling for analyst fixed effects alleviates concerns arising from the endogeneity of analyst-auditor connections. Nevertheless, omitted variables may explain such connections, leading to a positive association between the connections and analyst forecast performance even in the absence of analyst-auditor communications. We address this concern by exploiting the mandate that requires Chinese audit firms to rotate signatory auditors every five years, which acts as an exogenous shock that results in new or dropped connections.[22] We employ a difference-in-differences specification to test the effects of the new or dropped connections on analyst forecast performance.

CONNECT = 1). We similarly compare the changes in forecast bias percentile ranking using the estimated coefficients from column (4) in Table 4.

[22] Under Articles 3 and 5 issued by the CSRC and the Ministry of Finance (Oct 8, 2003), the signatory auditors must rotate every five years, or the end of the second year after the initial public offering (IPO) of a newly listed company.

We identify 15,602 company-years during our sample period that experience a change in the signatory auditor due to mandatory rotation. Companies are not required to disclose why they change auditors, so we follow prior studies by classifying auditor changes as mandatory when they occur after five years of tenure (Lennox et al. 2014). This reduces our sample to companies that experience a change in one of the signatory auditors during the sample period (n = 4,021). We also require these companies to have analyst forecasts issued one year before and one year after the auditor change. Our final sample comprises 5,796 company-analyst-year-forecast observations, representing 542 company-years that mandatorily rotate of one or more of the signatory auditors.

We create *POST,* which equals one if a forecast is issued after the auditor change and decompose *CONNECT* into two indicator variables. *NEW_CONNECT* is coded one if an analyst switches from being connected with neither auditor, to being connected with at least one of the two auditors after mandatory rotation. *DROP_CONNECT* is coded one if the switch is from a connected to an unconnected analyst. The control group comprises observations in which firms experience mandatory auditor rotation without any change in analysts' connectedness.

We then regress *REL_ACC* and *REL_BIAS* on *NEW_CONNECT*, *DROP_CONNECT*, *POST*, and the interaction terms *NEW_CONNECT* × *POST* and *DROP_CONNECT* × *POST*. We expect an improvement in analysts' performance when mandatory rotation results in a new connection (*NEW_CONNECT* × *POST* = 1), and a decline in performance when mandatory rotation results in a dropped connection (*DROP_CONNECT* × *POST* = 1). The results are presented in columns (2) and (4) of Table 5. As predicted, we find a positive (negative) coefficient on *NEW_CONNECT* × *POST* in the *REL_ACC* (*REL_BIAS*) regressions, significant at $p < 0.01$ ($p < 0.01$). Also as predicted, we find a negative (positive) coefficient on *DROP_CONNECT* × *POST* in the *REL_ACC* (*REL_BIAS*) regressions, significant at $p < 0.01$ ($p < 0.05$). Thus, consistent with our hypothesis, we find that forecast performance improves when mandatory rotation results in new analyst-auditor connections, and deteriorates when such connections are terminated.

4.5. Tests when auditors' private information is likely to be more useful to analysts

We identify three settings in which auditors are more likely to possess client-specific private information, and consequently, the benefits to analysts from communicating with auditors should be relatively greater. First, auditors typically commence their fieldwork toward the end of the client's fiscal year, which includes meeting with client management, identifying the major financial reporting issues, gathering initial evidence related to client companies' business activities, and evaluating the accounting choices related to how such transactions are reported in financial statements. Thus, finding stronger results for connected analysts who issue forecasts after the commencement of the auditor's fieldwork would be consistent with the auditor communicating information that helps analysts make more accurate and less biased forecasts. Empirically, we partition our sample on *YREND*, which indicates whether a forecast is issued near the end of the fiscal year. Because all Chinese companies have a December 31 year-end and the audit fieldwork often starts a few weeks before the year end, we code *YREND* as one if a forecast is issued between November 1st and the earnings announcement date, and zero otherwise.

Results presented in panel A of Table 6 show that the coefficient on *CONNECT* is positive (negative) in the *REL_ACC* (*REL_BIAS*) regression, and is larger (smaller) in the *YREND* = 1 partition than in the *YREND* = 0 partition, consistent with the effects of analyst-auditor connections being greater when forecasts are issued near the fiscal year end. Further, the Chow tests at the bottom of Panel A show that the magnitude of the *CONNECT* coefficient is significantly larger (smaller) in the *REL_ACC* (*REL_BIAS*) regression for the subsample where *YREND* = 1 as compared with the subsample where *YREND* = 0. Thus, our results are stronger for connected analysts who issue forecasts *after* the commencement of the auditor's fieldwork, which is consistent with auditors communicating information when they have access to such information.

We also expect that the auditor's information is more likely to improve analysts' forecasts when operating performance is less certain. We measure operational uncertainty using earnings volatility, which equals the standard deviation of earnings over the past three years (*E_VOL*). A firm is categorized as having high volatility (*E_VOL* = H) if its standard deviation of earnings over the past three years exceeds the sample median, and is categorized as having low volatility (*E_VOL* = L) otherwise. We then partition the sample and re-run our baseline regressions on each subgroup. Panel B of Table 6 presents the results. The coefficients on *CONNECT* are positive (negative) and significant in the *REL_ACC* (*REL_BIAS*) regression when earnings volatility is high (*E_VOL* = H), but insignificant when earnings volatility is low (*E_VOL* = L). Further, the Chow tests reported at the bottom of Panel B indicate that the coefficient on *CONNECT* is significantly larger (smaller) in the *REL_ACC* (*REL_BIAS*) regression in the subsample where *E_VOL* = H as compared with the subsample where *E_VOL* = L at $p < 0.01$ ($p < 0.001$). Thus, the effects of analyst-auditor connections are stronger when there is greater uncertainty in companies' operations, making the value of private information from auditors greater.[23]

We also partition our sample based on analyst forecast dispersion (*DISP*), a measure of the difficulty in forecasting earnings. If connected analysts use information from connected auditors, that information should be more valuable when earnings are more difficult to predict. The dispersion in analysts' forecasts (*DISP*) is calculated as the standard deviation of analyst earnings forecasts for the year. A firm is categorized as having high forecast dispersion (*DISP* = H) if its standard deviation of *DISP* exceeds the sample median, and is categorized as having low forecast dispersion (*DISP* = L) otherwise. We then re-run our baseline regressions on each subgroup. The results in panel C of Table 6 show that the coefficients on *CONNECT* are positive (negative) in the *REL_ACC* (*REL_BIAS*) regressions in both *DISP* = H and *DISP* = L subgroups and that the magnitudes of the coefficients are larger (smaller) in the *DISP* = H partition than in the *DISP* = L partition. These findings are consistent with connected auditors being particularly beneficial to connected analysts when earnings are difficult to forecast. [24]

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[23] In untabulated tests we also use two additional measures of complexity: *COMPX*, a factor score based on Feng et al. (2009) which captures the number of segments, the existence of foreign transactions, and restructurings during the year; and *OPQ*, a composite measure that aggregates the percentile ranks of the level of absolute discretionary accruals, earnings volatility, the number of segments, and the ratio of intangible assets over total assets. We then partition our sample based on the median value of *COMPX* and *OPQ*, and re-run our baseline regressions. Consistent with the results in Table 5, Panel B we find that analyst-auditor connections have a larger effect on forecast performance when companies operate in more complex and opaque environments.

[24] In untabulated tests we also partition our sample based on the direction of the news contained in the forecasts. We define a forecast as a good (bad) news forecast if the forecasted earning is higher (lower) than the preceding consensus forecast, and 0 otherwise. We find that while the coefficients on *CONNECT* remain mostly significant for both good news and bad news forecasts, the magnitudes of the coefficients are significantly larger in the subsample for good news forecasts.

5. Additional analyses

5.1 Analyst career advancement

Hong et al. (2009) find that better forecast performance improves an analyst's opportunities to advance their career. Thus, if connected auditors have an information advantage over unconnected auditors, then connected analysts should have relatively better career outcomes. Following Rees, Sharp, and Twedt (2015), we use two variables to measure analyst career advancement: *PROMOTE* and *STAR*. *PROMOTE* is an indicator variable equal to one if an analyst moves to a larger brokerage firm, and zero otherwise. *STAR* is an indicator variable equal to one if an analyst is an all-star analyst in the next year based on *Chinese New Fortune*'s annual voting by institutional investors, and zero otherwise. The results, presented in Table 7, find that the coefficients on *CONNECT* are positive and significant at conventional levels, consistent with analysts benefiting from their connections with auditors through improved career outcomes.

5.2 Auditor benefits

Communications between analysts and auditors could result in transferring information not only from auditors to analysts, but also from analysts to auditors. Analysts have extensive knowledge of their followed companies as well as a deep understanding of general economic trends. Therefore, analysts may provide connected auditors with useful client-specific information as well as macro-level information about the client's industry and the economy as a whole. If analysts share their private information with auditors, it could improve the auditor's ability to provide a high-quality audit. In addition, the delivery of higher quality audits, along with a more nuanced and deeper understanding of the client's business could make connected auditors more attractive to audit committees, thereby increasing the connected auditor's ability to retain its connected clients. Thus, in this section we test whether connected auditors provide higher quality audits to their connected clients and whether they are more likely to be retained by those clients.

The results of this analysis are presented in Table 8. As expected, Columns (1) and (2) find that the clients of connected auditors have fewer financial misstatements and report lower levels of discretionary accruals when compared to the clients of unconnected auditors. Column (3) further finds that the clients of connected auditors are less likely to switch to an unconnected auditor. These findings are consistent with connected auditors receiving information from connected analysts, which allows them to provide higher quality audits and increases their ability to retain connected clients.[25]

5.3. Analyst connections with senior and junior signatory auditors

As previously discussed, audit reports in China are signed by two auditors. The more senior auditor is typically an equity partner who monitors the overall work done by the audit engagement team. The less senior auditor is in charge of the fieldwork and supervises other members of the audit team but is typically not an equity partner. *Ex-ante*, it is unclear which of the two auditors is better informed about the client. The less senior auditor may have more private information given their daily involvement in the audit fieldwork. On the other hand, the more senior auditor may be better informed as a results of their regular communications with the client's senior management. Therefore, it is an empirical question whether analyst performance benefits more from connections with senior or junior auditors.

We test this by decomposing *CONNECT* into three variables: *CONNECT_JUNIOR* equals one if an analyst is connected with the junior auditor only, and zero otherwise; *CONNECT_SENIOR* equals one if an analyst is connected with the senior auditor only, and zero otherwise; *CONNECT_BOTH* equals one if an analyst is connected with both signatory auditors, and zero otherwise. We then re-run equation (1) after replacing *CONNECT* with the three indicator variables. In untabulated results, we find significant positive (negative) coefficients on *CONNECT_JUNIOR* and *CONNECT_SENIOR* in the *REL_ACC* (*REL_BIAS*) regressions. These findings are consistent with analysts gathering information from both auditors. The F-test on the differences between the coefficients on *CONNECT_JUNIOR* and *CONNECT_SENIOR* is statistically insignificant. We also find a positive (negative) and significant coefficient at $p < 0.05$ ($p < 0.10$) on *CONNECT_BOTH* in the *REL_ACC* (*REL_BIAS*) regressions, which suggests that being connected to both signatory auditors provides an incremental information advantage.

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[25] The auditor's primary area of expertise lies in their ability to understand the appropriate implementation of accruals-based GAAP accounting standards. This suggests that the information provided to analysts by connected auditors is more likely to improve the analysts' ability to forecast earnings rather than their ability to forecast cash flows. Consistent with this expectation, in untabulated tests we find that connected analysts are no better than unconnected analysts at forecasting cash flows for their connected clients.

5.4 Alternative measure of analyst-auditor connections

We also use a measure of analyst-auditor social connections that captures both school and geographic connections. Individuals who live and work near one another, and/or who were born in the same region, are more likely to interact and share cultural similarities (including their dialect) that facilitate communication.[26] We remeasure social connections as *CONNECT_SG,* which equals one if an analyst either attended the same university or works or was born in the same province as either of the signatory auditors (zero otherwise). In untabulated analysis we find that the coefficients on *CONNECT_SG* continue to be significant in the predicted directions in both the *REL_ACC* and *REL_BIAS* regressions ($p < 0.01$).[27]

5.5. Investor and analyst responsiveness to forecasts issued by connected analysts

Our primary findings indicate that the earnings forecasts of connected analysts are more accurate and less optimistically biased than those of unconnected analysts. As a result, earnings forecasts are likely to be more credible when they are issued by connected analysts. We test this prediction by examining the stock market response to analysts' forecast revisions (Abarbanell et al. 1995; Clement and Tse 2003). If connected analysts issue higher quality earnings forecasts, we expect a larger investor response when forecast revisions are issued by connected analysts. We test this by estimating the following model:

$$
\begin{aligned}
CAR_{i,j,t} \quad = \quad & \beta_0 + \beta_1\, REVISION_{ijt} + \beta_2\, REVISION_{ijt} \times CONNECT_{ijt} \\
& + \beta_3\, CONNECT_{jt} + Control\ variables + Industry\ fixed\ effects \\
& + Year\ fixed\ effects + Analyst\ fixed\ effects + \varepsilon \qquad (2)
\end{aligned}
$$

The dependent variable (*CAR*) is the three-day cumulative abnormal stock return surrounding the analyst's earnings forecast revision, where the daily abnormal return for each company is computed by subtracting the daily market return from the company's daily raw return. *REVISION* is the analyst's earnings forecast for the year minus the analyst's most recent prior forecast, scaled by the stock price at the beginning of the

[26] Although the official language in China is standard Mandarin there is significant heterogeneity in the native regional languages (referred to as dialects) across China, with most dialects being region specific.

[27] When we disaggregate *CONNECT_SG* into *CONNECT*, *CONNECT_LOCATION*, and the interaction term between *CONNECT* and *CONNECT_LOCATION*, we find the coefficients on *CONNECT* and *CONNECT_LOCATION* continue to be significant in the expected directions. However, the coefficients on the interaction term are insignificant, suggesting no incremental effects beyond those captured by analysts' social and geographical connections.

month prior to the revision. Our variable of interest is the interaction term, *REVISION* × *CONNECT*, which captures whether investors respond more strongly to the forecast revisions of connected analysts. We also include the control variables found in prior literature to be associated with the informativeness of analyst forecasts (Chen et al. 2016), as well as their interaction terms with *REVISION*.

Columns (1) and (2) of Table 9 report the results of this analysis. As expected, we find significant positive coefficients on *REVISION* × *CONNECT* ($p < 0.05$), indicating a stronger market reaction to forecast revisions issued by connected analysts. These results suggest that investors perceive earnings forecasts to be of higher quality when they are issued by connected rather than unconnected analysts.

We also expect that analysts respond more strongly to forecasts issued by connected analysts because those forecasts tend to be more accurate and less biased. To test this using the approach in Williams (1996). Specifically, we estimate the following model:

$$\begin{aligned} \ln N\_REV_{ijt}\ (RAF_{ijt}) = \quad & \beta_0 + \beta_1 FD_{ijt} + \beta_2 FD_{ijt} \times CONNECT_{ijt} \\ & + \beta_3 CONNECT_{jt} + \textit{Control variables} + \textit{Industry fixed effects} \\ & + \textit{Year fixed effects} + \textit{Analyst fixed effects} + \varepsilon \qquad (3) \end{aligned}$$

We use two dependent variables to capture analysts' responsiveness to forecasts: the *relative frequency* and the *average magnitude* of analysts' forecast revisions. The relative frequency is captured by ln*N_REV*, which equals the natural log of one plus the number of analysts who revise their forecasts in the 30 days following a forecast revision by analyst *i* for company *j* in the preceding month in year *t*, scaled by the total number of analysts following company *j* in year *t*. The magnitude of the forecast revision is captured by *RAF*, which equals the consensus forecast for company *j* in the month following the issuance of a revised forecast by analyst *i*, minus the consensus forecast for company *j* in the preceding month, deflated by the stock price of company *j* at the beginning of the month prior to the revision.

The independent variable, *FD*, measures the forecast deviation, which captures the difference between an analyst's forecast revision and the consensus forecast at the beginning of the month. The interaction term, *FD* × *CONNECT*, captures the incremental effect of the forecast deviation for the revisions issued by connected analysts. If analysts respond more strongly to forecasts issued by connected analysts, we expect the coefficient on *FD* × *CONNECT* to be significantly positive.

The results in columns (3) and (4) of Table 9 indicate that analysts revise their forecasts in response to the forecast revisions of other analysts. In particular, we find a positive and significant coefficient on *FD* in the forecast frequency (*lnN_REV*) regression, and a positive yet statically insignificant coefficient in the forecast revision (*RAF*) regression. Importantly, the coefficients on the interaction term *FD* × *CONNECT* are positive in both the frequency (ln*N_REV*) and magnitude (*RAF*), with the latter being statistically significant at the $p < 0.01$ level. This suggests that analysts and investors react more strongly to earnings forecasts issued by connected analysts. We note, however, that analysts and investors are not necessarily aware that connected analysts obtain inside information from connected auditors. Rather, it investors and analysts may simply learn over time that connected analysts issue more accurate forecasts.

6. Conclusion

We hypothesize that social connections between analysts and auditors are associated with superior analysts' forecast performance. Consistent with our hypothesis, we find that analysts issue more accurate and less biased forecasts when they are socially connected with the signatory auditor of a followed company. We also find that the effect of social ties on analyst forecast performance is stronger when auditors are better informed about the client and when the information is likely to be more useful to the analyst, as evidenced by forecasts issued near the end of the client's fiscal year, forecasts issued for companies operating in more opaque information environments, and for companies with greater earnings uncertainty. We further find that auditors benefit from their social connections with analysts, as evidenced by connected auditors delivering higher quality audits and having a greater ability to retain connected clients. Overall, our study contributes to the literature by finding evidence of a novel channel through which analysts obtain information that improves their forecasting performance and through which auditors improve the quality of their audits.

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APPENDIX 1: Variable Definitions

Variable name		Definition
Dependent Variables		
$REL\_ACC_{i,j,t}$	=	The relative forecast accuracy of analyst *i* for company *j* in year *t*, calculated as the negative of the difference between the absolute forecast error (forecasted earnings – actual earnings) of analyst *i* for company *j* in year *t* and the mean value of the absolute forecast error of all analysts who supplied forecasts for the same company-year, scaled by the stock price at the beginning of the fiscal year. The higher the value, the more accurate the forecast.
$REL\_BIAS_{i,j,t}$	=	The relative forecast bias of analyst *i* for company *j* in year *t*, calculated as the forecast bias (forecasted earnings – actual earnings) of analyst *i* for company *j* in year *t*, minus the mean value of forecast bias using all earnings forecasts issued for the same company during the fiscal year, scaled by the stock price at the beginning of the year. The higher the value, the more optimistic the earnings forecast.
$PROMOTION_{i,t+1}$		An indicator variable that equals 1 if analyst *i* moves from a below-median size brokerage house (in term of the total number of employed analysts) to an above-median size brokerage house in year t+1, and 0 otherwise.
$STAR_{i,t+1}$		An indicator variable that equals 1 if analyst *i* is voted as an all-star analyst by institutional investors in year *t+1*, 0 otherwise.
$MIS\_STATE_{j,t}$		An indicator variable that equals 1 if the current year net income is subsequently restated, and 0 otherwise.
$DA_{j,t}$		The performance-matched discretionary accruals for company *j* in year t as in Kothari et al (2005).
$SWITCH_{j,t}$		An indicator variable that equals 1 if a client company *j* switches to a new audit firm in year *t+1*, 0 otherwise.
$CAR_{i,j,t}$	=	The three-day cumulative stock return surrounding earnings forecast revision issued by analyst *i* for company *j* in year *t* adjusted by the market return.
$\ln N\_REV_{j,t}$	=	The natural log of one plus the number of analysts who revise their forecasts within 30 days following a forecast revision issued by analyst *i* for company *j* in the preceding month of year *t*, scaled by the total number of analysts following company *j* in year *t*.
$RAF_{j,t}$	=	Analyst consensus forecast revision for company *j* in the month following a forecast issued by analyst i for the company in year t. It is calculated as the analyst consensus forecast for company *j* in month *t* following the issuance of a revised forecast by analyst *i*, minus the consensus forecast for company *j* in the preceding month, deflated by the stock price of company *j* at the beginning of the month prior to the revision.
Explanatory Variables of Interest		
$CONNECT_{i.j,t}$	=	An indicator variable that equals 1 if analyst *i* graduated from the same educational institution as one of the signing auditors of company *j* in year *t*, and 0 otherwise.
$NEW\_CONNECT_{i.j,t}$	=	An indicator variable that equals 1 if analyst *i* for company *j* becomes connected with one of the new signing auditors in year *t* after mandatory rotation of the company's auditor, and 0 otherwise. The analyst is defined as connected with the auditor if they both graduated from the same educational institution.
$DROP\_CONNECT_{i.j,t}$	=	An indicator variable that equals 1 if analyst *i* for company *j* ceases to be connected with one of the new signing auditors in year *t* after the mandatory rotation of the company's auditor, and 0 otherwise. The analyst is defined as connected with the auditor if they both graduated from the same educational institution.
$YREND_{j,t}$	=	An indicator variable that equals 1 if a forecast for company *j* in year *t* is issued between

November 1 and the earnings announcement date, and 0 otherwise.

$LG\_DIFF_{j,t}$	=	An indicator variable that equals 1 if the difference between beginning of year *t* consensus analyst forecast and actual reported earnings for year *t*, scaled by beginning of year *t* stock price of company *j*, is greater than the sample median value, and 0 otherwise. Beginning-of-the-year consensus forecasts are those issued immediately after the earnings announcement for year *t-1* for company *j*.
$LG\_VOL_{j,t}$	=	An indicator variable that equals 1 if *VOLATILITY*, stock return volatility, which is calculated as the standard deviation of the standard deviation of daily stock returns over year *t-1* for firm j, is greater than the sample median, and 0 otherwise.
$REVISION_{i,j,t}$	=	The earnings forecast issued by analyst *i* for company *j* for year *t* minus the analyst's own prior forecast, scaled by the stock price at the beginning of the month prior to the revision **.**
$FD_{i,j,t}$	=	Analyst forecast deviation from the consensus forecasts for analyst *i* for company *j* in year *t*. It is the forecast issued by analyst *i* for company *j* in year *t*, minus the consensus forecast for the company in the preceding month, scaled by the stock price at the beginning of the month prior to the issuance of the forecast.
Control Variables		
$M\_CONNECT_{i,j,t}$	=	An indicator variable designating the existence of a school tie between an analyst and company management of a company followed by the analyst. It equals 1 if analyst *i* who follows company *j* graduated from the same college or university as one of the top four executives (chairman of the board, CEO, CFO, and the General Secretary of the board of directors) of company *j* in year *t*, and 0 otherwise.
$AFFILATE_{i,j,t}$	=	An indicator variable that equals 1 if analyst *i* issuing forecasts for company *j* in year *t* is affiliated with a brokerage company that has underwritten IPO/SEO transactions for the company in year *t-1*, and 0 otherwise.
$\ln GEXP_{i,t}$	=	The natural logarithm of 1 plus analyst forecasting experience in general, measured as the number of years analyst *i* has been in the CSMAR database prior to year *t*.
$\ln FEXP_{i,j,t}$	=	The natural logarithm of 1 plus the number of years that analyst *i* has issued forecasts for company *j* prior to year *t*.
$\ln NFIRM_{i,t}$	=	The natural logarithm of 1 plus the number of companies for which analyst *i* issued at least one earnings forecast in year *t*.
$\ln FREQ_{i,j,t}$	=	The natural logarithm of 1 plus the number of forecasts analyst *i* issued for company *j* in year *t*.
$\ln DAYS\_ELAP_{i,j,t}$	=	The natural logarithm of 1 plus the number of days between the date of analyst *i*'s forecast revision for company *j* in year *t* and the most recent preceding forecast of company *j*'s earnings by any analyst.
$\ln HORIZON_{i,j,t}$	=	The natural logarithm of 1 plus the number of days between the date of analyst *i*'s forecast revision for company *j* in year *t* and the company's annual earnings announcement date.
$\ln BSIZE_{i,t}$	=	The natural logarithm of 1 plus the total number of analysts employed by analyst *i*'s affiliated brokerage house in year *t*.
$COMMON_{i,j,t}$	=	An indicator variable that equals 1 if analyst *i*'s brokerage firm and company *j* share a common audit firm, 0 otherwise.
$\ln MV_{j,t}$	=	The natural logarithm of total market value of equity for company *j* at the beginning of the year *t*.
$MB_{j,t}$	=	Market to book ratio of common stockholders' equity for company *j* at the beginning of the year *t*.

TABLE 1: Sample Derivation

Description on analyst forecast sample	(Deleted)	Number of forecasts	Number of distinct analysts	Number of distinct signatory auditors	Number of distinct companies
Number of analyst forecasts in CSMAR from 2005-2019		726,728	6,129	7,501	3,464
Delete:					
(a) forecasts issued by the same analyst in the year (we keep only the last current-year annual earnings forecast issued prior to the earnings announcement for the company)	(429,609)	297,119	6,129	7,501	3,464
(b) missing school information for the analysts	(17,578)	279,541	6,051	6,879	3,400
(c) missing school information for the signatory auditors	(129,533)	150,008	2,184	4,976	3,019
(d) companies followed by fewer than three analysts	(3,109)	146,899	2,180	4,626	2,744
(e) missing value for control variables	(39,093)	107,806	1,982	4,377	2,399
Final sample used in Hypothesis tests without *M_CONNECT* variable	(39,093)	107,806	1,982	4,377	2,399
(1) when *CONNECT=0*		105,334	1,297	3,753	1,607
(2) when *CONNECT=1*		2,472	685	979	792
Final sample used in Hypothesis tests with non-missing management school information to code *M_CONNECT*	(17,022)	90,784	1,981	4,045	2,236

TABLE 2: The Ten Most Common Educational Institutions in Our Sample

Panel A: By the number of connected analyst-forecast-company years

Rank	Connected Analyst-company-years			Unconnected Analyst-company-years		
	University name	**#**	**%**	**University name**	**#**	**%**
1	Shanghai U. of Finance and Economics	265	10.72	Beijing University	8,521	8.09
2	Remin University	170	6.88	Tsinghua University	7,279	6.91
3	Beijing University	154	6.23	Fudan University	5,065	4.81
4	Fudan University	125	5.06	Shanghai Jiaotong University	4,500	4.27
5	Tsinghua University	98	3.96	Renmin University	3,237	3.07
6	Central University of Finance and Economics	73	2.95	Nankai University	3,114	2.96
7	Shanghai Jiaotong University	73	2.95	Shanghai U. of Finance and Economics	2,751	2.61
8	Wuhan University	68	2.75	Wuhan University	2,375	2.25
9	South West University of Finance and Economics	67	2.71	Zhejiang University	2,174	2.06
10	Zhongnan University of Economics and Law	61	2.47	Tongji University	1,884	1.79
11	Others	1318	53.32	Others	64,434	61.17
	All	2,472	100	All	105,334	100

Panel B: By the number of analysts and auditors

Rank	Analyst-company-years			Analyst-auditor-company-years		
	University name	**#**	**%**	**University name**	**#**	**%**
1	Beijing University	8,675	8.05	Zhongnan University of Economics and Law	9,673	6.51
2	Tsinghua University	7,377	6.84	Shanghai University of Finance and Economics	9,638	6.49
3	Fudan University	5,190	4.81	Remin University	5,038	3.39
4	Shanghai Jiaotong University	4,573	4.24	Zhejiang University of Finance and Economics	3,923	2.64
5	Renmin University	3,407	3.16	Sun Yat-Sen University	3,863	2.60
6	Nankai University	3,144	2.92	Xiamen University	3,673	2.47
7	Shanghai University of Finance and Economics	3,016	2.80	Central University of Finance and Economics	3,424	2.30
8	Wuhan University	2,443	2.27	Capital University of Economics and Business	3,264	2.20
9	Zhejiang University	2,226	2.06	Shanghai Lixin U. of Accounting and Finance	3,052	2.05
10	Tongji University	1,912	1.77	NorthWest U. of Finance and Economics	2,806	1.89
11	Others	65,843	61.08	Others	100,211	67.45
	All	107,806	100	All	148,565	100

TABLE 3: Descriptive Statistics for the Variables Used to Explain Analyst Forecast Performance

Variable names	N	Mean	Median	$CONNECT_{i,j,t}=1$ (N =2,472)		$CONNECT_{i,j,t}=0$ (N =105,334)		(*CONNECT*= 1) – (*CONNECT* = 0)	
				Mean	Median	Mean	Median	t-test	z-test
$REL\_ACC_{i,j,t}$	107,806	0.000	0.0009	0.0015	0.0011	-0.00003	0.0009	6.753***	4.091***
$REL\_BIAS_{i,j,t}$	107,806	0.000	-0.0005	-0.0011	-0.0007	0.00002	-0.0005	-4.698***	-1.923*
$M\_CONNECT_{i,j,t}$ +	90,784	0.058	0	0.082	0	0.057	0	5.157***	5.157***
$COMMON_{i,j,t}$	107,806	0.040	0	0.049	0	0.040	0	2.058**	2.058**
$AFFILIATE_{i,j,t}$	107,806	0.031	0	0.034	0	0.031	0	0.857	0.857
$GEXP_{i,j,t}$	107,806	5.513	5	5.658	5	5.509	5	2.274**	1.835*
$FEXP_{i,j,t}$	107,806	2.253	1	2.479	2	2.248	1	5.613***	4.581***
$NFIRM_{i,j,t}$	107,806	41.22	30	39.82	30	41.25	30	-1.745*	-1.583
$FREQ_{i,j,t}$	107,806	2.592	2	2.742	2	2.588	2	3.313***	4.932***
$DAYS\_ELAP_{i,j,t}$	107,806	11.310	3	10.75	2	11.32	3	-1.282	-1.758*
$HORIZON_{i,j,t}$	107,806	173.000	153	163.8	147	173.2	153	-4.521***	-4.081***
$BSIZE_{i,t}$	107,806	33.270	33	34.68	35	33.24	33	4.584***	4.966***

This table reports descriptive statistics for the variables used in the regression analyses for equation (1) and compares the *CONNECT* = 1 and *CONNECT* = 0 subsamples. The sample includes all forecasts issued for companies with at least three analysts following the company in a given year over the 2005-2019 sample period in the CSMAR financial analyst earnings forecast database. Variable definitions are in Appendix 1. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively, based on two-tailed t- (z-) statistics.

+ The number of observations is reduced to 90,784 for *M_CONNECT* due to missing data on school affiliation for the executives, including 2,472 observations for *CONNECT* = 1, and 88,336 observations for *CONNECT*=0.

TABLE 4: The Effects of Analyst-Auditor Connections on the Forecast Performance of Connected Analysts

Independent variables	Predicted Sign	$REL\_ACC_{i,j,t}$		$REL\_BIAS_{i,j,t}$	
		(1)	(2)	(3)	(4)
$\boldsymbol{CONNECT_{i,j,t}}$	**+/-**	**0.127***** **(7.955)**	**0.144***** **(8.750)**	**-0.101***** **(-5.108)**	**-0.116***** **(-5.617)**
$\boldsymbol{M\_CONNECT_{i,j,t}}$	**+/-**		**0.157***** **(13.994)**		**-0.125***** **(-8.296)**
$AFFILIATE_{i,j,t}$	+/-	0.026** (2.188)	0.025* (1.762)	-0.009 (-0.712)	-0.000 (-0.004)
$DM\_\ln GEXP_{i,j,t}$	+/-	0.024 (1.414)	0.031 (1.731)	0.002 (0.120)	0.010 (0.628)
$DM\_\ln FEXP_{i,j,t}$	+/-	0.020 (1.675)	0.015 (1.254)	-0.037*** (-3.854)	-0.034*** (-3.226)
$DM\_\ln NFIRM_{i,j,t}$	-/+	0.008 (0.479)	0.010 (0.528)	-0.053** (-2.799)	-0.058** (-2.894)
$DM\_\ln FREQ_{i,j,t}$	+/-	0.112*** (7.507)	0.121*** (7.475)	0.001 (0.079)	-0.005 (-0.324)
$DM\_\ln DAYS\_ELAP_{i\ i,j,t}$	+/-	0.009** (2.324)	0.010** (2.416)	-0.025*** (-5.693)	-0.024*** (-5.066)
$DM\_\ln HORIZON_{i,j,t}$	-/+	-0.483*** (-17.105)	-0.499*** (-17.363)	0.395*** (9.943)	0.409*** (10.052)
$DM\_\ln BSIZE_{i,t}$	+/-	0.010 (0.585)	0.008 (0.457)	0.011 (0.528)	0.012 (0.478)
$COMMON_{i,j,t}$	**+/-**	0.084*** (3.372)	0.078*** (2.985)	-0.088** (-2.888)	-0.087*** (-3.028)
adj. R^2		0.122	0.125	0.068	0.071
Analyst fixed effects		Yes	Yes	Yes	Yes
N		107,806	90,784	107,806	90,784

This table presents equation (1). The sample includes all forecasts issued for companies with at least three analysts following the company in a given year over the 2005-2019 sample period in the CSMAR financial analyst earnings forecast database. The predicted signs before and after "/" correspond to the *REL_ACC* and *REL_BIAS* regressions, respectively. Variable definitions are in Appendix 1. Variables with prefix "*DM*" are the de-meaned values of the corresponding variables. All coefficient estimates are presented as the percentage values of the estimated coefficients. Two-tailed *t*-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the analyst and year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5: Forecast Performance of Connected Analysts Following Mandatory Auditor Rotation

Independent Variables	Predicted Sign	$REL\_ACC_{i,j,t}$ (1)	$REL\_ACC_{i,j,t}$ (2)	$REL\_BIAS_{i,j,t}$ (3)	$REL\_BIAS_{i,j,t}$ (4)
$POST_{i,j,t}$	?/?	-0.002	-0.000	0.000	-0.011
		(-0.132)	(-0.034)	(0.008)	(-0.484)
$NEW\_CONNECT_{i,j,t}$	?/?	-0.193*	-0.238**	0.315***	0.309***
		(-1.911)	(-2.348)	(3.082)	(2.869)
$\boldsymbol{NEW\_CONNECT_{i,j,t} \times POST_{i,j,t}}$	**+/-**	**0.462*** **	**0.499*** **	**-0.596*** **	**-0.599*** **
		(2.730)	**(2.969)**	**(-3.561)**	**(-3.307)**
$DROP\_CONNECT_{i,j,t}$	?/?	0.093*	0.095*	0.035	0.024
		(1.735)	(1.783)	(0.382)	(0.264)
$\boldsymbol{DROP\_CONNECT \times POST_{i,j,t}}$	**-/+**	**-0.231*** **	**-0.258*** **	**0.182** **	**0.179** **
		(-2.642)	**(-2.601)**	**(2.034)**	**(2.201)**
$M\_CONNECT_{i,j,t}$	**+/-**		0.068**		-0.005
			(2.077)		(-0.124)
$AFFILIATE_{i,j,t}$	+/-	-0.003	0.013	0.036	0.042
		(-0.084)	(0.249)	(0.957)	(0.834)
$DM\_\ln GEXP_{i,j,t}$	+/-	0.044**	0.065***	-0.029	-0.041
		(2.232)	(2.693)	(-1.025)	(-1.284)
$DM\_\ln FEXP_{i,j,t}$	+/-	-0.018	-0.029**	-0.002	0.004
		(-1.192)	(-2.005)	(-0.091)	(0.167)
$DM\_\ln NFIRM_{i,j,t}$	-/+	-0.031***	-0.033***	0.030**	0.023
		(-2.874)	(-3.154)	(2.041)	(1.466)
$DM\_\ln FREQ_{i,j,t}$	+/-	0.098***	0.091***	-0.013	0.003
		(6.775)	(5.790)	(-0.842)	(0.232)
$DM\_\ln DAYS\_ELAP_{i,j,t}$	+/-	-0.011***	-0.013***	-0.012*	-0.006
		(-2.647)	(-3.039)	(-1.827)	(-0.834)
$DM\_\ln HORIZON_{i,j,t}$	-/+	-0.179***	-0.178***	0.121***	0.129***
		(-14.113)	(-12.059)	(7.623)	(8.049)
$DM\_\ln BSIZE_{i,t}$	+/-	0.007	0.008	0.040**	0.049***
		(0.607)	(0.644)	(2.266)	(2.658)
$COMMON_{i,j,t}$	**+/-**	-0.007	-0.005	-0.029	-0.014
		(-0.190)	(-0.116)	(-0.535)	(-0.252)
adj. R^2		0.093	0.095	0.029	0.033
Analyst fixed effects		Yes	Yes	Yes	Yes
N		5,796	4,840	5,796	4,840

This table presents a difference-in-differences OLS regression that examines analyst earnings forecast performance following mandatory rotation of the signatory auditor. The sample includes earnings forecasts issued by the same analysts in the year immediately before and after the rotation of the signatory auditor over the 2005-2019 sample period in the CSMAR financial analyst earnings forecast database. The predicted signs before and after "/" correspond to the *REL_ACC* and *REL_BIAS* regressions, respectively. Variable definitions are reported in Appendix 1. Variables with the prefix "*DM*" are the de-meaned values of the corresponding variables. All coefficient estimates are presented as the percentage values of the estimated coefficients. Two-tailed *t*-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the analyst and year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6: The Effects of Analyst-Auditor Connections When Communications are Likely to be More Useful

Panel A: For forecasts issued near the fiscal year-end

Independent Variables	Predicted Sign	$REL\_ACC_{i,j,t}$				$REL\_BIAS_{i,j,t}$			
		YREND = 1	*YREND = 0*	*YREND = 1*	*YREND = 0*	*YREND = 1*	*YREND = 0*	*YREND = 1*	*YREND = 0*
$\boldsymbol{CONNECT_{i,j,t}}$	**+/-**	**0.158*****	**0.107*****	**0.180*****	**0.121*****	**-0.131*****	**-0.081*****	**-0.153*****	**-0.092*****
		(3.897)	**(6.076)**	**(4.177)**	**(6.471)**	**(-3.011)**	**(-4.267)**	**(-3.583)**	**(-4.348)**
$M\_CONNECT_{i,j,t}$	+/-			0.191***	0.136***			-0.163***	-0.099***
				(7.014)	(8.525)			(-6.421)	(-6.134)
$AFFILIATE_{i,j,t}$	+/-	0.025	0.028*	0.042*	0.024	-0.012	-0.007	-0.011	0.003
		(1.308)	(1.934)	(1.857)	(1.304)	(-0.379)	(-0.417)	(-0.373)	(0.156)
$DM\_\ln GEXP_{i,j,t}$	+/-	0.042	0.049***	0.050	0.058***	-0.017	-0.024	-0.012	-0.016
		(1.402)	(3.378)	(1.633)	(3.863)	(-0.490)	(-1.501)	(-0.350)	(-0.897)
$DM\_\ln FEXP_{i,j,t}$	+/-	-0.001	0.022*	-0.009	0.017	-0.016	-0.042***	-0.006	-0.043***
		(-0.040)	(1.781)	(-0.443)	(1.359)	(-1.158)	(-3.417)	(-0.389)	(-3.221)
$DM\_\ln NFIRM_{i,j,t}$	-/+	-0.007	0.001	-0.006	0.001	-0.030	-0.048**	-0.035	-0.054***
		(-0.419)	(0.043)	(-0.324)	(0.033)	(-1.375)	(-2.828)	(-1.398)	(-3.132)
$DM\_\ln FREQ_{i,j,t}$	+/-	0.128***	0.076***	0.138***	0.084***	0.009	0.029*	0.000	0.024
		(6.554)	(4.735)	(6.621)	(4.398)	(0.388)	(1.816)	(0.001)	(1.396)
$DM\_\ln DAYS\_ELAP_{i,j,t}$	+/-	0.020***	0.005	0.022***	0.005	-0.036***	-0.019***	-0.034***	-0.019***
		(3.689)	(1.453)	(3.888)	(1.351)	(-5.688)	(-3.995)	(-4.861)	(-3.801)
$DM\_\ln HORIZON_{i,j,t}$	-/+	-0.500***	-0.626***	-0.515***	-0.655***	0.416***	0.558***	0.430***	0.580***
		(-18.966)	(-12.058)	(-19.440)	(-12.112)	(10.378)	(9.602)	(10.683)	(9.679)
$DM\_\ln BSIZE_{i,t}$	+/-	-0.020	0.017	-0.024	0.015	0.046	-0.002	0.045	0.000
		(-0.874)	(0.891)	(-0.897)	(0.740)	(1.541)	(-0.082)	(1.258)	(0.006)
$COMMON_{i,j,t}$	+/-	0.026	0.070***	0.028	0.064**	-0.046	-0.064**	-0.054	-0.064**
		(0.532)	(2.988)	(0.483)	(2.594)	(-0.843)	(-2.150)	(-0.814)	(-2.236)
adj. R^2		0.196	0.089	0.201	0.092	0.112	0.060	0.115	0.062
Analyst fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		36,110	71,695	30,440	60,344	36,110	71,695	30,440	60,344
Chow test *for* $\beta(YREND = 1) > \beta(YREND = 0)$		4.74** (p =0.030)		4.94** (p =0.026)		3.34* (p =0.068)		3.36* (p =0.067)	

This table presents equation (1) after partitioning the sample based on a dummy variable indicating whether an analyst forecast is issued from Nov 1 of the year till earnings announcement for the year (*YREND* =1), 0 otherwise (*YREND* =0). The sample includes all forecasts issued for companies with at least three analysts following the company in the given year over the 2005-2019 sample period in the CSMAR financial analyst forecast database. The predicted signs before and after "/" correspond to the *REL_ACC* and *REL_BIAS* regressions, respectively. Two-tailed *t*-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the analyst and year levels. Variable definitions are in Appendix 1. "*DM*" are the de-meaned values of the corresponding variables. All coefficient estimates are presented as the percentage values of the estimated coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel B: When earnings are more uncertain and opaquer

Independent Variables	Predicted Sign	$REL\_ACC_{i,j,t}$				$REL\_BIAS_{i,j,t}$			
		E_VOL =H	*E_VOL = L*	*E_VOL =H*	*E_VOL = L*	*E_VOL =H*	*E_VOL = L*	*E_VOL =H*	*E_VOL = L*
$\boldsymbol{CONNECT_{i,j,t}}$	**+/-**	**0.186*** (8.306)**	**0.069** (2.809)**	**0.209*** (9.051)**	**0.081*** (3.349)**	**-0.136*** (-4.777)**	**-0.065** (-2.157)**	**-0.157*** (-5.271)**	**-0.074** (-2.456)**
$M\_CONNECT_{i,j,t}$	+/-			0.210*** (8.830)	0.100*** (7.457)			-0.175*** (-5.206)	-0.072*** (-3.892)
$AFFILIATE_{i,j,t}$	+/-	0.038 (1.644)	0.012 (0.767)	0.045** (2.299)	0.005 (0.274)	-0.003 (-0.106)	-0.016 (-0.769)	0.014 (0.490)	-0.021 (-0.786)
$DM\_\ln GEXP_{i,j,t}$	+/-	0.040* (2.105)	0.003 (0.192)	0.046** (2.282)	0.009 (0.499)	0.003 (0.122)	0.001 (0.067)	0.013 (0.495)	0.011 (0.754)
$DM\_\ln FEXP_{i,j,t}$	+/-	0.029 (1.556)	0.009 (1.003)	0.025 (1.330)	0.004 (0.385)	-0.053*** (-3.548)	-0.022** (-2.594)	-0.055*** (-3.247)	-0.016 (-1.437)
$DM\_\ln NFIRM_{i,j,t}$	-/+	0.009 (0.427)	0.007 (0.464)	0.009 (0.387)	0.010 (0.584)	-0.071*** (-3.036)	-0.033* (-2.018)	-0.077*** (-3.015)	-0.037** (-2.187)
$DM\_\ln FREQ_{i,j,t}$	+/-	0.143*** (8.813)	0.078*** (4.823)	0.155*** (9.188)	0.083*** (4.191)	0.023 (1.019)	-0.019 (-1.356)	0.018 (0.747)	-0.027 (-1.670)
$DM\_\ln DAYS\_ELAP_{i,j,t}$	+/-	0.016* (2.101)	0.003 (1.183)	0.017* (2.117)	0.002 (0.785)	-0.035*** (-6.027)	-0.016*** (-3.676)	-0.032*** (-5.333)	-0.016*** (-3.394)
$DM\_\ln HORIZON_{i,j,t}$	-/+	-0.646*** (-16.881)	-0.318*** (-14.820)	-0.662*** (-16.443)	-0.330*** (-15.069)	0.483*** (8.515)	0.305*** (12.336)	0.502*** (8.748)	0.312*** (11.441)
$DM\_\ln BSIZE_{i,t}$	+/-	0.031 (1.221)	-0.015 (-0.815)	0.033 (1.227)	-0.021 (-1.025)	0.000 (0.001)	0.022 (1.037)	-0.001 (-0.036)	0.027 (1.063)
$COMMON_{i,j,t}$	+/-	0.104** (2.832)	0.066*** (3.846)	0.086** (2.259)	0.066*** (3.459)	-0.114** (-2.480)	-0.068*** (-3.648)	-0.105** (-2.390)	-0.073*** (-4.201)
adj. R^2		0.151	0.100	0.155	0.101	0.072	0.076	0.074	0.078
Analyst fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		53,708	53,924	45737	44,861	53,708	53,924	45,737	44,861
Chow test *for* $\beta(E\_VOL{=}H) > \beta(E\_VOL{=}L)$		14.36*** (p <0.001)		17.22*** (p <0.001)		3.09* (p =0.079)		3.77* (p =0.052)	

This table presents equation (1) after partitioning the sample based on a dummy variable indicating whether the forecast is issued for companies with the volatility of ROA over the past three years being greater than the annual sample median value (*E_VOL* = H), and 0 otherwise (*E_VOL* = L). The sample includes all forecasts issued for companies with at least three analysts following the company in the given year over the 2005-2019 sample period in the CSMAR financial analyst forecast database. The predicted signs before and after "/" correspond to the *REL_ACC* and *REL_BIAS* regressions, respectively. Two-tailed t-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the analyst and year levels. Variable definitions are in Appendix 1. "*DM*" are the de-meaned values of the corresponding variables. All coefficient estimates are presented as the percentage values of the estimated coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel C: When analyst forecast dispersion is high

Independent Variables	Predicted Sign	$REL\_ACC_{i,j,t}$				$REL\_BIAS_{i,j,t}$			
		DISP=H	*DISP =L*	*DISP=H*	*DISP =L*	*DISP=H*	*DISP =L*	*DISP=H*	*DISP =L*
$\boldsymbol{CONNECT_{i,j,t}}$	**+/-**	**0.172*****	**0.087*****	**0.199*****	**0.096*****	**-0.169*****	**-0.033**	**-0.193*****	**-0.041**
		(7.823)	**(3.942)**	**(8.806)**	**(4.315)**	**(-5.072)**	**(-1.249)**	**(-5.756)**	**(-1.454)**
$M\_CONNECT_{i,j,t}$	+/-			0.221***	0.104***			-0.169***	-0.085***
				(15.430)	(6.874)			(-5.639)	(-5.074)
$AFFILIATE_{i,j,t}$	+/-	0.041*	0.013	0.045	0.004	-0.025	0.005	-0.001	0.003
		(2.110)	(0.804)	(1.713)	(0.222)	(-1.116)	(0.284)	(-0.019)	(0.153)
$DM\_\ln GEXP_{i,j,t}$	+/-	0.052**	0.001	0.060**	0.006	0.008	0.005	0.017	0.009
		(2.397)	(0.056)	(2.532)	(0.311)	(0.280)	(0.344)	(0.549)	(0.643)
$DM\_\ln FEXP_{i,j,t}$	+/-	0.022	0.001	0.016	-0.006	-0.044**	-0.018**	-0.039**	-0.016**
		(1.585)	(0.106)	(1.231)	(-0.619)	(-2.972)	(-2.339)	(-2.516)	(-2.200)
$DM\_\ln NFIRM_{i,j,t}$	-/+	0.018	-0.000	0.021	-0.001	-0.061**	-0.047***	-0.065**	-0.052***
		(0.650)	(-0.010)	(0.735)	(-0.093)	(-2.244)	(-3.658)	(-2.217)	(-3.975)
$DM\_\ln FREQ_{i,j,t}$	+/-	0.142***	0.075***	0.156***	0.081***	-0.012	0.016	-0.021	0.010
		(5.428)	(6.588)	(5.518)	(5.808)	(-0.502)	(1.333)	(-0.724)	(0.771)
$DM\_\ln DAYS\_ELAP_{i,j,t}$	+/-	0.021***	-0.005	0.022***	-0.006	-0.035***	-0.011**	-0.035***	-0.009*
		(4.028)	(-1.375)	(4.467)	(-1.584)	(-5.673)	(-2.487)	(-5.103)	(-1.771)
$DM\_\ln HORIZON_{i,j,t}$	-/+	-0.626***	-0.342***	-0.658***	-0.349***	0.518***	0.273***	0.539***	0.285***
		(-13.756)	(-21.179)	(-13.649)	(-21.889)	(8.003)	(13.720)	(8.119)	(13.155)
$DM\_\ln BSIZE_{i,t}$	+/-	0.033	-0.008	0.029	-0.007	0.006	0.014	0.009	0.014
		(1.416)	(-0.517)	(1.193)	(-0.436)	(0.205)	(0.717)	(0.261)	(0.689)
$COMMON_{i,j,t}$	+/-	0.158***	0.007	0.135***	0.014	-0.134***	-0.039	-0.116***	-0.052*
		(4.456)	(0.374)	(3.715)	(0.657)	(-3.389)	(-1.538)	(-3.147)	(-2.050)
adj. R^2		0.149	0.104	0.157	0.105	0.089	0.053	0.093	0.055
Analyst fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		53,687	53,933	44,641	45,956	53,687	53,933	44,641	45,956
Chow test *for*		6.87***		10.01***		12.02***		14.75***	
$\beta(DISP=\text{H}) > \beta(DISP=\text{L})$		(p =0.009)		(p <0.002)		(p <0.001)		(p <0.001)	

This table presents equation (1) after partitioning the sample based on a dummy variable indicating whether forecast dispersions for a given company-year is higher than sample median (*DISP* = H), and 0 otherwise (*DISP* = L). The sample includes all forecasts issued for companies with at least three analysts over the 2005-2019 sample period in the CSMAR financial analyst forecast database. The predicted signs before and after "/" correspond to the *REL_ACC* and *REL_BIAS* regressions, respectively. Two-tailed t-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the analyst and year levels. Variable definitions are in Appendix 1. "*DM*" are the de-meaned values of the corresponding variables. All coefficient estimates are presented as the percentage values of the estimated coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 7: Analyst-Auditor Connections and Analyst Career Advancements

Independent variables	$PROMOTE_{j,t+1}$	$STAR_{j,t+1}$
	(1)	(2)
$CONNECT_{j,t}$	**0.137*** **	**0.079** **
	(3.732)	**(2.041)**
$lnBROKE\_SIZE_{j,t}$	0.027***	0.046***
	(9.153)	(11.950)
$NO\_FIRMS_{j,t}$	0.001	-0.020***
	(0.271)	(-4.500)
$NO\_IND_{j,t}$	-0.017	0.117***
	(-0.448)	(2.681)
$GEXP_{j,t}$	0.101	0.744***
	(1.203)	(5.050)
$NO\_FORECAST_{j,t}$	-0.000	0.011***
	(-0.117)	(6.051)
$AVG\_REL\_ACCURACY_{j,t}$	-0.001	-0.004**
	(-0.446)	(-2.176)
$AVG\_REL\_BOLD_{j,t}$	0.001	0.001
	(0.353)	(0.393)
Pseudo R^2	0.042	0.157
Industry and year fixed effects	Yes	Yes
N	9,519	9,519

This table presents logit regression results on the effects of analyst-auditor connections on analysts' career advancement. The dependent variables are *PROMOTION*, which equals 1 if an analyst moves from a below-median size brokerage house (in term of the total number of employed analysts) to an above-median size brokerage house, and 0 otherwise, and *STAR* which equals 1 if an analyst is voted as an all-star analyst by institutional investors in year t+1, 0 otherwise. Definitions for all other variables are in Appendix 1. Two-tailed *z*-test statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the analyst and year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8: The Effect of Analyst-Auditor Connections on Audit Quality and Client Retention

Independent variables	$MIS\_STATE_{j,t}$	$DA_{j,t}$	$SWITCH_{j,t+1}$
	(1)	(2)	(3)
$CONNECT_{j,t}$	**-0.162***	**-0.003****	**-0.238*****
	(-1.769)	**(-2.044)**	**(-2.688)**
$lnTA_{j,t}$	0.004	0.001	0.001
	(0.094)	(1.424)	(0.017)
$LEV_{j,t}$	1.176***	-0.009	-0.025
	(2.789)	(-1.643)	(-0.075)
$ROA_{j,t}$	-4.123***	0.015	-2.285***
	(-4.853)	(1.370)	(-3.430)
$LOSS_{j,t}$	0.547***	0.006***	0.259**
	(5.566)	(3.421)	(2.331)
$MB_{j,t}$	0.000	0.002***	0.014
	(0.013)	(8.478)	(1.137)
$INVR_{j,t}$	-0.820**	0.042***	0.250
	(-2.252)	(7.957)	(0.890)
$RECR_{j,t}$	0.884**	0.004	0.854**
	(2.123)	(0.633)	(2.527)
$QUICK_{j,t}$	-0.074***	-0.000	0.020
	(-3.440)	(-0.287)	(1.461)
$ATURN_{j,t}$	-0.005	0.005***	-0.018
	(-0.050)	(3.336)	(-0.242)
$SALE\_GROWTH_{j,t}$	0.181***	0.021***	0.102
	(3.083)	(15.487)	(1.589)
$OWNER_{j,t}$	-0.487**	0.007**	0.374**
	(-2.065)	(2.370)	(2.258)
$PRIVATE_{j,t}$	0.356***	0.004***	-0.329***
	(3.775)	(3.509)	(-4.973)
$FOREIGN_{j,t}$	-0.588**	0.000	-0.004
	(-2.472)	(0.201)	(-0.042)
$MAO_{j,t}$	1.699***	0.006*	0.904***
	(11.753)	(1.806)	(5.641)
$BIG10_{j,t}$	-0.104	-0.002*	-0.289***
	(-1.380)	(-1.901)	(-5.033)
$lnTEUNRE_{j,t}$	-0.196***	-0.002***	0.101**
	(-3.346)	(-2.650)	(2.292)
Pseudo R^2	0.070	0.114	0.050
Industry and year fixed effects	Yes	Yes	Yes
N	19,769	16,456	16,785

This table presents the results of analyzing analyst-auditor connections on client retention. *MISSTATE* equals 1 if the current year net income is subsequently restated, and 0 otherwise. The *DA* variable is performance-matched discretionary accruals following Kothari et al (2005). The *SWITCH* variable equals 1 if a client company switches to a new audit firm in the following year, 0 otherwise. The *CONNECT* variable is defined at the client company-year level and is coded 1 if company *j* is followed by at least one connected analyst in year *t*, 0 otherwise. Likewise. Definitions for all other variables are in Appendix 1. Two-tailed *z*-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the company and year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 9: The Responses of Investors and Analysts to the Earnings Forecasts of Connected Analysts

Independent variables	$CAR_{i,j,t}$		$\ln N\_REV_{i,t}$	$RAF_{i,t}$
	(1)	(2)	(3)	(4)
$REVISION_{i,j,t}$	-0.255	-0.318		
	(-0.656)	(-0.711)		
$CONNECT_{i,j,t}$	0.009***	0.009***	0.001	0.000
	(7.006)	(6.937)	(0.628)	(0.679)
$\boldsymbol{REVISION_{i,j,t} \times CONNECT_{i,j,t}}$	**0.129****	**0.129****		
	(2.034)	**(2.019)**		
$M\_CONNECT_{i,j,t}$		0.000	-0.002	0.000
		(1.499)	(-1.117)	(1.368)
$REVISION_{i,j,t} \times M\_CONNECT_{i,j,t}$		0.033		
		(0.383)		
$FD_{i,j,t}$			1.842**	0.470
			(2.005)	(0.539)
$\boldsymbol{FD_{i,j,t} \times CONNECT_{i,j,t}}$			**0.106**	**0.497*****
			(1.115)	**(3.105)**
$FD_{i,j,t} \times M\_CONNECT_{i,j,t}$			0.135	0.057
			(0.897)	(0.682)
$AFFILIATE_{i,j,t}$	-0.000	-0.000	0.002	-0.000
	(-1.142)	(-1.363)	(0.958)	(-0.341)
$\ln GEXP_{i,j,t}$	-0.000**	-0.000**	0.001	0.000
	(-2.160)	(-2.232)	(0.591)	(0.072)
$\ln FEXP_{i,j,t}$	0.000	0.000	-0.001	0.000
	(0.981)	(1.050)	(-1.078)	(0.570)
$\ln NFIRM_{i,j,t}$	-0.000*	-0.000	0.004***	0.000
	(-1.749)	(-1.583)	(6.142)	(0.290)
$\ln FREQ_{i,j,t}$	0.001***	0.001***	-0.016***	-0.000
	(4.586)	(3.874)	(-19.348)	(-1.607)
$\ln DAYS\_ELAP_{i,j,t}$	-0.000***	-0.000**	0.008***	-0.000
	(-2.630)	(-2.238)	(21.145)	(-1.144)
$\ln HORIZON_{i,j,t}$	-0.000***	-0.000**	-0.006***	-0.001***
	(-2.628)	(-2.328)	(-5.762)	(-5.215)
$\ln BSIZE_{i,t}$	0.000***	0.000***	0.005***	0.000
	(2.848)	(2.703)	(6.312)	(0.294)
$COMMON_{i,j,t}$	-0.001***	-0.002***	0.002	0.000
		(-3.612)	(0.840)	(0.381)
$\ln MV_{j,t}$	0.000	0.000	-0.017***	0.000
	(0.738)	(0.905)	(-17.443)	(0.397)
$MB_{j,t}$	-0.000	-0.000	-0.002***	-0.000***
	(-0.312)	(-0.461)	(-6.405)	(-4.387)
$REVISION_{i,j,t} \times COMMON_{i,j,t}$	-0.080	-0.091	0.220**	0.206
	(-0.964)	(-0.970)	(1.964)	(1.222)
$REVISION_{i,j,t} \times AFFILIATE_{i,j,t}$	-0.048	-0.044	(-0.310)	0.110
	(-0.877)	(-0.717)	0.083	(1.115)
$REVISION_{i,j,t} \times \ln GEXP_{i,j,t}$	0.039	0.037	(1.303)	-0.044
	(1.248)	(1.066)	-0.141**	(-0.593)
$REVISION_{i,j,t} \times \ln FEXP_{i,j,t}$	-0.039	-0.043	(-2.093)	0.125**
	(-1.034)	(-1.009)	-0.011	(2.021)
$REVISION_{i,j,t} \times \ln NFIRM_{i,j,t}$	-0.017	-0.018	(-0.267)	0.048
	(-0.979)	(-0.939)	0.037	(0.867)
$REVISION_{i,j,t} \times \ln FREQ_{i,j,t}$	0.092***	0.100***	(0.757)	0.172*
	(3.688)	(3.626)	-0.037*	(1.801)

$REVISION_{i,j,t} \times \ln DAYS\_ELAP_{i,j,t}$	0.004	0.005	(-1.943)	0.042
	(0.379)	(0.423)	0.110**	(1.047)
$REVISION_{i,j,t} \times \ln HORIZON_{i,j,t}$	0.058*	0.066*	(2.109)	-0.010
	(1.792)	(1.800)	-0.110*	(-0.165)
$REVISION_{i,j,t} \times \ln BSIZE_{i,t}$	0.014	0.019	(-1.821)	-0.002
	(0.336)	(0.405)	-0.093**	(-0.026)
$REVISION_{i,j,t} \times \ln MV_{j,t}$	-0.009	-0.009	(-2.542)	-0.030
	(-0.813)	(-0.742)	0.038***	(-0.833)
$REVISION_{i,j,t} \times MB_{j,t}$	0.012	0.015	(3.463)	0.029***
	(1.374)	(1.625)	(3.371)	(2.636)
adj. R^2	0.014	0.015	0.191	0.231
Year, industry, and analyst fixed effects	Yes	Yes	Yes	Yes
N	86,294	73,563	33,341	33,341

This table presents the regression results examining the market reaction and analysts' responsiveness to forecast revision by connected analysts. *CAR* is the three-day (-1, +1) return for company *j* surrounding the forecast revision issued by analyst *i* at time *t*, adjusted by market return during the same period of time. ln*N_REV* is the log of one plus the number of analysts who revise their forecasts in the 30 days following a forecast revision issued by analyst *i* for company *j* in year t. *RAF* is the price-deflated difference between the analyst consensus forecast for company *j* in the month following the issuance of a revised forecast by analyst *i*, minus the consensus forecast for company *j* in the preceding month. Definitions for all other variables are listed in Appendix 1. The sample includes all observations that have values for the variables used in the regression during our sample period over the 2005-2019 sample period in the CSMAR financial analyst forecasts database. Two-tailed *t*-statistics are presented in parentheses and calculated with standard errors adjusted for two-way clustering at the company and year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.