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Analyst teams

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Analyst Teams

Abstract

This paper examines the impact of teamwork on sell-side analysts' performance. Using a hand-collected sample of over 50,000 analyst research reports, we find that analyst teams issue more than 70% of annual earnings forecasts. In contrast, most prior research implicitly assumes that forecasts are issued by individual analysts. We document that analyst teams generate more accurate earnings forecasts than individual analysts and that the stock market reacts more strongly to forecast revisions issued by teams. Analyst teams also cover more firms, issue earnings forecasts more frequently, and issue less stale forecasts. Analysts working in teams are more likely to be voted as All-Star analysts in the future. Among analyst teams, we show that team size and team member ability are significantly associated with forecast accuracy. Moreover, using detailed analyst background information from LinkedIn, we find that forecast accuracy is positively associated with team diversity based on sell-side experience, educational background, and gender. Additional analyses suggest that analyst teams, especially more diverse ones, are more likely to issue cash-flow forecasts and use discounted cash-flow valuation models in their reports. These findings suggest that teamwork and team diversity play a crucial role in understanding sell-side analysts' performance.

Keywords: Teamwork; Analysts; Earnings Forecasts; Diversity; Market Reactions to Analyst Revisions; All-Star Analysts; Cash-Flow Forecasts; DCF Models; LinkedIn; Sell-Side; Education; Gender

JEL Classifications: D83, G11, G24, J24, M14, M41

Analyst Teams

1. Introduction

Teamwork is playing an increasingly important role in organizations including brokerage firms (Wei, 2005). Sell-side equity analysts often lead a team with research associates, whose responsibilities include creating and maintaining valuation models, assisting in writing research reports, interacting with institutional investors, and keeping in touch with the management of companies under coverage. The associates usually start with technical roles during the early stage of their career and gradually take on communication-based tasks as they gain more experience (Bradshaw, Ertimur, and O'Brien 2017). Anecdotal evidence suggests that the nature of working in teams could considerably improve analysts' performance. When Ms. Yates, who was selected as a Rising Star of Wall Street in 2014, talked about her cooperation with another analyst Robert Spingarn, she said "We've really run this franchise as a team over the past couple of years… [Robert and I] leverage the expertise from each other. The fact that together we cover more than 30 stocks allows us to have a more relevant and broader reach across the aerospace and defense sector (Institutional Investor, 2014)."

Despite the prevalence of analyst teams in the sell-side equity research industry, there is little empirical evidence on the impact of teamwork in the analyst literature. This is likely due to the unavailability of data on analyst teams' composition in standard databases such as I/B/E/S. The goal of this study is to fill this gap in the literature and examine the effect of teamwork on analyst performance.

To construct our sample, we start with annual earnings forecasts for U.S. firms from I/B/E/S over the period 2013 to 2016. We manually search Investext and find the analyst research report associated with each forecast issuance. We collect the full name of each I/B/E/S analyst and her team members and their professional designation information, such as CFA, CPA, P.Eng., and P.Geo.[1] Based on our sample of 51,781 forecasts issued by 2,434 I/B/E/S analysts on 3,216 companies, we find that analyst teams issue 73% of annual earnings forecasts. In contrast, most prior research does not consider whether analysts work in teams or individually and treats the analyst as an individual black box.

We first investigate whether analyst teams exhibit differential earnings forecast ability compared with individual analysts. We find that forecasts issued by analyst teams are significantly more accurate than those issued by individual analysts. Specifically, the forecast accuracy of analyst teams is 2.6% to 6.2% higher than that of individual analysts, after controlling for forecast features and analyst characteristics. We find consistent evidence using a changes framework, which keeps the analyst, covered company, and broker firm constant. The inferences also remain after controlling for the analyst's self-selection into teams using Heckman's (1979) two-stage procedure.

As earnings forecasts are not the only important output from sell-side analysts (Brown, Call, Clement, and Sharp, 2016), we next consider a broad portfolio of additional output measures. We find that analyst teams cover more firms in their portfolio, issue forecasts more frequently, and generate less stale forecasts. We also find that teamwork is positively related to the issuance of cash-flow forecasts and to achieving All-Star status in the following year (controlling for the current year's All-Star status). Using a randomly selected subsample of analyst reports, we show that analyst teams are more likely to employ more sophisticated discounted cash-flow (DCF) valuation models than individuals and we do not find that narratives systematically differ between teams and individuals. We further document that the market reacts more strongly to forecast revisions by

[1] We refer to the I/B/E/S analyst as the person whose name is associated with the forecast in I/B/E/S.

analyst teams. This finding suggests that investors are aware of the superior performance of analyst teams.

We then turn our attention to *within-team* analyses and first examine the impact of having a larger number of team members. The results suggest that team size is positively associated with earnings forecast accuracy, with the marginal return of having an additional member decreasing with team size. We also investigate the effect of team members' ability and the results show that the ability of team members has a significant impact on forecast accuracy after controlling for the lead analyst's characteristics.

Next, motivated by research in economics and organizational behavior, we test the effect of *diversity* on analyst team performance. To obtain personal background information, we search each I/B/E/S analyst and team member using their full name and broker firm information. Our primary data sources are LinkedIn and Relationship Science. We augment this information with Zoominfo.com, Bloomberg, Wall Street Transcript, and broker firm websites if necessary. We collect background information such as gender, education degrees, major areas of study, and the starting year in the sell-side industry. We then create a diversity score for each analyst team based on its members' educational background, years of sell-side experience, and gender. The results show that diversity has a significant and positive effect on forecast accuracy. We also find that more diverse teams are more likely to issue cash-flow forecasts. Based on the randomly selected subsample of analyst reports, we find that more diverse teams are more likely to use DCF valuation models and we do not find that diversity significantly affects the narratives of analyst reports.

Moreover, we conduct additional cross-sectional analyses to explore the relation between task complexity and the effect of teamwork. Our results provide some evidence suggesting that the superior forecasting performance for analyst teams, especially for the more diverse ones, is more salient when the covered firm has a more opaque information environment, such as firms with more segments and lower analyst coverage. The evidence is consistent with the findings in organizational behavior literature that task complexity augment the potential benefits of team diversity.

This study makes contributions to several strands of literature. First, our research contributes to the accounting literature by documenting the importance of organizational structure on understanding analysts' behavior and on the quality of information in capital markets. Sell-side analysts are among the most important information intermediaries (Bradshaw 2011) and examining what drives their behavior and performance helps us understand the nature of information in capital markets. Prior studies have documented that both external factors and analysts' innate characteristics are associated with their performance, including experience, portfolio complexity, and broker firm prestige (Mikhail, Walther, and Willis, 1997; Clement, 1999; Jacob, Lys, and Neale, 1999; Clement, Koonce, and Lopez, 2007), geographical proximity to the covered firm (Malloy, 2005; Bae, Stulz, and Tan, 2008; O'Brien and Tan, 2015), Chartered Financial Analyst (CFA) designation (De Franco and Zhou, 2009), educational link to firm management (Cohen, Frazzini, and Malloy, 2010), and pre-analyst industry working experience (Bradley, Gokkaya, and Liu, 2017). However, one feature of this literature is assuming analysts work individually without taking into account the effects of the analyst's team members. The reason is likely due to the fact that data on analyst teams' composition are not readily available in standard databases.

Our study fills this gap of literature by looking into the details of analyst teams' organizational structure. Using a dataset of analyst teams' composition and team members' demographical information, we provide novel evidence on the prevalence of teamwork in the equity-research industry by showing that more than 70% of earnings forecasts are issued by teams. More importantly, we document that teamwork and diversity within teams are significantly associated with analyst performance. Our paper highlights the idea that it is not just the lead analyst's characteristics, but also the features of her team members and their complementarity with the lead analyst that affect the quality of analyst outputs. Our findings suggest that the organizational structure of information intermediaries such as analysts plays an important role in determining the quality of information in capital markets.

There is limited prior research on analyst teams. Brown and Hugon (2009) indirectly infer the presence of analyst teams from the incidence of multiple names associated with one single analyst ID in I/B/E/S and find that analyst teams issue timelier but less accurate forecasts than individual analysts. However, fewer than 6% of observations in their sample are identified as analyst teams. In our sample, using a direct identification method, the proportion of teams is higher than 70%. In other words, most of the individuals in Brown and Hugon (2009) are likely to be teams as well and the comparison between team forecasts and individual forecasts in Brown and Hugon (2009) is likely between one type of team and other types of teams. In contrast, we use a more direct method to identify teams based on their research reports and thus have a more accurate measure with broader coverage of analyst teams.

A concurrent paper by Brightbill (2018) also identifies analyst teams based on research reports. She focuses on a sample of 89 companies from three industries, but has a relatively long sample period. She finds that teams generate more accurate forecasts than individuals after Reg FD, but less accurate forecasts in the pre-2000 period. She also provides evidence regarding forecasts bias and the effect of team tenure. In contrast, our sample consists of all US firms from all industries (except for financial and utility firms) in COMPUSTAT and our sample is three times as large as that in Brightbill (2018), thus enhancing the generalizability of our study. The consistency of findings on forecast accuracy between these two studies, despite the different focuses, help demonstrate the robustness and implications of our findings to other time periods. Importantly, we also collect detailed background information about analysts and their team members and we show that the effect of teamwork is associated with team diversity based on gender, education, and experience.

Another related study by Gao, Ji, and Rozenbaum (2018) finds that associate analyst fixed effects explain 17.6 percent more of the variation in forecast accuracy than lead analyst fixed effects do. In contrast, they find that lead analyst fixed effects explain three times more of the variation in forecast timeliness and 10.7 percent more of the variation in forecast bias than associate analyst fixed effects do. Unlike their focus on the explanatory power of associate analysts' fixed effects among teams, our study first compares the performance between analyst teams and individuals. Among analyst teams, we not only test the impact of associate analysts' own characteristics, but also look into their complementarity with the lead analysts. Our measure of team diversity is based on both the lead analyst's and associated analysts' features, which cannot be fully captured by associated analysts' fixed effects.

Second, our study contributes to the cross-disciplinary literature focusing on the differential performance between teams and individuals. Prior research has documented that teamwork can enhance individual productivity (Hamilton, Nickerson, and Owan, 2003; Boning, Ichniowski, and Shaw, 2007; Patel and Sarkissian, 2017). There is also evidence showing that team decisions are less extreme than those of individuals due to either the compromise effect or the selection effect of individuals in joining the team (Adams and Ferreira, 2009). However, most research in this literature are based on either small samples (Hamilton, Nickerson, and Owan, 2003; Boning, Ichniowski, and Shaw, 2007) or experimental settings (Cooper and Kagel, 2005; Blinder and Morgan, 2005). To the best of our knowledge, Patel and Sarkissian (2017) provide the only large sample empirical evidence which compares the performance of mutual funds managed by teams versus those managed by individuals. Our study provides new evidence to this literature using a different setting in which teams and individuals process information from capital markets and produce earnings forecasts and other outputs for the companies they follow. We employ a large sample and show that teams produce both high quality (accuracy) and quantity (portfolio size and frequency) of output. A distinct feature of our setting compared with prior studies is that we are able to observe analyst teams' performance in different types of activities, such as forecasting accuracy, narratives in reports, and career outcomes, while Patel and Sarkissian (2017) only measure the risk and returns of mutual funds. More importantly, we document that positive effects of teamwork increase with the diversity of the team in a large sample.

Finally, this paper is related to the cross-disciplinary literature on team diversity. On one hand, there is evidence that shows the positive effects of ability heterogeneity (Hamilton, Nickerson, and Owan, 2003), gender diversity (Hoogendoorn, Oosterbeek, and Praag, 2013; Kim and Starks, 2016; Apesteguia, Azmat, and Iriberri, 2012), origin diversity (Kahane, Longley, and Simmons, 2009), and education diversity (Dahlin, Weingart, and Hinds, 2005). One the other hand, several studies have also documented negative effects of diversity. For example, Adams, Akyol, and Verwijmeren (2018) and Giannetti and Zhao (2018) find that diversity leads to the lack of common ground and increases communication costs, which makes the decision-making process more erratic. Our study contributes new evidence to this literature on the positive effects of diversity using an analyst setting, in which we are able to employ a much larger sample than most of the field studies in the organizational behavior literature and to improve the external validity of our findings. The nature of the analyst setting also allows us to better quantify the performance of teams in multiple dimensions and the complexity of tasks, which enables us to better evaluate the potential benefits and costs of diversity.

2. Prior Literature and Hypotheses Development

As argued by Becker and Murphy (1992), teamwork allows a more extensive division of labor and improved productivity because returns to the time spent on tasks are higher for a more specialized worker. The optimal specialization is determined by the balance between returns to specialization and coordination costs. This economic insight explains why teamwork becomes more pervasive and workers become more specialized as knowledge and the economy grow.

Empirical studies have provided evidence in support of productivity improvement within teams. For instance, Hamilton, Nickerson, and Owan (2003) examine the adoption of teamwork at a garment plant and show that average worker productivity improves 14% after controlling for the self-selection effect of high-productivity workers joining teams. They further provide evidence that high-ability workers join teams first despite a loss in earnings, suggesting that they receive some non-pecuniary benefit by working in teams, such as the satisfaction obtained from decision authority.

However, established theories suggest that teamwork can create moral-hazard problems when actions taken by team members are not observable (Alchian and Demsetz, 1972; Holmström, 1982; Lorenz, Rauhut, Schweitzer, and Helbing, 2011). When the joint output by team members is the only observable indicator of labor inputs, each team member has an incentive to shirk, as their cheating behavior will not be identified. As Holmström (1982) shows, this free-rider problem may occur even when there is no uncertainty over output.

Regarding analyst teams, on one hand, a better division of labor may enhance the labor productivity of each member. The I/B/E/S analyst and her team members can each be specialized in one of the aspects of sell-side research. For example, the lead analyst can put more effort into communicating with clients and management of covered companies, while the associate analysts focus on the modeling tasks. This specialized labor division can improve the return to the time and resources spent on the individual tasks and therefore improves the overall performance of the team. On the other hand, it is hard to accurately measure the output at the individual level, which might weaken the incentives of each member. The output by analyst teams is mainly at the aggregate team level, such as earnings forecasts, stock recommendations, and research reports issued by the whole team. Coordination costs can also affect a team's performance in the analyst setting. The lead analyst needs to be involved with mentoring and communicating with the associate analysts, which might limit the time and effort that the lead analyst spends on other tasks (e.g., communicating with clients and the management of covered firms). Therefore, ex-ante, it is ambiguous whether teams would have better performance than individual analysts. The first hypothesis on the relation between teamwork and analyst performance is (in null form):

H1: Analyst teams do not have better performance than individual analysts.

The next three hypotheses focus on *within-team* issues and examine the relation between team characteristics and performance. In terms of the size of a team, arguments from Becker and Murphy (1992) and Holmström (1982) apply. Specifically, a larger number of members in a group improves the benefits of labor specialization and thus enhances the marginal productivity of the additional member. However, a larger team size may also exacerbate the moral-hazard problem and increase the coordination costs in teamwork. Therefore, the effect of team size on analyst team performance is not obvious and remains as an empirical question. The second hypothesis is (in null form):

H2: Analyst teams with a larger size do not have better performance than smaller ones.

Next, we consider the effect of ability at the team level. We argue that the competence of a team comes from two sources, the average ability of team members and the complementary effect due to the dispersion of ability among team members. Prior research provides rich evidence on the relation between analyst ability and forecasting performance. Clement (1999) uses cross-sectional regressions and shows that forecast accuracy is positively associated with analysts' general and firm-specific experience. Mikhail, Walther, and Willis (1997) use a time-series setting and find similar results. De Franco and Zhou (2009) show that CFA charterholders' forecast accuracy is statistically better than non-charterholders in some empirical specifications, while the economic significance of the difference is small. They find that charterholders improve their forecast timeliness after they receive their CFA charter, suggesting that charterholders have accumulated knowledge and improved their productivity during the CFA program, consistent with a human-capital explanation.

If the ability of analyst team members is associated with their contributions to team performance and if their ability is not perfectly correlated with the I/B/E/S analyst's ability, then we expect team members' ability to have an impact on the team's performance.[2] The third hypothesis is (in null form):

[2] For instance, a lead analyst with the CFA designation can work with either CFA team members or non-CFA team members. We expect team member's professional designations to impact team performance after controlling for the lead analyst's professional designation.

H3: Among analyst teams, team members' average ability is not associated with the team's forecasting performance, after controlling for the I/B/E/S analyst's ability.

The fourth set of hypotheses focuses on the complementary effects among team members. On one hand, a large literature in both economics and organizational behavior sheds light on the positive effect of diversity. Existing theories have established the positive association between team diversity and performance. Lazear (1998) argues that global firms hire workers with diverse backgrounds, which suggests that teamwork is beneficial due to complementarities in production and knowledge transfer among team members. Page (2007) indicates that a diverse board contributes different perspectives to corporate strategies. Stahl, Maznevski, Voigt, and Jonsen (2011) state that diversity is associated with differences in mental models, modes of perception, and solutions to problems and thus it enhances the team's creativity. Díaz-García, González-Moreno, and Saez-Martínez (2013) argue that diverse corporate boards tend to explore novel solutions facing problems, which leads to more radical innovation output.

There is ample empirical evidence on the positive effect of diversity along several dimensions. Regarding gender diversity, Apesteguia, Azmat, and Iriberri (2012) show that gender composition affects team economic performance in a business game in which each group performs the role of a general manager. They find that pure women teams are outperformed by more diverse teams. They show that the differences are driven by pure-women team's less risk taking behavior. In a field experiment in which undergraduate students start up a venture in teams, Hoogendoorn, Oosterbeek, and Praag (2013) find that teams with more balanced gender mixture have better performance than male-dominated teams. Kim and Starks (2016) show that female directors contribute special skills to corporate boards and thus improve firm value.

In terms of education diversity, Dahlin, Weingart, and Hinds (2005) argue that education affects the information, knowledge, and skill sets that people bring to a team. They employ a setting in which MBA students are randomly assigned to teams to work on case studies and provide consistent evidence showing that diverse educational backgrounds among team members enhance the range and depth of information use.

Concerning experience diversity, Guimerà, Uzzi, Spiro, and Amaral (2005) demonstrate that teams with all experienced members tend to homogenize their pool of knowledge and be less likely to have innovative ideas. Instead, teams with a combination of newcomers and experienced members are likely to have more diverse perspectives and contribute more innovative solutions.

Moreover, prior research has suggested that the positive effect of diversity should be most evident when the task is more complicated (Watson, Kumar, and Michaelson, 1993; Amason, 1996; Polzer, Milton, and Swann, 2002; Stahl, Maznevski, Voigt, and Jonsen, 2011). Stahl, Maznevski, Voigt, and Jonsen (2011) argue that task complexity augments the positive effect of diversity on performance by improving the potential gains from divergence and creativity. The intuition is that different perspectives and skills are needed to reach a successful solution for these tasks. Empirical studies provide support for this argument. For instance, Bowers, Pharmer, and Salas (2000) find that more diverse teams have better performance than homogeneous ones but only when the task is complicated.

The above studies document the bright side of diversity. However, there are also studies that highlight negative effects of diversity. Members with diverse backgrounds may have higher coordination costs, which decrease their ability to work as a team and leverage the expertise from each other. For example, Adams, Akyol, and Verwijmeren (2018) find that the diversity of corporate board members' skill sets is negatively associated with firm performance. They argue that the lack of common ground in skills may hurt directors' communications. Giannetti and Zhao (2018) show that board diversity increases communication costs, which makes the decision-making process more erratic and thus increases firm performance volatility.

In the analyst setting, we expect diversity to better equip analyst teams with the necessary skills to produce high-quality outputs. Li, Lin, and Lu (2018) show that both technical skills and social skills affect analysts' earnings forecast accuracy. We expect that teams with higher educational diversity (e.g., a team that has one member with a quantitative background and one member with a business background) are more likely to have advantages in both types of skills. In terms of experience diversity, we expect that diverse team members are more likely to have heterogeneous mental models about the covered firms and have different approaches to forecasting and valuation tasks, which could better challenge the status quo and catch up with new trends. For example, teams with both newcomers and experienced analysts may bring a fresh mind and have a better understanding of firms that have incorporated Blockchain technology into their business models than teams with only highly experienced analysts. Regarding gender diversity, teams with females may be more willing to take into account less aggressive assumptions when making forecasts. The less aggressive choices may not be even considered by all-male teams. The different perspective brought to the table by female team members could thus enhance the team's performance.

On the other hand, it is also possible that diversity may hurt analyst teams' performance. Diverse members are less likely to have common ground in terms of skills, which increases the coordination costs among members. When the covered firm is not complicated, the benefit of diversity may not outweigh the cost, leading to overall negative effects of diversity on analyst performance. Therefore, the effects of diversity on analyst teams' performance is an empirical question. The fourth set of hypotheses is (in null form):

H4a: Among analyst teams, performance is not associated with team diversity based on educational background, experience, and gender.

H4b: The effect of team diversity is not stronger when the covered firm is more complicated to analyze.

3. Sample Selection and Key Variables

3.1 Sample Selection

Table 1 summarizes the sample-selection process. We start with all analysts with at least one annual earnings forecast over the 2013 to 2016 period (1,544,049 forecasts, 5,722 firms, and 9,365 analysts). We then merge the data with CRSP/COMPUSTAT to obtain accounting and stock-price information (1,176,787 forecasts, 3,581firms, and 6,651 analysts). Following Bradley et al. (2017) we retain the most recent forecast with a horizon between one to 12 months (116,148 forecasts, 3,578 firms, and 5,608 analysts). For each analyst in the sample, we obtain the last name and the initial of their first name from the I/B/E/S recommendations database. We require that either the analyst last name or the broker ID be non-missing. After this filtering process, we obtain a sample of 94,868 forecasts, 3,546 individual firms, and 4,557 I/B/E/S analysts.

Then, for each forecast in the sample, we *manually* search Investext to find the associated analyst research report using the covered firm's name, broker firm ID, forecast issuance date, analyst's last name, and first name initial.[3] We obtain the full name of all the authors of each report as well as their professional designation information such as CFA, CPA, P.Eng., and P.Geo.[4] An example of the data-collection process can be found in Appendix B (and the associated figures). In order to compare performance between teams and individuals, we further require that each firm-year is covered by at least one team and one individual. This process gives us the main sample to examine the difference between team and individual forecasts, which consists of 51,781 forecasts, 3,216 firms, and 5,055 individuals including 2,434 I/B/E/S analysts and 2,621 team members.

Finally, for each forecast issued by analyst teams, we search for the analyst and her team members' background information based on their full name and broker firm information. Our primary data sources are LinkedIn and Relationship Science, two of the world's largest professional network websites. In a few cases, we augment this information with Zoominfo.com, Bloomberg, Wall Street Transcript, and broker firm websites. We collect the individuals' gender, the education major, level of degrees, and the starting year in the sell-side industry. This process leaves us with a sample of 30,273 forecasts, 2,850 firms, 1,409 I/B/E/S analysts, and 1,575 team members. This is the main sample for exploring the effect of team diversity.

3.2 Key Variables

3.2.1 Analyst Team Indicator and Team Diversity Measure

The key variables of interest include the indicator for analyst teams and analyst-team diversity. For each earnings forecast in the sample, if there is more than one author on the associated

[3] As Investext does not cover all broker houses, we acknowledge that our sample may have a selection bias (similar to most other studies in this line of research).

[4] P.Eng. refers to Professional Engineer and P.Geo. refers to Professional Geologist.

research report, we treat the forecast to be issued by an analyst team and the indicator *TEAM* equals one. Otherwise, the forecast is issued by an individual analyst and the value of *TEAM* is zero.[5]

Our definition of diversity is based on three dimensions: education, working experience in the equity-research industry, and gender. For education, we first split all majors into three categories, business/economics (e.g., finance, accounting, and economics), quantitative fields (e.g., math, physics, and engineering), and others (e.g., history, journalism, and English). Following prior studies (Bernile, Bhagwat, and Yonker 2018; Li and Wahid 2018), we use an HHI measure to capture educational diversity[6]:

$$\textit{HHI Education} = 1 - \sum_i (Number\ of\ team\ members\ in\ category_i\ /team\ size)^2.$$

To ease the comparisons between different dimensions of diversity, we then transform the educational diversity measure to into an indicator variable based on the diversity measure of other teams. Specifically, for each firm-year, if a team's education diversity measure is higher than the median value of all teams covering the same firm, then *Education Diversity* equals one. Otherwise, *Education Diversity* has the value of zero.

In terms of experience diversity, we start by taking the difference between the current year and each individual's starting year in the sell-side industry. Next, we calculate the standard deviation of experience within each team scaled by the mean value, following prior studies in the organizational behavior literature (e.g., Bedeian and Mossholder 2000). Then we construct an indicator *Experience Diversity* in a similar way as education diversity. The reason that we do not

[5] The pattern in our data suggests that an analyst can work with different team members for different firms. Therefore, we measure *TEAM* at the analyst-firm-year level.
[6] Our inferences are similar using other measures. For example, we have considered the distinct number of educational major categories of each team or an HHI measure based on further splitting each major category into undergraduate, graduate, and PhD levels (untabulated).

use the number of years that each individual shows up in I/B/E/S is that most non-I/B/E/S-analyst individuals never appear in I/B/E/S.

Regarding gender, the variable *Gender Diversity* equals one if an analyst team consists of both male and female members. If a team has only male or only female members, then *Gender Diversity* has the value of zero. Finally, we take the sum of *Education Diversity*, *Experience Diversity*, and *Gender Diversity* for each analyst team to construct an overall diversity score *Diversity*, ranging from zero to three.

3.2.2 Analyst Performance Measures and Control Variables

We use earnings forecast accuracy as our first proxy for analyst performance as earnings forecasts also serve as critical inputs for analysts' other research outputs, such as stock recommendations (Bradshaw 2004; Ertimur, Sunder, and Sunder 2006; Brown, Call, Clement, and Sharp, 2015) and target price forecasts (Gleason, Johnson, and Li, 2013). *Accuracy* is defined as the absolute value of the forecast error (annual earnings forecast less actual EPS reported by I/B/E/S), multiplied by -1 (so that the measure increasing with more accurate forecasts).

However, earnings forecasts are certainly not the only important dimension of sell-side analyst work. Consequently, we also consider an expanded portfolio of outcome measures that include the issuance of cash-flow forecasts in addition to earnings forecasts, market reaction to forecast revisions, the probability of becoming an All-Star analyst in the next year, the use of more sophisticated DCF analyses, and the narratives used in analyst reports.

We control for several analyst characteristics that are known to be associated with forecast performance. *Horizon* is the number of days between the forecast issuance date and the announcement date of the actual earnings value. *Frequency* is the total number of forecasts issued by an analyst for the specific firm. *Broker Size* is the total number of I/B/E/S analysts employed by the analyst's brokerage firm. *Number of Firms Covered* is the number of firms covered and *Number of Industries Covered* is the number of SIC 2-digit industries covered by the analyst. *I/B/E/S Analyst General Experience* is the number of years that the I/B/E/S analyst appears in I/B/E/S and *I/B/E/S Analyst Firm Experience* is the number of years that the analyst has provided annual forecasts for the specific firm. *Bundle* is an indicator that equals 1 if the analyst issues forecasts for more than one firm on the same day.[7] We also control for the analyst's All-Star status to mitigate the possibility that an All-Star analyst may have more resources to construct a team. (*Lag) All Star* is an indicator variable that equals one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in the (previous) current year. Appendix A provides detailed variable definitions.[8]

To control for systematic differences across firm-years and to facilitate comparison across observations, we standardize each of the performance measures and control variables to range from 0 to 1, following Clement and Tse (2003; 2005) and De Franco and Zhou (2009). Specifically, among all of the analysts providing a forecast for firm j at time t, each variable is transformed to be the distance relative to the minimum value and then scaled by the range of that variable.[9]

[7] Drake, Joos, Pacelli, and Twedt (2019) show that bundled forecasts are less accurate, less bold, and less informative to investors than un-bundled forecasts.
[8] We winsorize all continuous variables at the top and bottom 1% tails. Inferences are robust to winsorizing at other cut-offs or no winsorizing.
[9] The inferences remain similar if we use demeaned values of performance measures and analyst characteristics variables following Bradley et al. (2017) or if we use unadjusted values of each variable and include firm-year fixed effects to control for systematic differences across firm-years.

4. Main Results

4.1 Summary Statistics, Univariate Analyses, Correlations, and Determinants of *TEAM*

Table 2 presents summary statistics for the analyst performance measures and analyst characteristics both before and after the standardization process. Panels A and B show the distribution of each variable for the full sample. Panel C presents the Pearson's correlations of standardized variables. Panel D split the sample into analyst teams and individual analysts, respectively. Each variable is calculated per forecast and then aggregated by the analyst. The mean value of each variable is calculated and the differences for each measure between these two groups are presented in the last column. Panel E shows the forecasting accuracy for teams with different numbers of members.[10] Panel F presents the overall descriptive statistics on demographic information of I/B/E/S analysts and team members, and Panel G shows the demographic differences between these two groups.

Panel A shows that the mean value for *TEAM* is 0.73, suggesting that 73% of the annual forecasts in the sample are issued by analyst teams. Although not the main contribution of this study, it is worth noting that these forecasts are typically classified as being generated by individual analysts in prior literature.[11] On average, an I/B/E/S analyst issues 8 forecasts for each firm she covers, has 12.9 years of general experience, 4 years of firm-specific experience, covers 15 firms, and 3.6 industries. The average horizon for each forecast is 120.2 days and the average number of analysts that each brokerage house employs is 63.5. On average, 32% of the forecasts are bundled.[12]

[10] Team size of 1 refers to individual forecasts.
[11] Because we exclude firm-years that are only covered by individuals or teams, the 73% number should be interpreted as the lower bound for the prevalence of teamwork considering that the percentage of teams is even higher in the excluded observations.
[12] The percentage is lower than that in Drake et al. (2019), as we only consider one-year ahead earnings forecasts, whereas they also include forecasts with longer horizons.

Compared with Clement and Tse (2003, 2005) and De Franco and Zhou (2009), these summary statistics are within a reasonable range.

Panels C presents the Pearson correlations of the standardized variables. The correlation between *TEAM* and *Accuracy* is 0.045 and is significant at the 1 % level, which suggests that analyst teams have better forecasting performance than individuals. Panel D splits the full sample into team forecasts and individual forecasts and univariate test results are presented. The results show that analyst teams produce more accurate forecasts compared to individual analysts. Analyst teams are associated with more frequent forecast issuance, less stale forecasts, and larger portfolio size. The I/B/E/S analyst of each team has more firm-specific and general experience than an individual analyst and teams are more likely to issue bundled forecasts. And analysts working in teams are more likely to be voted as All-Star analysts. Overall, Panels C and D provide univariate evidence rejecting H1, suggesting that analyst teams have better performance than individual analysts.

Panel E of Table 2 shows the standardized forecast accuracy for each level of team size. 28% of earnings forecasts in the sample are issued by individual analysts, 38%, 24%, 8%, and 2% of forecasts are issued by analyst teams with 2 to more than 5 members, respectively. The results indicate that analyst teams of all size levels are more accurate than individuals and that teams with larger size tend to have higher accuracy. The univariate results reject H2, suggesting that *Team Size is* positively related to forecasting accuracy.

Panel F shows that 24% of I/B/E/S analysts and their team members are CFA charterholders, 87% are male, and 45% hold an MBA degree. On average, each person has 12 years of experience in the sell-side equity research industry. In terms of undergraduate education, 68% of analysts and team members have business or economics as their major, 29% have a quantitative major, and 11% have a major in other areas, such as English, history, or journalism. For graduate education, the proportions of degree holders in business/economics, quantitative, and other fields are 46%, 8%, and 2%, respectively. For doctoral education, the proportion of degree holders in these three categories are 1%, 4%, and 1%, respectively.

Panel G shows demographic differences between I/B/E/S analysts and their team members. The results show that the I/B/E/S analyst is more likely to hold a CFA designation, an MBA degree, and an educational background in other subjects, such as history, English, or journalism. The I/B/E/S analyst is also more likely to be male and has more experience than other team members.

4.2 Multivariate Regression Tests

4.2.1 Earnings Forecast Accuracy: Effect of Teamwork

To examine the effect of teamwork on analyst performance, we estimate the following OLS regression model

$$Performance_{ijt} = \alpha + \beta_1 TEAM_{jt} + \beta_2 Analyst\ Characteristics_{jt} + \beta_3 Forecast\ Characteristics_{jt} + \epsilon_{ijt}. \quad (1)$$

Performance is the standardized value of forecast accuracy as described in section 3.2.2. *TEAM* is the primary variable of interest and it is an indicator that equals 1 if the forecast is issued by an analyst team. We control for a number of analyst and forecast characteristics variables as described in section 3.2.3. Standard errors are heteroskedasticity-consistent and clustered at the analyst level.[13]

[13] The inferences remain unchanged using other clustering structures, such as at the firm or industry level.

Table 3 reports the multivariate regression results. In Panel A, the dependent variable is the standardized value of analyst forecast accuracy. Column 1 only includes *TEAM* as the independent variable, whereas Columns 2 and 3 introduce the control variables, including the lagged value of accuracy (Column 3).[14] In Column 4, we further control for the analyst's All Star status in the previous year.

The coefficient for *TEAM* is significantly positive at the 1% level (using two-sided tests) in all specifications. To interpret the economic significance of *TEAM*, we follow the approach adopted in De Franco and Zhou (2009). Specifically, we calculate the predicted value of *Accuracy* using the estimated coefficients from the regressions and the standardized values of the control variables. The results suggest that analyst teams are 2.6% to 6.2% more accurate than individual analysts using different specifications.[15] As a comparison, Bradley et al. (2017) show that analysts with prior industry working experience are 3.6% more accurate than those without such experience and De Franco and Zhou (2009) show that analysts with CFA designations are 4.1% more accurate than non-CFA analysts. Therefore, we interpret the documented effect of teamwork to be economically significant.[16]

Working in teams is likely not determined exogenously. The summary statistics in Table 2 show that there are systematic differences between analysts working in teams and those working individually. Though we include an extensive set of time-varying control variables to reduce such endogeneity concerns, it is possible that there are omitted variables that affect whether an analyst works in a team or individually and her forecast accuracy at the same time. In Panel B of Table 3,

[14] Lag value of *Accuracy* is the analyst's standardized forecast *Accuracy* for the same firm in the previous fiscal year.
[15] For example, the predicted value of *Accuracy* in Column 1 is 0.594 for individuals and 0.631 for analyst teams, suggesting that teams are 0.631/0.594-1=6.23% more accurate than individuals. Specially, the predicted value for individuals is the intercept 0.594, and the predicted value 0.631 for analyst teams is 0.594+0.037×1=0.631.
[16] We obtain similar results (untabulated) if using the unadjusted value of forecast accuracy and control variables. In untabulated analyses, we also find that our findings are robust to controlling for whether team members other than the I/B/E/S analyst have ever appeared in I/B/E/S.

we employ a *changes specification* to further control for potential analyst-level and firm-level time-invariant omitted variables. We essentially keep the covered *firm*, *analyst*, and the *broker* firm *constant* and explore the impact of the changes in analyst teams' composition on changes in their performance.

Team membership is persistent over time in our sample. Specifically, 93.3% of the analysts working in teams for the current firm-year continue to work in teams in the following firm-year and 26.9% of the analysts working individually in the current firm-year switch to working in teams in the following firm-year. Team membership is also consistent across firms for each analyst-year. If an analyst works in teams for a firm-year, then she also works in teams for 97% of other covered firms in the same year.[17]

We calculate the changes in *Accuracy*, *TEAM*, and control variables at the *analyst-firm* level. Each analyst has at most four forecasts for each firm in the four-year panel data, so we end up with a three-year panel data using the changes framework (i.e., these tests likely suffer from low power).

The dependent variable in all columns is *Change in Accuracy*. Columns 1 shows that switching from individual work to teamwork is associated with significantly better forecasting accuracy. The coefficients are significant at the 5% level (using two-sided tests). The results are similar in Column 2, which further controls for changes in control variables and the lag value of controls. Column 3 further adds industry fixed-effects and year fixed-effects and the inferences are unchanged.

To further alleviate potential effects of analysts' self-selection into teams, we employ a Heckman two-stage procedure in Panel C. In the first stage, we estimate a probit model in which

[17] To further validate our measure of *TEAM*, which intends to captures whether analysts work with other people or just by themselves, we *manually check* 100 random cases of changes in *TEAM* over time. In 81 cases, we are able to collect the full employment history of team members and in 71 cases (88%) the changes in *TEAM* correspond to the changes in team members' employment status. This percentage should be interpreted as the lower bound of the accuracy of *TEAM* because there might be reasons other than changes in employment status that affect whether a research associate works with the lead analyst.

the dependent variable is the *TEAM* indicator. The independent variables include the controls in Panel A and several firm characteristics variables.[18] Then we calculate the inverse Mills ratio (*IMR*) based on the first-stage regression and include it in the second stage.[19] Column 2 presents the second-stage regression results and shows that the coefficient for *TEAM* is still positive and significant at the 1% level.

Overall, Panels B and C confirm the findings on the superior earnings forecast accuracy by analyst teams and show that the effect documented in Panel A is less likely due to endogeneity issues.[20] This empirical evidence rejects H1 and suggests that teamwork is positively associated with forecasting performance.

4.2.2 Forecast Accuracy: The Impact of Team Size

In Table 4, we consider the effect of having additional team members. The dependent variable is the standardized value of *Accuracy*. Column 1 uses the full sample and Column 2 uses only forecasts issued by analyst teams. To examine the marginal effect of having an additional team member, we add the squared term of *Team Size*, *Team Size2*, to the regressions.

The coefficients for *Team Size* and *Team Size2* are statistically significant in both columns. Specifically, the results show that having an additional member in a team is associated with better forecast accuracy, but that the marginal return decreases as the number of team members increases. The findings suggest that the positive effect of teamwork due to complementary skills or better

[18] It is possible that analysts with less experience and worse forecasting performance are more likely to need help from others and thus work in teams. We control for analyst experience and previous-year forecast accuracy in the first-stage regression. As shown in Panel C of Table 3, our results do not support this argument.
[19] The *IMR* is based on the probit estimate and it is calculated as the ratio of the standard normal probability density function divided by its cumulative probability.
[20] In untabulated tests, we use each analyst's covered firms without variation in *TEAM* as the control group. This sample is more balanced with respect to the number of treated and control observations. The results are similar to the findings in Panel B of Table 3.

division of labor dominates the negative effect due to coordination costs or moral hazard, and that the negative effect increases at a higher rate as the team becomes larger. Overall, the results in Table 4 reject *H2* and indicate that analyst teams with more members are associated with better forecast accuracy.

4.2.3 Forecast Accuracy: The Effect of Analyst and Team Members' Ability

Table 5 presents the results of the effect of analyst and team member ability. We measure their ability based on the professional designations that they disclose in research reports and sell-side working experience and MBA-degree status that we collect from LinkedIn and other sources. We also explore whether gender plays a role in the sample, as Green, Jegadeesh, and Tang (2009) show that female analysts issue less accurate earnings forecasts than male analysts. *I/B/E/S Analyst Pro Designation* equals 1 if the I/B/E/S analyst holds a professional designation, such as CFA, CPA, P.Eng., or P.Geo. The variable *Member Pro Designation* is the proportion of team members with professional designations within an analyst team. *I/B/E/S Analyst Experience* is the standardized years' of experience by the I/B/E/S analyst, and *Member Experience* is the standardized average experience of the team members. *I/B/E/S Analyst MBA* is an indicator that equals one if the I/B/E/S analyst holds an MBA degree, and *Member MBA* is the proportion of the team members with MBA degrees. *I/B/E/S Analyst Female* is an indicator that equals one if the I/B/E/S analyst is female, and *Member Female* is the proportion of female members of each team. The dependent variable is *Accuracy* in all columns.

The coefficients for the I/B/E/S analyst ability measures are insignificant in all columns, while the coefficient for the team-member ability measures is positive (negative) and significant at the 10% (5%) level in Column 1 (Column 2). The coefficients are significant at the 5% level or better if all variables are included in the regression (Column 5). The results suggest that analyst teams with more team members holding professional designations and analyst teams with less experienced members issue more accurate forecasts.[21] The results suggest that the ability of team members has a significant impact on the forecasting performance of a team after controlling for the lead analyst's status. The insignificant coefficients for the other ability measures suggest that the level of lead analyst's and team members' MBA education or gender do not incrementally impact team performance in our sample.

4.2.4 Forecast Accuracy: The Effect of Team Diversity

The results on the effect of team diversity are presented in Table 6, in which the sample only consists of analyst teams. The dependent variable is *Accuracy* and the test variable is *Diversity* in Column 1, a score ranging from 0 to 3 based on team member experience, educational background, and gender. In Columns 2 to 4, we separately run similar regressions for each component of *Diversity* and in Column 5 we include all diversity measures in one regression model. We control for *Team Size*, *Team Size2*, analyst and team member ability measures, and other forecast characteristics employed in prior sections.

The estimated coefficient for *Diversity* is positive and statistically significant at the 1% level, implying that analyst teams with a more diverse background generate more accurate forecasts compared with less diverse teams. Economically, *Diversity* increasing by one is associated with a 2.3% increase in forecast accuracy in terms of the sample mean value.[22] The coefficients for *Education Diversity* and *Experience Diversity* are significant at the 10% and 1% level, respectively,

[21] In untabulated tests, we find that the effect of professional designations mainly comes from CFA, not CPA, P.Eng., or P.Geo. These results add to those reported by De Franco and Zhou (2009).
[22] 2.3% is calculated as the estimated coefficient 0.014 divided by sample mean 0.62 (0.014/0.62=2.3%).

while the coefficient for *Gender Diversity* is not significant at conventional levels. The findings suggest that the effect of *Diversity* mainly comes from the education and experience dimensions.

Overall, the results in Table 6 reject Hypothesis 4a and suggest that forecasting performance is positively associated with diversity among analyst teams.

4.2.5 Effects of Task Complexity

We present the regression results on task complexity in Table 7. We use the number of segments (*Complicated Firm*) and analyst coverage (*Low Coverage*) to measure the complexity of the covered firm. The dependent variable is *Accuracy* in all models. In Columns 1 to 3, we compare the performance between analyst teams and individuals. In Columns 4 and 6, we explore the differential effect of diversity for complicated firms. The interaction terms between the diversity measure and the firm complexity measures examine the incremental impact of task complexity. The complexity measures are indicator variables based on the median value in each year. More detailed descriptions can be found in Appendix A.

In Columns 1 and 3, *TEAM* × *Complicated Firm* is positive and statistically significant, implying that analyst teams generate more accurate forecasts for firms with more segments. In Columns 5 and 6, *Diversity* × *Low Coverage* is statistically significant at the 5% level, indicating that the effect of team diversity is more salient when the covered firm has lower analyst coverage. The results in Table 7 provide some limited evidence rejecting Hypothesis 4b and support the argument that team diversity plays a larger role when the underlying task is more complex.

4.3 Cash-Flow Forecasts

Recently there has been a trend toward analysts also disseminating operating cash-flow forecasts, followed by an increase of academic research on this topic starting with the study by DeFond and Hung (2003). They find that analysts respond to market participants' demand for additional value-relevant information and provide cash-flow forecasts for firms with large accruals, heterogeneous accounting choices relative to industry peers, volatile earnings, high capital intensity, and poor financial health. Consistent with this demand hypothesis, Call, Chen, and Tong (2009) show that analysts' earnings forecasts are of higher quality when accompanied with cash-flow forecasts. They also conclude that analysts' cash-flow forecasts provide incremental value to their earnings forecasts. Mohanram (2014) shows that analysts' cash-flow forecasts contribute useful information to the capital markets by mitigating accrual mispricing.

Overall, this strand of literature shows that cash-flow forecasts provide useful information to the market and that analysts who provide cash-flow forecasts have a more structured approach for forecasting tasks. To better understand the mechanism through which that analyst teams have better forecasting performance than individuals, we examine whether analyst teams are more likely to issue cash-flow forecasts than individuals. We employ logit regressions in which the dependent variable is an indicator that equals one if the analyst issues at least one cash-flow forecast for the firm-year. The results are presented in Table 8. In Columns 1 to 3, we find that *TEAM* is positively and significantly (at the 1% level using two-sided tests) associated with the issuance of cash-flow forecasts. The results are robust to including the full set of control variables. The odds ratio ranges from 1.10 to 1.89 for these three specifications, suggesting that analyst teams are 1.10 to 1.89 times as likely to issue cash-flow forecasts as individuals.

We employ similar specifications to examine the effect of *Diversity* within teams and the results are tabulated in Columns 4 to 6. The coefficients for *Diversity* are positive and significant at the 1% level, which show that more diverse teams are more likely to issue cash-flow forecasts than less diverse ones. Overall, these findings are consistent with the argument that teamwork allows analysts or their team members to be more specialized in forecasting tasks and thus have a more structured approach to forecasting.

4.4 DCF Valuation Models

We further explore the channels through which analyst teams perform better than individuals, by looking into the details of analyst reports. Prior research documents that analysts use DCF model in response to the market's demand for information and shows that the informativeness of analyst research is higher when valuation analyses are conducted based on DCF models (Demirakos, Strong, and Walker 2010; Tan and Yu 2019). We randomly select 100 reports from our sample and then manually read these reports to identify the valuation models used by the analysts. The sample consists of 32 individual analysts and 68 analyst teams. Among the 32 individuals (68 analyst teams), 6.25% (30.77%) use discounted cash-flow models as the dominant model for valuation analyses. The difference is significant at the 5% level using a two-sample t-test (two-sided).

We additionally employ a logit regression model, controlling for other analyst and forecast characteristics. The results are presented in Table 9, in which the dependent variable is an indicator that equals one if DCF models are used in the report, and zero otherwise. The first two columns compare teams with individuals and Columns 3 and 4 test the effect of *Diversity* among analyst teams. The coefficients for *TEAM* are positive and significant at the 10% level. The odds ratios are 5.80 and 5.57 based on the models in Columns 1 and 2, respectively, meaning that analyst teams are 5.80 and 5.57 times as likely to use DCF models in their reports as individuals. Similar regressions are employed in Columns 3 and 4, and the coefficients for *Diversity* are positive and significant at the 5% level and 1% level, respectively. The results indicate that analyst teams with higher *Diversity* are more likely to employ DCF models than less diverse ones. Consistent with the results for cash-flow forecasts in section 5.1.1, these findings on valuation models indicate that analyst teams, especially the more diverse ones, have a more structured approach for forecasting and valuation tasks, and thus enhance the informativeness of their overall research.

4.5. Additional Details of Analyst Reports: Length and Readability

In untabulated analyses, we further look into the narratives of reports written by analyst teams and individuals. Following De Franco, Hope, Vyas, and Zhou (2015), we focus on several measures of analyst report readability: length, Flesch Reading Ease, Flesch Kincaid Index, and Gunning Fog Index.[23]

First, we compare the reports written by teams with those by individuals. Univariate analyses show that reports written by teams have lower Flesch Kincaid Index and Fog Index and higher Flesch Kincaid Index. The differences are significant at the 5% level or better. However, the results are not significant after controlling for analyst characteristics in regressions. Among analyst teams, we do not find that diversity is significantly associated with any readability measure using

[23] Length is defined as the number of characters. Flesch Reading Ease = 206.8 – (1.015×words per sentence) – (84.6×syllables per word). Flesch Kincaid Index = (11.8 × syllables per word) + (0.39 × words per sentence) – 15.59. Fog = (words per sentence + percent of complex words) × 0.4.

either univariate tests or regressions. Taken together, our evidence suggests that teamwork and diversity do not significantly affect the narratives of analyst reports.

4.6 Market Reactions to Forecast Revisions

The results in the prior section show that analyst teams, especially those with higher diversity, have superior forecasting performance than individual analysts. In this section, we explore whether the capital market is aware of this differential performance by examining market reactions to forecast revisions. *REVISION* is defined as the difference between the revised forecast and the old forecast, scaled by the old forecast.[24] We focus on the three-day market adjusted returns $CAR_{[-1,1]}$ for each firm around forecast revisions.

The regression results are tabulated in Table 10. In Panel A, we examine whether the market reacts differently to revisions issued by teams compared with those by individuals. The variable of interest is the interaction term between *TEAM* and *REVISION*. Column 1 only includes the interaction term and their main effects, Column 2 adds all the analyst and forecast controls employed in prior tables, and Column 3 further includes firm level controls. The coefficients for *Team*×*Revision* are significant at the 5% or 10% levels using different specifications, suggesting that investors react more strongly to revisions issued by teams than by individuals. The results suggest that the market is aware of the superior earnings-forecasting performance by analyst teams and places greater attention on teams' forecast revisions.[25]

In Panel B, we turn to examine the effects of *Diversity* on the market's reaction to revisions issued by analyst teams. Only revisions issued by teams are included in the analyses. The variable

[24] Our inferences are robust to scaling by stock price following Christie (1987).

[25] Our inferences are unchanged if we exclude forecast revisions that experience concurrent earnings announcement in a three-day window. And our inferences (untabulated) are robust to measuring market reaction using intraday return following Keskek, Tse, and Tucker (2014).

of interest is *Diversity×REVISION*. In Column 1, the coefficient for the interaction term is not significantly different from zero, suggesting that the market does not react differently to revisions issued by more diverse teams. The results are similar if we add more controls in Columns 2 and 3. The findings indicate that the market fails to incorporate the superior performance of more diverse teams into stock prices, which is not surprising as it is demanding to collect the biographical information of each analyst and their team member to evaluate the diversity level of each team.

4.7 All-Star Status

We next consider whether teamwork helps analysts achieve favorable career outcomes. Specifically, we examine whether analysts who work in teams in a given year are more likely to be selected for All-Star analysts in the *following* year. We estimate a logit model and control for whether the analyst has All-Star status in the *current* year and for the average forecasting accuracy across all firms (as well as all other control variables). The unit of observation is at the analyst-year level and the value of control variables are based on the mean value across all firms covered by each analyst-year.

The findings are presented in Table 11. In first three columns, we use the full sample and compare the future all-star status of analysts working in teams versus individuals. We find that *TEAM is* positively and significantly (as the 1% level using a two-sided test) associated with subsequent All-Star nomination using all specifications.[26] The odds ratio ranges from 2.09 to 3.78, suggesting that analysts working in teams are 2.09 to 3.78 times as likely to become an all-star analyst in the following year as individual analysts. The finding is consistent with the analyst's

[26] The inferences remain similar if we employ an OLS model.

team members helping to improve the quality of the work of the analyst, which in turn increases the likelihood of achieving All-Star status.

The findings on All-Star status have important implications for understanding the incentives faced by analyst teams and individuals, as it is among the top factors that drive analysts' compensation (Groysberg, Healy, and Marber, 2011; Brown et al. 2015). The significant effect of *TEAM* on All-Star status after controlling for earnings forecast accuracy suggests that teamwork helps enhance analysts' performance on other duties as well. The results are consistent with the idea that teamwork allows a better division of labor among team members. The lead analysts can be more focused on tasks such as communicating with clients, keeping in touch with covered firms' management, and arranging investor events. Overall, combined with our evidence regarding earnings forecast accuracy, the findings support the notion that teamwork is associated with superior analyst performance.

In Columns 4 to 6, we examine the effect of *Diversity* on all-star status among teams. The coefficients of *Diversity* are not significant, indicating that *Diversity* does not affect future all-star status, at least in the following year.

5. Robustness Tests

It is possible that large brokers have more resources and thus their analysts are more likely to work in teams. To ensure the effects of teamwork are not merely capturing the differences between large and small brokers, we further limit our sample to brokers with *both* teams and individuals. The results are tabulated in Column 1 of Table 12. The sample size reduces by 4% due to this filter. The coefficient for *TEAM* continues to be positive and significant at the 1% level. In Columns 2 and 3, we add more explicit broker-size controls, including controlling for non-linearity:

TOP10 Broker is an indicator variable that equals one if the broker is one of the largest 10 in the current year and *Broker Size2* is the squared term of *Broker Size*. The coefficients of *TEAM* remain significant at the 1% level in both columns.[27] Overall, we provide more evidence showing that the impact of teamwork is not simply reflecting a broker-size effect.

6. Conclusion

Teamwork is becoming prevalent in the sell-side equity research industry. However, there is little evidence on how teamwork impacts analyst performance. The goal of this paper is to fill this gap in the literature. Using a hand-collected sample of over 50,000 analyst research reports, we find that analyst teams issue more than 70% of annual earnings forecasts. We document that analyst teams have significantly more accurate earnings forecasts than individual analysts. The results are similar using a changes framework, which controls for time-invariant analyst-level, broker-level, and firm-level omitted variables. The inferences also remain unchanged after controlling for analysts' self-selection into joining teams using Heckman's two-stage procedure. We show that analysts working in teams are more likely to be selected as All-Star analysts in the future and that the market is aware of the superior performance of analyst teams. We also document that analyst teams are more likely to issue cash-flow forecasts and use DCF valuation models in their reports.

Moreover, using a novel hand-collected dataset with detailed background information on individual analysts, we document that forecast accuracy is positively associated with team diversity based on sell-side experience, educational background, and gender. We further find that the effect of teamwork and diversity is stronger when the covered firms are more complicated.

[27] Similarly, no inferences are affected if we include the squared root of *Broker Size* as an additional control variable.

This article is one of the first to directly identify analyst teams based on their research reports and provides new evidence suggesting that teamwork, though overlooked by the prior literature, is an important characteristic that is associated with analyst performance. Our findings have important implications for academic researchers who focus on sell-side analysts. We document that the organizational structure of information intermediaries such as analyst teams plays an important role in driving the nature of information in the capital markets.

This study has certain limitations. One limitation is the relatively short and recent data period due to the high cost of hand data-collection. The generalizability of the findings to earlier time periods might be limited. Further, although the changes framework and controlling for the analyst self-selection into teams reduce endogeneity concerns, it is possible that there are some time-varying unobservable variables that are correlated with both variations in analyst team composition and forecast accuracy. Finally, in this study, we only consider the potential benefits of analysts' teamwork for the capital markets, but we cannot directly observe the monetary costs of employing analyst teams due to data limitations. In other words, cost-benefit analyses of employing analyst teams within a broker are beyond the scope of our paper.

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Appendix A: Variable Definitions

Variable	Definition
Standardized	
Accuracy	The absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1.
I/B/E/S Analyst Experience	The difference between the year when the forecast is issued and the year that the I/B/E/S analyst entered sell-side research industry. The data is obtained from LinkedIn and other sources if necessary.
Member Experience	The average value of team members' experience, which is the difference between the year when the forecast is issued and the year that the analyst entered sell-side research industry. The data is obtained from LinkedIn and other sources if necessary.
Education Diversity	Indicator variable based on HHI Education = 1-$\sum_i (Number\ of\ team\ members\ in\ category_i\ /team\ size)^2$, where categories include business/econ, quantitative, and others.
Experience Diversity	Indicator variable based on the coefficient of variation defined as the standard deviation of the experience of all team members scaled by the mean value.
Frequency	The total number of forecasts issued by an analyst for the specific firm within each year.
Horizon	The number of days between the forecast issuance date and the announcement date of the actual earnings value.
Broker Size	The total number of I/B/E/S analysts employed by the analyst's brokerage firm.
Number of Firms Covered	The number of firms covered by the analyst within each year.
Number of Industries Covered	The number of SIC2 industries covered by the analyst within each year.
I/B/E/S Analyst Firm Experience	The number of years that the I/B/E/S analyst has provided annual forecasts for the specific firm in I/B/E/S.
I/B/E/S Analyst General Experience	The number of years that the I/B/E/S analyst has shown up in I/B/E/S.
Not Standardized	
TEAM	Indicator variable is one if the associated research report for the forecast has more than one authors, and zero otherwise.
Individual to TEAM	Indicator variable is one if *TEAM* changes from zero to one relative to previous year at the analyst-firm level.
TEAM to Individual	Indicator variable is one if *TEAM* changes from one to zero relative to previous year at the analyst-firm level.
CAR[-1, 1]	Three-day market adjusted cumulative return for each firm around forecasts revisions.
Revision	The difference between the revised forecast and the old forecast scaled by the old forecast.
Team Size	The number of authors on the associated research report for each forecast.
Team Size2	The squared value of *Team Size*.

Lead Analyst Pro Designation	Indicator variable is one if the I/B/E/S analyst has professional designations, such as CFA, CPA, P.Eng, and P.Geo, and zero otherwise.
Member Pro Designation	The proportion of team members that have professional designations, such as CFA, CPA, PENG, and P.Geo.
Lead Analyst MBA	Indicator variable is one if the I/B/E/S analyst holds a MBA degree and zero otherwise.
Member MBA	The proportion of team members other than the I/B/E/S analyst that have MBA degrees.
Lead Analyst Female	Indicator variable is one if the I/B/E/S analyst is female and zero otherwise.
Member Female	The proportion of team members that are female.
IBES Member	Indicator variable is one if the team have members that are I/B/E/S analysts and zero otherwise.
Gender Diversity	Indicator variable is one if the team has both male and female members and zero otherwise.
Diversity	Sum of *Education Diversity, Gender Diversity,* and *Experience Diversity*.
Bundle	Indicator variable is 1 if the analyst issues forecasts for more than 1 firm on the same day and zero otherwise.
SIZE	The log value of the total asset of the covered firm in the fiscal year prior to the earnings forecast.
B/M	Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity.
ROA	Income before extraordinary items divided by total assets at the end of year t.
Analyst Coverage	The total number of I/B/E/S analysts that cover the firm.
Segments	The total number of segments that the firm has.
Volatility	The standard deviation of monthly returns in the past 12 months prior to the earnings forecast.
Complicated Firm	Indicator variable is one if the number of segments is higher than the median value among all firms in the same year.
Low Coverage	Indicator variable is one if analyst coverage is lower than the median value among all firms in the same year.
Future All-Star	Indicator variable that equals one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t+1, and zero otherwise.
All-Star	Indicator variable that equals one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise.
DCF	Indicator variable equals one if discounted cash flow model is used in the analyst report.

Appendix B: An Example of the Data-Collection Process

We search for the corresponding research report for each earnings forecast in our sample by matching the covered firm name, brokerage firm name, I/B/E/S analyst last name and first name initial, and forecast issuance date. Then we manually extract the name of the authors of the report and their professional designations if available.

Figure A1 presents a report issued by Wells Fargo on Dec 18, 2014. The covered firm is Genomic Health, Inc. The authors include Tim Evans, who is the analyst listed in the I/B/E/S, and Luke Sergott. The corresponding forecast is treated as being issued by a team because there are two authors listed on the report.

Figure A2 presents another report issued by the same analyst in May 2015. The covered firm is Myriad Genetics, Inc. This forecast is treated as being issued by an individual analyst, as there is only one author listed on the report. Actually, Luke Sergott joins another brokerage company Evercore in April 2015.

Figure A1: Example of Data-Collection Process

December 18, 2014

WELLS FARGO SECURITIES

Equity Research

Genomic Health, Inc.

GHDX: Initiating Coverage With Market Perform Rating

Market Perform

Sector: Diagnostics
Underweight

Initiation of Coverage

- **Summary.** We are initiating coverage of GHDX with a Market Perform rating, a 12-month, DCF-derived valuation range of $33-35, and 2014/2015 EPS estimates of -$0.82/-$0.49. We believe the company has substantial growth opportunities, particularly in prostate cancer and in international markets, with upside optionality in liquid biopsy tests. The company has done a good job protecting its franchise and driving reimbursement with extensive clinical data, but competitive threats and reimbursement hurdles still loom large. Also, long-term profitability remains uncertain. Given these factors and current valuation levels, we believe the risk/reward profile is balanced.

- **Prostate and international could accelerate growth.** We believe the company's investments in its prostate cancer test and in international markets will allow revenue growth to accelerate in the 2015-18 time frame, following many years of decelerating growth. The addressable markets are large: In 2020, we forecast the company's addressable U.S. prostate market to be $625 million and the international market to be $2.5 billion. These figures compare to total company revenue of about $280 million in 2014, about $45 million of which is international and only a nominal amount of which is prostate. DCIS is a smaller opportunity ($150 million by our estimate) but is growing off a very small base today. The primary gating factor for revenue growth in these large market segments is the timing and level of reimbursement, which has historically been difficult to predict. Also, these growth drivers could be partially offset by some erosion in the core invasive breast cancer franchise.

- **Competitive advantage via data.** The company has invested significant resources validating its tests and demonstrating clinical utility in numerous journal articles and conference presentations. Studies are aimed at validating the test's accuracy, demonstrating that the test offers meaningful information to alter physician behavior, and demonstrating that the test offers an economic benefit to payers. Because of the company's significant investments, Oncotype DX has been accepted as standard of care for invasive breast cancer in the U.S., and we believe the growing body of data on other tests and indications will create similar traction. It is time consuming and expensive to generate useful data, which we believe gives Genomic Health a strong (but not insurmountable) competitive advantage.

- **FOR MORE INFORMATION.** Please see our report entitled "Cancer MDx: Personalized Medicine's Acid Test."

Valuation Range: $33.00 to $35.00 from NE to NE
Our valuation range is DCF-based (WACC = 10.5%; terminal NOPLAT growth = 2%) and represents an EV/Sales multiple of 3.2x our 2015 estimate. Risks include: (1) intensifying competition; (2) reimbursement coverage delays or cuts; (3) pricing pressure from competition or payers; (4) limited profitability; and (5) FDA regulation of LDTs.

Investment Thesis:
We believe the company has substantial growth opportunities in prostate cancer and in international markets. We also think the company has done a good job generating valuable clinical data. However, potential near-term competition and lack of profitability keep us on the sidelines.

	2013A	2014E		2015E	
EPS		Curr.	Prior	Curr.	Prior
Q1 (Mar.)	($0.03)	($0.24) A	NC	($0.12)	NE
Q2 (June)	(0.10)	(0.15) A	NC	(0.12)	NE
Q3 (Sep.)	0.02	(0.20) A	NC	(0.12)	NE
Q4 (Dec.)	(0.28)	(0.23)	NE	(0.13)	NE
FY	($0.40)	($0.82)	NE	($0.49)	NE
CY	($0.40)	($0.82)		($0.49)	
FY P/EPS	NM	NM		NM	
Rev.(MM)	$262	$280		$310	

Source: Company Data, Wells Fargo Securities, LLC estimates, and Reuters
NA = Not Available, NC = No Change, NE = No Estimate, NM = Not Meaningful
V = Volatile, ♦ = Company is on the Priority Stock List

Ticker	GHDX
Price (12/18/2014)	$31.44
52-Week Range:	$23-38
Shares Outstanding: (MM)	31.7
Market Cap.: (MM)	$1,010.9
S&P 500:	2,047.70
Avg. Daily Vol.:	143,908
Dividend/Yield:	$0.00/0.0%
LT Debt: (MM)	$0.0
LT Debt/Total Cap.:	0.0%
ROE:	NE
3-5 Yr. Est. Growth Rate:	NE
CY 2014 Est. P/E-to-Growth:	NM
Last Reporting Date:	11/04/2014

Source: Company Data, Wells Fargo Securities, LLC estimates, and Reuters

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Please see page 4 for rating definitions, important disclosures

Figure A2: Example of Data-Collection Process

May 5, 2015

WELLS FARGO SECURITIES

Equity Research

Myriad Genetics, Inc.

MYGN: FQ3 2015 Earnings Full Analysis

Market Perform / V

Sector: Diagnostics
Underweight

- **What to do from here.** FQ3 makes the second quarter in a row to see a significant reduction in FY 2015 guidance, which is bound to leave a sour taste in investors' mouths. Once again, the primary reasons are delays in reimbursement, both in the U.S. and internationally. While delays in the diagnostics business seem to be the exception rather than the rule and are largely outside of management's control, they still may be likely to shake credibility in guidance. All of this stated, however, we still think the market may be overestimating how quickly Myriad is likely to lose market share to lower-priced competition. In fact, this quarter, the company indicated it did not see any share loss on a sequential basis, which is notable, despite being difficult to verify. And while delays in prostate reimbursement are frustrating, we still believe a reacceleration of growth once reimbursement starts to flow could help sentiment on the stock. Balancing all these factors continues to leave us decidedly neutral on the stock. Reducing our FY 2015/2016 EPS to $1.45/$1.89 from $1.53/$1.96 previously and reducing our valuation range to $33-34 from $35-37 previously.
- **Financial highlights.** MYGN reported FQ3 EPS of $0.40 on revenue of $180MM compared to consensus of $0.39 on revenue of $183MM. The company believes severe weather was a $4MM headwind to revenue and a $0.03 headwind to EPS, although investors are likely to be frustrated with that explanation since GHDX seemed to manage through the weather issues with a less dramatic impact.
- **Guidance highlights.** The company reduced FY 2015 EPS guidance to $1.44-1.46 from $1.50-1.55 previously, while reducing revenue guidance to $720-722MM from $730-740MM previously. The company cites the impact of severe weather of FQ3 revenue, the delay of Medicare reimbursement for Prolaris until FY 2016, and a delay in international reimbursement.
- **Other highlights.** The company acquired a clinic in Germany for the purposes of facilitating penetration of the German market by allowing Myriad to negotiate reimbursement with government and private insurance providers while also collaborating with hospitals and physicians. The company did not disclose the revenue contribution of the clinical but indicates the acquisition will be slightly accretive to EPS. The acquisition cost Myriad about $20-25 million. Even though the revenue contribution may be small, adding it to the revenue mix makes the guidance reduction look more severe.

Valuation Range: $33.00 to $34.00 from $35.00 to $37.00
Our valuation range is DCF-based (WACC = 11.0%; terminal NOPLAT growth = 2%) and represents an P/E multiple of 15x our CY2015 estimate. Risks include: (1) intensifying competition in hereditary breast cancer testing; (2) reimbursement coverage delays or cuts; (3) pricing pressure from competition or payers; and (4) FDA regulation of laboratory developed tests (LDTs).

Investment Thesis:
We acknowledge the growing risks to Myriad's core franchise with lower-priced tests coming on the market. However, we think consensus may underappreciate the stickiness of Myriad's myRisk test among physicians. We believe focus may shift to growth in the prostate market once that test begins receiving reimbursement.

Earnings Estimate Revised Down

	2014A	2015E		2016E	
EPS		**Curr.**	**Prior**	**Curr.**	**Prior**
Q1 (Sep.)	$0.68	$0.25 A	NC	**$0.42**	**0.48**
Q2 (Dec.)	0.66	0.40 A	NC	**0.47**	**0.46**
Q3 (Mar.)	0.60	**0.40 A**	**0.39**	**0.49**	**0.50**
Q4 (June)	0.47	**0.41**	**0.50**	**0.52**	**0.51**
FY	$2.46	**$1.45**	**1.53**	**$1.89**	**1.96**
CY	$1.72	$1.69		$2.09	
FY P/EPS	14.0x	23.8x		18.3x	
Rev.(MM)	$778	$721		$789	

Source: Company Data, Wells Fargo Securities, LLC estimates, and Reuters
NA = Not Available, NC = No Change, NE = No Estimate, NM = Not Meaningful
V = Volatile, *= Company is on the Priority Stock List*

Non-GAAP EPS excludes amortization of acquired intangible assets.

Ticker	MYGN
Price (05/05/2015)	$34.54
52-Week Range:	$31-42
Shares Outstanding: (MM)	71.1
Market Cap.: (MM)	$2,455.8
S&P 500:	2,089.46
Avg. Daily Vol.:	750,775
Dividend/Yield:	$0.00/0.0%
LT Debt: (MM)	$0.0
LT Debt/Total Cap.:	0.0%
ROE:	27.0%
3-5 Yr. Est. Growth Rate:	22.0%
CY 2015 Est. P/EPS-to-Growth:	0.9x
Last Reporting Date:	05/05/2015

Source: Company Data, Wells Fargo Securities, LLC estimates, and Reuters

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Please see page 6 for rating definitions, important disclosures and required analyst certifications

Table 1: Data Screening and Collection

	Forecasts	Firms	Analysts	Analysts & Team Members
Obtain all analysts' annual EPS forecasts over the 2013 to 2016 period from IBES detail history database	1,544,049	5,722	9,365	NA
Merge forecasts with CRSP/COMPUSTAT to obtain accounting and stock price information	1,176,787	3,581	6,651	NA
Keep the most recent forecast with horizon between one month to 12 months	116,148	3,578	5,608	NA
Obtain analyst last name and initial of first name from IBES recommendations database. Remove observations with missing analyst name information, associated with research departments or two analysts sharing the same analyst ID.	94,868	3,546	4,557	NA
Search each forecast through Investext and obtain the full name and designation information of all authors from analyst research reports. Remove firm-years that are only covered by teams or individuals.	51,781	3,216	2,434	5,055
For each forecast issued by analyst teams, search each author's background information using her full name and broker ID through LinkedIn, Relationship Science, and other possible sources such as Zoominfo.com, Bloomball Street Transcripts, and broker firms' official websites.	30,273	2,850	1,409	2,984

Table 2: Descriptive Statistics on Earnings Forecasts and Analyst Characteristics

This table reports the summary statistics for the main variables used in this study. Panels A and B present the distribution of analyst characteristics variables and firm-level control variables based on raw value and standardized values, respectively. Panel C presents the Pearson's correlations of standardized variables. Panel D present the univariate differences of each variable between analyst teams and individuals using standardized values. Panel E presents the distribution of forecast accuracy by team size. Panels F presents the summary statistics for individual demographic variables and Panel G reports the difference between the I/B/E/S analyst and her team members. See Appendix A for detailed variable definitions. Analyst forecasts data are from I/B/E/S, analyst team composition data are based on research reports from Investext, stock price data are from CRSP, and firm characteristics are from Compustat. Demographic information about analysts and team members is obtained from LinkedIn and augmented by other public sources. The sample period is 2013-2016. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Distribution of Raw Forecast and Analyst Characteristics (N=51,781)

Characteristic	Mean	p25	Median	p75
TEAM	0.73	0.00	1.00	1.00
Frequency	8.17	5.00	8.00	10.00
Horizon	120.21	90.00	104.00	119.00
Broker Size	63.52	27.00	54.00	104.00
Number of Firms Covered	14.89	10.00	14.00	19.00
Number of Industries Covered	3.53	2.00	3.00	5.00
I/B/E/S Analyst Firm Experience	4.03	1.00	3.00	6.00
I/B/E/S Analyst General Experience	12.87	5.00	11.00	19.00
Bundle	0.32	0.00	0.00	1.00
All Star	0.14	0.00	0.00	0.00
SIZE	7.85	6.62	7.88	9.04
B/M	0.67	0.22	0.42	0.76
ROA	-0.01	-0.01	0.03	0.07
R&D	0.09	0.00	0.03	0.11
Segments	4.18	1.00	3.00	6.00
Institution Ownership	0.59	0.46	0.62	0.76
Analyst Coverage	20.57	10.00	18.00	28.00
Volatility	0.11	0.06	0.09	0.13

Panel B: Distribution of Standardized Forecast Performance and Analyst Characteristics Variables (N=51,781)

Characteristic	Mean	p25	Median	p75
Accuracy	0.62	0.33	0.75	0.96
Frequency	0.49	0.19	0.50	0.79
Horizon	0.39	0.02	0.23	0.81
Broker Size	0.47	0.12	0.43	0.85
Number of Firms Covered	0.46	0.15	0.44	0.75
Number of Industries Covered	0.40	0.00	0.33	0.67
I/B/E/S Analyst Firm Experience	0.46	0.09	0.50	0.83
I/B/E/S Analyst General Experience	*0.44*	*0.10*	*0.39*	*0.79*

Panel C: Correlation Table based on Standardized Variables

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	*Accuracy*										
(2)	*TEAM*	**0.0451**									
(3)	*Frequency*	**0.0800**	**0.130**								
(4)	*Horizon*	**-0.251**	**-0.0434**	**-0.162**							
(5)	*Broker Size*	-0.0037	**0.335**	**0.111**	**-0.0199**						
(6)	*Number of Firms Covered*	0.0056	**0.162**	**0.118**	**0.0191**	**0.152**					
(7)	*Number of Industries Covered*	**-0.0261**	**0.0134**	**0.0362**	**0.0332**	**-0.00861**	**0.450**				
(8)	*I/B/E/S Analyst Firm Experience*	-0.0130	**0.0751**	**0.295**	**0.0600**	**0.0257**	**0.146**	**0.0672**			
(9)	*I/B/E/S Analyst General Experience*	0.00583	**0.0336**	**0.0512**	**0.0223**	**-0.0325**	**0.231**	**0.149**	**0.333**		
(10)	*Bundle*	0.00693	**0.0310**	**0.0468**	**-0.0714**	**0.0511**	**0.124**	**0.0557**	**0.0150**	**0.0269**	
(11)	*All Star*	**0.0281**	**0.196**	**0.120**	**-0.0457**	**0.350**	**0.176**	**0.0844**	**0.107**	**0.148**	**0.0349**

Bolded values indicate correlation significance at the 1 percent level.

Panel D: Difference between Analyst Teams and Individual Analysts (Standardized Values)

	Analyst Teams (N=5,150)	Individual Analysts (N=2,593)	
	Mean	Mean	t (Individual-Team)
Accuracy	0.61	0.58	-5.76***
Frequency	0.47	0.39	-11.96***
Horizon	0.40	0.44	5.85***
Broker Size	0.52	0.31	-27.19***
Number of Firms Covered	0.34	0.27	-10.12***
Number of Industries Covered	0.32	0.33	0.69
I/B/E/S Analyst Firm Experience	0.42	0.39	-5.69***
I/B/E/S Analyst General Experience	0.38	0.36	-2.43*
Bundle	0.34	0.33	-0.87
All Star	0.11	0.03	-14.81***

Panel E: Team Size and Forecast Accuracy

Team Size	Mean	%
1 (Individuals)	0.59	28.20%
2	0.62	37.95%
3	0.64	23.61%
4	0.64	8.01%
5+	0.62	2.23%
Total	0.62	100.00%

Panel F: Distribution of Individual Demographic Information

	Mean	p25	Median	p75
CFA	0.24	0.00	0.00	0.00
Male	0.87	1.00	1.00	1.00
MBA	0.45	0.00	0.00	1.00
Experience	12.27	6.00	11.00	17.00
Undergrad Bus/Econ	0.68	0.00	1.00	1.00
Grad Bus/Econ	0.46	0.00	0.00	1.00
PhD Bus/Econ	0.01	0.00	0.00	0.00
Undergrad Quant	0.29	0.00	0.00	1.00
Grad Quant	0.08	0.00	0.00	0.00
PhD Quant	0.04	0.00	0.00	0.00
Undergrad Quant	0.11	0.00	0.00	0.00
Grad Other	0.02	0.00	0.00	0.00
PhD Other	0.01	0.00	0.00	0.00

Panel G: Differences between I/B/E/S Analysts and Team Members

	I/B/E/S Analyst	Team Member	t (Member - Analyst)
CFA	0.34	0.17	-11.56***
Male	0.92	0.84	-7.87***
MBA	0.52	0.40	-7.31***
Experience	17.20	8.76	-38.39***
Undergrad Bus/Econ	0.60	0.74	8.89***
Grad Bus/Econ	0.54	0.41	-7.55***
PhD Bus/Econ	0.02	0.01	-0.79
Undergrad Quant	0.30	0.27	-1.66
Grad Quant	0.09	0.08	-0.70
PhD Quant	0.04	0.03	-1.51
Undergrad Quant	0.13	0.10	-2.61**
Grad Other	0.03	0.01	-2.87**
PhD Other	0.02	0.01	-2.70**

Table 3: Analyst Performance Regression Analyses

This table presents the OLS regression results on the effect of teamwork in Panels A and B. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. It is then standardized at the firm-year level, ranging from 0 to 1. *Individual to TEAM (TEAM to Individual)* is an indicator variable that equals one if *TEAM* changes from zero (one) to one (zero) relative to previous year at the analyst-firm level. *Change in Accuracy* is the change in *Accuracy* at the analyst-firm level. In Panel C, a first-stage profit model is estimated in the first column and *IMR* is the inverse mills ratio calculated based on the probit model. An OLS regression is estimated in Column 2 which further includes the *IMR.* All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Forecast Accuracy Regression

	(1)	(2)	(3)	(4)
	Accuracy	*Accuracy*	*Accuracy*	*Accuracy*
TEAM	0.037***	0.031***	0.030***	0.031***
	(6.94)	(6.22)	(6.19)	(6.26)
Frequency		0.046***	0.044***	0.042***
		(7.98)	(7.65)	(7.39)
Horizon		-0.230***	-0.229***	-0.227***
		(-47.50)	(-47.40)	(-46.37)
Broker Size		-0.027***	-0.027***	-0.026***
		(-4.45)	(-4.44)	(-4.33)
Number of Firms Covered		0.018**	0.018**	0.018**
		(2.45)	(2.41)	(2.54)
Number of Industries Covered		-0.028***	-0.027***	-0.026***
		(-4.48)	(-4.30)	(-4.14)
I/B/E/S Analyst Firm Experience		-0.018***	-0.014***	-0.014***
		(-3.36)	(-2.69)	(-2.64)
I/B/E/S Analyst General Experience		0.014**	0.014**	0.015**
		(2.18)	(2.28)	(2.44)
Bundle		-0.011***	-0.011***	-0.011***
		(-2.97)	(-2.91)	(-2.87)
Lag Accuracy			0.042***	0.041***
			(9.28)	(9.08)
Lag All Star				0.011*
				(1.72)
Clustering	Analyst	Analyst	Analyst	Analyst
Constant	0.594***	0.688***	0.662***	0.653***
	(125.56)	(115.99)	(100.66)	(85.87)
Observations	51,781	51,781	51,781	51,781
Adj. R-squared	0.00202	0.0672	0.0690	0.0715

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: Analyst Forecast Accuracy, Change Specification

	Change in Accuracy		
	(1)	(2)	(3)
Individual to TEAM	0.027**	0.021**	0.023**
	(2.11)	(2.24)	(2.44)
TEAM to Individual	-0.002	-0.007	-0.004
	(-0.13)	(-0.62)	(-0.36)
Change in Controls		Yes	Yes
Lag Controls		Yes	Yes
Industry FE			Yes
Year FE			Yes
Clustering	Analyst	Analyst	Analyst
Observations	29,564	29,564	29,564
Adj. R-squared	0.000126	0.483	0.485

Panel C: Analyst Forecast Accuracy, Heckman Two-Stage Model

VARIABLES	(1) First Stage *TEAM*	(2) Second Stage *Accuracy*
TEAM		0.019***
		(3.89)
IMR		-0.206***
		(-12.29)
Frequency	0.305***	0.017***
	(7.22)	(2.88)
Horizon	-0.042	-0.219***
	(-1.61)	(-44.26)
Broker Size	1.144***	-0.134***
	(18.31)	(-12.54)
Number of Firms Covered	0.500***	-0.028***
	(6.89)	(-3.47)
Number of Industries Covered	-0.135**	-0.011*
	(-2.12)	(-1.72)
I/B/E/S Analyst Firm Experience	0.148***	-0.026***
	(3.84)	(-4.74)
I/B/E/S Analyst General Experience	0.004	0.012*
	(0.06)	(1.87)
Bundle	0.012	-0.010***
	(0.47)	(-2.62)
Lag Accuracy	-0.015	0.040***
	(-0.79)	(8.75)
Lag All Star	0.465***	-0.016**
	(5.19)	(-2.34)
SIZE	0.117***	
	(8.62)	
B/M	-0.007	
	(-0.56)	
ROA	0.080	
	(1.14)	
Analyst Coverage	0.001	
	(0.45)	
Segments	-0.013***	
	(-3.94)	
Volatility	0.396*	
	(1.85)	
Constant	-1.170***	0.827***
	(-10.52)	(44.19)
Clustering	Analyst	Analyst
Observations	51,781	51,781
Pseudo R2	0.158	
Adj. R-squared		0.0730

z-statistics in parentheses for Column (1), and robust t-statistics in parentheses for Column (2)
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Team Size and Forecasting Performance

This table presents the OLS regression results regarding the effects of analyst team size. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. It is then standardized at the firm-year level, ranging from 0 to 1. *Team Size* is the number of authors of the corresponding research report and *Team Size2 is the squared term of Team Size.* All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	(1) Full Sample	(2) Among Teams
	Accuracy	*Accuracy*
Team Size	0.047***	0.054***
	(5.47)	(2.79)
Team Size2	-0.007***	-0.008**
	(-4.25)	(-2.58)
Frequency	0.043***	0.042***
	(7.58)	(6.31)
Horizon	-0.228***	-0.221***
	(-47.21)	(-39.08)
Broker Size	-0.033***	-0.031***
	(-5.14)	(-4.20)
Number of Firms Covered	0.016**	0.012
	(2.22)	(1.50)
Number of Industries Covered	-0.027***	-0.021***
	(-4.26)	(-2.91)
I/B/E/S Analyst Firm Experience	-0.015***	-0.019***
	(-2.78)	(-3.11)
I/B/E/S Analyst General Experience	0.013**	0.013*
	(1.99)	(1.78)
Bundle	-0.011***	-0.012***
	(-2.91)	(-2.94)
Lag Accuracy	0.042***	0.047***
	(9.25)	(8.82)
Lag All Star	0.009	0.008
	(1.43)	(1.15)
Constant	0.534***	0.526***
	(33.31)	(17.20)
Clustering	Analyst	Analyst
Observations	51,781	37,654
Adj. R-squared	0.0693	0.0649

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Team Member Ability and Forecasting Performance

This table presents the OLS regression results regarding the effect of analyst and team members' ability. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. It is then standardized at the firm-year level, ranging from 0 to 1. *I/B/E/S Analyst Pro Designation* is an indicator that equals one if the analyst holds professional designations, e.g., CFA, CPA, P.Eng., and P.Geo., and *Member Pro Designation* is the proportion of team members that hold professional designations. *I/B/E/S Analyst Experience* is the number of yeas that the analyst works in the sell-inside industry and *Member Experience* is the average value of each member's experience. *I/B/E/S Analyst MBA* is an indicator that equals one if the analyst has a MBA degree and *Member MBA* is the proportion of team members that has a MBA degree. *I/B/E/S Analyst Female* is an indicator that equals one if the analyst is female and *Member Female* is the proportion of team members that are female. All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	(1) *Accuracy*	(2) *Accuracy*	(3) *Accuracy*	(4) *Accuracy*	(5) *Accuracy*
I/B/E/S Analyst Pro Designation	0.004				0.004
	(0.76)				(0.72)
Member Pro Designation	0.026*				0.039**
	(1.72)				(2.31)
I/B/E/S Analyst Experience		-0.003			-0.002
		(-0.41)			(-0.28)
Member Experience		-0.019**			-0.023***
		(-2.53)			(-3.03)
I/B/E/S Analyst MBA			0.001		0.001
			(0.19)		(0.11)
Member MBA			0.002		0.007
			(0.32)		(1.14)
I/B/E/S Analyst Female				0.003	0.005
				(0.29)	(0.43)
Member Female				-0.005	-0.004
				(-0.58)	(-0.53)
Controls	Yes	Yes	Yes	Yes	Yes
Clustering	Analyst	Analyst	Analyst	Analyst	Analyst
Observations	37,654	30,273	30,273	30,273	30,273
Adj. R-squared	0.0680	0.0464	0.0462	0.0462	0.0467

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects of Diversity

This table presents the OLS regression results regarding the effects of diversity. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. It is then standardized at the firm-year level, ranging from 0 to 1. *Diversity* is the total score based *on Education Diversity*, *Experience Diversity*, and *Gender Diversity*. The detailed description can be found in section 3.2.1. All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) *Accuracy*	(2) *Accuracy*	(3) *Accuracy*	(4) *Accuracy*	(5) *Accuracy*
Diversity	0.014***				
	(4.12)				
Education Diversity		0.010*			0.010*
		(1.87)			(1.76)
Experience Diversity			0.017***		0.018***
			(3.11)		(3.15)
Gender Diversity				-0.001	-0.001
				(-0.10)	(-0.22)
Team Size	0.036	0.038*	0.043*	0.042*	0.042*
	(1.61)	(1.70)	(1.95)	(1.89)	(1.93)
Team Size2	-0.006*	-0.006*	-0.007*	-0.006*	-0.007*
	(-1.66)	(-1.69)	(-1.90)	(-1.83)	(-1.95)
I/B/E/S Analyst Pro Designation	0.003	0.003	0.003	0.004	0.004
	(0.49)	(0.60)	(0.58)	(0.65)	(0.74)
Member Pro Designation	0.040**	0.039**	0.042**	0.040**	0.047***
	(2.41)	(2.32)	(2.52)	(2.38)	(2.79)
I/B/E/S Analyst Experience	-0.002	-0.002	-0.004	-0.004	-0.002
	(-0.28)	(-0.39)	(-0.69)	(-0.65)	(-0.35)
Member Experience	0.008	0.007	0.007	0.006	0.007
	(1.28)	(1.16)	(1.14)	(1.03)	(1.21)
I/B/E/S Analyst MBA	-0.002	0.002	-0.004	0.001	-0.003
	(-0.25)	(0.22)	(-0.50)	(0.10)	(-0.44)
Member MBA	-0.010	-0.020**	-0.011	-0.022***	-0.007
	(-1.18)	(-2.57)	(-1.29)	(-2.92)	(-0.88)
I/B/E/S Analyst Female	-0.003	0.004	0.004		
	(-0.32)	(0.41)	(0.42)		
Member Female	-0.018**	-0.005	-0.005		
	(-2.02)	(-0.56)	(-0.63)		
Frequency	0.040***	0.039***	0.039***	0.039***	0.040***
	(5.52)	(5.45)	(5.43)	(5.39)	(5.58)
Horizon	-0.188***	-0.188***	-0.188***	-0.188***	-0.187***
	(-31.03)	(-31.14)	(-31.06)	(-31.14)	(-30.62)
Broker Size	-0.023***	-0.022***	-0.023***	-0.022***	-0.022***
	(-2.99)	(-2.91)	(-3.01)	(-2.91)	(-2.94)
Number of Firms Covered	0.026***	0.025***	0.025***	0.025***	0.025***
	(3.14)	(3.11)	(3.10)	(3.06)	(3.07)

Number of Industries Covered	-0.023***	-0.023***	-0.022***	-0.023***	-0.022***
	(-2.94)	(-2.98)	(-2.84)	(-2.92)	(-2.87)
I/B/E/S Analyst Firm Experience	-0.017**	-0.017**	-0.017**	-0.017**	-0.017**
	(-2.46)	(-2.45)	(-2.40)	(-2.44)	(-2.44)
Lag Accuracy	0.036***	0.037***	0.037***	0.037***	0.035***
	(6.18)	(6.23)	(6.23)	(6.26)	(5.86)
Bundle	-0.010*	-0.010*	-0.010*	-0.010*	-0.009
	(-1.85)	(-1.88)	(-1.87)	(-1.89)	(-1.63)
Lag All Star	0.011	0.011	0.012	0.011	0.012
	(1.43)	(1.44)	(1.52)	(1.45)	(1.56)
Constant	0.577***	0.584***	0.570***	0.582***	0.565***
	(17.28)	(17.51)	(17.05)	(17.43)	(17.02)
Observations	30,273	30,273	30,273	30,273	30,273
Clustering	Analyst	Analyst	Analyst	Analyst	Analyst
Adj. R-squared	0.0484	0.0479	0.0481	0.0478	0.0495

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Teamwork and Task Complexity

This table presents the OLS regression results regarding the impact of task complexity on teamwork and diversity. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. It is then standardized at the firm-year level, ranging from 0 to 1. *TEAM* is an indicator that equals one if the associated research report for the forecast has more than one author, and zero otherwise. *Diversity* is the total score based on *Education Diversity*, *Experience Diversity*, and *Gender Diversity*. All remaining variables are defined in Appendix A. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Accuracy	*Accuracy*	*Accuracy*	*Accuracy*	*Accuracy*	*Accuracy*
TEAM×Complicated Firm	0.021***		0.021***			
	(2.65)		(2.65)			
TEAM×Low Coverage		-0.005	-0.004			
		(-0.60)	(-0.47)			
Diversity×Complicated Firm				-0.000		0.001
				(-0.04)		(0.12)
Diversity×Low Coverage					0.013**	0.013**
					(2.52)	(2.51)
TEAM	0.021***	0.025***	0.016**			
	(3.67)	(3.82)	(2.18)			
Diversity				0.014***	0.004	0.004
				(3.61)	(0.94)	(0.79)
Complicated Firm	-0.014**		-0.018***	0.002		-0.001
	(-2.08)		(-2.61)	(0.32)		(-0.20)
Low Coverage		-0.065***	-0.066***		-0.069***	-0.069***
		(-9.44)	(-9.58)		(-9.60)	(-9.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst
Observations	51,781	51,781	51,781	30,273	30,273	30,273
Adj. R-squared	0.0692	0.0772	0.0773	0.0483	0.0534	0.0534

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Teamwork and Cash-Flow Forecasts

This table presents the logit regression results regarding the impact of teamwork on issuance of cash-flow forecasts and the use of sophisticated valuation models. *TEAM* is an indicator that equals one if the associated research report for the forecast has more than one author, and zero otherwise. *Diversity* is the total score based on *Education Diversity*, *Experience Diversity*, and *Gender Diversity*. Dependent variable is an indicator that equals one if the analyst issues at least one cash-flow forecast for the covered firm-year. All remaining variables are defined in Appendix A. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Among Teams	(5) Among Teams	(6) Among Teams
TEAM	0.640***	0.073**	0.073***			
	(18.96)	(1.99)	(1.98)			
Diversity				0.206***	0.137***	0.137***
				(9.70)	(6.23)	(6.22)
Controls		Yes	Yes		Yes	Yes
Lag Accuracy			Yes			Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm & Analyst	Firm & Analyst	Firm & Analyst	Firm & Analyst	Firm & Analyst	Firm & Analyst
Pseudo R2	0.161	0.237	0.237	0.0754	0.156	0.156
Observations	51,781	51,781	51,781	30,273	30,273	30,273

Table 9: Teamwork and Valuation Models

This table presents the logit regression results regarding the impact of teamwork on the use of DCF valuation models. *TEAM* is an indicator that equals one if the associated research report for the forecast has more than one author, and zero otherwise. *Diversity* is the total score based on *Education Diversity*, *Experience Diversity*, and *Gender Diversity*. *DCF* is an indicator that equals one if discounted cash flow model is used in the analyst report. All remaining variables are defined in Appendix A. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Among Teams	Among Teams
VARIABLES	DCF	DCF	DCF	DCF
TEAM	1.62*	1.61*		
	(1.83)	(1.83)		
Diversity			0.796**	1.052***
			(2.26)	(2.48)
Controls	Yes	Yes	Yes	Yes
Firm Characteristics		Yes		Yes
Observations	100	100	68	68
Fixed Effects	Year	Year	Year	Year
Clustering	Analyst	Analyst	Analyst	Analyst
Pseudo R2	0.156	0.170	0.234	0.279

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Market Reactions to Forecast Revisions

This table presents the OLS regression results regarding the effects of teamwork on the informativeness of forecast revisions. *CAR [-1, 1]* is the three-day market-adjusted return for each firm around forecasts revisions. *TEAM* is an indicator that equals one if the associated research report for the forecast has more than one author, and zero otherwise. *Revision* is the difference between the revised forecast and the old forecast scaled by the old forecast. *Diversity* is the total score based on *Education Diversity*, *Experience Diversity*, and *Gender Diversity*. All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Teamwork and Market Reactions to Forecast Revisions

	CAR[-1, 1]		
	(1)	(2)	(3)
Team×Revision	0.009*	0.011**	0.011**
	(1.80)	(2.10)	(2.07)
Revision	0.083***	0.069***	0.067***
	(19.09)	(15.74)	(15.30)
TEAM	-0.001	-0.001	-0.001
	(-1.38)	(-0.87)	(-0.90)
Controls		Yes	Yes
Firm Characteristics			Yes
Observations	50,836	50,836	50,836
Fixed Effects	No	Year & Firm	Year & Firm
Clustering	Firm & Analyst	Firm & Analyst	Firm & Analyst
Adj. R-squared	0.0424	0.184	0.187

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel B: Diversity and Market Reactions to Forecast Revisions

	CAR[-1, 1]		
	(1)	(2)	(3)
Diversity×Revision	-0.002	-0.003	-0.004
	(-0.46)	(-0.87)	(-1.01)
Revision	0.096***	0.088***	0.083***
	(20.42)	(17.19)	(16.23)
Diversity	0.001*	0.001**	0.001*
	(1.85)	(2.25)	(1.86)
Controls		Yes	Yes
Firm Characteristics			Yes
Observations	29,985	29,985	29,985
Fixed Effects	No	Year & Firm	Year & Firm
Clustering	Firm & Analyst	Firm & Analyst	Firm & Analyst
Adj. R-squared	0.0466	0.176	0.194

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Teamwork and All-Star Status

This table presents the logit regression results regarding the effects of teamwork on future *All Star* status. *Future All-Star* (*All-Star*) is an indicator that equals one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t+1 (t), and zero otherwise. *TEAM* is an indicator that equals one if the associated research report for the forecast has more than one author, and zero otherwise. *Diversity* is the total score based on *Education Diversity*, *Experience Diversity*, and *Gender Diversity*. All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	Future All-Star					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Full Sample	Full Sample	Full Sample	Among Teams	Among Teams	Among Teams
TEAM	1.330***	0.736***	0.741***			
	(6.71)	(2.89)	(2.94)			
Diversity				-0.068	-0.086	-0.082
				(-0.55)	(-0.63)	(-0.60)
All-Star	5.353***	4.582***	4.591***	4.961***	4.573***	4.576***
	(32.72)	(24.01)	(24.01)	(26.74)	(22.62)	(22.67)
Accuracy			-0.454			-0.120
			(-1.23)			(-0.31)
Controls		Yes	Yes		Yes	Yes
Observations	7,172	7,172	7,172	4,050	4,050	4,050
Fixed Effects	No	Year	Year	No	Year	Year
Clustering	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst
Pseudo R2	0.592	0.626	0.626	0.564	0.594	0.594

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Robustness Tests

This table presents the results from robustness tests. *Accuracy* is the absolute value of the difference between the forecasted EPS and the actual EPS, and then multiplied by -1. It is then standardized at the firm-year level, ranging from 0 to 1. *All-Star* is an indicator that equals 1 if the analyst is ranked in the top three or as a runner-up by Institutional Investor in the current year and zero otherwise. All remaining variables are defined in Appendix A. Analyst forecast characteristics variables are standardized as described in Section 3.2.2. t-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
VARIABLES	*Accuracy*	*Accuracy*	*Accuracy*
TEAM	0.025***	0.025***	0.019***
	(5.06)	(5.06)	(3.83)
Frequency	0.038***	0.038***	0.037***
	(6.54)	(6.53)	(6.33)
Horizon	-0.226***	-0.226***	-0.224***
	(-45.78)	(-45.77)	(-45.08)
Broker Size	-0.031***	-0.030***	0.144***
	(-4.93)	(-3.91)	(6.56)
Broker Size2			-0.184***
			(-8.35)
Top10 Broker		-0.002	0.021***
		(-0.36)	(3.03)
Number of Firms Covered	0.013*	0.013*	0.013*
	(1.81)	(1.81)	(1.84)
Number of Industries Covered	-0.026***	-0.026***	-0.025***
	(-4.17)	(-4.17)	(-3.96)
I/B/E/S Analyst Firm Experience	-0.014***	-0.014***	-0.014**
	(-2.67)	(-2.67)	(-2.53)
I/B/E/S Analyst General Experience	0.011*	0.011*	0.012*
	(1.75)	(1.72)	(1.90)
Bundle	-0.011***	-0.011***	-0.011***
	(-3.00)	(-3.00)	(-2.83)
Lag Accuracy	0.044***	0.044***	0.043***
	(9.58)	(9.58)	(9.32)
Lag All Star	0.012*	0.013*	0.011
	(1.87)	(1.89)	(1.61)
Constant	0.672***	0.672***	0.654***
	(99.32)	(98.87)	(91.23)
Clustering	Analyst	Analyst	Analyst
Observations	49,571	49,571	49,571
Adj. R-squared	0.0668	0.0668	0.0686

Robust t-statistics in parentheses.
*** p<0.01, ** p<0.05, * p<0.1