Common Ownership and Analyst Forecasts*

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ABSTRACT

We examine the effect of the common ownership relation between brokerage houses and the firms covered by their analysts (referred to as co-owned brokerage houses, co-owned firms, and connected analysts, respectively) on analyst forecast performance. Common ownership can help the connected analysts to have better access to co-owned firms, leading to higher quality analyst research. However, common owners have incentives for higher valuation for the co-owned firms, and thus can exert pressure on the connected analysts to issue optimistically biased research reports for these firms. We find that common ownership improves analyst forecast accuracy. This result is robust to a difference-in-differences design that exploits exogenous shocks to common ownership. The effects vary systematically with the quality of alternative sources of information that analysts can access for the co-owned firms. Overall, our paper contributes to the literature by documenting that common ownership can facilitate information communication.

Keywords: common ownership, analyst forecasts, institutional environments

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1 INTRODUCTION

In the last three decades, publicly traded companies have become increasingly interconnected by having the same large shareholders, mostly institutional investors. We refer to the phenomenon that large shareholders have equity stakes in multiple companies as common ownership. An emerging literature examines the effect of common ownership on various corporate decisions, such as the pricing of products, the collaborations among industry peers, and corporate disclosures (e.g., Elhauge 2015; He and Huang 2017; Azar, Schmalz, and Tecu 2018; Park, Sani, Shroff, and White 2019).[1]

However, while most of these studies focus on common ownership in industry peers or firms connected through production along the supply chain, based on 13F filings, more than 53% of U.S. institutional investors hold portfolio firms from more than one industry at the one-digit SIC code level. In addition, 25% of institutional investors hold at least one financial institution and one industrial firm. Given the prevalence of common ownership between a financial and a non-financial firm, it is important to understand the economic consequences of such common ownership. In this paper, we focus on the common ownership between brokerage houses and firms covered by the brokerage houses (hereafter co-owned brokerage houses and co-owned firms, respectively) and examine how it affects the quality of earnings forecasts issued by the analysts employed by the co-owned brokerage houses (hereafter connected analysts) for the co-owned firms.

Common ownership can affect analyst forecast performance for two non-exclusive reasons. First, common ownership can help connected analysts to obtain access to co-owned firms, allowing them to have more interactions with firms' management and obtain information about firms' operations and investments. While such information is likely

[1] These studies have led to a hot debate on the antitrust effect of common ownership. For example, the antitrust regulatory bodies in the U.S. and Europe are conteplating the adverse impact of common ownership among industry peers on the extent of competition and customer welfare (e.g., FTC Hearing 2018).

immaterial, when combined with other information analysts possess, it can improve analyst forecast accuracy (Brown, Call, Clement, and Sharp 2015; Cheynel and Levine 2020). We refer to this prediction as the information hypothesis.

Second, common owners might exploit their ownership and control to exert undue influence on co-owned brokerage houses for self-serving purposes through their communications with management (e.g., Kempf, Manconi, and Spalt 2016; Fichtner, Heemskerk, and Garcia-Bernardo 2017). Given common owners' preference for higher value of co-owned firms, the connected analysts might be under pressure to issue optimistic forecasts for co-owned firms, especially when common owners intend to sell their shares in the near future. If this is the case, we expect that common ownership reduces analyst research independence and induces connected analysts to issue optimistically biased forecasts for co-owned firms. We refer to this prediction as the conflicts-of-interest hypothesis.

Using a sample of 321,905 analyst forecasts from the 1990 – 2019 period, we find evidence that is consistent with the information hypothesis. In particular, we find that connected analysts issue more accurate forecasts than other analysts covering the same firms. These results suggest that common ownership improves forecast performance. However, we do not find results consistent with the conflicts-of-interest hypothesis: the forecasts issued by connected analysts do not differ from those by non-connected analysts in forecast bias.

The documented effect of common ownership on analyst forecast performance may be subject to endogeneity concern if some unobservable variables are correlated with both analysts' choice of following firms with common ownership and their forecast performance. While our empirical design of comparing forecast performance of connected and non-connected analysts covering the same firms and controlling for firm-year fixed effects controls for unobservable firm-year effects on analyst forecast performance, we conduct three additional tests to further alleviate the endogeneity concern. First, we employ the mergers of financial institutions as exogenous shocks that lead to the formation of common ownership between brokerage houses and the followed firms. Using a difference-in-differences (DiD) design, we obtain the same inferences as those from the main results. Second, we use the propensity score matching (PSM) approach to generate a matched sample, in which the connected and non-connected analysts have similar characteristics. The inferences based on the matched sample continue to be the same. Lastly, we perform a falsification test: for each connected analyst, we randomly select a non-co-owned firm she covers as a pseudo co-owned firm, and compare her forecast performance with other analysts covering the same firm. We do not find any difference in forecast performance. All these tests suggest that endogeneity is unlikely to drive our results.

We perform several cross-sectional tests to reinforce the main inferences and to provide additional insights. Because we only find results consistent with the information hypothesis regarding forecast accuracy, not the conflicts-of-interest hypothesis regarding forecast bias, our cross-sectional analyses focus on the factors that strengthen or weaken the information hypothesis. First, we argue that when common owners hold a large stake in the firm and the brokerage house, their incentives and influence on forecast performance are stronger. As such, the effect of common ownership increases with its level. Second, we consider factors that might affect the incremental value of the information acquired through common ownership on analyst forecast accuracy. We argue that the incremental effect of the facilitation role of common ownership for analysts to get access to firm information should be stronger and the effect of common ownership should be greater when firms' earnings are more difficult to forecast, and when analysts have fewer alternative sources of information to generate earnings forecasts for the firm. Consistent with the predictions, we find that the effect of common ownership on forecast accuracy is more pronounced when the percentage of the ownership that common owners have in the firms and the brokerage houses is high, and when firms have poorer earnings quality, have greater operational complexity, and do not provide management forecasts.[2]

To further triangulate the inferences on the information hypothesis that common ownership helps connected analysts to obtain access to firm management and facilitate their information acquisition activities, we conduct two sets of additional tests. First, we explicitly test the underlying argument for the information hypothesis by investigating the mechanism through which connected analysts obtain favorable treatment in information acquisition activities. Using analysts' ability to ask questions during firms' earnings conference calls as a proxy for their access to firm management (e.g., Mayew 2008), we find that compared with other analysts covering the same firms, connected analysts are more likely to ask questions during co-owned firms' earnings conference calls.[3] Second, because more accurate forecasts might reflect the information already compounded into the stock prices rather than the information obtained via common ownership, we investigate the informativeness of earnings forecasts using the short-window market reactions surrounding the issuance of these forecasts. We find that earnings forecasts issued by connected analysts are associated with stronger market reactions than those issued by other, non-connected analysts, consistent with the finding that the forecasts issued by connected analysts are more accurate and more

[2] Although the main effect of common owners on analyst forecast bias is statistically insignificant, we explore the economic incentives that can strengthen or weaken the common ownership-induced conflicts of interest. First, as optimistically biased analyst forecasts can help uphold high stock prices, it is possible that common owners have stronger incentives to induce connected analysts to issue favorable forecasts before selling their shares of the co-owned firms. We use the ex-post reduction in common owners' holdings in the firm to capture their trading incentives. Second, prior research suggests that institutional investors with a short investment horizon care more about short-term stock price movements and focus more on the trading gains than those with a long investment horizon (e.g., Bushee and Goodman 2007; Chen, Harford, and Li 2007). Therefore, it is possible that the effect of common ownership on analyst forecast bias is more pronounced when common owners have a shorter investment horizon. To test this prediction, we follow Gaspar, Massa, and Matos (2005) and use the frequency that common owners balance their positions on all of the stocks in their portfolios in a quarter, referred to as the churn rate, as the proxy for their investment horizon. However, we do not find any results consistent with the predictions.

[3] In un-tabulated tests, we investigate whether the Fair Disclosure (FD) regulation passed by the SEC in Aug 2000, which intends to prevent selective disclosure by publicly-traded firms to market professionals and certain shareholders, has any effect on the association between common ownership and forecast performance. We do not find any mitigation effect of Regulation FD on the association.

informative.

Our study contributes to the literature in two ways. First, we contribute to the literature on the economic consequences of common ownership by examining the effect of common ownership between brokerage houses and firms on analyst research quality. Extant studies suggest that common ownership reduces product market competition because firms within the network of common ownership tend to coordinate (e.g., Elhauge 2015; He and Huang 2017; Azar et al. 2018). However, most of these studies focus on industry peers. Given that common ownership also occurs among firms not in the same product market, it is important to undersand the economic consequences of such common ownership.[4]

Second, we contribute to the literature on analyst research by identifying another important determinant of analyst research quality: the common ownership between brokerage houses and their covered firms. Such common ownership can induce conflicts of interests that impair analyst research independence, but at the same time, it can also facilitate information communications between analysts and co-owned firms' management, leading to improved forecast performance.

Our results suggest that common ownership is associated with more accurate analyst forecasts and we do not find results suggesting the forecasts issued by connected analysts to be more optimistically biased. That is, we find that the information effect of common ownership dominates its conflicts-of-interest effect. This result is likely due to the strong investor protection and tough legal enforcements by the Securities and Exchange Commission (SEC), which reduce conflicts of interest faced by equity analysts (Mehran and

[4] While Kedia, Rajgopal, and Zhou (2017) also examine the common ownership between a financial institution, Moody's, and its rated firms, our paper differs from Kedia et al. (2017) in several important dimensions. First, unlike Kedia et al. (2017), who document an adverse effect of common ownership on the credit ratings issued by Moody's, we investigate the effect of common ownership on *equity* analysts' forecast performance. Due to the differences in regulatory and institutional environments for credit and equity analysts, the results documented in Kedia et al. (2017) might not generalize to our setting. Second, focusing on analyst forecast performance, including both forecast bias and accuracy, allows us to examine both the positive and negative effects of common ownership. Doing so will be difficult, if possible at all, in the credit rating setting. Lastly, we indeed document that common ownership improves analyst forecast performance.

Stulz 2007; Kadan, Madureira, Wang, and Zach 2009). For example, under the Global Settlement Agreement in 2003 between the SEC and ten major investment banks in the U.S., investment banks agreed to insulate their analyst research departments from their investment banking businesses to ensure analysts' independence. In addition, the SEC requires analysts to disclose matters that might give rise to conflicts of interest in their research reports.[5] These measures are documented to be highly effective in improving analyst research independence and forecast performance (e.g., Kadan et al. 2009). Thus, whether common ownership has a similar effect on analyst forecast performance in countries with different institutional environment as in the U.S. is unclear and is left to future research to explore.

The rest of the paper proceeds as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes data and research design. Section 4 presents the main empirical results, and Section 5 reports additional analyses. Section 6 concludes.

2 RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

2.1 Literature review on common ownership

In the last three decades, publicly traded companies have become increasingly interconnected by having the same large shareholders. Common ownership blurs firm boundaries, influences the objectives of co-owned firms, and facilitates the strategic coordination among the co-owned firms (e.g., Elhauge 2015). Unlike a standalone relationship between a shareholder and a firm, a common shareholder maximizes its stake in all co-owned firms, rather than the profit of individual portfolio firms. A stream of recent studies examine the effect of common ownership among firms in the same product market on

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[5] Under the Global Settlement, the ten largest U.S. investment banks agreed to implement a series of reforms to improve analyst independence, such as separating research from investment banking business, linking analyst compensation to stock-picking ability, and disclosing any conflicts of interest faced with analysts in analyst reports. The SEC has also imposed various other disclosure and regulatory requirements to improve analyst research independence. See SEC's investor publication, "Analysing Analyst Recommendations." https://www.sec.gov/tm/reportspubs/investor-publications/investorpubsanalystshtm.html.

market competition. For example, Elhauge (2015), He and Huang (2017), and Azar et al. (2018) find that common ownership facilitates the strategic cooperation between peer firms in the same industry and reduces product market competition. Focusing on the common ownership in the supply chain setting, Freeman (2018) argues that common ownership mitigates frictions associated with incomplete contracting and information asymmetry and fosters cooperation between co-owned firms in the supply chain, improving the longevity of the supply chain relationship.

Common ownership also helps facilitate information communication among firms in the same common ownership network. For example, Matvos and Ostrovsky (2008) find that common ownership can facilitate information communication between acquirers and targets, allowing the common owner to undertake acquisitions that maximize the total value of the acquirer and the target.[6] Park et al. (2019) and Pawliczek and Skinner (2018) argue that common ownership improves the information environment of co-owned firms because the relaxed product competition among co-owned firms reduces the proprietary cost of disclosures and incentivizes these firms to increase voluntary disclosures.

However, while prior studies primarily focus on common ownership among firms in the same product market, around 25% of U.S. institutional investors hold at least one financial institution and one industrial firm simultaneously, based on their 13F filings. In this paper, we focus on one type of such common ownership, that between brokerage houses and firms covered by these brokerage houses, and investigate its effect on the quality of analyst research.

2.2 Hypothesis development

Common ownership can affect analyst forecast performance in two ways. First,

[6] Prior studies also provide evidence on the information communication role of common ownership in other settings, such as the credit market (Massa and Žaldokas 2017).

common ownership can have a positive effect on analysts' earnings forecast accuracy, which we refer to as the "information hypothesis". Information acquisition is an important task for analysts and plays a critical role in improving analyst forecast accuracy (e.g., Chen, Cheng, and Lo 2010; Cheng, Du, Wang, and Wang 2016). Due to their career and reputation concerns, financial analysts have strong incentives to acquire information so that their research quality is higher (e.g., Harford, Jiang, Wang, and Xie 2019). Prior research finds that common ownership fosters information sharing among the parties held by the common owner (e.g., He and Huang 2017). It is thus conceivable that common ownership can help the analysts to connect with management of their covered co-owned firms. Thus, compared with non-connected analysts, connected analysts likely have better access to management and obtain more information about these firms. Connected analysts might also have preferential treatment in information gathering activities such as conference calls, investor relationship meetings, and corporate site visits. While the information obtained through better communications with firm management might be immaterial on its own, it can be combined with other information analysts have to generate more accurate forecasts (Brown et al. 2015; Cheynel and Levine 2020). Thus, our first hypothesis is as follows:

> ***H1 (Information hypothesis):*** *Ceteris paribus, earnings forecasts issued by connected analysts are more accurate than those issued by non-connected analysts covering the same firm.*

We are not suggesting that common owners provide information about the co-owned firms directly to connected financial analysts or help these analysts to approach the firms. Instead, we argue that connected analysts use the common ownership between their employers and the covered firms to seek favorable treatment in information gathering activities. To the extent that connected analysts fail to do so, we will not find results consistent with H1.

Second, common ownership can also have a negative effect on analyst forecast performance, which we refer to as the “conflicts-of-interest hypothesis”. Under this hypothesis, we argue that common ownership between a brokerage house and the firm followed by its analysts can reduce the independence of analyst research and lead these analysts to issue biased forecasts for the interest of common owners. Given their holdings of co-owned firms’ shares, common owners generally prefer that their portfolio firms have higher share prices, which can lead to higher fund performance and improve fund inflow and fund managers’ compensation (e.g., Chevalier and Ellison 1997; Sirri and Tufano 1998).

Besides the incentives, common owners also have the ability to influence analyst research. Common owners’ ownership position in the brokerage houses allows them to influence the brokerage houses’ operational decisions, including the tone of analyst research. We provide detailed discussions of the mechanisms through which common owners can influence co-owned brokerage houses’ operations in the next section. In practice, brokerage houses decide which analyst reports to disseminate (Maber, Groysberg, and Healy 2014). The dissemination process of analyst research allows the brokerage houses to influence the contents of analyst research reports or select the optimistic research reports so that the disseminated research reports provide optimistic prospects of the covered firms. As a result, the forecasts issued by connected analysts are more optimistically biased than those issued by other analysts covering the same firms. The second hypothesis is thus stated as follows:

H2 (Conflicts-of-interest hypothesis): *Ceteris paribus, earnings forecasts issued by connected analysts are more optimistically biased than those issued by non-connected analysts covering the same firm.*

Given the different predictions of the two hypotheses, the net effect of common ownership on analyst forecast performance is an empirical question. We postulate that whether the information effect or the conflicts-of-interest effect dominates depends on the strength of the institutional environments, including the regulatory environment on investor protection and legal enforcements. Prior studies suggest that market participants, including financial analysts, behave differently under institutional environments with stronger reputational capital (e.g., Leuz, Nanda, and Wysocki 2003; Bushman and Piotroski 2006; Mehran and Stulz 2007; Bradshaw, Huang, and Tan 2019). They find that strong investor protection and legal enforcements impose higher costs on analysts' opportunistic behavior, thus alleviating the self-serving behavior of market participants and analyst forecast biases. That is, strong institutional environments can mitigate the adverse effect of common ownership on analyst research independence. Whether the mitigation effect of institutional environment is strong enough so that the information effect dominates is an empirical question.

2.3 The mechanisms through which common owners influence firm decisions

As with other studies on common ownership, an important issue for this study, particularly for the conflicts-of-interest argument, is the mechanisms through which common owners influence portfolio firms' decisions. Prior studies provide detailed discussions of and ample evidence on how common owners can influence portfolio firms' decisions.[7] Specifically, common owners can influence corporate decisions through (1) the direct communication with firms' management; (2) voting on shareholder proposals, election of directors, changes to corporate structure or charter, executives compensation, or proxy contests; and (3) the threat of exit, i.e., selling their shares. In addition, Azar et al. (2018) and Schmalz (2018) suggest that managers of co-owned firms take common owners' interest into consideration without their explicit involvement.

There are two common criticisms on common ownership studies related to the underyling mechanisms. The first is that comon owners usually have a very small ownership stake on the co-owned firms and thus have little influence on their decisions. To address this

[7] For example, see Brav, Jiang, Partnoy, and Thomas (2008), Cronqvist and Fahlenbrach (2009), Aghion, Van Reenen, and Zingales (2013), Edmans (2014), Appel, Gormley, and Keim (2016), McCahery, Sautner, and Starks (2016), Azar et al. (2018), Edmans, Levit, and Reilly (2018), Schmalz (2018), and Appel, Gormley, and Keim (2019).

issue, as discussed later, we restrict our sample of common owners to blockholders, i.e., those with ownership of 5% or higher. As a result, the average ownership of common owners on co-owned firms is 8.1% and on the co-owned brokerage houses is 7.7%, as reported in panel A of Table 2. Given the high ownership stake, common owners have both the incentives and abilities to influence co-owned firms' and brokerage houses' decisions.

The second common criticism is that because the majority of common owners in the U.S. are passive investors such as index funds, they usually do not have the incentive or ability to influence investees' corporate decisions. However, recent resarch suggests that because the index funds and other passive investors tend to hold shares for a long time and cannot sell shares of poorly-performing firms, they care more about the long-term performance and governance of their portfolio firms (e.g., Appel et al. 2016, 2019).[8] These studies also suggest that the largely "passive" asset management firms, such as Blackrock, State Street, and Vanguard, engage with corporate management "behind the scence", and play an important role in many corporate governance decisions.[9] Many fund companies comment that while they are passive investors, they are not passive owners. Besides the "voice" means, fund companies also actively vote on shareholder proposals. He, Huang, and Zhao (2019) find that common owners' vote is an effective mechanism to influence corporate decisions and they tend to vote against management in shareholder-sponsored governance proposals. Note that although shares are managed by individual funds under the same institution, most of these institutions have a central team in charge of governance and stewardship process, and they always vote with a single voice (Schmalz 2018). Please see

[8] This mentality is summarized succinctly by the former CEO of Vanguard Funds, F. William McNabb, in one of his speeches, "We're going to hold your stock when you hit your quarterly earnings target. And we'll hold it when you don't. We're going to hold your stock if we like you. And if we don't. We're going to hold your stock when everyone else is piling in. And when everyone else is running for the exits. That is precisely why we care so much about good governance." https://corpgov.law.harvard.edu/2015/06/24/getting-to-know-you-the-case-for-significant-shareholder-engagement/

[9] See Boone and White (2015), Dimson, Karakas, and Li (2015), Appel et al. (2016), Kempf et al. (2016), McCahery et al. (2016), Fichtner et al. (2017), and Schmidt and Fahlenbrach (2017). Also see "Meet the new corporate power brokers: Passive investors," *Wall Street Journal*. October 24, 2016.

Appel et al. (2016, 2019), Fichtner et al. (2017), and Schmalz (2018) for detailed discussions and analyses.

In summary, the above discussions suggest that common owners have both the incentives and abilities to influence corporate decisions through the engagement with management (voice) and voting on governance and corporate decisions (vote). To the extent that common owners have weak incentives and abilitities to influence co-owned firms and brokerage houses, we will not find results consistent with the hypotheses.

3 DATA AND RESEARCH DESIGN

3.1 Data

To construct the sample, we first identify all analyst annual forecasts issued after the earnings announcement for the last year, but before the fiscal-year end of the current year for the U.S. firms that are followed by at least two analysts as in prior studies (e.g., Hilary and Hsu 2013). We limit the firms to non-financial firms (2-digit SIC code not between 60 and 69), and obtain analyst forecast data from the I/B/E/S database and employ the last forecast issued by each analyst for a firm-year. To identify whether a publicly-listed firm and a brokerage house share a common owner, we collect the ownership data from Thomson's CDA/Spectrum database (form 13F). We only keep the shareholders whose holdings in both brokerage houses and firms are at least 5% of the outstanding shares to increase the power of the test; common owners with a smaller ownership likely have limited influence on the co-owned brokerage houses and firms. We then match the names of the shareholders of the listed firms with those of the brokerage houses whose analysts have been following the firms. For each firm-year, we require at least one analyst employed by the co-owned brokerage house (i.e., connected analyst) and one non-connected analyst following the same firm in the year. We obtain financial information and stock price information from Compustat and CRSP, respectively. The final sample includes 321,905 analyst forecasts issued for 23,776 firm-years in the period of 1990-2019. Table 1 summarizes the sample selection process.

Panel A of Table 2 presents descriptive statistics on the level of common ownership. Each firm-year has 1.363 common owners on average. The common owners hold an average of 8.1% of the co-owned firms and 7.7% of the co-owned brokerage houses. Panel B of Table 2 lists the top twenty common owners for our sample firms. Because we restrict common owners to 13F institutions, the list includes exclusively financial institutions.

3.2 Research Design

We use a pooled OLS regression to test H1 and H2:

$$ACCURACY_{ijt}, BIAS_{ijt}, = \beta_0 + \beta_1 COMMON_{ijt} + \gamma Controls + Firm\_year\ FE + Broker\ FE + \varepsilon_{ijt}, \quad (1)$$

where *i*, *j*, *t* denote analyst *i*, firm *j*, and year *t*, respectively. The unit of observations is at the firm-year-analyst level, and the sample includes the latest annual earnings forecasts issued by connected and non-connected analysts for the same firm-year of co-owned firms. The dependent variable is analyst forecast accuracy or bias. Following prior studies (e.g., Gormley and Matsa 2014), forecast accuracy ($ACCURACY_{ijt}$) is defined as the negative 100 times the absolute value of the difference between analyst *i*'s annual EPS forecast and actual EPS for firm *j* in year *t*, deflated by the stock price immediately after the earnings announcements of the previous year, i.e., $-100 \times \frac{|EPS\ Forecast_{ijt} - Actual\ EPS_{jt}|}{Price_{jt-1}}$.[10] The higher the value of $ACCURACY_{i,j,t}$ is, the more accurate analyst *i*'s earnings forecast is. Similarly, forecast bias (*BIAS*) is defined as 100 times the unsigned value of the difference between analyst *i*'s annual EPS forecast and actual EPS for firm *j* in year *t*, deflated by the stock price immediately after the earnings announcements of the previous year, i.e., $100 \times$

[10] Following prior studies (e.g., Cheong and Thomas 2010; Duchin, Matsusaka, and Ozbas 2010; Piotroski and So 2012), we also use total assets per share as the deflator and obtain the same inferences. Separately, our inferences remain the same when we use the range of analyst forecast error (the difference between the maximum and minimum forecast error) as the deflator. The same applies to the relative forecast bias measure.

$\frac{EPS\ Forecast_{ijt} - Actual\ EPS_{jt}}{Price_{jt-1}}$. The higher the value of $BIAS_{ijt}$ is, the more optimistic analyst *i*'s earnings forecast is.

Our independent variable of interest is the indicator variable for common ownership, $COMMON_{ijt}$, which equals one if analyst *i*'s brokerage house shares a common owner with firm *j* in year *t*, and zero otherwise. When the dependent variable is *ACCURACY*, H1 predicts the coefficient on *COMMON* to be positive. When the dependent variable is *BIAS*, H2 predicts that the coefficient on *COMMON* is positive.

Because each firm is covered by multiple analysts, we adjust standard errors by clustering at the firm levels (Petersen 2009). Note that we use the raw values of the variables and include firm-year fixed effects in the regression model (Gormley and Matsa 2014), instead of adjusting both the dependent and independent variables by their corresponding firm-year means as in earlier papers in the analyst literature (e.g., Clement 1999; Malloy 2005; Call, Chen, and Tong 2009). The mean-adjusted specification yields the same inferences. We also include brokerage house fixed effects to control for time-invariant characteristics of the brokerage houses on analyst forecast performance.

Following prior research (Sonney 2009; Luo and Nagarajan 2015), we control for the analyst characteristics that likely affect analyst performance, including the number of firms followed by the analyst (*NFIRM*), the number of industries followed by the analyst (*NIND*), the analyst's general experience (*GEXP*), firm-specific experience (*FEXP*), and forecast frequency in the year (*FREQ*), the horizon of the forecast (*HORIZON*), and the size of the brokerage house (*BANALYST*). The Appendix presents variable definitions. We winsorize all continuous variables at the 1% and 99% level to alleviate the effect of extreme values.

3.3 Descriptive statistics

Panel A of Table 3 presents descriptive statistics, which are similar to those reported in prior studies (e.g., Call et al. 2009). The sample analysts follow an average of 16.23 firms

(*NFIRM*) and 3.81 industries (*NIND*), have an average of 11.25 (3.92) years of general (firm-specific) forecast experience (*GEXP* and *FEXP*), and issue 3.71 forecasts in a year (*FREQ*). The forecasts are on average issued 95.4 days before the fiscal year end (*HORIZON*). In addition, brokerage houses on average employ 64.4 analysts (*BANALYST*).

Panel B of Table 3 presents the differences in analyst and forecast characteristics between connected analysts (*COMMON* = 1) and non-connected analyses (*COMMON* = 0). Forecasts issued by connected analysts are significantly more accurate (*ACCURACY*), and less optimistically biased (*BIAS*) than those issued by non-connected analysts. In addition, connected analysts cover more firms (*NFIRM*) in fewer industries (*IND*), are more experienced (*GEXP* and *FEXP*), issue forecasts more frequently (*FREQ*), have shorter forecast horizon (*HORIZON*), and are employed by larger brokerage houses (*BANALYST*) than non-connected analysts. These differences indicate the importance of controlling for these characteristics in the regression analyses.

Panel C of Table 3 reports the correlation table for the variables. we find that most of the correlation coefficients are small, except that between the number of covered firms and the number of covered industries (0.44), that between general and firm experience (0.52), and that between forecast frequency and forecast horizon (-0.45). We find that the highest VIF score for the variables in analyses is much smaller than the conventional cut-off value of 10, suggesting that multicollinearity is not an issue for the analyses.

4 MAIN EMPIRICAL RESULTS

4.1 Main results – Tests of H1

Tables 4 reports the regression results from tests of H1 based on Equation (1) with *ACCURACY* as the dependent variable. H1 (the information hypothesis) predicts that connected analysts issue more accurate forecasts and thus the coefficient on *COMMON* in the regression is expected to be positive.

As reported in Column (1) of Table 4, we find that the coefficient on *COMMON* is significantly positive (t = 2.87). This result is consistent with H1, suggesting that connected analysts issue more accurate forecasts than other analysts following the same firms. Following He and Huang (2017) and Freeman (2018), we replace the dummy variable *COMMON* with the number of common owners that analysts' affiliated brokerage houses and their covered firms have, denoted as *N_COMMON*, as an alternative measure for the extent that analysts can leverage the common ownership relationship in their communication with firm management. The higher the value of *N_COMMON* is, the greater is the benefit that analysts might gain from the common ownership relationship in facilitating information communication with firm management, thus the greater is the effect of common ownership on analyst research. Column (2) of Table 4 show a positive and significant coefficient on *N_COMMON,* consistent with that reported in column (1) in the table.

The results for the control variables are generally consistent with those reported in prior research (e.g., Kini, Mian, Rebello, and Venkateswaran 2009; Sonney 2009). For example, we find that analysts who issue more frequent forecasts (ln*FREQ*), with shorter horizon (ln*HORIZON*), and are employed by larger brokerage houses with greater resources (ln*BANALYST*) are more accurate. We also find forecasts issued by analysts who cover more firms (ln*NFIRM*), have shorter firm experience (ln*FEXP*) are more accurate.[11]

Table 5 shows the results testing H2 on the conflicts-of-interest hypothesis when the dependent variable is *BIAS*. We find that the coefficient on *COMMON* is negative yet statistically insignificant at the conventional levels in column (1), suggesting that connected analysts are not different from other analysts in their forecast biases. This result remains

[11] Prior studies, such as Gu and Xue (2008), Kini, Mian, Rebello, and Venkateswara (2009), and Sonney (2009), also document a negative association between analyst firm-specific experience and forecast accuracy.

insignificant when we replace *COMMON* with *N_COMMON* shown in column (2). We also repeat the analyses using analysts' stock recommendation to test H2. Un-tabulated results yield similar inferences that connected analysts do not issue more favorable recommendations than non-connected analysts.

Taking together, the results in Tables 4 and 5 are consistent with the informational effect of common ownership (H1), leading to a positive effect of common ownership on analyst forecast accuracy, and are not consistent with the conflicts-of-interest hypothesis (H2).

4.2 Addressing the potential endogeneity concern

Endogeneity concern can arise when omitted factors are correlated with both connected analyst's decision to cover a co-owned firm and their forecast performance for the firm. For example, a co-owned brokerage house might assign a high-ability analyst to follow the co-owned firm. If this is the case, the difference in innate abilities between connected and non-connected analysts might explain the documented differences in forecast performance between these two groups of analysts. While our empirical analyses control for analyst characteristics and thus alleviate this concern, we conduct three sets of analyses to further address the endogeneity concern.

4.2.1 Using exogenous shocks to common ownership to address the endogeneity

Our first approach is to utilize exogenous shocks to common ownership and employ a difference-in-differences (DiD) design to examine the effect of common ownership on analyst forecast performance. The exogenous shock we exploit is the merger of financial institutions, which can lead to a formation of common ownership between a brokerage house and the firms followed by its affiliated analysts. The merger of two financial institutions, usually unrelated to the fundamentals of their portfolio firms (He and Huang 2017), results in the merging institutions' portfolios under the merged entity. Empirically, we require (1) the brokerage house to be held by one of the merging institutions and the firm to be held by the other merging institution in the year prior to the merger, and (2) the brokerage house and the firm to be held simultaneously by the surviving institution after the merger. During our sample period, we identify 18,434 broker-firm-years that experience the formation of common ownership (representing 1,160 co-owned firms and 133 co-owned brokerage houses). For each co-owned firm, the treatment analysts are those employed by the brokerage houses that experience the formation of common ownership relation with the firm, and the control analysts are the other, non-connected analysts covering the same firm.

To implement the DiD analyses, we require analysts of the treatment and control brokerage houses to issue at least one earnings forecast for the firm three years before (the pre-event period) and three years after (the post-event period) the merger. We also require a firm-year is covered by at least one analyst from the treatment brokerage house and one analyst from the control brokerage house. These data requirements control for analyst and firm-year fixed effects, but further reduces the sample size, resulting in a final sample of 16,051 forecasts issued for 324 firms. The regression specification for the DiD analysis is as follows:

$$ACCURACY_{ijt}, BIAS_{ijt}, = \beta_0 + \beta_1 TREAT_{ij} + \beta_2 TREAT_{ij} \times POST_{jt} + \gamma Controls + Firm\_year\ FE + Broker\ FE + \varepsilon_{ijt}, \quad (2)$$

where $TREAT_{ij}$ is the indicator for the treatment sample and equals 1 if analyst *i* works in a brokerage house that experiences a change in common ownership with firm *j*, and 0 otherwise. $POST_{jt}$ is the indicator variable for the post-event years. Because the events occurred in different years, we continue to include firm-year fixed effects in the regression. Our variable of interest is the interaction term, *TREAT* × *POST*. Because the merger of financial institutions leads to a *formation* of common ownership, we expect the coefficient on *TREAT* × *POST* to be positive in the analysis of forecast accuracy (bias) based on H1 (H2). In other words, the formation of common ownership leads to improved accuracy or increased bias.

Panel A of Table 6 reports the regression results. We find that the coefficient on *TREAT* × *POST* is significantly positive in the *ACCURACY* regression in Column (1), consistent with H1 and the results in Table 4. However, we find that the coefficient on *TREAT* × *POST* is negative yet statistically insignificant in Column (2), the *BIAS* regression. These results indicate that the exogenous formation of common ownership improves analyst forecast accuracy, consistent with the information hypothesis in H1, but has no effect on analyst forecast bias, inconsistent with H2.

4.2.2 Propensity score matching approach

The second approach we use to address the endogeneity issue is the propensity score matching (PSM) approach, which can help control for the non-linear effect of the differences in analyst characteristics between connected and non-connected analysts on forecast performance. Specifically, we first predict the likelihood of an analyst covering a firm in a year being a connected analyst by estimating a logit model using the analyst/broker characteristics used in Equation (1). Next, for each connected analyst covering a firm-year, we identify one non-connected analysts covering the same firm-year with the closest likelihood of being a connected analyst. This process leads to a final sample includes 118,818 forecasts issued for 3,349 firms, an equal number of forecasts by connected and non-connected analysts.[12] Panel B of Table 6 reports the regression results using the reduced sample after the PSM procedure. We continue to find a significantly positive coefficient on *COMMON* in the analysis of *ACCURACY*. Interestingly, we find a significantly negative coefficient on *COMMON* in the analysis of *BIAS*, rejecting H2.

[12] The un-tabulated covariate balance of the variables used in the regression analyses suggests that the differences in most of the covariates are insignificant at conventional levels, except for forecast frequency, forecast horizon, and broker size. However, these differences are very small and the differences in the variance ratios for these variables are mostly insignificant.

4.2.3 Falsification test

Lastly, we conduct a falsification test to ensure that our results are not spurious or driven by connected analysts' characteristics. For this purpose, we randomly select a firm followed by the connected analysts as the pseudo-co-owned firm (*COMMON_Pseudo* =1), and then identify all other analysts following the same firm in the year as non-connected analysts (*COMMON_Pseudo* =0). Using the same research design, we estimate Equation (1) and produce one set of coefficients. We then reiterate the same randomization process and estimate Equation (1) 100 times. Lastly, we report the mean coefficients and their corresponding t-values for all independent variables in Panel C of Table 6. Consistent with our expectation, the coefficients on *COMMON_Pseudo* are on average insignificant for neither of the regressions.

In sum, the analyses reported in this section suggest that the documented effect of common ownership on analyst forecast performance is unlikely to be driven by endogeneity, analyst characteristic differences between connected and non-connected analysts, or a spurious effect.

4.3 Cross-sectional analyses

In this section, we conduct cross-sectional analyses conditioning on the factors that affect the value of the information obtained by connected analysts from co-owned firms, and thus its effects on analyst forecast accuracy (H1). We focus on cross-sectional analyses on H1, not H2, because we only find evidence consistent with the former. Such analyses can shed light on the potential mechanisms through which common ownership affects analyst forecast performance.

We first consider the extent of influence common owners have on the firms and the brokerage houses, that affect the accessibility of analysts to firm management and thus analyst forecast accuracy. We then consider three additional factors that likely affect the incremental value of the information obtained by connected analysts from the covered co-owned firms: earnings quality, forecast difficulty, and the availability of alternative sources of information such as management forecasts.

4.3.1 Common owners' ownership stakes

Following He and Huang (2017) and Freeman (2018), we test whether the level of the common ownership in the co-owned firms and brokerage houses has explanatory power for analyst forecast accuracy incremental to the effect of *COMMON*. We use two dummy variables to capture the extent of influence that the common owner has on the co-owned firm and brokerage house, *HSTAKE_F* and *HSTAKE_B*, which equal one if the percentage of common owners' ownership in the co-owned firm and brokerage house is in the top 10 percentile of their sample distribution, respectively. We expect that the greater is the percentage of ownership that common owners have on the covered firm and the brokerage house, the greater their incentives and abilities are, thus the greater is the effect of common ownership on analyst research performance. Table 7 reports the regression results. We find that while the coefficients on *COMMON* remain positive and significant, the coefficients on *HSTAKE_F* and *HSTAKE_B* are significantly positive, consistent with the incremental power of high ownership stakes on the informational effect of common ownership on analyst forecast accuracy. We do not include both variables in the same regression because the two ownership variables are highly correlated with a correlation coefficient of 0.67, resulting in a multi-collinearity issue.

4.3.2 Alternative courses of information

*Earnings quality***.** Theory suggests that when investors have multiple information signals, the value of one signal is stronger (weaker) when the other signal is of lower (higher) quality. In the setting of analyst forecasts, prior research finds that analysts' private information is more valuable in improving their earnings forecast accuracy when earnings quality is lower (e.g., Barth, Kasznik, and McNichols 2001). It thus follows that the information obtained from co-owned firms via common ownership is more valuable to the connected analysts when the co-owned firms' earnings quality is lower. To capture earnings quality, we use the absolute value of discretionary working capital accruals (*DD*) estimated using the Dechow and Dichev (2002) model; a higher value of *DD* indicates lower earnings quality. We then construct an indicator variable for firms with *DD* above the sample median, *HIGH_DD*, and add its interaction with *COMMON* to the regression model. Column (1) of Table 8 reports the regression results. Consistent with our expectation, we find that the coefficients on *COMMON* × *HIGH_DD* is significantly positive, suggesting that the effect of common ownership on forecast accuracy is more pronounced for firms with poorer earnings quality.

Operation complexity. Prior studies show that operation complexity increases the cost of collecting and disseminating information to external parties, leading to a higher level of information asymmetry (e.g., Jung and Kwon 1988). Thus, the additional information collected by connected analysts is more valuable when operation complexity is higher. To measure operation complexity, we follow Feng, Li, and McVay (2009) and construct a factor score (*COPX*) based on the number of segments and whether the firm has foreign operations and restructuring transactions. A higher value of *COPX* implies greater difficulty in forecasting the firm's earnings. We then construct an indicator variable for firms with *COPX* above the sample median, *HIGH_COPX*, and add its interaction with *COMMON* to the regression model. Column (2) of Table 8 reports the regression results. Consistent with our expectation, we find that the coefficient on *COMMON* × *HIGH_COPX* is significantly positive, suggesting that the effect of common ownership on forecast accuracy is more pronounced when it is more difficult to forecast a firm's earnings.

Availability of management forecasts. When other sources of public information are available, the value of the information obtained from co-owned firms via common ownership is lower. Given that a common source of public information is management forecasts, we expect that the effect of common ownership on forecast accuracy is going to be lower when managers issue management forecasts. To test this prediction, we obtain the management forecast data from the I/B/E/S Guidance database, and add the interaction term of *COMMON* and an indicator variable, *MGT_FC,* which equals 1 if a firm has issued any earnings forecast prior to the issuance of analyst forecast in the year, and 0 otherwise. Column (3) of Table 8 reports the regression results. We find that the coefficient on *COMMON* × *MGT_FC* is significantly negative, suggesting that when management provides earnings forecasts, the effect of common ownership on analyst forecast accuracy is reduced.

5 ADDITIONAL ANALYSES

5.1 Connected analysts' access to firm management

One key premise underlying H1 is that connected analysts use common ownership between their employers and the covered firms to seek favorable treatment in information acquisition activities, thus gaining information advantages over other analysts. In this section, we test this underlying assumption by using the likelihood of analysts asking questions during firms' earnings conference calls as a proxy for their access to firm management, as in Mayew (2008).[13] While analysts can have access to firm management via other means, such as office meetings and social interactions, such means are unobservable. Thus, we investigate whether connected analysts are more likely to ask questions during the Q&A sessions of firms' earnings conference calls than other non-connected analysts.

Panel A of Table 9 reports the regression results. The dependent variable ASK_FREQ_{ijt} is the natural logarithm of one plus the number of times analyst *i* asks questions during

[13] Mayew (2008) argues that managers can use their discretion to give some analysts more opportunities to ask questions during firms' conference calls, while discriminating against others.

conference calls held by firm *j* in year *t*. We follow Meyew (2008) for the choice of the control variables included in the regression model. As reported in the table, the coefficient on *COMMON* is significantly positive (t = 2.14), consistent with the expectation that common ownership facilitates analysts' information acquisition activities, improving the accuracy of their forecasts for co-owned firms.

An alternative explanation for the results in Panel A of Table 9 is that connected analysts exert greater efforts in the information acquisition of the co-owned firms due to their higher economic incentives associated with the common ownership and therefore ask more questions during conference calls. To test this conjecture, we regress the level of analyst effort, proxied for by the natural logarithm of one plus the number of forecasts an analyst issues in year (*lnFREQ*), on *COMMON*. Panel B of Table 9 reports the regression results. We find that the coefficient on *COMMON* is significantly negative, rejecting the alternative explanation that greater research efforts by connected analysts explain the results reported in Panel A of Table 9.

Collectively, the results in Table 9 suggest that connected analysts' preferential access to firm management through common ownership, not their effort, at least partially explains their better forecast performance for the co-owned firms.

5.2 Market reaction to the issuance of analyst forecasts

Under the information hypothesis, we argue that analysts obtain information from co-owned firms and thus have more accurate forecasts. If so, the market reaction to such forecasts should be stronger. To test whether this prediction holds, we investigate whether the market reaction to earnings forecasts issued by connected analysts differ from that for non-connected analysts. For this purpose, we conduct a short-window market reaction to forecast revisions, by calculating cumulative market-adjusted returns in two alternative windows, a three-day window and a five-day window, surrounding the issuance of earnings forecasts.

Table 10 reports the regression results. The main variable of interest is the interaction terms between *COMMON* and earnings forecast revisions, *FREV*, calculated as analyst forecast minus the latest consensus annual EPS forecast issued 90 days prior to the issuance of the focal forecast, divided by stock price immediately after the earnings announcements of the previous year. We include a list of control variables suggested in prior studies that might affect the market reaction to analyst earnings forecasts (e.g. Cheng et al. 2016; Chan, Lin, Yu, and Zhao 2018). Consistent with the information content of analysts' forecast revision, we find that the coefficient on *FREV* is significantly positive in both columns. More importantly, we find that the coefficient on *COMMOM* × *FREV* is significantly positive, suggesting that the market reacts more positively to forecast revisions issued by connected analysts than to those by non-connected analysts. This result is consistent with the earlier finding that connected analysts issue more accurate forecasts than non-connected analysts.[14] Overall, the results suggest that investors react more positively to the more accurate forecasts issued by connected analysts.

6 CONCLUSION

We examine the effect on analyst forecast performance of the common ownership between brokerages houses and the firms followed by the analysts employed by the brokerage houses. On the one hand, common ownership helps analysts to be connected with firm management and to have better access to the information about the firms that share the same owners as the analysts' brokerage houses, leading to higher quality analyst research. On the other hand, common ownership can also reduce the independence of analysts because through their ownership and control over the brokerage houses, common owners can exert

[14] We repeat the analyses on the differential market reaction upon stock recommendations issued by connected analysts as opposed to non-connected analysts. Un-tabulated results suggest an incremental positive (negative) and significant market reactions upon strong buy (strong sell) recommendations issued by connected analysts, consistent with forecasts and stock recommendations issued by connected analysts being more credible.

pressure on the analysts to issue biased research reports on the firms in their portfolios.

We find that connected analysts issue more accurate, and not more optimistically biased, forecasts than non-connected analysts. Such effects are robust after using various approaches in addressing the endogeneity of common ownership. We also find that such effect is stronger when common owners' ownership in the co-owned firms and brokerage houses is higher, i.e., when the influence common owners has is stronger. We find that the effect is also stronger when the incremental value of the information obtained by connected analysts from the covered co-owned firms is greater, that is, when firms have lower earnings quality and greater forecast difficulty, and do not issue management forecasts.

Overall, our paper contributes to the literature by documenting that common ownership can facilitate better communications with financial analyses and enhance firms' information environments.

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Appendix: Variable Definitions

Variable	**Definition**
Dependent variables for forecast bias and accuracy analyses	
$ACCURACY_{ijt}$	Analyst forecast accuracy, calculated as -100 × $\lvert EPS\ Forecast_{ijt} – Actual\ EPS_{jt} \rvert$ / Stock price one day after the earnings announcement date of the previous year. $EPS\ Forecast_{ijt}$ is analyst *i*'s annual EPS forecast for firm *j* in year *t*; $Actual\ EPS_{jt}$ is the actual EPS for firm *j* in year *t*. Analysts' latest annual EPS forecasts for year *t* issued before the earnings announcement are used. The higher the value is, the more accurate the forecast is.
$BIAS_{ijt}$	Analyst forecast bias, calculated as 100 × ($EPS\ Forecast_{ijt}$ – $Actual\ EPS_{jt}$) / Stock price one day after the earnings announcement date of the previous quarter. The variable definitions are the same as above. The higher the value is, the more optimistically biased the forecast is.
Independent variables for forecast bias and accuracy analyses	
$COMMON_{ijt}$	A dummy variable for the common ownership relation between brokerage houses and covered firms, equal to 1 if the forecast is issued by a connected analyst *i* – defined as the analyst who is employed by a brokerage house that shares common shareholders with firm *j* in year *t*, and 0 otherwise.
N_COMMON_{ijt}	The number of common shareholders between brokerage houses and covered firms in year *t*.
Control variables for forecast bias and accuracy analyses	
$NFIRM_{it}$	The natural logarithm of 1 plus the number of firms followed by an analyst *i* in year *t*.
$NIND_{it}$	The natural logarithm of 1 plus the number of (two-digit SIC code) industries that analyst *i* follows in year *t*.
$GEXP_{it}$	Analyst general experience, measured as the natural logarithm of 1 plus the number of years analyst *i* has been in the database (IBES) till year *t*.
$FEXP_{it}$	Analyst firm-specific experience, measured as the natural logarithm of 1 plus the number of years analyst *i* has been issuing forecasts for firm *j* in the database (IBES) till year *t*.
$FREQ_{ijt}$	The natural logarithm of 1 plus the total number of annual earnings forecasts issued by analyst *i* for firm *j* in year *t*.
$HORIZON_{ijt}$	The natural logarithm of 1 plus the number of days between the date when the forecast is issued by analyst *i* for firm *j* and the fiscal year-end date of year *t*.
$BANALYST_{it}$	The natural logarithm of 1 plus the number of analysts who are affiliated with the brokerage house of analyst *i* in year *t*.
Conditioning variables for cross-sectional analyses of forecast bias and accuracy	
$HIGH\_DD_{jt}$	An indicator variable for low accrual quality, 1 if the absolute value of firm *j*'s discretionary accruals in year *t* is higher than the sample median, and 0 otherwise. Discretionary accruals are the residuals from the Dechow and Dichev (2002) regression model estimated

	annually for each of Fama and French's (1997) 48 industries with at least 20 firms in year *t*.
HIGH_COPX$_{jt}$	An indicator variable for high operational complexity, 1 if firm *j*'s operational complexity in year *t* is higher than the sample median, and 0 otherwise. Operational complexity is calculated as the principle factor from a factor analysis of the number of geographic and operating segments (Computat item, GEOSEG & OPSEG), the existence of foreign transactions (FCAQ), and the existence of restructuring changes (RCPQ) (Feng et al. 2009).
MGT_FC$_{ijt}$	An indicator variable for management forecast issuance, 1 if firm *j* releases management earnings forecasts before the issuance of the forecast by analyst *i* in year *t*.
Additional variables for the analyses of conference calls	
ASK_FREQ$_{ijt}$	The nature logarithm of 1 plus the number of times analyst *i* asks questions during conference calls of firm *j* during year *t*.
lagSBUY$_{ijt}$	A dummy variable that equals 1 if the last stock recommendation issued by analyst *i* for firm *j* in year *t-1* is a strong buy, and 0 otherwise.
lagBUY$_{ijt}$	A dummy variable that equals 1 if the last stock recommendation issued by analyst *i* for firm *j* in year *t-1* is a buy, and 0 otherwise.
lagSELL$_{ijt}$	A dummy variable that equals 1 if the last stock recommendation issued by analyst *i* for firm *j* in year *t-1* is a sell, and 0 otherwise.
lagSSELL$_{ijt}$	A dummy variable that equals 1 if the last stock recommendation issued by analyst *i* for firm *j* in year *t-1* is a strong sell, and 0 otherwise.
lagASK_DUM$_{ijt}$	A dummy variable that equals 1 if analyst *i* participates in conference calls of firm *j* in year *t-1*, and 0 otherwise.
CC_OTHER$_{ijt}$	The nature logarithm of 1 plus the number of other firms' conference calls analyst *i* following firm *j* participates in year *t*.
Additional variables for the analyses of market reaction to earnings forecast revisions	
CAR$_{ijt}$*(-w, w)*	The cumulative abnormal return (firm *j*'s stock return minus the value-weighted market return as in Clement and Tse (2003)) in the [-*w*, *w*] window surrounding the issuance date of analyst *i's* earnings forecast for firm *j* in year *t* (day 0).
FREV$_{ijt}$	Analyst forecast revision, defined as analyst *i*'s annual EPS forecast for firm *j* in year *t*, minus the latest consensus annual EPS forecast in the 90 days prior to the issuance of the forecast, scaled by stock price immediately after the earnings announcements of the previous year.

Table 1 Sample selection

Sample selection process	# firm-years	# forecasts
Firm-years followed by at least two analysts during the sample period of 1990 – 2019*	76,527	
Firm-years with common ownership with at least one brokerage house	34,988	
Firm-years with at least one connected analyst and at least one non-connected analyst**	23,776	
Forecasts issued by connected analysts	23,776	140,238
Forecasts issued by non-connected analysts	23,776	181,667
Final sample	23,776	321,905

* We restrict our sample to common stocks (*SHRCD* in CRSP = 10 or 11) of non-financial firms.
** For each firm-year, we focus on the last annual earnings forecast issued by each analyst after the previous year's earnings announcement and before the current year's fiscal-year-end.

Table 2 Descriptive statistics on common owners

Panel A: Descriptive statistics on common owners' ownership

	N	Mean	Q1	Median	Q3	STD
The number of common owners between a firm and a brokerage house	140,238	1.363	1.000	1.000	2.000	0.584
Ownership in the co-owned firm	140,238	0.081	0.063	0.075	0.093	0.024
Ownership in the co-owned brokerage house	140,238	0.077	0.058	0.067	0.078	0.048

Panel B: Top 20 common owners by frequency of appearance

Rank	Financial institution	*Freq*	%*
1	Vanguard Group, Inc.	67,054	47.81%
2	Fidelity Management & Research	25,135	17.92%
3	Blackrock Inc.	9,727	6.94%
4	Barclays Bank Plc.	6,938	4.95%
5	T. Rowe Price Associates, Inc.	6,640	4.74%
6	State Str Corporation	4,377	3.12%
7	AXA Financial, Inc.	3,201	2.28%
8	Wellington Management Co., LLP.	2,631	1.88%
9	Capital Research & Management Co.	2,134	1.52%
10	Dimensional FD Advisors, Inc.	1,764	1.26%
11	Legg Mason Inc.	1,071	0.76%
12	MSDW & Company	987	0.70%
13	Goldman Sachs & Company	905	0.65%
14	Private Capital Management, Inc.	690	0.49%
15	Mellon Bank N.A.	677	0.48%
16	Capital World Investors	650	0.46%
17	Prudential Insurance Co/Amer	585	0.42%
18	Royce & Associates, LLC.	544	0.39%
19	Morgan J P & Co. Inc.	523	0.37%
20	Earnest Partners, LLC.	408	0.29%
	Sub-total	136,641	97.43%
	Total number of firm-year-forecasts observations with *COMMON* =1	140,238	

Panel A presents descriptive statistics on common owners' ownership conditional on *COMMON* = 1. The observation unit is at the firm-year-forecast level. Panel B presents the top 20 financial institutions by frequency of appearance in *COMMON*=1 subsample. *Freq* is the frequency count of the number of times an analyst's affiliated financial institution appears as a common owner. The total number of observations is 140,238 firm-year-analysts when *COMMON* =1.

**%* is calculated as *Freq* divided by 140,238.

Table 3 Summary statistics on the variables used in the analyses

Panel A: Summary statistics

Variable name	N	Mean	Q1	Median	Q3	STD
COMMON	321,905	0.436	0.000	0.000	1.000	0.496
ACCURACY	321,905	-0.954	-0.679	-0.217	-0.070	2.620
BIAS	321,905	0.140	-0.243	-0.037	0.174	1.881
NFIRM	321,905	16.230	11.000	15.000	20.000	8.575
IND	321,905	3.813	2.000	3.000	5.000	2.635
GEXP	321,905	11.250	4.000	9.000	17.000	8.549
FEXP	321,905	3.920	1.000	2.000	6.000	4.542
FREQ	321,905	3.713	2.000	3.000	5.000	2.195
HORIZON	321,905	95.430	53.000	65.000	122.000	79.610
BANALYST	321,905	64.400	21.000	50.000	97.000	53.240

Panel B: Comparative descriptive statistics

Variable name	*COMMON* = 1 (N = 140,238)			*COMMON* = 0 (N = 181,667)			t-test for the difference in means (p-value)	Wilcoxon test for the difference in medians (p-value)
	Mean	Median	STD	Mean	Median	STD		
ACCURACY	-0.899	-0.191	2.630	-0.996	-0.240	2.612	<0.01	<0.01
BIAS	0.111	-0.039	1.811	0.163	-0.035	1.932	<0.01	<0.01
NFIRM	16.990	16.000	7.981	15.640	14.000	8.962	<0.01	<0.01
IND	3.691	3.000	2.409	3.908	3.000	2.794	<0.01	<0.01
GEXP	11.960	10.000	8.703	10.700	9.000	8.388	<0.01	<0.01
FEXP	4.315	3.000	4.706	3.616	2.000	4.387	<0.01	<0.01
FREQ	3.910	4.000	2.251	3.562	3.000	2.138	<0.01	<0.01
HORIZON	91.110	64.000	76.210	98.770	65.000	81.970	<0.01	<0.01
BANALYST	87.270	81.000	52.360	46.740	28.000	46.810	<0.01	<0.01

Panel A presents descriptive statistics for the main variables used in the analyses for full sample covering the 1990-2019 period. Panel B presents comparative descriptive statistics on main variables for the connected (*COMMON* =1) and non-connected (*COMMON* =0) analyst subsamples. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% levels.

Table 3 (cont'd)

Panel C: Pearson correlation matrix for main variables

Variable name	1	2	3	4	5	6	7	8	9
1.COMMON	1								
2.ACCURACY	0.02	1							
	(<0.01)								
3.BIAS	-0.01	-0.39	1						
	(<0.01)	(<0.01)							
4.lnNFIRM	0.10	0.02	-0.02	1					
	(<0.01)	(<0.01)	(<0.01)						
5.lnIND	-0.03	0.05	0.01	0.44	1				
	(<0.01)	(<0.01)	(<0.01)	(<0.01)					
6.lnGEXP	0.08	0.02	-0.01	0.35	0.18	1			
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)				
7.lnFEXP	0.09	0.02	-0.01	0.23	0.10	0.52	1		
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)			
8.lnFREQ	0.08	0.05	-0.04	0.22	0.03	0.10	0.19	1	
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)		
9.lnHORIZON	-0.03	-0.10	0.06	-0.12	-0.02	0.01	0.05	-0.45	1
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	
10.lnBANALYST	0.44	0.03	-0.01	0.06	-0.08	0.04	0.03	0.07	-0.03
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)

This panel presents the correlation matrix for the main variables used in the analyses. Two tailed p-values are in parentheses. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% levels.

Table 4 The effect of common ownership on analyst forecast accuracy

Dependent Variable =	*ACCURACY* (1)	(2)
COMMON	0.0195***	
	(2.87)	
N_COMMON		0.0110**
		(2.34)
lnNFIRM	0.0398***	0.0398***
	(5.36)	(5.36)
lnIND	-0.0129	-0.0130
	(-1.45)	(-1.46)
lnGEXP	-0.0039	-0.0038
	(-1.10)	(-1.09)
lnFEXP	-0.0227***	-0.0227***
	(-6.67)	(-6.66)
lnFREQ	0.3414***	0.3413***
	(26.11)	(26.11)
lnHORIZON	-0.3162***	-0.3162***
	(-35.30)	(-35.29)
lnBANALYST	0.0261***	0.0267***
	(2.77)	(2.83)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	321,905	321,905
Adjusted R^2	0.790	0.790

This table presents the regression analyses of analyst forecast accuracy (*ACCURACY*) on the common ownership relation between brokerage houses and the firms covered by the brokerage houses' analysts (*COMMON* or *N_COMMON*). The sample period is from 1990 to 2019. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table 5 The effect of common ownership on analyst forecast bias

Dependent Variable =	*BIAS*	
	(1)	(2)
COMMON	-0.0080	
	(-1.23)	
N_COMMON		0.0002
		(0.06)
lnNFIRM	-0.0199***	-0.0200***
	(-2.90)	(-2.91)
lnIND	0.0027	0.0027
	(0.33)	(0.34)
lnGEXP	0.0067**	0.0067**
	(2.10)	(2.12)
lnFEXP	0.0077**	0.0077**
	(2.42)	(2.40)
lnFREQ	-0.1069***	-0.1069***
	(-11.23)	(-11.23)
lnHORIZON	0.1354***	0.1354***
	(17.59)	(17.59)
lnBANALYST	-0.0188**	-0.0197**
	(-2.00)	(-2.10)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	321,905	321,905
Adjusted R^2	0.638	0.638

This table presents the regression analyses of analyst forecast bias (*BIAS*) on the common ownership relation between brokerage houses and the firms covered by the brokerage houses' analysts (*COMMON* or *N_COMMON*). The sample period is from 1990 to 2019. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table 6 Tests to address the potential endogeneity issue

Panel A: DiD analyses after the merger of financial institutions

Dependent Variable =	*ACCURACY* (1)	*BIAS* (2)
TREAT	-0.0644	0.0940**
	(-1.63)	(2.28)
TREAT × POST	0.0987**	-0.0458
	(2.01)	(-0.89)
lnNFIRM	0.0663**	-0.0450
	(2.14)	(-1.37)
lnIND	-0.0395	-0.0261
	(-1.20)	(-0.74)
lnGEXP	-0.0060	-0.0084
	(-0.39)	(-0.65)
lnFEXP	-0.0362**	0.0310**
	(-2.35)	(2.13)
lnFREQ	0.3580***	-0.2138***
	(7.68)	(-5.75)
lnHORIZON	-0.3214***	0.2138***
	(-12.15)	(8.09)
lnBANALYST	0.0217	0.0124
	(0.46)	(0.31)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	16,051	16,051
Adjusted R^2	0.757	0.659

Panel A of this table presents the DiD regression results for the effect of the formation of common ownership between firms and brokerage houses caused exogenously by the mergers of financial institutions from 1990-2019 on analyst forecast accuracy and biases. *TREAT* is an indicator variable that equals 1 for treatment forecast observations issued by analysts who are affiliated with the brokerage houses that experience the formation of common ownership with the covered firms due to financial institutions mergers, and 0 for other analysts cover the same firm-year in the control sample. *POST* is an indicator that equals 1for the three-year period after the mergers, and 0 for the thee-year period before the mergers. Please see the Appendix for the definitions of all other variables. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table 6 (cont'd)

Panel B: Regression analyses using the PSM sample

Dependent Variable =	*ACCURACY* (1)	*BIAS* (2)
COMMON	0.0273***	-0.0230**
	(2.64)	(-2.40)
lnNFIRM	0.0495***	-0.0194*
	(4.14)	(-1.85)
lnIND	-0.0104	-0.0168
	(-0.71)	(-1.35)
lnGEXP	-0.0096*	0.0167***
	(-1.91)	(3.23)
lnFEXP	-0.0172***	-0.0023
	(-3.43)	(-0.46)
lnFREQ	0.3270***	-0.0886***
	(18.35)	(-6.32)
lnHORIZON	-0.2845***	0.1146***
	(-26.77)	(11.96)
lnBANALYST	0.0083	-0.0206
	(0.50)	(-1.23)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	118,818	118,818
Adjusted R^2	0.791	0.630

Panel B presents the regression analyses on the effect of analyst forecast accuracy (*ACCURACY*) and bias (*BIAS*) on the common ownership relation between brokerage houses and the firms covered by the brokerage houses' analysts using the sample generated by a propensity score matching approach. Specifically, we first predict the likelihood of an analyst covering a co-owned firm in a year based on the list of analyst-, and broker-characteristics in Equation (1). We then match one connected analyst with a non-connected analyst covering the same firm-year with the closest likelihood of being a connected analyst. The sample period is from 1990 to 2019. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table 6 (cont'd)

Panel C: Falsification test

Dependent Variable =	*ACCURACY* (1)	*BIAS* (2)
COMMON_Pseudo	0.0079	-0.0040
	(1.00)	(-0.52)
lnNFIRM	0.0507***	-0.0194***
	(6.94)	(-2.99)
lnIND	-0.0177**	0.0040
	(-2.18)	(0.52)
lnGEXP	-0.0079**	0.0084**
	(-2.47)	(2.67)
lnFEXP	-0.0255***	0.0078**
	(-8.02)	(2.66)
lnFREQ	0.3316	-0.1217***
	(27.88)	(-12.79)
lnHORIZON	-0.2986***	0.1481***
	(-36.42)	(20.35)
lnBANALYST	0.0288***	-0.0231***
	(3.24)	(-2.73)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	335,531	335,531
Adjusted R^2	0.791	0.640

Panel C of this table presents the falsification test results on the effect of the pseudo common ownership between firms and brokerage houses on analyst forecast accuracy and biases. *COMMON_Pseudo* is an indicator that equals 1 for pseudo connected analysts, and 0 otherwise. More specifically, we randomly select a firm followed by the connected analysts as the pseudo-co-owned firm (*COMMON_Pseudo* =1), and then identify all other analysts following the same firm in the year as non-connected analysts (*COMMON_Pseudo* =0). We estimate Equation (1) and produce one set of coefficients. We then reiterate the randomization process and estimate Equation (1) 100 times. This table reports the mean of the coefficients and their corresponding t-values. The sample period is from 1990 to 2019. Please see the Appendix for the definitions of all other variables. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Table 7 The incremental effect of common ownership on analyst forecast accuracy

Dependent Variable =	*ACCURACY*	
	(1)	(2)
COMMON	0.0149**	0.0136*
	(2.12)	(1.88)
HSTAKE_F	0.0326*	
	(1.90)	
HSTAKE_B		0.0240**
		(2.03)
lnNFIRM	0.0399***	0.0399***
	(5.37)	(5.37)
lnIND	-0.0130	-0.0130
	(-1.46)	(-1.45)
lnGEXP	-0.0039	-0.0039
	(-1.12)	(-1.11)
lnFEXP	-0.0228***	-0.0227***
	(-6.67)	(-6.67)
lnFREQ	0.3413***	0.3414***
	(26.12)	(26.11)
lnHORIZON	-0.3162***	-0.3162***
	(-35.30)	(-35.30)
lnBANALYST	0.0259***	0.0258***
	(2.75)	(2.74)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	321,905	321,905
Adjusted R^2	0.790	0.790

This table presents the regression results on the effect of the size of the common owner's ownership stake in co-owned firms and brokerage houses on analyst accuracy. *HSTAKE_F (HSTAKE_B)* is an indicator variable that equals 1 if the ownership of the common owner in the co-owned firm (co-owned brokerage house) is above the 90th percentile of the sample distribution, and 0 otherwise. The sample period is from year 1990 to 2019. Please see the Appendix for the definitions of all other variables. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses. Standard errors are adjusted for clustering at the firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Common ownership and forecast accuracy – The conditional effect of accrual quality, operational complexity, and management forecasts

Dependent Variable =		*ACCURACY*	
	(1)	(2)	(3)
COMMON	0.0110	0.0104	0.0363***
	(1.42)	(1.32)	(3.83)
COMMON × *HIGH_DD*	0.0184*		
	(1.86)		
COMMON × *HIGH_COPX*		0.0220**	
		(2.02)	
COMMON × *MGT_FC*			-0.0394***
			(-3.73)
MGT_FC			0.1121***
			(3.49)
lnNFIRM	0.0442***	0.0399***	0.0393***
	(5.69)	(5.37)	(5.31)
lnIND	-0.0265***	-0.0131	-0.0124
	(-2.91)	(-1.46)	(-1.39)
lnGEXP	-0.0028	-0.0038	-0.0039
	(-0.79)	(-1.09)	(-1.10)
lnFEXP	-0.0225***	-0.0228***	-0.0224***
	(-6.21)	(-6.68)	(-6.57)
lnFREQ	0.3323***	0.3413***	0.3396***
	(23.32)	(26.11)	(25.84)
lnHORIZON	-0.3085***	-0.3162***	-0.3121***
	(-32.53)	(-35.29)	(-34.13)
lnBANALYST	0.0269***	0.0261***	0.0265***
	(2.68)	(2.76)	(2.80)
Firm-year FE	Yes	Yes	Yes
Brokerage FE	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes
Observations	272,282	321,905	321,905
Adjusted R^2	0.792	0.790	0.790

This table reports the regression results on the effect of common ownership on analyst forecast accuracy, conditional on accrual quality, operational complexity, and the availability of management earnings forecasts. The sample period is from 1990 to 2019. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses. Standard errors are adjusted for clustering at the firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 Conference call participation and analysts' effort

Panel A: Common ownership and conference call participation

Dependent Variable =	*ASK_FREQ*
COMMON	0.0119**
	(2.14)
lnNFIRM	-0.2070***
	(-25.03)
lnIND	-0.0247***
	(-3.03)
lnGEXP	-0.0266***
	(-6.70)
lnFEXP	0.0350***
	(7.94)
lnFREQ	0.2508***
	(40.98)
lnHORIZON	-0.0155***
	(-7.73)
lnBANALYST	0.0224**
	(2.45)
lagACCURACY	0.0006
	(0.20)
lagASK_DUM	0.4311***
	(60.87)
CC_OTHER	0.3072***
	(73.97)
lagSBUY	0.1894***
	(10.43)
lagBUY	0.1907***
	(10.07)
lagHOLD	0.0506***
	(2.86)
lagSELL	-0.0405**
	(-2.11)
Firm-year FE	Yes
Brokerage FE	Yes
Cluster by firm	Yes
Observations	88,206
Adjusted R^2	0.557

This table presents the regression results on the effect of common ownership on the frequency of analysts asking questions in conference calls of co-owned firms (*ASK_FREQ*). The sample period is from 2002 to 2019. Please see the Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses. Standard errors are adjusted for clustering at the firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 (cont'd)

Panel B: Common ownership and analyst effort

Dependent Variable =	*lnFREQ*
COMMON	-0.0050**
	(-2.40)
lnNFIRM	0.1697***
	(55.92)
lnIND	-0.0331***
	(-10.02)
lnGEXP	-0.0333***
	(-27.67)
lnFEXP	0.0940***
	(62.10)
lnHORIZON	-0.2179***
	(-137.98)
lnBANALYST	-0.0032
	(-1.07)
Firm-year FE	Yes
Brokerage FE	Yes
Cluster by firm	Yes
Observations	321,905
Adjusted R^2	0.415

This table presents the regression results on the effect of common ownership on analyst forecast frequency. *lnFREQ* is the natural logarithm of one plus the number of the earnings forecasts an analyst issues for the firm during the year. The sample period is from 1990 to 2019. Please see the Appendix for the definitions of all other variables. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses. Standard errors are adjusted for clustering at the firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10 Market reaction to earnings forecast revisions

Dependent Variable =	*CAR (-1,+1)* (1)	*CAR (-2,+2)* (2)
FREV	0.8428***	0.8927***
	(23.34)	(23.26)
COMMON × *FREV*	0.1189***	0.1139***
	(3.09)	(2.75)
COMMON	0.0002	0.0002
	(0.66)	(0.62)
ln*NFIRM*	-0.0005	-0.0007*
	(-1.38)	(-1.82)
ln*IND*	-0.0002	0.0001
	(-0.57)	(0.18)
ln*GEXP*	0.0000	0.0002
	(0.09)	(0.96)
ln*FEXP*	0.0001	0.0000
	(0.46)	(0.18)
ln*FREQ*	-0.0003	-0.0004
	(-0.82)	(-0.87)
ln*HORIZON*	0.0001	0.0002
	(0.49)	(0.64)
ln*BANALYST*	-0.0007	-0.0007
	(-1.57)	(-1.39)
Firm-year FE	Yes	Yes
Brokerage FE	Yes	Yes
Cluster by firm	Yes	Yes
Observations	310,937	310,936
Adjusted R^2	0.390	0.391

This table presents the regression results on the differential market reactions to analysts' forecast revisions issued by connected analysts as opposed to non-connected analysts. The sample period is from 1990 to 2019. Please see the Appendix for the definitions of all other variables. All continuous variables are winsorized at the top and bottom 1% level. Robust *t*-statistics are in parentheses. Standard errors are adjusted for clustering at the firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.