Analyst Team Diversity and Analyst Performance

Xianjie He
Shanghai University of Economics and Finance
Oliver Rui
China Europe International Business School
Shan Wu
China Europe International Business School

Abstract

In this paper, we examine how diversity attributes affect team forecast performance. We find that diversity in general has a positive association with team forecast accuracy. This result is consistent with the idea that team members with different knowledge sets may pay attention to or extract different information about the same stock and thus achieve better performance than a single analyst. We also find that diversity has a negative impact on the timeliness of forecasts. This finding indicates that it takes time for a diversified team to reach an agreement. In addition, we find that diversity is negatively associated with the probability of becoming a star. This finding indicates that a homophilic environment enjoys the benefit of lowering communication cost and improving relationships between team members. Our further tests show that it is mainly cognitive diversity other than demographic diversity that affects team forecast performance.

Keywords: Team diversity; forecast accuracy; timeliness of forecasts; star analysts

Analyst Team Diversity and Analyst Performance

1 Introduction

Given the increasing complexity of the stock market, forecasts by teams of analysts can draw on a wider range of sources and more timely information, and these information advantages are valued by investors (Brown and Hugon (2009)). Therefore, it is important to explore factors that influence team performance. In this paper, we examine how diversity attributes affect team forecast performance.

Teams are an essential way for firms to gain and sustain a competitive advantage in a rapidly changing and highly competitive external environment. Research has examined the relationship between team diversity and team performance in several areas, such as human capital management in general (Han, Han, and Brass (2014), Joshi and Roh (2009) and van Knippenberg and Schippers (2007)), venture capital (Gompers, Mukharlyamov, and Xuan (2016), Hegde and Tumlinson (2014), Hochberg, Lindsey, and Westerfield (2015)) and audit firms (Linden and Knechel (2016)). However, relatively little attention has been paid to teams of sell-side analysts whose work is usually a team work. Sell-side analysts provide us with a rich setting for investigating the impact of diversity on information intermediates in cooperative environments. An analyst team may be able to compile, filter, and analyze information about stocks more efficiently. Team members enjoy the benefits of exchange insights and integrating different sources of information when producing forecasts. However, diversity may also have adverse effects, such as communication problems and coordination issues (Dahlin, Weingart, and Hinds (2005)). In other words, people who share affinities are more likely to work together smoothly (Gompers, Mukharlyamov, and Xuan (2016) and Giannetti et al. (2017)). Therefore, whether and to what extent diversity improves or worsens analyst team performance remains an interesting empirical question.

While it is commonly known that analyst reports a team work, in the U.S., only 10% of analyst reports have multiple authors; in China the figure is 35%, which is more than 3 times of that of U.S. In U.S. culture, single-author reports are more common, although stock or industry research is a team effort. The analyst who made the biggest contribution is listed as a report's author in the U.S. This cultural difference is identified by Hofstede (1980 and 2001), who bases his cross-cultural comparisons on the contrast between individualism versus collectivism. Following this theory, most of the literature finds that Eastern countries (e.g., China and Korea) have high collectivism scores, whereas Western countries (e.g., the U.S. and U.K.) favor individualism (Aaker and Lee (2001), Hofstede and Minkov (2010), House, Quigley, and de Luque (2010), Manrai and Manrai (2011), and Yoo, Donthu, and Lenartowicz (2011)). These studies explain why U.S. analyst reports tend to have a single author name, while Chinese analyst reports tend to list the names of all team members. The personal background information of analysts is disclosed in China. The unique dataset enables us to identify the diversity among team members and to examine the effects of diversity on team performance.

We begin by examining the relationship between analysts' earnings forecast accuracy and team aggregated diversity. Studies on the role of diversity in cooperative environments have focused on one or two particular diversity factors (e.g., Gompers, Mukharlyamov, and Xuan (2016) and Brochet et al. (2016)). In this paper, we aggregate nine diversity attributes at both the demographic level and cognitive level. Demographic diversity captures affinities such as place of birth, age and gender. Cognitive diversity is defined as the extent to which the group reflects differences in knowledge, including beliefs, ideas, viewpoints, opinions, assumptions, preferences and perspectives. It is measured by experience and educational background. This approach enables us to examine the overall impact of diversity on team performance over different dimensions. Our main analyses examine regression of forecast accuracy on the aggregate diversity attributes. We find that diversity in general has a positive association with team forecast accuracy. This result is consistent with the idea that team members with different knowledge sets may pay attention to or gather and analyze different information about the same stock and thus achieve better performance than a single analyst.

Our second measure on team performance is forecast timeliness because prior studies document a trade-off between forecast accuracy and timeliness. Our empirical result shows that diversity has a negative impact on the timeliness of forecasts. This finding indicates that it takes time for a diversified team to reach an agreement. A heterogeneous team benefits from broader information and different perspectives, but integrating information and reaching conclusions becomes time-consuming. This shows that a diversified analyst team has advantage over information analysis, rather than information propagation (Livnat and Zhang (2012)). In order to completely evaluate team effort, we take into account the characteristics of lead analysts at the demographic and cognitive levels. Our finding is robust to the inclusion of firm and year fixed effects.

Gaining star status is very important to careers in investment banking (Krigman, Shaw, and Womack (2001)). Such social recognition makes star analysts more influential and earn much more than non-star analysts (Fang and Peress (2009)). We therefore examine the impact of aggregated diversity on the probability of becoming a star analyst. After controlling for forecast accuracy, we find that diversity is negatively associated with the probability of becoming a star analyst. This finding indicates that a homophilic environment enjoys the benefit of lowering communication cost and improving relationships between team members (McPherson, Smith-Lovin, and Cook (2001)). Therefore, an affinitive group may be better able to convey tacit information or make joint decisions in a timely and productive fashion. These advantages are greatly valued by investors, especially those institutional investors who vote in star analyst elections.

Diversity can be decomposed into demographic and cognitive levels (Harrison and Klein (2007)). Therefore, we investigate which dimension of diversity has a greater effect on team analyst performance. We find it is mainly cognitive diversity that plays a more pronounced role in influencing team forecast performance. Of the six diversity attributes on the cognitive level, we show that groups with working experience diversity, college major diversity, and college nature diversity and that are newly formed have higher forecast accuracy. However, the opposite is true for becoming a star analyst, after controlling for forecast accuracy. That is, affinity helps team members become star analysts. This is consistent with Emery and Li (2009), who show that star status is largely a "popularity contest." They find that social recognition is important for obtaining this award. That is, a potential star analyst must stand out through support from users of analyst reports. For a team possessing similar characteristics and backgrounds, team members tend to interact and bond well with each other and reach the same opinion (Gompers, Mukharlyamov, and Xuan (2016)). Due to homophily, team members tend to support the potential star analyst by reaching the same conclusion about a stock when communicating with institutional investors or the media.

Our paper makes the following contributions to the literature. First, it provides a nuanced view of team diversity on team performance in cooperative environments. Finance and economics research has examined the impact of team diversity on bank loans, venture capital, and auditing (Downar, Ernstberger, and Koch (2016), Gompers, Mukharlyamov, and Xuan (2016)), Linden and Knechel (2016), Giannetti and Yafeh (2012) and Cannella, Park, and Lee (2008)). We shed light on how diversity affects the team performance of sell-side analysts in this paper because they are important information intermediaries to improve the efficiency of capital markets.

Second, to the best of our knowledge, our paper is the first to examine nine diversity factors at both demographic and cognitive levels. Studies have focused on only one or a few factors, such as gender, education background, ethnicity, or culture (Zimmerman and Brouthers (2012), Bradley, Gokkaya, and Liu (2015), Gompers et al., (2016), and Merkley, Michaely, and Pacelli (2017)).

Third, our study has practical implications for investors and analysts. For investors who rely on analyst research to form their earnings expectations and develop their own target price or stock recommendations, it is better to choose team members with diversified profiles because they are more accurate in earnings forecasts. By contrast, for investors who prefer the information discovery role rather than information interpretation from an analyst team, it is better to choose less diversified teams, as these teams tend to issue more timely reports. Analysts who are concerned about their careers should be aware they are more likely to become stars in a homophilic environment.

The remainder of this paper proceeds as follows. Section 2 reviews the literature on team diversity and develops the hypotheses. Section 3 introduces the data and methodology. Section 4 presents our empirical results and discussion. Section 5 provides a summary and conclusions.

2 Literature Review and Hypotheses Development

Extensive research has shown that earnings forecast accuracy is one of the most important outputs from financial analysts (Clement (1999), Clement and Tse (2003), Hall and Tacon (2010), Dechow and You (2012), Walther and Willis (2013) and Rees, Sharp, and Twedt (2015)). Investors' response to forecast revisions increases with the expected accuracy (Gleason and Lee (2003)). Therefore, we first examine the overall effect of diversity on team forecast accuracy.

Diversity is the differences in group members with respect to a particular attribute (Harrison and Klein (2007)). Diversity can be beneficial to cooperation, but also may cause disharmony. Studies have shown that people are more likely to get along with others from similar backgrounds (Ingram and Roberts (2000), Mcpherson, Smith-Lovin, and Cook (2001) and Gompers, Mukharlyamov, and Xuan (2016)). Reagans, Zuckerman, and McEvily (2004) find that internal density has a positive effect on team performance. Internal density (i.e., solid network connections) occurs more frequently with people who share similar backgrounds (Byrne (1971); Brass (1985); Galaskiewicz, Blau, and Schwartz (1986); Zenger and Lawrence (1989); Ely (1994) and Mcpherson, Smith-Lovin, and Cook (2001)). Similarly, Williams and O'Reilly (1998) predict that dissimilarities among team members may give rise to adverse social categorization processes that impair team functioning. Hence, it is worth empirically testing whether the benefits of team diversity outweigh the disadvantages in terms of team forecast performance.

However, other studies have demonstrated the positive impact of team diversity on organizations. Both decision-making theory (Talke, Salomo, and Rost (2010)) and social network theory (Burt (1992)) show that diversified groups have more task-related knowledge and broader social networks. This heterogeneous interaction environment can generate innovative ideas that differentiate the group from others (Cheng, Luckett, and Schulz (2003)). Moreover, Schilpzand and Martins (2010) find that diversified groups pay attention to different perspectives and share their unique knowledge. Team members from different backgrounds can reach different constituencies outside the team (Reagans, Zuckerman, and McEvily (2004)). In terms of the analyst literature, Soltes (2014) and Huang, Zang, and Zheng (2014) find that investors view private or unique information disclosed in analyst reports as extremely valuable. Gompers, Mukharlyamov, and Xuan (2016) show that venture capital partners who are less diversified tend to have a lower investment success rate. These findings lead us to make the following hypothesis.

Hypothesis 1A The diversity of analyst teams is positively correlated with team forecast accuracy.

The team diversity literature has two main lines, one examining demographic diversity (Jackson and Joshi (2004); Harrison and Klein (2007); Schilpzand and Martins (2010); Zimmerman and Brouthers (2012)) and the other examining cognitive diversity (Jehn, Northcraft, and Neale (1999); Pelled, Eisenhardt, and Xin (1999); Jackson and Joshi (2004); Shin et al. (2012); Liao and Long (2016)). Diversity at the demographic level demonstrates affinities among team members, while diversity at the cognitive level focuses on knowledge-related differences.

Teams with cognitive heterogeneity can achieve better performance (Shin et al. (2012)). Schilpzand and Martins (2010) conclude that cognitively diversified teams have larger knowledge sets and better knowledge processing and integration skills. Liao and Long (2016) show that cognitive team diversity is positively related to individual team member creativity. Demographic diversity may also lead to differences in team performance (e.g., Bunderson and Sutcliffe, 2002; Pelled, Eisenhardt, and Xin, 1999; Jackson and Joshi, 2004; Zimmerman and Brouthers, 2012). However, empirical studies of the relationship between demographic heterogeneity and team performance have been disappointing, and meta-analytic results have failed to demonstrate such a relationship. Accurate forecasts benefit from different thinking styles, knowledge, creativity, and skills, which come from cognitive differences. Therefore, cognitive diversity among team members could play a more profound role in forecast accuracy than demographic diversity. This conjecture leads us to make the following hypothesis.

Hypothesis 1B Analyst teams' diversity at the cognitive level is positively correlated team forecast accuracy.

Following the diversity literature (Kearney, Gebert, and Voelpel (2009), Gul, Wu, and Yang (2013), van Knippenberg and Schippers (2007), and Zimmerman and Brouthers (2012)), we measure diversity attributes using nine factors, three at the demographic level (place of birth, age, and gender) and six at the cognitive level (working experience, foreign education, major, college, team working years, and prior employers).

Second, we adopt forecast timeliness to assess analyst performance. Cooper, Day, and Lewis (2001) find that analyst performance rankings based on timeliness are more informative than rankings based on forecast accuracy. Livnat and Zhang (2012) show that timely revisions are more likely to perform an information transmission role, while non-timely revisions are more likely to have an information discovery/analysis role. Investors who are eager for prompt information prefer timely reports (Brown and Hugon (2009)). However, investors who are interested in information interpretation, or who invest in stocks with great complexity, demand reports that offer thorough stock assessments even if they are not prompt. Diversified teams enjoy higher accuracy due to the comprehensive processing and integration of knowledge, but it takes time. Different opinions and thinking styles could require analysts to engage in lengthier discussion to reach agreement in their forecasts. Team diversity motivates members to incorporate new knowledge and interpret unfamiliar information, which increases processing time. Thus, there could be a trade-off between forecast accuracy and timeliness (Brown and Hugon (2009)). As argued before, we believe that cognitive diversity among team members plays a more pronounced role in forecast timeliness. We therefore make the following hypotheses.

Hypothesis 2A Diversity factors are negatively correlated with team forecast timeliness.

Hypothesis 2B Analyst teams' diversity at the cognitive level is negatively correlated with team forecast timeliness.

Lastly, analyst star status is greatly valued by investors, analysts themselves, and brokerage houses. Star analysts have more power to influence the market (Fang and Peress (2009) and Kerl and Ohlert (2015)) and their opinions are disseminated more broadly due to extensive media coverage (Bonner, Hugon, and Walther (2007) and Groysberg, Lee, and Nanda (2008)). Furthermore, star awards increase analysts' reputation and lead to high compensation and greater career path (Emery and Li (2009) and Fang and Yasuda (2009)). Team plays an important role in the star analyst forecast ability. Groysberg, Lee, and Nanda (2008) and Groysberg and Lee (2009) show that star analysts who move with their teams perform better than stars who move alone. Therefore, we investigate the role of team diversity in analysts' star status as well.

Team diversity could potentially be beneficial to become stars. Fang and Yasuda (2014) and Kerl and Ohlert (2015) find that star analysts enjoy higher forecast accuracy than non-stars. Heterogeneous team provides members with different sources of information and pay attention to different aspects of the same stock. These advantages of team diversity lead to higher accuracy and thus higher probability to become stars.

On the other side, Emery and Li (2009) and Hall and Tacon (2010) find that social recognition is the determinant for being elected as a star, as the analyst's opinion needs to be confirmed and disseminated widely by her team members. Therefore, team harmony is important for becoming a star analyst. The homophily literature shows that people who share similarities are more likely to bond well (Currarini, Jackson, and Pin (2009)). Smith-Lovin and Cook (2001) find that solid network connections occur more frequently between people sharing the similar backgrounds. In a heterogeneous environment, people tend to compare their opinions with those of others, according to social comparison theory. Such a comparison is detrimental to interaction and cohesion between team members under certain conditions (Suls and Wheeler, 2012). This leads us to make the following hypotheses.

Hypothesis 3A The diversity of analyst teams is negatively correlated with the star status of team members.

Hypothesis 3B Analyst teams' diversity at the cognitive level has a negative impact on the star status of team members.

3 Data and Methodology

3.1 Sample of team analysts

Our data were collected from the Chinese Research Data Services Platform (CNRDS), Stock Market and Accounting Research (CSMAR), and WIND. They were drawn from a pool of Chinese listed firms from 2000 to 2015. The dataset includes 3,020 firms. There are 824,405 observations per annual forecast per firm. Among them, 35% of the analyst reports are of multiple authors. This figure for U.S. analyst reports is around 10%. The much higher proportion of co-authorship in analyst reports from the Chinese market enables us to better understand the impact of team diversification on forecast performance. Among the multi-author analyst report sample, 74% have two analysts, 22.7% have three analysts, 2.9% have four analysts, and 0.25% have five analysts. Therefore, we only include analyst teams with two or three analysts, which accounts for 97% of all analyst teams.

3.2 Dependent variables

As developed in the hypotheses section, we adopt three measures to capture team performance: EPS forecast accuracy, forecast timeliness and change of star analyst status within the team.

3.2.1. Measure of EPS forecast accuracy ($accuracy_{ijt}$)

Analyst forecast accuracy ($accuracy_{ijt}$) is defined as the maximum absolute forecast errors for analysts following firm *j* in year *t*, minus the absolute forecast errors for analyst *i* following firm *j* in year *t*, scaled by the difference between the maximum and minimum absolute forecast errors for analysts following firm *j* in year *t*. By definition, accuracy is bounded from 0 (for the least accurate forecast) to 1 (for the most accurate forecast) for easy comparison between different firms and industries (Clement and Tse (2003))[1].

$$accuracy_{ijt} = \frac{AFE\max_{jt} - AFE_{ijt}}{AFE\max_{jt} - AFE\min_{jt}}$$

$$AFE_{ijt} = \left| ForecastedEPS_{ijt} - ActualEPS_{jt} \right|$$

3.2.2. Measure of timeliness ($timeliness_{ijt}$)

Following Brown and Hugon (2009), we measure forecast timeliness as follows:

$$timeliness_{ijt} = \frac{T_0}{T_1}$$

where T_0 is the number of days between the preceding forecast and the current forecast, and T_1 is the number of days between the subsequent and current forecasts. A higher value of $timeliness_{ijt}$ represents more prompt forecast revisions. Consistent with other dependent variables, this calculation of timeliness has been adjusted for time and company differences.

3.2.3. Measure of the change of star status ($deltaSTAR_{it}$)

Apart from forecast accuracy and timeliness, being elected a star analyst exerts a great influence in the market as well as within brokerage houses (Leone and Wu (2007) and Emery and Li (2009)). Star analyst awards are given by *New Fortune* magazine in China, which is similar to *Institutional Investor* magazine and *the Wall Street Journal* in American star analysts awards. With 18 years of star analysts' election, *New Fortune* magazine is the most

[1] There are different ways of measuring forecast accuracy. The relative forecast accuracy measure we adopt here is commonly used. The transformation is also adopted in all other control variables, which preserves the relative distances among each characteristic's measures for firm *j* in year *t*. This allows comparisons of regression model coefficients.

influential entity for Chinese all-star analyst awards. Analysts are assessed according to their industry knowledge, written reports, stock recommendations, earnings estimations, timely communication with investors, responsiveness to investor requests, etc. To capture the impact of the team diversity on an individual member's becoming a star analyst, we focus on analysts who are non-stars in the current year. The team should have more influence on junior non-star analysts than star analysts in terms of their star status.

Following Leone and Wu (2007), STAR equals one if at least one of the team members is chosen as a star analyst, and zero otherwise. We measure the change of star status between the current year and the following two years, as it takes several years for the team to influence the change in star status. That is, $deltaSTAR_{it}$ equals one if at least one team member's star status changes from 0 (in year *t*) to 1 (in year *t+1* or year *t+2*), and zero otherwise.

3.3 Research design: team forecast accuracy

To test our **H1A** that diversity has positive impact on team forecast accuracy, we estimate the following cross-sectional regression.

$$
\begin{aligned}
accuracy_{ijt} &= \beta_0 + \beta_1 diversity_{ijt} + \beta_2 fr_{ijt} + \beta_3 fh_{ijt} + \beta_4 Num\_Ind_{it} + \beta_5 Num\_Co_{it} \\
&+ \beta_6 Num\_Ana_{ijt} + \beta_7 \log Follow_{jt} + \beta_8 \log MV_{jt} + \beta_9 \log BTM_{jt} + \beta_{10} gender_{ijt} \\
&+ \beta_{11} born_{ijt} + \beta_{12} age_{ijt} + \beta_{13} experience_{ijt} + \beta_{14} major_{ijt} + \beta_{15} accounting_{ijt} \\
&+ \beta_{16} catgri_{ijt} + \beta_{17} accountancy_{ijt} + \beta_{18} foreign_{ijt} + \beta_{19} star_{ijt} + \beta_{20} topUni_{ijt} \\
&+ \beta_{21} Year\_F.E + \beta_{22} Industry\_F.E + \varepsilon_{ijt}
\end{aligned}
$$

Where *diversity* is a measure of aggregated diversity, as the average of demographic diversity and cognitive diversity. Demographic diversity is the average of *birthplace diversity, gender diversity,* and *age diversity* (Zimmerman and Brouthers (2012)). Cognitive diversity is the average of *experience diversity, school diversity, group diversity, employer diversity,* and *foreign diversity (*Kearney, Gebert, and Voelpel (2009)). To isolate the effect of individual ability from team effect, we control for lead analysts characteristics. Consistent with prior analyst studies (Richardson, Teoh, and Wysocki (2004)), we also control for firm characteristics and forecast characteristics. Following Clement and Tse (2005), we only include the last forecast revisions per analyst team per company per year. Year and industry fixed effects are included with robust standard errors. All of the control variables are defined in detail in the next section.

To test **H1B**, we investigate the impact of demographic diversity and cognitive diversity on team forecast accuracy separately.

$$
\begin{aligned}
accuracy_{ijt} &= \beta_0 + \beta_1 demo\_div_{ijt} + \beta_2 cog\_div_{ijt} + \beta_3 fr_{ijt} + \beta_4 fh_{ijt} + \beta_5 Num\_Ind_{it} \\
&+ \beta_6 Num\_Co_{it} + \beta_7 Num\_Ana_{ijt} + \beta_8 \log Follow_{jt} + \beta_9 \log MV_{jt} + \beta_{10} \log BTM_{jt} \\
&+ \beta_{11} gender_{ijt} + \beta_{12} born_{ijt} + \beta_{13} age_{ijt} + \beta_{14} experience_{ijt} + \beta_{15} major_{ijt} + \beta_{16} accounting_{ijt} \\
&+ \beta_{17} catgri_{ijt} + \beta_{18} accountancy_{ijt} + \beta_{19} foreign_{ijt} + \beta_{20} star_{ijt} + \beta_{21} topUni_{ijt} + \beta_{22} Year\_F.E \\
&+ \beta_{23} Industry\_F.E + \varepsilon_{ijt}
\end{aligned}
$$

Finally, we explore the impact of nine diversity attributes on team performance. Different types of diversity have different effects on group behavior (Williams and O'Reilly (1998) and Dahlin, Weingart, and Hinds (2005)). Research has focused on one or two diversity factors. Gender diversity has been shown to be beneficial in different dimensions of cooperation management and performance. For example, McGuinness, Vieito, and Wang (2017) conclude that gender diversity on boards is positively correlated with corporate social responsibility performance. At the cognitive level, Shin and Zhou (2007) find that educational diversity is positively related to team creativity. Dahlin, Weingart, and Hinds (2005) show a curvilinear relationship between national diversity and the range of information use. Gompers, Mukharlyamov, and Xuan (2016) conclude that venture capitalists are more willing to syndicate with people with similar career backgrounds, but these groups have a low investment success rate. Thus, we investigate the relationship between each attribute of diversity and team performance in the following model.

$$
\begin{aligned}
accuracy_{ijt} &= \beta_0 + \beta_1 genderDiv_{ijt} + \beta_2 bornDiv_{ijt} + \beta_3 ageDiv_{ijt} + \beta_4 \exp Div_{ijt} + \beta_5 majorDiv_{it} \\
&+ \beta_6 catgriDiv_{it} + \beta_7 groupDiv_{ijt} + \beta_8 employDiv_{jt} + \beta_9 foreignDiv_{jt} + + \beta_{10} gender_{ijt} \\
&+ \beta_{11} born_{ijt} + \beta_{12} age_{ijt} + \beta_{13} \exp erience_{ijt} + \beta_{14} major_{ijt} + \beta_{15} accounting_{ijt} + \beta_{16} catgri_{ijt} \\
&+ \beta_{17} accoun\tan cy_{ijt} + \beta_{18} foreign_{ijt} + \beta_{19} star_{ijt} + \beta_{20} topUni_{ijt} + \beta_{21} fr_{ijt} + \beta_{22} fh_{ijt} + \beta_{23} Num\_Ind_{it} \\
&+ \beta_{24} Num\_Co_{it} + \beta_{25} Num\_Ana_{ijt} + \beta_{26} \log Follow_{jt} + \beta_{27} \log MV_{jt} + \beta_{28} \log BTM_{jt} \\
&+ \beta_{29} Year\_F.E + \beta_{30} Industry\_F.E + \varepsilon_{ijt}
\end{aligned}
$$

3.4 Research design: timeliness of team forecast reports

To test **H2A** that diversity has a negative impact on team forecast timeliness, we estimate the following cross-sectional regression. $timeliness_{ijt}$ measures the promptness of analyst forecasts. Due to how timeliness is calculated, the first and last forecasts for every firm are dropped. Year and industry fixed effects are included with robust standard errors. Variable definitions are provided in detail in the next section.

$$
\begin{aligned}
timeliness_{ijt} &= \beta_0 + \beta_1 diversity_{ijt} + \beta_2 fr_{ijt} + \beta_3 fh_{ijt} + \beta_4 Num\_Ind_{it} + \beta_5 Num\_Co_{it} \\
&+ \beta_6 Num\_Ana_{ijt} + \beta_7 \log Follow_{jt} + \beta_8 \log MV_{jt} + \beta_9 \log BTM_{jt} + \beta_{10} gender_{ijt} \\
&+ \beta_{11} born_{ijt} + \beta_{12} age_{ijt} + \beta_{13} \exp erience_{ijt} + \beta_{14} major_{ijt} + \beta_{15} accounting_{ijt} \\
&+ \beta_{16} catgri_{ijt} + \beta_{17} accoun\tan cy_{ijt} + \beta_{18} foreign_{ijt} + \beta_{19} star_{ijt} + \beta_{20} topUni_{ijt} \\
&+ \beta_{21} Year\_F.E + \beta_{22} Industry\_F.E + \varepsilon_{ijt}
\end{aligned}
$$

To test **H2B**, we investigate the impact of demographic diversity and cognitive diversity on team forecast timeliness separately. Year and industry fixed effects are included with robust standard errors. Variable definitions are provided in detail in the next section.

$$
\begin{aligned}
timeliness_{ijt} &= \beta_0 + \beta_1 demo\_div_{ijt} + \beta_2 cog\_div_{ijt} + \beta_3 fr_{ijt} + \beta_4 fh_{ijt} + \beta_5 Num\_Ind_{it} \\
&+ \beta_6 Num\_Co_{it} + \beta_7 Num\_Ana_{ijt} + \beta_8 \log Follow_{jt} + \beta_9 \log MV_{jt} + \beta_{10} \log BTM_{jt} \\
&+ \beta_{11} gender_{ijt} + \beta_{12} born_{ijt} + \beta_{13} age_{ijt} + \beta_{14} \exp erience_{ijt} + \beta_{15} major_{ijt} + \beta_{16} accounting_{ijt} \\
&+ \beta_{17} catgri_{ijt} + \beta_{18} accoun\tan cy_{ijt} + \beta_{19} foreign_{ijt} + \beta_{20} star_{ijt} + \beta_{21} topUni_{ijt} + \beta_{22} Year\_F.E \\
&+ \beta_{23} Industry\_F.E + \varepsilon_{ijt}
\end{aligned}
$$

We further decompose demographic and cognitive diversity into nine factors. This allowed us to examine the association between individual diversity attributes and team forecast timeliness.

$$\begin{aligned} timeliness_{ijt} &= \beta_0 + \beta_1 genderDiv_{ijt} + \beta_2 bornDiv_{ijt} + \beta_3 ageDiv_{ijt} + \beta_4 \exp Div_{ijt} + \beta_5 majorDiv_{it} \\ &+ \beta_6 catgriDiv_{it} + \beta_7 groupDiv_{ijt} + \beta_8 employDiv_{jt} + \beta_9 foreignDiv_{jt} + +\beta_{10} gender_{ijt} \\ &+ \beta_{11} born_{ijt} + \beta_{12} age_{ijt} + \beta_{13} \exp erience_{ijt} + \beta_{14} major_{ijt} + \beta_{15} accounting_{ijt} + \beta_{16} catgri_{ijt} \\ &+ \beta_{17} accoun\tan cy_{ijt} + \beta_{18} foreign_{ijt} + \beta_{19} star_{ijt} + \beta_{20} topUni_{ijt} + \beta_{21} fr_{ijt} + \beta_{22} fh_{ijt} + \beta_{23} Num\_Ind_{it} \\ &+ \beta_{24} Num\_Co_{it} + \beta_{25} Num\_Ana_{ijt} + \beta_{26} \log Follow_{jt} + \beta_{27} \log MV_{jt} + \beta_{28} \log BTM_{jt} \\ &+ \beta_{29} Year\_F.E + \beta_{30} Industry\_F.E + \varepsilon_{ijt} \end{aligned}$$

3.5 Research design: change of star status

To test **H3a** that diversity has a negative impact on team star status, we estimate the following cross-sectional regression. *deltaSTAR* is the change of star status between the current year and following two years. *diversity* is a measure of aggregated diversity as the average of demographic diversity and cognitive diversity. $accuracy_{ij}$ is the average forecast accuracy of team *i* in year *t*. For each analyst team, we calculate the average value of each characteristic, so one observation per analyst team per year is retained. Year and industry fixed effects are included with robust standard errors. Variable definitions are given in detail in the next section.

$$\begin{aligned} deltaSTAR_{ijt} &= \beta_0 + \beta_1 diversity_{ijt} + \beta_2 accuracy_{it} + \beta_3 fr_{it} + \beta_4 fh_{ijt} + \beta_5 Num\_Ind_{it} \\ &+ \beta_6 Num\_Co_{it} + \beta_7 Num\_Ana_{ijt} + \beta_8 \log MV_{jt} + \beta_9 \log BTM_{jt} + \beta_{10} gender_{ijt} \\ &+ \beta_{11} born_{ijt} + \beta_{12} age_{ijt} + \beta_{13} \exp erience_{ijt} + \beta_{14} major_{ijt} + \beta_{15} accounting_{ijt} \\ &+ \beta_{16} catgri_{ijt} + \beta_{17} accoun\tan cy_{ijt} + \beta_{18} foreign_{ijt} + \beta_{19} topUni_{ijt} + \beta_{20} Year\_F.E \\ &+ \beta_{21} Industry\_F.E + \varepsilon_{ijt} \end{aligned}$$

To test **H3b** (that the impact of demographic and cognitive diversity separately), we estimate the following models:

$$\begin{aligned} deltaSTAR_{ijt} &= \beta_0 + \beta_1 demo\_div_{ijt} + \beta_2 cog\_div_{ijt} + \beta_3 accuracy_{it} + \beta_4 fr_{it} + \beta_5 fh_{ijt} \\ &+ \beta_6 Num\_Ind_{it} + \beta_7 Num\_Co_{it} + \beta_8 Num\_Ana_{ijt} + \beta_9 \log MV_{jt} + \beta_{10} \log BTM_{jt} \\ &+ \beta_{11} gender_{ijt} + \beta_{12} born_{ijt} + \beta_{13} age_{ijt} + \beta_{14} \exp erience_{ijt} + \beta_{15} major_{ijt} + \beta_{16} accounting_{ijt} \\ &+ \beta_{17} catgri_{ijt} + \beta_{18} accoun\tan cy_{ijt} + \beta_{19} foreign_{ijt} + \beta_{20} topUni_{ijt} + \beta_{21} Year\_F.E \\ &+ \beta_{22} Industry\_F.E + \varepsilon_{ijt} \end{aligned}$$

$$
\begin{aligned}
deltaSTAR_{ijt} &= \beta_0 + \beta_1 genderDiv_{ijt} + \beta_2 bornDiv_{ijt} + \beta_3 ageDiv_{ijt} + \beta_4 \exp Div_{ijt} + \beta_5 majorDiv_{it} \\
&+ \beta_6 catgriDiv_{it} + \beta_7 groupDiv_{ijt} + \beta_8 employDiv_{jt} + \beta_9 foreignDiv_{jt} + \beta_{10} accuracy_{it} + \beta_{11} fr_{it} \\
&+ \beta_{12} fh_{ijt} + \beta_{13} Num\_Ind_{it} + \beta_{14} Num\_Co_{it} + \beta_{15} Num\_Ana_{ijt} + \beta_{16} \log MV_{jt} + \beta_{17} \log BTM_{jt} \\
&+ \beta_{18} gender_{ijt} + \beta_{19} born_{ijt} + \beta_{20} age_{ijt} + \beta_{21} \exp erience_{ijt} + \beta_{22} major_{ijt} + \beta_{23} accounting_{ijt} \\
&+ \beta_{24} catgri_{ijt} + \beta_{25} accoun\tan cy_{ijt} + \beta_{26} foreign_{ijt} + \beta_{27} topUni_{ijt} + \beta_{28} Year\_F.E \\
&+ \beta_{29} Industry\_F.E + \varepsilon_{ijt}
\end{aligned}
$$

3.6 Demographic diversity

Demographic diversity at the aggregated level is the average of *gender diversity*, *birthplace diversity* and *age diversity* (Jackson and Joshi (2004); van Knippenberg and Schippers (2007) and Zimmerman and Brouthers (2012)). *Gender diversity* is an indicator variable equal to one if team members have different genders and zero otherwise. *Birthplace diversity* is an indicator variable equal to one if team members were born in different provinces and zero otherwise. *Age diversity* is a measure of the age gap between team members, which equals one if the age difference is greater or equal to five years and zero otherwise. For teams with three analysts, we categorize the participants by five-year increments (i.e., 26-30, 31-35, 36-40, etc.). *Age diversity* is then measured by $1-\Sigma P^2_i$, where P_i is the portion of a team's members in the *i*th category.

3.7 Measures of cognitive diversity

Cognitive diversity at the aggregated level is the average of *experience diversity*, *major diversity*, *school diversity*, *group diversity*, *employer diversity*, and *foreign diversity* (Kearney, Gebert, and Voelpel (2009), Cohen, Frazzini, and Malloy (2010), Gul, Wu, and Yang (2013) and Gompers, Mukharlyamov, and Xuan (2016)). *Experience diversity* is the measure of working years difference, which equals one if the difference of number of working years between team analysts is greater or equal to five years and zero otherwise. For three-analyst groups, we categorize participants by five-year increments (i.e., 0-5, 6-10, 11-15, etc.). *Age* *diversity* is then measured by $1-\Sigma P^2_i$, where P_i is the portion of a team's members in the *i*th category. *Major diversity* is a measure of the difference in majors of team members, which equals one if their college majors were different and zero otherwise. *School diversity* is a measure of the nature of the universities. There are 14 types of universities: comprehensive, business, polytechnic, normal, language, politics, ethnicity, agriculture, medicine, arts, sports, liberal arts, and TAFE (Technical and Further Education). The variable equals one if the categories of their graduation universities are different and zero otherwise. *Group diversity* is a measure of team affinity, which equals one if the members have worked as a team for less than three years and zero otherwise. *Employer diversity* is a measure of difference in prior employers among team members, which equals one if they did not share the same prior employer and zero otherwise. *Foreign diversity* is the measure of foreign education experience of lead analysts, which equals one if the lead analyst has foreign education experience and zero otherwise.

3.8 Control variables

Following the literature on analyst forecasts and social diversification (Clement and Tse (2003), Lehavy, Li, and Merkley (2011) and Walther and Willis (2013); Bonner, Hugon, and Walther (2007); Brown and Hugon (2009); Datta, Iskandar-Datta, and Sharma (2011); Loughran and Mcdonald (2014); Reagans, Zuckerman, and McEvily (2004) and Huang and Wright (2015)), we include the following variables to control for analysts' characteristics and portfolio complexities.

3.8.1 Analyst characteristic proxies

We include the following five analyst characteristics: forecast horizon, number of forecast revisions, number of companies followed, number of industries following, and number of analysts working in a brokerage house.

Forecast horizon is the number of days between analyst *i*'s estimation and firm *j*'s earnings announcement in year *t*. Forecast horizon is different from one of the dependent variables: timeliness. Forecast horizon measures how close the report date is to the earnings announcement date, while forecast timeliness measures how prompt analysts revise their forecasts based on new information. (Brown and Hugon (2009)). Clement and Tse (2005) include the number of revisions on firm *j* written by analyst *i* in year *t*. It is reasonable to argue that an analyst revises a report because she acquires valuable information that turns out to be inconsistent with her earlier conclusions. Therefore, higher accuracy is expected for the analysts with higher forecast frequency. Following the methodology of Clement and Tse (2005), we measure the number of firms followed by counting firm tickers for which analysts issued forecasts. The measure of the number of industries analyst *i* follows in year *t* is calculated as the number of industries followed by analyst *i* following firm *j* in year *t* minus the average number of industries followed by analysts who followed firm *j* in year *t*, with this difference scaled by the average number of industries followed by analysts following firm *j* in year *t*.[2] Num_Ana_{ijt} is a proxy for brokerage house size. It is calculated as the number of analysts in the brokerage house. Large brokerage houses tend to have better access to resources.

3.8.2 Proxy for portfolio complexities

We further use firm size and the book-to-market ratio to capture portfolio complexities. Larger firms have more complex businesses and higher variation than smaller ones. Therefore, following Kothari, Li, and Short (2009), firm size $Ln(MV)_{jt}$ is incorporated as the natural log of firm *j*'s market value at the end of year *t*. Book-to-market ratio is a proxy for the growth or riskiness of the firm. Growth firms have more unrecorded, intangible assets

[2] The industry classification is based on the CSRC industry code.

whose valuation depends heavily on future profitability. $Ln(BTM)_{jt}$ is the natural log of the ratio of book value of equity to market value of firm *j* at the end of year *t*.

4 Results and Discussion

4.1 Descriptive statistics

We report descriptive statistics in Table 1. Panel A presents standardized variables. For consistency and comparability among the variables, they are standardized between zero and one. *ageDiv* and *expDiv* are exceptions, as age and amount of experience are continuous variables. We follow Kearney, Gebert, and Voelpel (2009) to calculate team diversity. Chinese analysts have similar forecast characteristics to U.S. analysts, such as forecast accuracy, horizon, revisions, and number of industries followed. Panel B shows the distribution of raw data. Chinese analysts tend to have less working experience as analysts than their U.S. counterparts (Clement and Tse (2005)), because sell-side analysts are a relatively new career in China. In terms of brokerage house size, the average number of analysts per house is 106, while that in the U.S. is 30. Consequently, Chinese analysts follow fewer stocks (mean=12.7) and industries (mean=3.5) than U.S. analysts.

[Insert Table 1 around here]

We report the correlations between forecast performance and diversity factors in Panel C. Forecast accuracy is positively correlated with aggregated and demographic diversity. No single diversity factor is significantly correlated with any other, indicating the independence of each measure of diversity. Consistent with Clement and Tse (2003), accuracy is negatively correlated with forecast horizon and positively correlated with forecast revisions. In addition, accuracy is positively correlated with number of companies followed and number of analysts following the company and negatively correlated with book-to-market size, which is consistent with Horton, Serafeim, and Wu (2017).

4.2 Team diversity and forecast accuracy

We report the results on team diversity and forecast accuracy in Table 2. This table presents estimates of Eq. (1), where the dependent variable is aggregated diversity. Column (1) controls for firm and analyst characteristics, following the analyst literature (Horton, Serafeim, and Wu (2017)). Column (2) adds control variables for lead analysts' characteristics. By doing so, we disentangle team effort from individual ability. Column (3) includes year and industry characteristics to take year and industry variations into consideration. The coefficient on *diversity* is positive and significant in all three columns, indicating that overall, diversity is positively correlated with team forecast accuracy. This result shows that a diversified analyst team has benefits in terms of forecast accuracy that overcome the disadvantages of diversity. This finding is consistent with the diversity literature (Schilpzand and Martins (2010)).

[Insert Table 2 around here]

Among the standardized control variables, the coefficient estimates for forecast horizon and number of industries followed are negative and significantly different from zero, which is consistent with Clement and Tse (2003). The coefficient on number of analysts following a company is negatively significant, which is consistent with Horton, Serafeim, and Wu (2017). The coefficient on number of companies followed is positively significant, which differs from Clement and Tse (2003). As stated earlier, Chinese analysts tend to follow fewer industries. That is to say, the stocks they follow tend to be in the same industry. Therefore, we observe a positive relationship between the size of coverage portfolio and forecast accuracy. The coefficient on brokerage house size is negative and statistically significant. As indicated in Table 1, there are many state-owned brokerage houses with a large number of employees in China. Their research departments are normally quite new, and the analysts are less experienced. Therefore, we observe lower forecast accuracy in these larger state-owned brokerage houses.

In Table 3, we separate aggregated diversity into the demographic and cognitive levels, where the dependent variable is still forecast accuracy. Similar to Table 2, Column (1) controls for basic firm and analyst characteristics. Column (2) adds control variables for lead analysts' characteristics, while column (3) includes year and industry fixed effects. The results for each column are consistent. The coefficient on demographic diversity (*demo_div*) is insignificant. The coefficient on cognitive diversity (*cog_div*) is positive and significant at the 1% level. That is to say, cognitive diversity is more important than demographic diversity for producing accurate forecasts. This finding is consistent with decision-making theory, which indicates that team members with cognitive diversity have more information resources and different insights for analyzing stocks (Talke, Salomo, and Rost (2010)). These advantages enable them to fulfill information discovery and information interpretation tasks better than non-diverse teams.

[Insert Table 3 around here]

We further extend our investigation of diversity to individual factors in Table 4. Four out of six cognitive diversity factors load with positive and statistically significant results. The significance of working experience diversity (*expDiv*) shows that teams benefit when senior and junior professionals work together. In terms of educational background, we observe positive effects on major diversity (*majorDiv*) and college nature diversity (*catgriDiv*). This finding means that complementary educational backgrounds improve forecast accuracy due to the different training and decision-making processes equipped through college education. Lastly, teams that have worked together for a shorter period (*groupDiv*) tend to have higher forecast accuracy. There is less difference in forecast accuracy for teams that have worked together for a long time. The reason may be that they share the similar networks, and hence get less access to unique information. Among the three demographic diversity factors, birth place diversity (*bornDiv*) is negatively correlated with forecast accuracy. Geographic similarity makes people feel close to each other. Currarini, Jackson, and Pin (2009) show that people tends to bond well with the individual of similar background. This theory indicates that a heterogeneous team environment could increase communication cost and lead to disharmony. Overall, teams' forecast accuracy benefits from cognitive diversity and geographic similarity.

[Insert Table 4 around here]

4.3 Team diversity and forecast timeliness

We examine the impact of diversity on the timeliness of team forecast reports in Table 5. $timeliness_{ijt}$ measures how quickly analyst teams revise their forecasts. The coefficients on aggregated diversity ($diversity_{ijt}$) are negative and significant in all three columns. Consistent with **H2A**, this result shows that diversity has a negative impact in producing prompt reports. Members with different backgrounds tend to have different perspectives. Although this diversity improves team forecast accuracy, the cost is it takes time to reach agreement.

Among control variables, forecast horizon (fh_{ijt}), number of companies followed (Num_Co_{ijt}) and log number of analysts following the company ($logFollow_{jt}$) are negatively correlated with forecast timeliness. These show that analysts revise their forecasts in more timely and productive manner when earning announcement dates are approaching, when analysts follow fewer companies and when there are more analysts following the companies. Forecast revisions (fr_{ijt}) and book to market ratio (($logbtm_{it}$)) are positively related to forecast timeliness. These suggest that for analysts with more forecast revisions and for firms that are undervalued, analysts tend to issue more prompt revisions.

We decompose aggregated diversity into the demographic and cognitive levels in Table 6, where the dependent variable is still forecast timeliness. The coefficient on cognitive diversity (cog_div_{ijt}) is negative and significant at the one percent level while that on demographic diversity ($demo\_div_{ijt}$) is not significant. Consistently with finding on forecast accuracy, cognitive difference plays a more pronounced role in forecast performance than demographic difference. This demonstrates that it is the different task-related knowledge and trainings that matter in forecast timeliness. Team members with cognitive diversity are more likely to issue forecast revisions in a less prompt manner.

Table 7 illustrates the individual diversity factors that influence forecast timeliness. Gender diversity (*genderDiv*) at the demographic level and experience diversity (*expDiv*), major diversity (*majorDiv*), and foreign education diversity (*foreignDiv*) at the cognitive level have negative relationships with team forecast timeliness. These results demonstrate that teams with the same gender, working experience, college majors, and overseas training tend to reach the same conclusion faster. Taken the results from team forecast accuracy, we observe that team members with diversified knowledge tend to issue accurate forecast, with the cost of forecast timeliness.

4.4 Team diversity and star status

We examine the impact of team diversity on the probability of achieving star analyst status in Table 8. The dependent variable is *deltaSTAR*, which equals one if a non-star member becomes a star in the following two years and zero otherwise. Column (1) controls for basic firm and analyst characteristics. Column (2) adds control variables for lead analysts' characteristics, while column (3) includes year and industry fixed effects. After controlling for analyst average forecast accuracy, we observe a negative and significant coefficient on aggregate diversity. Williams and O'Reilly (1998) show that people prefer to work with others who are similar rather than dissimilar as birds of a feather flock together. Star election is like a beauty contest (Emery and Li (2009)), which requires teams to share the same opinion and lend full support to a team member. Therefore, in terms of becoming a star analyst, team homophily plays a profound role.

[Insert Table 8 around here]

Among the control variables, the coefficients on brokerage house size (*no_ana_ana*) and average market value (*logmv_ana*) of followed stocks are positive and statistically different from zero. The coefficients on book-to-market ratio (*logbtm_anan*) and gender (*gender1*) are negative and statistically significant. These findings are consistent with the "beauty contest" argument advanced by Emery and Li (2009). Analysts at the big brokerage houses and following big companies are more likely to stand out and catch the public's attention. Leone and Wu (2007) find a positive and significant relationship between accuracy and star status. Li et al. (2013) show that female analysts have a higher probability of becoming stars. The coefficient on average accuracy (*acc_ana*) is not significant here, as our dependent variable is the change of star status (*deltaSTAR*), not star status. This setting is similar to the control for star status in the current year; therefore, accuracy is not significant for becoming a star analyst.

Table 9 shows that cognitive diversity drives the results on achieving the star status. Column (1) controls for basic firm and analyst characteristics. Column (2) adds control variables for lead analysts' characteristics, while column (3) includes year and industry fixed effects. We find the coefficient estimates for cognitive diversity (*cog_div*) are negative and significant at the 5% level in the full model (column (3)). As with the results for forecast accuracy, cognitive difference plays a more pronounced role than demographic difference.

Analysts with similar cognitive backgrounds tend to come to the same conclusions about a stock, due to their similar training or knowledge sets.

[Insert Table 9 around here]

Table 10 shows that three out of six factors in cognitive diversity exert negative impacts on star status. The coefficients on *majorDiv* and *majorDiv* are negative and significant at the 5% level. Analysts with similar knowledge sets or ways of thinking tend to have similar opinions. The negative coefficient on *groupDiv* also shows that people who work together for a long time tend to know each other more. This homophily creates social conformity and group thinking, which is required for group members to fully support one team member in becoming a star analyst. At the demographic level, we observe a negative relationship between gender diversity and change in star status.

[Insert Table 10 around here]

5 Conclusions

In this paper, we investigate whether different types of diversity have a beneficial or detrimental impact on team analysts' performance. We find that diversity in general has a positive association with team forecast accuracy. This result is consistent with the idea that team members with different knowledge sets may pay attention to or extract different information about the same stock and thus achieve better performance than a single analyst. We also find that diversity has a negative impact on the timeliness of forecasts. This finding indicates that it takes time for a diversified team to reach an agreement. In addition, we find that diversity is negatively associated with the probability of becoming a star. This finding indicates that a homophilic environment enjoys the benefit of lowering communication cost and improving relationships between team members. Our further tests show that it is mainly cognitive diversity other than demographic diversity that affects team forecast performance.

Our research should interest brokerage houses that aim to increase team performance by making full use of diversity. In addition, our research has implications for institutional investors who spend millions of dollars each year buying and selecting analysts' forecasts. These investors should pay attention to the different backgrounds of team analysts. Lastly, our research should interest regulators who monitor diversity in the financial institution environment.

Reference

Bonner, Sarah E., Artur Hugon, and Beverly R. Walther, 2007, Investor Reaction to Celebrity Analysts: The Case of Earnings Forecast Revisions, *Journal of Accounting Research* 45, 481–513.

Bradley, Daniel J., Sinan Gokkaya, and Xi Liu, 2017, Before an Analyst Becomes an Analyst: Does Industry Experience Matter?, *Journal of Finance* 72, 751-792.

Brochet, F, GS Miller, P Naranjo, and G Yu, 2016, Managers' cultural background and disclosure attributes, working paper, Stanford Unviersity.

Brown, Lawrence D., and Artur Hugon, 2009, Team earnings forecasting, *Review of Accounting Studies* 14, 587–607.

Burt, Ronald S., 1992, Structural holes: The social structure of competition, *Harvard University Press, Cambridge Massachussetts*, 38–40.

Cheng, Mandy M., Peter F. Luckett, and Axel K‐D. Schulz, 2003, The Effects of Cognitive Style Diversity on Decision‐Making Dyads: An Empirical Analysis in the Context of a Complex Task, *Behavioral Research in Accounting*.

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

Clement, Michael B., and Senyo Y. Tse, 2005, Financial Analyst Characteristics and Herding Behavior in Forecasting, *The Journal of Finance* 60, 307–341.

Clement, Michael B, and Senyo Y. Tse, 2003, Do Investors Respond to Analysts' Forecast Revisions as if Forecast Accuracy Is All That Matters?, *The Accounting Review* 78, 227–249.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010, Sell-side school ties, *Journal of Finance* 65, 1409–1437.

Cooper, Rick A., Theodore E. Day, and Craig M. Lewis, 2001, Following the leader: : A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383–416.

Dahlin, K. B., L. R. Weingart, and P. J. Hinds, 2005, Team Diversity and Information Use., *Academy of Management Journal* 48, 1107–1123.

Datta, Sudip, Mai Iskandar-Datta, and Vivek Sharma, 2011, Product market pricing power, industry concentration and analysts' earnings forecasts, *Journal of Banking and Finance* 35, 1352–1366.

Dechow, Patricia M., and Haifeng You, 2012, Analysts' Motives for Rounding EPS Forecasts, *The Accounting Review* 87, 1939–1966.

Downar, Benedikt, Jjrgen Ernstberger, and Christopher W. Koch, 2016, Reviewing a Friend - The Role of Social Ties in Review Work in Auditing, *SSRN Electronic Journal*.

Emery, Douglas R., and Xi Li, 2009, Are the Wall Street Analyst Rankings Popularity Contests?, *Journal of Financial and Quantitative Analysis* 44, 411.

Fang, L., and a. Yasuda, 2009, The Effectiveness of Reputation as a Disciplinary Mechanism in Sell-Side Research, *Review of Financial Studies* 22, 3735–3777.

Fang, Lily H., and Ayako Yasuda, 2014, Are Stars' Opinions Worth More? The Relation Between Analyst Reputation and Recommendation Values, *Journal of Financial Services Research*, 1–35.

Fang, Lily, and Joel Peress, 2009, Media Coverage and the Cross-section of Stock Returns, *Journal of Finance* 44, 2023–2052.

Giannetti, Mariassunta, and Yishay Yafeh, 2012, Do Cultural Differences Between Contracting Parties Matter? Evidence from Syndicated Bank Loans, *Management Science* 58, 365–383.

Giannetti, Mariassunta, Mengxin Zhao, U S Securities, and Exchange Commission, 2017, Board Ancestral Diversity and Firm Performance, working paper, SEC.

Gleason, CA, and CMC Lee, 2003, Analyst forecast revisions and market price discovery, *The Accounting Review* 78, 193–225.

Gompers, Paul A., Vladimir Mukharlyamov, and Yuhai Xuan, 2016, The cost of friendship, *Journal of Financial Economics* 119, 626–644.

Groysberg, B., and L.-E. Lee, 2009, Hiring Stars and Their Colleagues: Exploration and Exploitation in Professional Service Firms, *Organization Science* 20, 740–758.

Groysberg, Boris, Linda-eling Lee, and Ashish Nanda, 2008, Can They Take It With Them ? The Portability of Star Knowledge Workers ' Performance, *Management Science* 54, 1213–1230.

Gul, Ferdinand A., Donghui Wu, and Zhifeng Yang, 2013, Do individual auditors affect audit quality? Evidence from archival data, *Accounting Review* 88, 1993–2023.

Hall, Jason L., and Paul B. Tacon, 2010, Forecast accuracy and stock recommendations, *Journal of Contemporary Accounting and Economics* 6, 18–33.

Han, Jing, Jian Han, and Daniel J. Brass, 2014, Human capital diversity in the creation of social capital for team creativity, *Journal of Organizational Behavior* 35, 54–71.

Harrison, David A., and Katherine J. Klein, 2007, What's the difference? Diversity constructs as separation, variety, or disparity in organizations, *Academy of Management Review* 32, 1199–1228.

Hegde, Deepak, and Justin Tumlinson, 2014, Does Social Proximity Enhance Business Partnerships? Theory and Evidence from Ethnicity's Role in U.S. Venture Capital, *Management Science* 60, 2355–2380.

Hochberg, Yael V., Laura A. Lindsey, and Mark M. Westerfield, 2015, Resource accumulation through economic ties: Evidence from venture capital, *Journal of Financial Economics* 118, 245–267.

Horton, Joanne, George Serafeim, and Shan Wu, 2017, Career concerns of banking analysts, *Journal of Accounting and Economics* 63, 231–252.

Huang, Allen H., Amy Y. Zang, and Rong Zheng, 2014, Evidence on the Information Content of Text in Analyst Reports, *The Accounting Review* 89, 2151–2180.

Huang, Wei, and Brian Wright, 2015, Analyst earnings forecast under complex corporate ownership in China, *Journal of International Financial Markets, Institutions and Money* 35, 69–84.

Ingram, Paul, and Peter W. Roberts, 2000, Friendships among Competitors in the Sydney Hotel Industry, *American Journal of Sociology* 106, 387–423.

Jackson, Susan E., and Aparna Joshi, 2004, Diversity in social context: A multi-attribute, multilevel analysis of team diversity and sales performance, *Journal of Organizational Behavior* 25, 675–702.

Jehn, Karen a., Gregory B. Northcraft, and Margaret a. Neale, 1999, Why Differences Make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups, *Administrative Science Quarterly* 44, 741–763.

Joshi, Aparna, and Hyuntak Roh, 2009, The role of context in work team diversity research: A meta-analytic review, *Academy of Management Journal* 52, 599–627.

Kearney, Eric, Diether Gebert, and Sven C Voelpel, 2009, When and How Diversity Benefits Teams : the Importance of Team Members ’ Need for Cognition, *Academy of Management Journal* 52, 581–598.

Kerl, Alexander, and Martin Ohlert, 2015, Star-analysts' Forecasts Accuracy and the Role of Corporate Governance, *Journal of Financial Research* 38, 93–120.

Kothari, S. P., Xu Li, and James E. Short, 2009, The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis, *The Accounting Review* 84, 1639–1670.

Krigman, Laurie, Wayne H. Shaw, and Kent L. Womack, 2001, Why do firms switch underwriters?, *Journal of Financial Economics* 60, 245–284.

Leone, Andrew, and J Wu, 2007, What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts, *Simon School of Business Working Paper No. FR 02-12*.

Li, Xi, Rodney N. Sullivan, Danielle Xu, and Guodong Gao, 2013, Sell-Side Analysts and Gender: A Comparison of Performance, Behavior, and Career Outcomes, *Financial Analysts Journal* 69.

Liao, Zhongju;, and Siying Long, 2016, Cognitive Diversity, Alertness, and Team Performance, *Social Behavior and Personality: An International Journal* 44, 209–220.

Linden, Christophe Van, and W Robert Knechel, 2016, Engagement team composition , audit production and audit quality, *Working Paper*, 1–43.

Livnat, Joshua, and Yuan Zhang, 2012, Information interpretation or information discovery: which role of analysts do investors value more?, *Review of Accounting Studies* 17, 612–641.

Livnat, Joshua, and Yuan Zhang, 2012, Information interpretation or information discovery: which role of analysts do investors value more?, *Review of Accounting Studies* 17, 612–641.

Loughran, Tim, and Bill Mcdonald, 2014, Measuring Readability in Financial Disclosures, *The Journal of Finance* 69, 1643–1671.

McGuinness, Paul B., João Paulo Vieito, and Mingzhu Wang, 2017, The role of board gender and foreign ownership in the CSR performance of Chinese listed firms, *Journal of Corporate Finance* 42, 75–99.

Mcpherson, Miller, Lynn Smith-Lovin, and James M Cook, 2001, Birds of a Feather: Homophily in Social Networks, *Annual Review of Sociology* 27, 415–444.

Merkley, Kenneth, Roni Michaely, and Joseph Pacelli, 2017, The Value of Cultural Diversity on Wall Street : Evidence from Sell-Side Analysts ’ Forecasts, working paper, Cornell University.

Pelled, Lisa Hope, Kathleen M. Eisenhardt, and Katherine R. Xin, 1999, Exploring the black box: An analysis of work group diversity, conflict, and performance, *Administrative Science Quarterly* 44, 1–28.

Reagans, Ray, Ezra Zuckerman, and Bill McEvily, 2004, How to make the team: Social Networks vs. Demography as Criteria for Designing Effective Teams, *Administrative Science Quarterly* 49, 101–133.

Rees, Lynn, Nathan Sharp, and Brady Twedt, 2015, Who's heard on the Street? Determinants and consequences of financial analyst coverage in the business press, *Review of Accounting Studies* 20, 173–209.

Richardson, Scott, Siew Hong Teoh, and Peter D. Wysocki, 2004, The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives, *Contemporary Accounting Research* 21, 885–924.

Schilpzand, M. C., and L. L. Martins, 2010, Cognitive Diversity and Team Performance: the Roles of Team Mental Models and Information Processing, *Academy of Management Proceedings* 2010, 1–6.

Shin, S. J., T.-Y. Kim, J.-Y. Lee, and L. Bian, 2012, Cognitive Team Diversity and Individual Team Member Creativity: A Cross-Level Interaction, *Academy of Management Journal* 55, 197–212.

Shin, Shung J., and Jing Zhou, 2007, When is educational specialization heterogeneity related to creativity in research and development teams? Transformational leadership as a moderator., *Journal of Applied Psychology* 92, 1709–1721.

Soltes, Eugene, 2014, Private Interaction Between Firm Management and Sell-Side Analysts, *Journal of Accounting Research* 52, 245–272.

Talke, Katrin, Sören Salomo, and Katja Rost, 2010, How top management team diversity affects innovativeness and performance via the strategic choice to focus on innovation fields, *Research Policy* 39, 907–918.

van Knippenberg, D., and M.C. Schippers, 2007, Work group diversity, *Annual Review of Psychology* 58, 515–541.

Walther, Beverly R., and Richard H. Willis, 2013, Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy?, *Review of Accounting Studies* 18, 207–227.

Williams, Katherine Y., and Charles A. O'Reilly, 1998, Demography and Diversity in Organizations: A Review of 40 Years off Research, *Research in Organizational Behavior*.

Zimmerman, Monica A., and Keith D. Brouthers, 2012, Gender heterogeneity, entrepreneurial orientation and international diversification, *International Journal of Gender and Entrepreneurship* 4, 20–43.

Table 1
Descriptive statistics on team analyst and firm characteristics

This table reports descriptive statistics for analyst teams observations from 2007-2015. Analysts' background and forecast characteristics are derived from CNRDS data. We restrict the sample to forecasts issued no earlier than 1 year and no later than 30 days before the fiscal-year end. Panel A reports the descriptive statistic for analyst team and forecast characteristics. Panel B reports the descriptive statistics for raw (unscaled) analyst team and forecast characteristics. Panel C reports correlations among scaled characteristics. Analyst team performance measures are *accuracy,* forecast accuracy and *deltaSTAR,* the change of star status. Diversity measures at aggregated level are *demographic diversity* and *cognitive diversity*. *demographic diversity* includes gender diversity, born diversity and age diversity. *cognitive diversity* includes experience diversity, major diversity, category diversity, group diversity, employ diversity and foreign diversity. See appendix for the definition of all control variables.

Panel A: Distribution of analyst team and forecast characteristics

Variable	Variable Description	N	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Accuracy	standardized forecast accuracy	9156	0.69	0.31	0	0.50	0.8	0.95	1
GenderDiv	gender diversity	9156	0.55	0.5	0	0.00	1	1	1
BornDiv	born diversity	9156	0.92	0.25	0	1.00	1	1	1
AgeDiv	age diversity	9156	0.22	0.13	0	0.12	0.2	0.31	0.86
ExpDiv	working experience diversity	9156	0.49	0.37	0	0.20	0.46	0.75	1.41
MajorDiv	major diversity	9156	0.82	0.34	0	0.67	1	1	1
CatgriDiv	school category diversity	9156	0.35	0.45	0	0.00	0	1	1
GroupDiv	group working year diversity	9156	0.92	0.27	0	1.00	1	1	1
EmployDiv	prior employer diversity	9156	0.02	0.14	0	0.00	0	0	1
ForeignDiv	foreign school diversity	9156	0.2	0.4	0	0.00	0	0	1
Star	STAR status dummy	9156	0.36	0.48	0	0.00	0	1	1
Accountancy	prior accountancy profession dummy of analyst 1	9156	0.15	0.36	0	0.00	0	0	1
Accounting	accounting major dummy of analyst 1	9156	0.48	0.5	0	0.00	0	1	1
Gender	gender of analyst1	9156	0.69	0.46	0	0.00	1	1	1
Born	born place of analyst 1	9156	15.8	8.26	1	10.00	16	22	31

(The table continues on the next page.)

Panel A: Distribution of analyst team and forecast characteristics, cont.

Age	years after college of analyst1	9156	15.15	4.79	2	12.00	14	18	34
Experience	years of experience of analyst 1	9156	3.41	2.83	0	1.00	3	5	17
Major	major of analyst1	9156	47.26	24.63	1	38.00	49	63	108
Catgri	school category of analyst 1	9156	2.08	1.92	1	1.00	1	2	11
TopUn	985 university of graduation	9156	0.46	0.57	-1	0.00	0	1	1
Foreign1	foreign school of analyst1	9156	0.1	0.3	0	0.00	0	0	1
fr	standardized forecast revisions	9156	0.26	0.35	0	0.00	0	0.5	1
fh	standardized forecast horizon	9156	0.4	0.32	0	0.10	0.35	0.61	1
Num_Ind	standardized average number of industry followed	9156	0.23	0.25	0	0.00	0.15	0.33	1
Num_Co	standardized average number of company followed	9156	0.25	0.25	0	0.07	0.18	0.36	1
Num_Ana	standardized brokerage house size	9156	0.53	0.3	0	0.31	0.49	0.74	1
logFollow	log number of analysts follow firm *j*	9156	3.61	0.63	0.69	3.26	3.71	4.08	4.65
logmv	log market value	9156	23.25	1.19	21.1	22.42	23.05	23.87	27.49
logbtm	log book to market ratio	9156	-0.28	1	-2.31	-0.98	-0.41	0.32	2.78
Diversity	aggregated diversity	9156	0.5	0.11	0.11	0.42	0.5	0.57	0.9
Demo_div	demographic diversity at aggregated level	9156	0.56	0.2	0	0.40	0.67	0.73	0.87
Cog_div	cognitive diversity at aggregated level	9156	0.47	0.14	0	0.36	0.46	0.56	1
DeltaSTAR	change of STAR status	1107	0.26	0.44	0	0.00	0	1	1
Acc_ana	average accuracy per year	1107	0.63	0.23	0	0.50	0.66	0.79	1
Fr_ana	average forecast revisions per year	1107	0.22	0.26	0	0.00	0.13	0.4	1
No_ind_ana	average number of forecast industries per year	1107	0.1	0.16	0	0	0.02	0.16	0.98
No_co_ana	average number of forecast companies per year	1107	0.1	0.14	0	0.00	0.03	0.14	0.88
No_ana_ana	average brokerage house size per year	1107	0.5	0.28	0	0.29	0.45	0.71	1
Logmv_ana	average log market value per year	1107	23.17	0.96	21.11	22.53	23.01	23.67	27.22
Logbtm_ana	average log book to market ratio per year	1107	-0.35	0.86	-2.27	-0.89	-0.49	0.06	2.78

Panel B: Raw Data

Variable	Variable Description	N	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Afa	absolute forecast error	9156	0.12	0.18	0	0.02	0.06	0.14	1.33
Age_college1	years after college of analyst1	9156	15.15	4.79	2	12	14	18	34
Age_college2	years after college of analyst2	9049	13.47	4.73	5	10	12	16	34
Age_college3	years after college of analyst3	6026	12.62	4.62	0	9	12	14	34
Age_work1	years of experience of analyst 1	9156	3.41	2.83	0	1	3	5	17
Age_work2	years of experience of analyst 2	9033	3.02	2.98	0	1	2	4	16
Age_work3	years of experience of analyst 3	5077	2.64	2.95	0	1	2	3	17
Top985	985 universities dummy	9156	0.46	0.57	-1	0	0	1	1
Accounting1	accounting major dummy of analyst 1	9156	0.48	0.5	0	0	0	1	1
Accounting2	accounting major dummy of analyst 2	9156	0.51	0.5	0	0	1	1	1
Accounting3	accounting major dummy of analyst 3	6093	0.24	0.43	0	0	0	0	1
Accountancy1	prior accountancy profession dummy of analyst 1	9156	0.15	0.36	0	0	0	0	1
Accountancy2	prior accountancy profession dummy of analyst 2	9156	0.13	0.34	0	0	0	0	1
Accountancy3	prior accountancy profession dummy of analyst 3	10801	0.08	0.27	0	0	0	0	1
Groupyear	number of years groups work together	9156	1	1.04	0	0	1	2	7
Mv	market value	9156	3.40E+10	9.10E+10	1.50E+09	5.40E+09	1.00E+10	2.30E+10	8.70E+11
Btm	book to market ratio	9156	1.39	2.3	0.1	0.38	0.66	1.37	16.15
Fr	number of forecast revisions	9156	2.13	1.77	1	1	1	3	28
Fh	forecast horizon in days	9156	178.67	94.13	30	102	168	239	366
Wno_ind	average number of industry followed	9156	3.52	2.14	1	2	3	5	13
Wno_co	average number of company followed	9156	12.66	8.62	1	6	11	17	47
Wno_ana	brokerage house size	9156	106.19	53.61	7	69	100	144	241
Wno_follow	number of analysts following the company	9156	43.86	23.01	2	26	41	59	105
Time	timeliness	4354	4.64	13.46	0	0	0.26	2	125
STAR1	STAR status of analyst 1	1107	0.1	0.3	0	0	0	0	1
STAR2	STAR status of analyst 2	1107	0.06	0.23	0	0	0	0	1

Panel C: Correlation Matrix

	accuracy	GenderDiv	BornDiv	AgeDiv	ExpDiv	MajorDiv	CatgriDiv	GroupDiv	EmployDiv	ForeignDiv	Star
GenderDiv	0.0121	1									
BornDiv	-0.016	0.0589	1								
AgeDiv	0.0117	0.0548	-0.0455	1							
ExpDiv	-0.016	-0.0078	-0.0324	0.1491	1						
MajorDiv	-0.003	-0.0934	0.0206	0.0415	0.0817	1					
CatgriDiv	-0.009	-0.0094	-0.0714	0.1021	-0.0822	-0.0714	1				
GroupDiv	0.0115	-0.0108	0.0268	0.0282	0.1178	-0.0173	-0.1002	1			
EmployDiv	-0.003	-0.0489	0.0264	0.0144	0.0301	0.0263	-0.002	0.0389	1		
ForeignDiv	-0.007	-0.045	-0.0392	0.0692	0.0409	-0.082	0.1465	0.0136	-0.0075	1	
Star1Dum	0.0462	0.0442	-0.0611	-0.002	-0.0439	-0.1199	0.024	-0.0362	-0.0832	0.0851	1
Accountancy	-0.042	0.0228	0.0021	-0.029	0.0875	0.0743	0.0484	0.0414	-0.0267	0.0085	-0.1003
Accounting	0.041	-0.007	-0.0498	-0.097	-0.125	-0.1217	0.0151	-0.0311	-0.0011	0.0722	0.0701
Gender	-0.016	-0.3818	-0.0471	-0.029	-0.0073	0.0508	0.0814	-0.0739	0.0346	-0.0687	-0.0884
Born	0.0055	-0.0241	0.0059	-0.061	-0.0743	0.0137	0.0138	-0.0499	0.0256	-0.0601	-0.0228
Age	-0.007	-0.05	-0.0002	0.429	0.0261	0.0748	0.0613	-0.1052	-0.0042	0.0931	-0.0261
experience	0.0322	0.0594	-0.058	0.1682	0.0605	-0.0022	0.0538	-0.1112	-0.0248	0.1087	0.1859
Major	0.0015	-0.0909	-0.0624	-0.018	-0.0731	0.0549	-0.0312	-0.0604	0.0087	-0.0799	0.0305
Catgri	0.0124	0.0781	0.0578	-0.097	-0.0839	-0.0207	0.2402	-0.02	0.0773	0.0684	-0.028
TopUni	0.0263	-0.0071	0.0358	0.0107	-0.0303	0.0495	-0.4673	0.0631	-0.004	-0.121	0.0082
Foreign	-0.005	-0.0264	-0.0378	-0.077	-0.0551	-0.1137	0.0163	0.044	0.0232	0.5327	0.0638
fr	0.147	0.0132	0.0119	-0.046	-0.0799	-0.0485	0.0225	-0.081	-0.0212	-0.0018	0.0923
fh	-0.424	-0.0093	-0.0159	0.0318	0.0592	0.0348	0.0375	0.018	0.0013	0.0153	-0.0955
Num_Ind	0.0048	-0.0085	0.0309	-0.099	-0.0953	0.0427	0.0511	0.0164	-0.0573	-0.0795	-0.0029
Num_Co	0.0257	0.0227	0.0409	-0.127	-0.0941	-0.0178	0.044	0.005	-0.0786	-0.0592	0.1065
Num_Ana	-0.056	0.0984	-0.006	-0.048	0.0479	-0.0062	-0.0779	0.0386	-0.0396	-0.012	0.1776
logFollow	0.1289	0.0539	0.0011	0.0105	-0.0109	-0.0547	-0.0596	-0.0078	0.0088	0.0309	0.0336
logmv	0.0685	-0.0297	-0.019	-0.06	-0.0813	-0.0484	-0.0717	-0.0321	0.0135	0.0534	0.0498
logbtm	-0.064	-0.0094	-0.0412	-2E-04	-0.0088	-0.0607	0.0299	-0.0128	-0.0279	0.12	0.1292

(The table continues on the next page.)

Panel C: Correlation Matrix, cont.

	Accountancy	Accounting	Gender	Born	Age	experience	Major	Catgri	TopUni	Foreign	fr	fh
Accounting	-0.1575	1										
Gender	0.0857	-0.0507	1									
Born	-0.058	0.1765	0.0058	1								
Age	0.0959	-0.1341	0.058	0.029	1							
experience	-0.1189	-0.0072	-0.2407	-0.048	0.3552	1						
Major	-0.0659	-0.0116	-0.037	0.077	0.0855	-0.0024	1					
Catgri	-0.0006	0.1603	-0.0089	0.101	-0.0654	-0.0537	-0.0378	1				
TopUni	-0.0498	-0.0463	-0.0715	-0.029	-0.038	-0.0422	-0.0412	-0.1491	1			
Foreign	0.0202	0.1621	-0.0322	-0.085	-0.0566	-0.0523	-0.115	0.191	-0.0568	1		
fr	-0.0447	0.0327	0.0208	0.062	0.0245	0.1079	0.001	0.0188	-0.0099	0.0041	1	
fh	0.0631	-0.0618	-0.0161	-0.034	0.0356	-0.046	0.0222	-0.0205	0.0043	0.0043	-0.373	1
Num_Ind	-0.001	0.0434	0.0219	0.084	0.0079	-0.0046	0.0285	0.0975	0.0521	-0.0203	0.14	-0.066
Num_Co	-0.0357	0.0729	-0.004	0.092	-0.0256	0.0246	0.0673	0.0538	0.0175	-0.009	0.1982	-0.079
Num_Ana	-0.0635	0.0116	-0.1324	0.025	-0.1116	-0.0499	0.0428	-0.0439	0.0943	-0.0138	-0.03	0.0228
logFollow	-0.0085	0.0221	-0.0404	-0.045	-0.0158	0.0162	-0.0413	-0.004	0.075	0.0323	-0.063	0.0239
logmv	-0.0013	0.0668	-0.0031	-0.053	0.0374	-0.0193	-0.0368	-0.0236	0.0912	0.1117	0.0167	-0.047
logbtm	-0.0162	0.1225	0.0048	-0.093	0.0519	0.0685	-0.0276	-0.0993	-0.0266	0.1367	0.0243	0.0347

(The table continues on the next table.)

Panel C: Correlation Matrix, cont.

	Wfh1	Num_Ind	Num_Co	Num_Ana	logFollow	logmv
Num_Ind	-0.0659	1				
Num_Co	-0.0786	0.6768	1			
Num_Ana	0.0228	0.0436	0.0693	1		
logFollow	0.0239	-0.1619	-0.1434	-0.123	1	
logmv	-0.047	-0.0665	-0.0266	-0.084	0.4255	1
logbtm	0.0347	-0.1254	0.006	0.022	0.0862	0.323

Table 2

Team diversity and forecast accuracy

This table reports the ordinary least squares estimation results of diversity on team forecast *accuracy*, for the years 2001-2015. *accuracy* is team forecast accuracy. Column (1) only uses basic control variables following prior analyst forecasts literature. Column (2) adds controls for lead analysts characteristics. Column (3) adds year and industry fixed effect with robust p-values in parentheses. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

Dependent Variable= Accuracy			
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
Diversity	**0.069*** **	**0.081*** **	**0.069** **
	(2.74)	**(2.84)**	**(2.41)**
fr	-0.004	-0.004	-0.004
	(-0.43)	(-0.40)	(-0.49)
fh	-0.410***	-0.407***	-0.411***
	(-43.40)	(-41.78)	(-37.32)
Num_Ind	-0.040***	-0.039**	-0.045**
	(-2.59)	(-2.45)	(-2.47)
Num_Co	0.053***	0.043***	0.058***
	(3.36)	(2.70)	(3.24)
Num_Ana	-0.031***	-0.037***	-0.030***
	(-3.20)	(-3.60)	(-2.68)
logFollow	0.069***	0.065***	0.064***
	(13.84)	(12.68)	(10.30)
logmv	0.002	0.002	0.007**
	(0.67)	(0.81)	(2.08)
logbtm	-0.020***	-0.022***	-0.019***
	(-6.74)	(-7.04)	(-4.96)
Gender		-0.007	-0.006
		(-1.02)	(-0.85)
Born		-0.000	-0.001**
		(-1.25)	(-2.20)
Age		0.001	0.001
		(1.23)	(0.91)
Experience		0.000	0.000
		(0.07)	(0.21)
Major		0.000*	0.000
		(1.84)	(1.08)
Accounting		0.016**	0.019***
		(2.53)	(2.98)
Catgri		-0.001	-0.001
		(-0.37)	(-0.61)
Accountancy		-0.011	-0.014*
		(-1.28)	(-1.73)
Foreign		-0.004	0.000
		(-0.41)	(0.01)

(The table continues on the next page.)

TABLE 2 (Cont.)			
Star		0.006	0.008
		(0.92)	(1.17)
TopUni		0.014***	0.015***
		(2.63)	(2.74)
Constant	0.534***	0.510***	0.364***
	(8.34)	(7.55)	(3.06)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	9609	9156	9156
Adjusted R^2	0.206	0.205	0.209

Table 3

Demographic and cognitive diversity and forecast accuracy

This table reports the ordinary least squares estimation results of diversity on team forecast *accuracy*, for the years 2001-2015. *demographic diversity* is aggregated diversity at demographic level. *cognitive diversity* is aggregated diversity at cognitive level. *accuracy* is team forecast accuracy. Column (1) only uses basic control variables following prior analyst forecasts literature. Column (2) adds controls for lead analysts characteristics. Column (3) adds year and industry fixed effect with robust p-values in parentheses. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

Dependent Variable= Accuracy			
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
Demo_div	-0.000	-0.011	-0.015
	(-0.01)	(-0.71)	(-0.94)
Cog_div	**0.067*****	**0.088*****	**0.080*****
	(3.37)	**(3.95)**	**(3.54)**
fr	-0.003	-0.003	-0.003
	(-0.36)	(-0.28)	(-0.36)
fh	-0.411***	-0.408***	-0.411***
	(-43.45)	(-41.87)	(-37.40)
Num_Ind	-0.041***	-0.041**	-0.047**
	(-2.65)	(-2.56)	(-2.57)
Num_Co	0.054***	0.046***	0.060***
	(3.45)	(2.85)	(3.38)
Num_Ana	-0.030***	-0.036***	-0.029***
	(-3.04)	(-3.53)	(-2.61)
logFollow	0.070***	0.066***	0.065***
	(13.96)	(12.84)	(10.43)
logmv	0.002	0.002	0.007**
	(0.64)	(0.74)	(2.06)
logbtm	-0.021***	-0.023***	-0.019***
	(-6.81)	(-7.08)	(-4.95)
Gender		-0.013*	-0.012*
		(-1.84)	(-1.65)
Born		-0.000	-0.001**
		(-1.31)	(-2.27)
Age		0.001	0.001
		(1.42)	(1.10)
Experience		-0.000	-0.000
		(-0.19)	(-0.06)
Major		0.000	0.000
		(1.59)	(0.83)
Accounting		0.016**	0.019***
		(2.56)	(3.04)
Catgri		-0.000	-0.001
		(-0.26)	(-0.49)

(The table continues on the next page.)

TABLE 3 (Cont.)			
Accountancy		-0.011	-0.015*
		(-1.35)	(-1.81)
Foreign		-0.009	-0.005
		(-0.92)	(-0.47)
Star		0.006	0.008
		(0.97)	(1.22)
TopUni		0.016***	0.017***
		(2.97)	(3.08)
Constant	0.535***	0.521***	0.378***
	(8.36)	(7.69)	(3.17)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	9609	9156	9156
Adjusted R^2	0.206	0.206	0.210

Table 4
Expanded factors of team diversity and forecast accuracy

This table reports the ordinary least squares estimation of nine diversity attributes on team forecast accuracy, for the years 2001-2015. *accuracy* is team forecast accuracy. *gender* diversity and *age diversity* are diversity factors at demographic level. *experience diversity, major diversity, school diversity, group diversity, employ diversity* and *foreign diversity* are diversity factors at cognitive level. Robust p-values in parentheses, based on Huber–White adjusted standard errors. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

Dependent Variable= Accuracy			
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
GenderDiv	0.003	0.001	-0.002
	(0.61)	(0.13)	(-0.25)
BornDiv	**-0.028****	**-0.027****	**-0.021***
	(-2.48)	**(-2.35)**	**(-1.76)**
AgeDiv	**0.048****	0.028	0.009
	(2.15)	(1.06)	(0.33)
ExpDiv	0.009	0.013	**0.014***
	(1.18)	(1.55)	**(1.70)**
MajorDiv	**0.015***	**0.020****	**0.019****
	(1.80)	**(2.24)**	**(2.15)**
CatgriDiv	**0.012***	**0.026*****	**0.024*****
	(1.82)	**(3.31)**	**(3.05)**
GroupDiv	**0.027****	**0.027****	**0.020***
	(2.56)	**(2.45)**	**(1.71)**
EmployDiv	-0.012	-0.015	-0.006
	(-0.59)	(-0.72)	(-0.30)
ForeignDiv	0.001	-0.005	-0.005
	(0.15)	(-0.59)	(-0.57)
Gender		-0.012*	-0.011
		(-1.66)	(-1.53)
Born		-0.000	-0.001**
		(-1.14)	(-2.13)
Age		0.001	0.001
		(1.03)	(0.97)
experience		-0.000	0.000
		(-0.04)	(0.06)
Major		0.000*	0.000
		(1.65)	(0.95)
Accounting		0.016**	0.020***
		(2.56)	(3.06)
Catgri		-0.001	-0.001
		(-0.39)	(-0.64)
Accountancy		-0.012	-0.016*
		(-1.43)	(-1.88)

(The table continues on the next page.)

TABLE 4 (Cont.)

Foreign		0.006	0.009
		(0.47)	(0.72)
Star		0.005	0.007
		(0.82)	(1.10)
TopUni		0.018***	0.019***
		(3.17)	(3.29)
fr	-0.002	-0.002	-0.003
	(-0.19)	(-0.19)	(-0.31)
fh	-0.411***	-0.408***	-0.411***
	(-43.46)	(-41.89)	(-37.42)
Num_Ind	-0.042***	-0.044***	-0.049***
	(-2.68)	(-2.75)	(-2.70)
Num_Co	0.056***	0.046***	0.060***
	(3.56)	(2.87)	(3.34)
Num_Ana	-0.030***	-0.036***	-0.030***
	(-3.04)	(-3.52)	(-2.61)
logFollow	0.070***	0.066***	0.065***
	(13.91)	(12.82)	(10.42)
logmv	0.002	0.003	0.007**
	(0.86)	(0.93)	(2.14)
logbtm	-0.021***	-0.023***	-0.019***
	(-6.80)	(-7.15)	(-5.01)
Constant	0.519***	0.506***	0.351***
	(7.92)	(7.33)	(2.93)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	9609	9156	9156
Adjusted R^2	0.207	0.207	0.210

Table 5

Team diversity and forecast timeliness

This table reports the ordinary least squares estimation of diversity on the timeliness of team forecast, for the years 2001-2015. Timeliness is measured using the ratio (higher means timlier), T_0/T_1, where T_0 (T_1) is the cumulative number of days the N preceding (subsequent) forecasts lead (lag) the forecast of interest. The T_0/T_1 ratio is adjusted to a relative basis to be consistent with our accuracy measure. Column (1) only uses basic control variables following prior analyst forecasts literature. Column (2) adds controls for lead analysts characteristics. Column (3) adds year and industry fixed effect. Robust p-values in parentheses, based on Huber–White adjusted standard errors. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

Dependent variable= timeliness			
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
diversity	**-0.060****	**-0.084*****	**-0.075*****
	(-2.42)	**(-3.07)**	**(-2.68)**
fr	0.017**	0.020**	0.022***
	(2.16)	(2.49)	(2.71)
fh	-0.123***	-0.126***	-0.125***
	(-12.63)	(-13.56)	(-12.74)
Num_Ind	0.027	0.043**	0.032*
	(1.53)	(2.47)	(1.79)
Num_Co	-0.034**	-0.023	-0.019
	(-1.99)	(-1.40)	(-1.09)
Num_Ana	-0.010	-0.008	-0.007
	(-0.95)	(-0.72)	(-0.62)
logFollow	-0.072***	-0.070***	-0.071***
	(-11.66)	(-11.73)	(-11.22)
logmv	-0.003	-0.003	-0.002
	(-0.86)	(-1.09)	(-0.63)
logbtm	0.013***	0.007*	0.014***
	(3.35)	(1.96)	(3.35)
gender		0.008	0.007
		(1.23)	(1.01)
born		-0.001	-0.001*
		(-1.59)	(-1.89)
age		0.001	0.001
		(0.78)	(0.83)
experience		-0.004***	-0.004***
		(-3.44)	(-3.35)
major		-0.000	-0.000
		(-1.49)	(-1.52)
accounting		-0.027***	-0.022***
		(-4.38)	(-3.36)
catgri		-0.000	0.000
		(-0.26)	(0.13)

(The table continues on the next page.)

TABLE 5 (Cont.)

accountancy		0.011	0.013
		(1.18)	(1.38)
foreign		-0.027***	-0.028***
		(-2.81)	(-2.80)
star		-0.011*	-0.006
		(-1.79)	(-0.93)
topUni		-0.008	-0.009
		(-1.46)	(-1.61)
constant	0.698***	0.608***	0.697***
	(5.89)	(8.80)	(5.79)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	9926	9562	9555
Adjusted R^2	0.050	0.051	0.054

Table 6
Demographic and cognitive diversity and forecast timeliness

This table reports the ordinary least squares estimation of demographic and cognitive diversity on the timeliness of team forecast, for the years 2001-2015. Timeliness is measured using the ratio (higher means timlier), T_0/T_1, where T_0 (T_1) is the cumulative number of days the N preceding (subsequent) forecasts lead (lag) the forecast of interest. The T_0/T_1 ratio is adjusted to a relative basis to be consistent with our accuracy measure. Column (1) only uses basic control variables following prior analyst forecasts literature. Column (2) adds controls for lead analysts characteristics. Column (3) adds year and industry fixed effect. Robust p-values in parentheses, based on Huber–White adjusted standard errors. Asterisks denote statistical significance at the 1% ($***$), 5% ($**$), or 10% ($*$) levels. See appendix for the definition of all other variables.

	Dependent variable= timeliness		
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
demo_div	-0.015	-0.020	-0.017
	(-0.97)	(-1.20)	(-1.03)
cog_div	**-0.044****	**-0.061*****	**-0.055*****
	(-2.30)	**(-3.01)**	**(-2.64)**
fr	0.017**	0.019**	0.021***
	(2.13)	(2.45)	(2.66)
fh	-0.123***	-0.126***	-0.125***
	(-12.63)	(-13.55)	(-12.74)
Num_Ind	0.027	0.043**	0.033*
	(1.54)	(2.50)	(1.81)
Num_Co	-0.034**	-0.024	-0.020
	(-2.01)	(-1.43)	(-1.13)
Num_Ana	-0.010	-0.008	-0.007
	(-0.98)	(-0.73)	(-0.62)
logFollow	-0.072***	-0.071***	-0.071***
	(-11.66)	(-11.74)	(-11.24)
logmv	-0.003	-0.003	-0.002
	(-0.87)	(-1.08)	(-0.62)
logbtm	0.014***	0.007**	0.014***
	(3.37)	(1.98)	(3.36)
gender		0.010	0.008
		(1.36)	(1.13)
born		-0.001	-0.001*
		(-1.59)	(-1.89)
age		0.001	0.001
		(0.74)	(0.79)
experience		-0.004***	-0.004***
		(-3.36)	(-3.28)
major		-0.000	-0.000
		(-1.43)	(-1.47)
accounting		-0.027***	-0.022***
		(-4.36)	(-3.35)

(The table continues on the next page.)

TABLE 6 (Cont.)

catgri		-0.000	0.000
		(-0.30)	(0.09)
accountancy		0.011	0.013
		(1.20)	(1.40)
foreign		-0.026***	-0.027***
		(-2.67)	(-2.67)
star		-0.011*	-0.006
		(-1.79)	(-0.93)
topUni		-0.008	-0.009*
		(-1.51)	(-1.66)
constant	0.698***	0.604***	0.693***
	(5.89)	(8.71)	(5.75)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	9926	9562	9555
Adjusted R^2	0.050	0.051	0.054

Table 7

Expanded factors of diversity and forecast timeliness

This table reports the ordinary least squares estimation of nine diversity attributes on the timeliness of team forecast, for the years 2001-2015. Timeliness is measured using the ratio (higher means timlier), T_0/T_1, where T_0 (T_1) is the cumulative number of days the N preceding (subsequent) forecasts lead (lag) the forecast of interest. The T_0/T_1 ratio is adjusted to a relative basis to be consistent with our accuracy measure. Robust p-values in parentheses, based on Huber–White adjusted standard errors. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

	Dependent variable= timeliness		
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
genderDiv	**-0.015***	**-0.014**	**-0.013***
	(-2.62)	**(-2.10)**	**(-1.91)**
bornDiv	0.018	0.015	0.014
	(1.61)	(1.29)	(1.15)
ageDiv	0.019	0.011	0.016
	(0.85)	(0.42)	(0.56)
accountDiv	0.027***	0.013	0.006
	(3.92)	(1.47)	(0.72)
expDiv	**-0.018**	**-0.019**	**-0.018**
	(-2.23)	**(-2.19)**	**(-2.05)**
majorDiv	**-0.015***	**-0.017***	**-0.018***
	(-1.67)	**(-1.83)**	**(-1.82)**
catgriDiv	-0.010	-0.010	-0.004
	(-1.34)	(-1.25)	(-0.51)
groupDiv	0.007	0.002	0.003
	(1.04)	(0.29)	(0.39)
employDiv	-0.001	-0.008	-0.008
	(-0.03)	(-0.35)	(-0.36)
foreignDiv	**-0.032***	**-0.023***	**-0.024***
	(-4.66)	**(-2.62)**	**(-2.60)**
star	-0.014**	-0.010	-0.006
	(-2.35)	(-1.55)	(-0.86)
topUni	-0.007	-0.009	-0.009
	(-1.22)	(-1.55)	(-1.47)
fr	0.019**	0.020**	0.022***
	(2.43)	(2.52)	(2.75)
fh	-0.121***	-0.124***	-0.124***
	(-13.21)	(-13.35)	(-12.56)
Num_Ind	0.038**	0.042**	0.032*
	(2.25)	(2.41)	(1.75)
Num_Co	-0.029*	-0.021	-0.017
	(-1.72)	(-1.26)	(-0.94)
Num_Ana	-0.006	-0.007	-0.005
	(-0.53)	(-0.62)	(-0.42)

(The table continues on the next page.)

TABLE 7 (Cont.)

logFollow	-0.071***	-0.070***	-0.071***
	(-12.09)	(-11.70)	(-11.18)
logmv	-0.002	-0.003	-0.002
	(-0.85)	(-0.99)	(-0.57)
logbtm	0.005	0.007*	0.014***
	(1.48)	(1.93)	(3.36)
gender		0.009	0.008
		(1.21)	(1.05)
born		-0.001	-0.001*
		(-1.56)	(-1.73)
age		0.001	0.000
		(0.71)	(0.57)
experience		-0.003**	-0.003**
		(-2.34)	(-2.33)
major		-0.000	-0.000
		(-1.21)	(-1.32)
accounting		-0.025***	-0.021***
		(-3.92)	(-3.18)
catgri		-0.000	0.000
		(-0.07)	(0.14)
accountancy		0.003	0.010
		(0.29)	(0.87)
foreign		-0.016	-0.016
		(-1.36)	(-1.37)
constant	0.528***	0.571***	0.650***
	(7.93)	(8.11)	(5.34)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	9933	9562	9555
Adjusted R^2	0.049	0.051	0.054

Table 8

Team diversity and STAR status

This table reports the ordinary least squares estimation results of diversity on the change of STAR status for the years 2001-2015. *deltaSTAR* is the change of star status between the following two years and the current year. Column (1) only uses basic control variables following prior analyst forecasts literature. Column (2) adds controls for lead analysts characteristics. Column (3) adds year and industry fixed effect with robust p-values in parentheses. The sample only contains teams without star in year *t*. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

Dependent Variable= DeltaSTAR			
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
Diversity	-0.574	**-1.478****	**-1.571****
	(-0.92)	**(-2.08)**	**(-2.12)**
Acc_ana	0.126	0.121	0.026
	(0.42)	(0.37)	(0.08)
Fr_ana	-0.366	-0.499	-0.524
	(-1.17)	(-1.51)	(-1.50)
No_ind_ana	0.494	0.667	0.297
	(0.66)	(0.86)	(0.35)
No_co_ana	-0.969	-1.069	-0.404
	(-1.13)	(-1.21)	(-0.41)
No_ana_ana	3.144***	3.201***	3.445***
	(11.61)	(10.87)	(10.84)
Logmv_ana	0.186**	0.163*	0.247**
	(2.22)	(1.87)	(2.39)
Logbtm_ana	-0.169*	-0.181*	-0.304**
	(-1.83)	(-1.82)	(-2.26)
Gender		-0.417**	-0.328*
		(-2.35)	(-1.80)
Born		-0.015	-0.016*
		(-1.52)	(-1.68)
Age		0.001	-0.001
		(0.07)	(-0.08)
Experience		0.033	0.037
		(1.00)	(1.07)
Major		-0.003	-0.002
		(-1.01)	(-0.77)
Accounting		-0.128	-0.143
		(-0.79)	(-0.83)
Catgri		-0.009	-0.029
		(-0.19)	(-0.58)
Accountancy		-0.005	0.041
		(-0.03)	(0.20)
Foreign		0.217	0.290
		(0.79)	(1.09)

(The table continues on the next page.)

TABLE 8 (Cont.)			
TopUni		-0.046	-0.147
		(-0.32)	(-1.02)
Constant	-6.851***	-5.227**	-5.838*
	(-3.42)	(-2.47)	(-1.78)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	1203	1107	1092
Pseudo R^2	0.1193	0.1315	0.1619

Table 9
Demographic and cognitive diversity and STAR status

This table reports the ordinary least squares estimation results of diversity on the change of STAR status for the years 2001-2015. *deltaSTAR* is the change of star status between the following two years and the current year. *demographic diversity* is aggregated diversity at demographic level. *cognitive diversity* is aggregated diversity at cognitive level. Column (1) only uses basic control variables following prior analyst forecasts literature. Column (2) adds controls for lead analysts characteristics. Column (3) adds year and industry fixed effect with robust p-values in parentheses. The sample only contains teams without star in year *t*. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

	Dependent Variable= DeltaSTAR		
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
Demo_div	0.031	-0.243	-0.208
	(0.08)	(-0.59)	(-0.47)
Cog_div	-0.599	**-1.254****	**-1.380****
	(-1.18)	**(-2.10)**	**(-2.18)**
Acc_ana	0.131	0.136	0.042
	(0.43)	(0.41)	(0.12)
Fr_ana	-0.374	-0.515	-0.545
	(-1.20)	(-1.55)	(-1.55)
No_ind_ana	0.518	0.695	0.321
	(0.69)	(0.89)	(0.37)
No_co_ana	-1.004	-1.103	-0.430
	(-1.16)	(-1.24)	(-0.44)
No_ana_ana	3.144***	3.207***	3.462***
	(11.60)	(10.87)	(10.82)
Logmv_ana	0.184**	0.161*	0.248**
	(2.20)	(1.85)	(2.39)
Logbtm_ana	-0.165*	-0.177*	-0.298**
	(-1.79)	(-1.78)	(-2.21)
Gender		-0.375**	-0.274
		(-2.02)	(-1.40)
Born		-0.015	-0.016*
		(-1.51)	(-1.67)
Age		0.000	-0.002
		(0.02)	(-0.15)
Experience		0.035	0.038
		(1.04)	(1.12)
Major		-0.003	-0.002
		(-0.99)	(-0.77)
Accounting		-0.132	-0.147
		(-0.81)	(-0.85)
Catgri		-0.010	-0.029
		(-0.22)	(-0.59)
Accountancy		-0.004	0.041
		(-0.02)	(0.20)

(The table continues on the next page.)

TABLE 9 (Cont.)			
Foreign		0.265	0.349
		(0.94)	(1.27)
TopUni		-0.071	-0.177
		(-0.48)	(-1.16)
Constant	-6.835***	-5.221**	-5.931*
	(-3.41)	(-2.46)	(-1.79)
Year FE	No	No	Yes
Industry FE	No	No	Yes
N	1203	1107	1092
Pseudo R^2	0.1198	0.1319	0.1626

Table 10
Expanded factors of team diversity and STAR status

This table reports the ordinary least squares estimation of nine diversity attributes on the change of STAR status, for the years 2001-2015. The sample only contains teams without star in year *t*. *deltaSTAR* is the change of star status between the following two years and the current year. *gender* diversity and *age diversity* are diversity factors at demographic level. *experience diversity, major diversity, school diversity, group diversity, employ diversity* and *foreign diversity* are diversity factors at cognitive level. Robust p-values in parentheses, based on Huber–White adjusted standard errors. Asterisks denote statistical significance at the 1% (∗∗∗), 5% (∗∗), or 10% (∗) levels. See appendix for the definition of all other variables.

Dependent Variable= DeltaSTAR			
	Basic Control	Lead Analysts Control	Full Model
	(1)	(2)	(3)
GenderDiv	-0.188	**-0.319***	**-0.348***
	(-1.29)	**(-1.92)**	**(-1.96)**
BornDiv	**0.850****	**0.856****	**0.899****
	(2.41)	**(2.37)**	**(2.45)**
AgeDiv	-0.042	-0.454	-0.247
	(-0.08)	(-0.78)	(-0.39)
ExpDiv	0.339*	0.163	0.165
	(1.78)	(0.77)	(0.76)
MajorDiv	**-0.725*****	**-0.703*****	**-0.706*****
	(-3.26)	**(-2.91)**	**(-2.90)**
CatgriDiv	**-0.572*****	**-0.683*****	**-0.681*****
	(-2.91)	**(-3.05)**	**(-3.05)**
GroupDiv	**-0.956****	**-0.941****	**-0.885***
	(-2.18)	**(-2.05)**	**(-1.84)**
EmployDiv	-0.602	-0.531	-0.542
	(-1.20)	(-1.03)	(-0.98)
ForeignDiv	0.558***	0.536**	0.393
	(3.01)	(2.29)	(1.60)
Acc_ana	0.133	0.150	0.044
	(0.45)	(0.47)	(0.13)
Fr_ana	-0.340	-0.531	-0.531
	(-1.08)	(-1.56)	(-1.50)
No_ind_ana	0.623	0.702	0.428
	(0.80)	(0.89)	(0.51)
No_co_ana	-0.912	-0.905	-0.326
	(-1.07)	(-1.06)	(-0.34)
No_ana_ana	3.113***	3.224***	3.480***
	(11.21)	(10.73)	(10.47)
Logmv_ana	0.163*	0.153*	0.232**
	(1.93)	(1.74)	(2.15)
Logbtm_ana	-0.191*	-0.192*	-0.327**
	(-1.89)	(-1.76)	(-2.37)

(The table continues on the next page.)

TABLE 10 (Cont.)

Accountancy		-0.021	0.014
		(-0.10)	(0.07)
Accounting		-0.118	-0.148
		(-0.70)	(-0.83)
Gender		-0.368**	-0.280
		(-2.00)	(-1.38)
Born		-0.017*	-0.017*
		(-1.80)	(-1.73)
Age		0.002	-0.003
		(0.15)	(-0.20)
Experience		0.038	0.043
		(1.16)	(1.21)
Major		-0.003	-0.002
		(-0.99)	(-0.78)
Catgri		0.023	0.003
		(0.48)	(0.05)
TopUni		-0.174	-0.263*
		(-1.13)	(-1.70)
Foreign		-0.201	-0.030
		(-0.65)	(-0.10)
Constant	-5.922***	-4.806**	-5.189
	(-2.91)	(-2.29)	(-1.61)
Year FE	No	No	No
Industry FE	No	No	No
N	1203	1107	1092
Pseudo R^2	14.71%	15.76%	18.49%