Do Groups Outperform Individuals? Evidence from Earnings Forecasts

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ABSTRACT: Prior research on social psychology reports mixed evidence on whether groups outperform individuals while accounting studies suggest that the judgment and decision making quality of groups versus individuals be contingent on different performance dimensions. In this study, we investigate whether groups of sell-side analysts have better performance in making earnings forecasts than individual analysts. Using data from China where the number of analyst groups is comparable to that of individual analysts, we find that analyst groups make more accurate earnings forecasts than individual analysts while group and individual analysts do not differ significantly in their forecast timeliness. Further analyses document that analyst groups outperform individual analysts in forecast accuracy for forecasted firms of larger size, with higher institutional ownership, and followed by more analysts. Our findings imply that teamwork in making earnings forecasts enhances forecast accuracy without reducing forecast timeliness, especially when there is greater competition among sell-side analysts to satisfy information needs on the capital market.

Keywords: Analyst groups; Individual analysts; Forecast accuracy; Forecast timeliness

Data Availability: Data used in this study are available from public sources indicated in the text.

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I. INTRODUCTION

Social psychology studies indicate that it is not necessarily the case that groups[1] achieve higher quality of judgment and decision making than individuals (Kerr and Tindale 2004; Bonner 2007; Hackman and Katz 2009). Mixed empirical evidence shows that groups sometimes outperform individuals while sometimes do not (e.g. Dugosh & Paulus 2005; Nijstad & Stroebe 2006; Litchfield 2008; Mas and Moretti 2009). The relative performance of groups against individuals tends to depend on the dimension of judgment and decision making quality being investigated (Bonner 2007), diversified skills and cognitive processes owned by group members (Armstrong 2001), motivation and efforts inspired by formation of groups (Kerr and Tindale 2004), distribution of unique information or knowledge within groups (Steiner 1972; Einhorn et al. 1977; Larson et al. 1994; Littlepage et al. 1995; Wittenbaum et al. 1999; Kerr and Tindale 2004), and characteristics or organization of groups (Mullen and Copper 1994; Gully et al. 1995; Bonner 2007). In addition, Steiner (1966) identified five types of tasks (disjunctive tasks, conjunctive tasks, additive tasks, compensatory tasks, and complementary tasks) for consideration of comparison between group and individual performance. Under such a framework, more empirical evidence is needed to enhance the understanding of whether group performance is superior to individual performance.

In applied accounting setting, prior studies on group performance versus individual performance report consistent results with those in psychology, i.e., groups do not always achieve better performance than individuals. For instance, Stocks and Harrell (1995) require groups and individuals to use six or nine information cues to predict financial distress

[1] We use the terms "group" and "team" interchangeably in this paper.

(bankruptcy, loan default, failure to pay preferred stock dividend, or asset liquidation). They find that groups outperform individuals at both the six-cue and nine-cue information levels except when the performance measure is judgment accuracy at the six-cue information level. Their results suggest that as information level increases the performance difference between groups and individuals also increases due to more information processing difficulties experienced by individuals. In contrast, Casey (1980) finds that individual bank loan officers do not make less accurate bankruptcy predictions than groups. For another example, Brown and Hugon (2009) compare the earnings forecast performances between team and individual sell-side financial analysts, and they examine two dimensions of analysts' forecasts--accuracy and timeliness. Their empirical results show that teams provide less accurate but timelier earnings forecasts than individual analysts in general and their team members when these team members are making individual forecasts. In brief, previous accounting research that focuses on users of accounting information and compares the group performance with individual performance reaches indecisive conclusions on whether groups perform better than individuals. More empirical evidence from the accounting context may shed light on the benefits and costs associated with forming groups in processing of accounting information.

In practice of the broker industry, teamwork has been widely encouraged and taken as contributing to business success. Groysberg et al. (2004) examine star stock analysts from 78 investment banks in the United States and find that when star analysts change investment banks those analysts who bring to new employers together with their teams of research analysts, salespeople, and traders actually perform better than those who move only on their own. This finding implies that teamwork improves star analysts' performance. Furthermore, Groysberg et al. summarize that star analysts from Lehman Brothers attributed their outstanding performance

to "a team-based research process" and mention that in Lehman Brothers every analyst needed to refer to at least two other analysts in his or her presentation. They also introduce that John Whitehead, Goldman Sachs's co-leader from 1976 to 1985, once reminded an analyst, "At Goldman Sachs, we never say I".[2] However, Groysberg et al. document that star analysts experience the greatest decline in performance when they are hired to strengthen the current research teams in their new employers. The result cautions that the effect of teamwork on analysts' performance may be more complex than anticipated and more research can be done in this area to help facilitate the understanding of analysts working in groups in the broker industry.

In this study we investigate the effect of forming a group on judgment and decision making quality for users of accounting information in the brokerage industry. Specifically, we examine whether sell-side analyst groups have greater performance than individual analysts in terms of earnings forecast accuracy and timeliness. Using data from China where analysts make earnings forecasts in groups as commonly as they make forecasts solo,[3] we use relative measures for accuracy and timeliness as our dependent variables and an indicator group variable as our variable of interest. Controlling the effect of other potential variables on forecast accuracy or timeliness, we find that analyst groups make more accurate forecasts on earnings per share (EPS) than individual analysts and that there is no significant difference in forecast timeliness between groups of analysts and individual analysts. Also, we investigate the analysts who forecast both in groups and on their own and compare accuracy and timeliness of earnings forecasts made by these analysts between when they are forecasting as members in groups (their group forecasts)

[2] Groysberg, Nanda, and Nohria. The Risky Business of Hiring Stars. *Harvard Business Review* (May 2004) page 98.
[3] Brown and Hugon (2009) examine team earnings forecasting performance using U.S. data. In their study, they identify 1,645 team-years versus 26,770 individual-years observations during the sample period from 1993 to 2005. Following Brown and Hugon (2009), we identify 9,226 group-years versus 10,909 individual-years observations during the sample period from 2005 to 2012. This may imply that Chinese sell-side analysts are more likely to make earnings forecasts in groups than their U.S. counterparts.

and when they are forecasting as individuals (their individual forecasts). The results show that analysts' earnings forecasts are more accurate when they are forecasting with other analysts in groups than when they are forecasting solo. However, forecast timeliness does not significantly differ between when analysts forecast as group members and when analysts forecast as individuals. In sum, the results suggest that teamwork helps analysts improve their forecast accuracy while they do not sacrifice forecast timeliness.

Furthermore, we conduct some cross-sectional analysis to investigate under what circumstances the effect of forming a group on forecasting performance is more salient. We conjecture that analysts form groups to achieve a competitive advantage over their peers and predict that analyst groups are more likely to outperform individual analysts when the competition among analysts is tougher. As indicated by prior literature (e.g. Healy and Palepu 2001; Ramnath et al. 2008; Beyer et al. 2010), there tends to be more analysts following for large firms or firms with higher institutional ownership, which may naturally result in higher competition among analysts. We divide the sample into sub-samples based on the median value of size, institutional ownership, and the number of analysts following of the forecasted firms, respectively. We run regressions for each sub-sample and find that groups make more accurate forecasts than individuals when forecasted firms are larger, have higher institutional ownership, or are followed by more analysts. In contrast, the effect of organizing groups on forecast accuracy is not significant for smaller firms, firms with lower institutional ownership, or firms followed by fewer analysts. For forecast timeliness, group forecasts do not significantly differ from individual forecasts regardless of size, institutional ownership, or the number of analysts following of the forecasted firms. It seems that analysts are willing to team up for more accurate but not timelier earnings forecasts to gain an edge in competing with their peers.

In addition, we perform more empirical tests. First, we use earnings forecast optimism as an alternative measure for analysts' performance (e.g. Gu and Wu 2003). Consistent with our results on forecast accuracy, we find that group forecasts are less optimistic than individual forecasts in general and that for those analysts who forecast both as group members and as solo forecasters their group forecasts are less optimistic than their individual forecasts. Second, we examine capital market reactions to analysts' forecast revisions and document that market reactions to earnings forecasts revised by analyst groups are insignificantly different from those to earnings forecasts revised by individual analysts. This insignificance may be due to that analyst groups and individual analysts have similar timeliness in earnings forecasts. Third, we compare forecast performance of group members when they are making their individual forecasts with forecast performance of individual analysts who are never affiliated with any groups and only make solo earnings forecasts. We report that individual forecasts made by group members are not more accurate but less timely than individual forecasts made by analysts belonging to no group. This finding implies that compared to those analysts who only make solo forecasts, analysts achieve more accurate and timelier forecasts from forming groups and working together.

Finally, we examine what firm characteristics are likely to induce analysts to combine into groups and follow. Similar to Brown and Hugon (2009), we document that larger firms, firms with higher institutional ownership, firms in financial distress, and firms followed by more analysts, are more likely to be followed by analyst groups. This finding is consistent with the cross-sectional results and supports that analysts are inclined to form groups in order to outperform their peers when there is more competition. Also, analyst groups are more likely to

be established to satisfy investors' greater information demand for accurate prospects of forecasted firms, such as firms with higher bankruptcy risk.

The study extends prior research in several dimensions. First, we supplement current literature on forecast performance of sell-side analysts by demonstrating that forming analyst groups helps improve forecast accuracy but not lower forecast timeliness. Using U.S. data, Brown and Hugon (2009) find that analyst teams trade off accuracy for timeliness. That is, analyst teams provide less accurate but timelier earnings forecasts than individual analysts. In contrast, we show that analyst groups may not necessarily make a tradeoff between accuracy and timeliness. Earnings forecasts made by analyst groups are as timely as those made by individual analysts, but more accurate. This may explain why it is so popular that Chinese analysts choose to work together and issue earnings forecasts in the name of groups. Additional analyses illustrate that the effect of analyst groups on forecast accuracy is more salient for larger firms and firms with higher institutional ownership or greater analysts following, and that firm size, institutional ownership, and the number of analysts following are positively associated with the likelihood of group following. These empirical results are consistent with prior literature (Abarbanell et al. 1995; Park and Stice 2000; Clement and Tse 2003; Gleason and Lee 2003) in the sense that investors may value forecast accuracy and analysts form groups to achieve an advantage over their peers when the competition among analysts becomes more severe.

Second, the paper complements previous studies on judgment and decision making quality in a group setting. In answer to Hackman and Katz (2009) where they suggest that particular attention be paid to various types of tasks in group behavior and performance research, we use a specific task of making earnings forecasts to examine the relative performance of groups versus individuals. Furthermore, whether group judgment and decision making is better

than that of individuals relies on specification of the dimension of judgment and decision making quality (Einhorn et al. 1977; Gigone and Hastie 1997; Bonner 2007). We investigate three quality dimensions of analysts' earnings forecasts[4] and attempt to provide more comprehensive evidence in comparing group performance with individual performance.

Finally, Bonner (2007) summarizes that experimental studies on group behavior and performance typically use subjects who are brought to form groups only for research purposes and share no teamwork experiences before participating in the experiments. Also, experiment researchers find serious difficulties in getting large numbers of subjects, especially professional subjects, for their group studies. These two limitations challenge the external validity and restrict the generalizability of results from experimental research. Using archival data, the study can examine natural groups where group members share some working experience and conduct large-sample empirical tests.[5] Results based on this methodology may be better generalized and supplement the studies based on experimental methods.

Section 2 reviews the relevant literature and develops our hypotheses. Section 3 discusses research design and describes the model specification. We report our empirical findings in Section 4 and provide concluding remarks in Section 5.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Earnings Forecast Accuracy

Prior psychological studies that examine group judgment and decision making compare group performance with individual performance and try to identify potential reasons why group

[4] We examine analysts' forecast accuracy and timeliness in our main analyses and forecast optimism for an additional test.

[5] In our archival analysis we try to control for other moderating variables that may affect accuracy and timeliness of earnings forecasts made by sell-side financial analysts.

performance may differ from individual performance. Some studies attribute the difference to what dimension of quality is measured for performance evaluation (Einhorn et al. 1977; Gigone and Hastie 1997; Bonner 2007). It is implied that group performance may be superior to individual performance on some dimensions of quality while inferior to individual performance on the other dimensions. Some research indicates that groups outperform individuals because when group members aggregate their individual judgments and decisions to form group judgments and decisions random errors or group members' individual judgment and decision biases in different directions are cancelled with each other (McNees 1992; Bonner 2007). Also, group performance may exceed individual performance because group members provide diverse skills and enhance cognitive processes in making group judgment and decisions (Armstrong 2001; Kerr and Tindale 2004). In contrast, group performance may be lower than individual performance when group members possess similar biases in individual judgment and decision making and working in groups amplifies these biases (Armstrong 2001). For instance, Bonner (2007) indicates that if the analysts in the same group are all optimistic in their earnings forecasts the group as a whole makes more optimistic forecasts than individual group members. To sum up, there is indecisive conclusion on the relative performance of groups versus individuals.

In addition, motivation plays a role in relative performance of groups against individuals under the assumption that increased motivation and efforts result in better performance. On the one hand, motivation in a group can be higher than that for individuals. First, some group members may make considerably greater efforts in the group setting because they are concerned that other group members may be less motivated and dampen the group's performance and they are willing to compensate for that (Kerr and Tindale 2004). Second, group members may be proud of being in a successful group and achieve greater utility from a group outcome than from

an individual outcome (Levine and Moreland 1990; Karau and Williams 1993). Third, group members may be worried that they are assessed by other group members and willing to establish and maintain good impressions on the fellow group members. This concern tends to raise group members' arousal, motivation, and efforts (Steiner 1972; Bonner 2007). On the other hand, working in a group may lower group members' motivation and induce them to exert less effort compared to what they would do as individuals. Group members may like to take a free ride with other members and thus work less hard (Karau and Williams 1993; Mas and Moretti 2009). Also, group members may find other group members identical with themselves and develop a feeling of being redundant in a group, which discourages them from making substantial contributions to the group judgment and decision making (Shepperd 1993; Bonner 2007). In brief, considering the effect of motivation on group behavior and performance, we still have competing arguments on whether groups outperform individuals.

Furthermore, information or knowledge distribution within groups may also affect the relative performance of groups versus individuals. Diverse information held by group members can supplement with each other and lead to better judgment and decisions made by the whole group (Armstrong 2001; Bonner 2007). However, the most useful information or best knowledge may not always be incorporated in group judgment and decision making for following reasons. First, groups tend to over-rely on shared information rather than on information uniquely possessed by one group member while the unique information may be the best for judgment and decision making (Stewart and Stasser 1995; Wittenbaum et al. 1999; Kerr and Tindale 2004; Schulz-Hardt 2006). Second, groups tend to misjudge the group members who have the most appropriate information for achieving superior performance (Einhorn et al. 1977; Littlepage et al. 1997; Kerr and Tindale 2004). This occurs because groups evaluate a group member's

contribution based much more on that person's demographic characteristics, status, or behavioral style than on the person's actual information or knowledge level (Hackman and Katz 2009). In sum, groups may not make full use of group members' information or knowledge and whether groups achieve better performance than individuals is still an open question.

A number of studies on users of financial information compare group performance with individual performance in an accounting context. For instance, O'Brien (1988) reports that the solo most current earnings forecast is more accurate than the mean and median forecasts while Brown (1991) shows that timely composites of analysts' annual earnings forecasts are more accurate than the mean of all the forecasts. Bloomfield et al. (1996) find that the accuracy of group judgments in estimating share values depends in part on group members' ability to observe communication of confidence held by other group members in their solo judgments. Groysberg et al. (2008) examine the performance of an investment committee in Lehman Brothers which selects stocks recommended by its financial analysts and report that on average the committee's selections generate substantial abnormal returns. They imply that research recommendation committees may be established to enhance the quality of analysts' research. Brown and Hugon (2009) study the relative performance of teams of sell-side analysts against individual analysts in terms of earnings forecast accuracy and demonstrate that team forecasts are less accurate than individual forecasts in general and team members' individual forecasts in particular.

Earnings forecast accuracy is one important dimension of analysts' judgment and decision making quality and greater forecast accuracy suggests better performance for analysts (Ramnath et al. 2008; Beyer et al. 2010). Groups of analysts may make more accurate forecasts than individual analysts for several reasons. First, group members have diverse backgrounds and skills that can potentially lead to higher-quality cognitive processes in making earnings forecasts.

Second, analysts may have greater motivation and exert more efforts in the group setting to make up for other group members' inferior performance, derive higher utility from a more accurate group forecast, and maintain good reputation among fellow group members. Third, a group of analysts aggregate individual group members' information in forecasting earnings. This higher information level for the group as a whole lays a solid foundation for its better performance. In contrast, analyst groups may issue less accurate earnings forecasts than individual analysts. Analysts may share similar cognitive patterns or biases in making forecasts and forming a group may aggravate rather than mitigate these biases and cause group forecasts to be less accurate. Also, analysts may be less motivated in a group as they tend to take a free ride and develop a feeling of being redundant with other fellow analysts in the group. In addition, an analyst group suffers from over-reliance on common information within the group and flawed weighting on the information or knowledge level of group members. This may cause the group to provide earnings forecasts less accurate than what the group could potentially achieve when information or knowledge possessed by group members were optimally used. Therefore, whether groups of analysts outperform individual analysts in making more accurate earnings forecasts is still an empirical question and we summarize our hypotheses (in the alternative form) as follows:

H1a: Analyst groups make more accurate earnings forecasts than individual analysts.

H1b: Analyst groups make less accurate earnings forecasts than individual analysts.

2.2 Earnings Forecast Timeliness

Earnings forecast timeliness is another important dimension of analysts' judgment and decision making quality and there tends to be a trade-off between forecast accuracy and timeliness (Cooper et al. 2001; Clement and Tse 2003; Brown and Hugon 2009; Beyer et al. 2010). For example, Cooper et al. (2001) find that analysts identified with timelier forecasts

affect stock prices more than analysts with less timely forecasts and also document that rankings of analysts' performances based on forecast timeliness are more informative than rankings based on forecast accuracy. In addition, some theoretical research examines the relationship between forecast accuracy and timeliness assuming the timing of analysts' forecasts is endogenous rather than exogenous. Gul and Lundholm (1995) indicate that if analysts can choose when to issue their earnings forecasts they prefer to make accurate forecasts, and if the level of accuracy is given they tend to make as timely forecasts as possible. Guttman (2010) predicts that higher accuracy of the analyst's private information results in higher accuracy of the public information if this analyst issues his or her forecast and other analysts tend to make forecasts immediately afterwards.

Brown and Hugon (2009) argue that making earnings forecasts can be treated as a kind of complementary task, which can be divided into sub-tasks and assigned to different group members. Due to this division of research tasks, analyst groups achieve a competitive advantage over individual analysts in searching and processing more firm-specific information and becoming timelier in issuing earnings forecasts. The authors report empirical results that earnings forecasts made by analyst groups are timelier than those made by individual analysts. However, making earnings forecasts may be a kind of conjunctive task, where the performance of a group relies on the performance level of the least competent member in the group (Hackman and Katz 2009). The group may not necessarily exceed individuals in providing timely forecasts. In addition, whether analyst groups outperform individual analysts in forecast accuracy is indefinite and in turn the relative timeliness of group forecasts versus individual forecasts is open to empirical study as some empirical literature suggests that there is a trade-off between forecast accuracy and timeliness. Considering that the timing of analysts' forecasts may be endogenous,

we find greater difficulty in making directional predictions on whether group forecasts are timelier than individual forecasts. Therefore, we put our hypotheses regarding earnings forecast timeliness (in the alternative form) below:

H2a: Analyst groups make timelier earnings forecasts than individual analysts.

H2b: Analyst groups make less timely earnings forecasts than individual analysts.

2.3 Competition among Analysts

The existence of groups composed of sell-side financial analysts suggests that analyst groups have some certain advantages over individual analysts and forming groups meets a market research demand and benefits the brokerage firms. We conjecture that when competition among analysts becomes greater analysts are more likely to collaborate and work in groups as they may feel supported by their fellow group members and achieve better performance than their peers who work alone. Bhushan (1989) indicates that the demand for analyst forecasts increases with the size of forecasted firms due to higher benefits of private information for larger firms. More analysts tend to follow larger firms and thus the competition among analysts is stronger. Also, O'Brien and Bhushan (1990) imply that institutional investors require information for given firms to help with their investment decisions and to satisfy standards of fiduciary responsibility. Higher institutional ownership tends to attract more analysts following and there is more pressure on analysts to outperform their peers in meeting institutional investors' information needs. In addition, the number of analysts following may be mechanically (positively) associated with the extent of competition among analysts as it becomes harder for a given analyst to be superior to others who also issue earnings forecasts for the same firm. Therefore, analysts may attempt to form groups to gain an edge over their peers when there is more severe competition in providing useful information to investors. In other words, the effect

of working in groups on analysts' earnings forecasts may be more salient if there is more intense competition among analysts. We put our hypotheses in the below:

H3: The effect of analyst groups (relative to individual analysts) on earnings forecasts accuracy is more salient for larger firms and firms with higher institutional ownership or more analysts following.

H4: The effect of analyst groups (relative to individual analysts) on earnings forecasts timeliness is more salient for larger firms and firms with higher institutional ownership or more analysts following.

III. RESEARCH DESIGN

3.1 Sample Selection

Our data are all from the China Stock Market and Accounting Research (CSMAR) database. We focus on annual earnings forecast observations and our sample period covers from 2005 to 2012.[6] We exclude those observations with missing analysts' names, no annual earnings forecasts or forecasted fiscal years, and unknown forecasted firms. We identify analyst groups by the presence of multiple names in the field of "Analysts' Names" recorded in the CSMAR database. From the data provided in CSMAR, we prepare a separate translation file which includes observations of analysts' names-year-brokerage names.[7] For empirical tests involving analysts who make earnings forecasts both individually and as group members, we hand-match the forecast observations based on a given analyst's name, the affiliated brokerage name, and the

[6] Our sample starts from annual earnings forecasts on fiscal year 2005 as there are relatively few annual forecasts observations on fiscal years before 2005.
[7] Here "year" is the calendar year, not the fiscal year for which earnings forecasts are made.

year when the analyst is working in the affiliated brokerage. In addition, we remove those observations with unavailable data to calculate the dependent and control variables.[8]

3.2 Variable Measurement

Our key variable of interest is a group dummy variable, which equals 1 if analyst i that makes a given annual earnings forecast corresponds to a name field containing at least two different names (a group) and 0 if analyst i corresponds to a name field containing only one name (an individual).

One of analysts' performance measures is earnings forecast accuracy. Following prior literature (Clement and Tse 2003; Brown and Hugon 2009), we use a relative accuracy measure. Specifically, we calculate analyst i's forecast accuracy for firm j in fiscal year t as the maximum absolute forecast error for those analysts who follow firm j in fiscal year t minus the absolute forecast error of analyst i following firm j in fiscal year t, with this difference divided by the range of absolute forecast errors for those analysts who follow firm j in fiscal year t.

The other measure for analysts' performance is earnings forecast timeliness. Consistent with the forecast accuracy measure and previous research (Brown and Hugon 2009), we also use a relative timeliness measure. Specifically, we calculate analyst i's forecast timeliness for firm j in fiscal year t as the number of days between the immediately preceding forecast and the forecast of interest divided by the number of days between the forecast of interest and the immediately succeeding forecast. This variable is standardized as the timeliness of analyst i following firm j in fiscal year t minus the minimum timeliness for those analysts who follow firm j in fiscal year t, with this difference divided by the range of timeliness for those analysts who follow firm j in fiscal year t.

[8] Because of this we have different sample sizes for different empirical analyses.

3.3 Empirical Model

3.3.1 Association between Analyst Groups and Forecast Accuracy

In order to control for the forecasting performance differences caused by inter-firm and temporal differences, we match the performance of analyst groups with that of individual analysts on firm-year to examine the effect of forming an analyst group on earnings forecast accuracy. In other words, we focus on the firm-year[9] observations of which annual earnings are forecasted by at least an analyst group and an individual analyst. Following prior literature, we control in our empirical model for forecast horizon (O'Brien 1988), forecast frequency (Jacob et al. 1999), the number of industries followed (Clement 1999), brokerage size (Clement 1999), and industry forecasting experience (Mikhail et al. 1997; Brown and Hugon 2009). Based on the prior literature (Clement and Tse 2003; Brown and Hugon 2009), we standardize the proxy for earnings forecast accuracy and the control variables. We estimate the following model to examine the association between analyst groups (relative to individual analysts) and forecast accuracy:

$$ACCURACY_{i,j,t}=\alpha_0+\alpha_1 GROUP_{i,j,t}+\alpha_2 FAGE_{i,j,t}+\alpha_3 FREQ_{i,j,t}+\alpha_4 NIND_{i,j,t}+\alpha_5 BSIZE_{i,j,t}$$
$$+\alpha_6 IEXP_{i,j,t}+\varepsilon_{i,j,t} \quad (1)$$

In the above model, the dependent variable ACCURACY and the dummy variable GROUP are defined the same as in the preceding section. FAGE is analyst i's forecast age, calculated as the number of days from the forecast date to the earnings announcement date for analyst i following firm j in fiscal year t minus the minimum forecast horizon for those analysts who follow firm j in fiscal year t, with this difference divided by the range of forecast horizons for those analysts who follow firm j in fiscal year t. FREQ refers to analyst i's forecast frequency,

[9] Here firm-year refers to a forecasted firm in a given fiscal year.

defined as the number of firm j forecasts made by analyst i following firm j in fiscal year t minus the minimum number of firm j forecasts made by those analysts who follow firm j in fiscal year t, with this difference divided by the range of the numbers of firm j forecasts made by those analysts who follow firm j in fiscal year t. NIND is the number of industries followed by analyst i, calculated as the number of industries followed by analyst i following firm j in fiscal year t minus the minimum number of industries followed by those analysts who follow firm j in fiscal year t, with this difference divided by the range of the numbers of industries followed by those analysts who follow firm j in fiscal year t. BSIZE refers to analyst i's brokerage house size, defined as the number of analysts employed by the brokerage house which employs analyst i following firm j in fiscal year t minus the minimum number of analysts employed by the brokerage houses which employ analysts following firm j in fiscal year t, with this difference divided by the range of the numbers of analysts employed by the brokerage houses which employ analysts following firm j in fiscal year t. IEXP is analyst i's industry forecasting experience, standardized as the number of prior forecasting years for analyst i following firm j's industry in fiscal year t minus the minimum number of prior forecasting years for those analysts who follow firm j's industry in fiscal year t, with this difference divided by the range of the numbers of prior forecasting years for those analysts who follow firm j's industry in fiscal year t. $\varepsilon_{i,j,t}$ refers to the error term. The subscripts i, j, t indicate analyst i, forecasted firm j, and forecasted fiscal year t, respectively.

Coefficients in the above empirical model are estimated from the OLS regression and standard errors are adjusted for both heteroskedasticity and intra-analyst error correlation. A significant and positive (negative) coefficient estimate on the GROUP dummy variable suggests that analyst groups make more (less) accurate earnings forecasts than individual analysts.

3.3.2 Association between Analyst Groups and Forecast Timeliness

Consistent with prior literature (e.g. Brown and Hugon 2009) and our estimation for forecast accuracy, we estimate the following model to investigate whether analyst groups outperform individual analysts in making timelier earnings forecasts:

$$TIMELINESS_{i,j,t}=\beta_0+\beta_1 GROUP_{i,j,t}+\beta_2 FAGE_{i,j,t}+\beta_3 FREQ_{i,j,t}+\beta_4 NIND_{i,j,t}+\beta_5 BSIZE_{i,j,t}$$
$$+\beta_6 IEXP_{i,j,t}+\mu_{i,j,t} \quad (2)$$

In the above model, all the variables are defined the same as in the above except that $\mu_{i,j,t}$ refers to the error term. A significant and positive (negative) coefficient on the GROUP dummy variable is consistent with the prediction that group forecasts are timelier (less timely) than individual forecasts.

IV. EMPIRICAL RESULTS

4.1 Descriptive Statistics and Univariate Tests

Consistent with our regression analysis, our descriptive statistics and univariate tests are based on a matched-sample of firm-year observations of which annual earnings are forecasted by at least an analyst group and an individual analyst. Table 1 compares means and medians of forecast characteristics between analyst groups and individual analysts. The univariate analyses based on standardized, relative measures of forecast characteristics at the analyst-year level show that group forecasts are more accurate and timely than individual forecasts.[10] In addition, compared to individual analysts, analyst groups on average have longer forecast horizons, make

[10] Brown and Hugon (2009) suggest that forecast accuracy and timeliness are correlated with other forecast characteristics. Thus it is better to examine the effect of analyst groups on forecast accuracy and timeliness by regression analyses in multivariate settings.

fewer forecasts, and cover fewer industries. Analyst groups tend to be affiliated with larger broker houses[11] and have less industry forecasting experience[12].

[Insert Table 1 here]

Table 2 presents Pearson (Spearman rank) correlations of the key analyst-year standardized variables. Correlations between ACCURACY and GROUP are positive and significant, implying that analyst groups tend to make more accurate earnings forecasts than individual analysts. Also, correlations between TIMELINESS and GROUP are positive and significant, implying that individual forecasts are less timely than group forecasts.[13] For the correlations between ACCURACY and the control variables, we document that forecast accuracy is significantly and negatively correlated with the forecast horizon, significantly and negatively correlated with the forecast frequency, significantly and negatively correlated with the number of industries covered by a given analyst, significantly and negatively correlated with the size of the broker house where the analyst is working, and significantly and negatively correlated with the analyst's industry forecasting experience. Regarding the correlations between TIMELINESS and the control variables, we report that forecast timeliness is significantly and positively correlated with the forecast horizon, significantly and negatively correlated with the forecast frequency, significantly and negatively correlated with the number of industries covered, and significantly and negatively correlated with the analyst's industry forecasting experience. Forecast timeliness may be negatively correlated with the size of the broker house (Spearman correlation is significant but Pearson is not). In addition, correlations among the control variables

[11] This is consistent with Brown and Hugon (2009) that larger brokerage houses have necessary resources to establish and maintain analyst groups.

[12] Analysts may form groups to make up for their lack of industry forecasting experience and gain a competitive advantage over their peers who forecast solo.

[13] After controlling for other variables that may affect forecast timeliness in the regression analysis, we report an insignificant association between the group dummy variable and timeliness.

suggest that when the earnings announcement date approaches, earnings forecasts tend to be made more frequently, and issued by an analyst following fewer industries, employed by a smaller broker, and with shorter industry forecasting experience. Those analysts who cover more industries, work in larger brokers, and have greater industry forecasting experience, increase forecast frequencies. Analysts from smaller broker houses or with more industry forecasting experiences tend to cover more industries in their forecasts. Analysts' industry forecasting experiences are likely to accumulate in larger broker houses.

[Insert Table 2 here]

4.2 Main Regression Results

Table 3 presents results from the above Equation (1) to examine the earnings forecast accuracy of analyst groups relative to that of individual analysts. Column (1) reports results based on the sample where group forecasts are compared with individual forecasts in general. The coefficient on the GROUP dummy variable is positive and significant (0.008, p-value = 0.011). This finding indicates that on average analyst groups make more accurate earnings forecasts than individual analysts. Column (2) displays results based on the sample where group forecasts are evaluated against individual forecasts made by group members in terms of accuracy. The coefficient on the GROUP dummy variable is positive and significant (0.010, p-value = 0.006). This is consistent with the result in column (1) and implies that groups as a whole make more accurate forecasts than group members making forecasts individually. Also, we find that the analysts who forecast closer to the earnings announcement dates, provide less frequent forecasts, cover fewer industries, work for smaller broker houses, or have more industry forecasting experiences, make more accurate forecasts. In sum, our results show that analyst

groups make more accurate earnings forecasts than individual analysts. The empirical evidence supports hypothesis H1a, but not H1b.

[Insert Table 3 here]

Table 4 reports results from the above Equation (2) to investigate whether analyst groups outperform individual analysts in terms of earnings forecasts timeliness. Column (1) illustrates results based on the sample where timeliness of group forecasts are compared with that of individual forecasts in general. The coefficient on the GROUP dummy variable is positive but insignificant (0.002, p-value = 0.503). This finding suggests that analyst groups do not make less timely earnings forecasts than individual analysts in general. Column (2) demonstrates results based on the sample where timeliness of group forecasts is compared with that of solo forecasts made by members comprising the groups. Similar to the result in column (1), the coefficient on the GROUP dummy variable is positive but insignificant (0.003, p-value = 0.304). This insignificant result implies that there is no significant difference in terms of timeliness between group forecasts and individual forecasts made by group members. Also, we document that the analysts who forecast farther from the earnings announcement dates, provide less frequent forecasts, cover more industries, work for larger broker houses, or have less industry forecasting experiences, issue timelier forecasts. In brief, our estimates indicate that analyst groups do not differ from individual analysts in making timely earnings forecasts and that analyst groups do not sacrifice forecast timeliness to achieve more accurate forecasts. Neither hypothesis H2a nor hypothesis H2b is supported by evidence on forecast timeliness.

[Insert Table 4 here]

4.3 Cross-sectional Analyses

We further investigate whether analyst groups outperform individual analysts in making more accurate and timely earnings forecasts particularly when analysts face higher competition pressure from peers. Panel A, Table 5 presents results from estimating the above Equation (1) to examine the accuracy of group forecasts relative to individual forecasts for large and small firms, respectively. We use the median value of the size[14] of forecasted firms to divide the original sample into the large and small sub-samples. In columns (1) and (2), we compare the accuracy of group forecasts with that of individual forecasts in general. The coefficient on GROUP is significantly positive for large firms (0.015, p-value = 0.001) but insignificant for small firms (0.003, p-value = 0.387). In columns (3) and (4), we examine the accuracy of forecasts made by groups versus that of solo forecasts made by group members. Consistent with the results in columns (1) and (2), we report a significant and positive coefficient on GROUP for large firms (0.015, p-value = 0.002), but not for small firms (0.005, p-value = 0.208). Panel B, Table 5 shows results from estimating the above Equation (2) to investigate the timeliness of group forecasts versus that of individual forecasts for large and small firms, respectively. In columns (1) and (2), group forecasts are compared with individual forecasts universally in terms of timeliness. Neither of the coefficients on the GROUP dummy variable is significant. In columns (3) and (4), the timeliness of group forecasts is compared with that of individual forecasts made by group members in particular. Similarly, both of the coefficients on the GROUP variable are insignificant. In sum, the results suggest that analyst groups make more accurate earnings forecasts than individual analysts for large firms but not for small firms and that analyst groups do not outperform individual analysts in issuing timelier forecasts regardless of the size of forecasted firms.

[14] Size is measured as the natural logarithm of firm j's beginning-of-the-year market value in fiscal year t.

[Insert Table 5 here]

Panel A, Table 6 presents results from estimating the above Equation (1) to evaluate the accuracy of group forecasts versus that of individual forecasts for firms with high and low institutional ownership, respectively. We use the median value of the percentage of shares held by institutional investors to divide the original sample into the high and low institutional ownership sub-samples. In columns (1) and (2), we evaluate the accuracy of group forecasts versus that of individual forecasts in general. The coefficient on GROUP is significant and positive for firms with high institutional ownership (0.012, p-value = 0.004) but insignificant for firms with low institutional ownership (0.003, p-value = 0.434). In columns (3) and (4), we examine the accuracy of forecasts made by groups relative to that of forecasts made by group members individually. Consistent with the results in columns (1) and (2), we document a significant and positive coefficient on GROUP for firms with high institutional ownership (0.012, p-value = 0.005), but not for firms with low institutional ownership (0.006, p-value = 0.183). Panel B, Table 6 demonstrates results from estimating the above Equation (2) to investigate the effect of forecasting in groups (relative to forecasting individually) on the earnings forecast timeliness for firms with high and low institutional ownership, respectively. In columns (1) and (2), the timeliness of group forecasts is compared with that of individual forecasts overall. Neither of the coefficients on the GROUP dummy variable is significant. In columns (3) and (4), the timeliness of group forecasts is compared with that of individual forecasts provided by group members in particular. Similarly, neither of the coefficients on the GROUP variable is significant. In brief, the results imply that analyst groups make more accurate earnings forecasts than individual analysts for firms with high institutional ownership but not for firms with low

institutional ownership and that analyst groups do not provide less timely forecasts than individual analysts regardless of the portion of shares held by institutional investors.

[Insert Table 6 here]

Panel A, Table 7 presents results from estimating the above Equation (1) to assess the accuracy of group forecasts against that of individual forecasts for firms with more and fewer analysts following, respectively. We use the median value of the number of analysts following to divide the original sample into the more and fewer sub-samples. In columns (1) and (2), we compare the accuracy of group forecasts with that of individual forecasts in general. The coefficient on GROUP is significant and positive for firms with more analysts following (0.014, p-value = 0.001) but insignificant for firms with fewer analysts following (-0.001, p-value = 0.749). In columns (3) and (4), we examine the accuracy of forecasts made by groups versus that of forecasts made by group members solo. Consistent with the results in columns (1) and (2), we find a significant and positive coefficient on GROUP for firms followed by more analysts (0.013, p-value = 0.002), but not for firms followed by fewer analysts (0.002, p-value = 0.620). Panel B, Table 7 displays results from estimating the above Equation (2) to investigate the timeliness of group forecasts versus that of individual forecasts for firms with more and fewer analysts following, respectively. In columns (1) and (2), the timeliness of group forecasts is compared with that of individual forecasts in general. The coefficients on the GROUP dummy variable are not significant. In columns (3) and (4), the timeliness of group forecasts is compared with that of individual forecasts issued by group members in particular. The coefficients on the GROUP variable are not significant, either. To sum up, the results indicate that group forecasts are more accurate than individual forecasts for firms followed by more analysts other than firms followed

by fewer analysts and that group forecasts are as timely as individual forecasts no matter how many analysts are following.

[Insert Table 7 here]

To summarize the results reported in Tables 5, 6, and 7, we find that analyst groups make more accurate forecasts than individual analysts for larger firms, firms with higher institutional ownership, and firms followed by more analysts. These results are consistent with that analysts tend to organize into groups to obtain an advantage over their peers in providing earnings forecasts in face of greater competition. However, analyst groups do not issue less timely forecasts than individual analysts no matter how intense analysts are competing with each other. The empirical evidence documented in the above supports hypothesis H3, but not H4.

4.4 Earnings Forecast Optimism

We use earnings forecast optimism as an alternative measure for analyst performance and examine whether analyst groups outperform individual analysts. Consistent with our model specification on forecast accuracy and timeliness, we estimate the following model to compare forecast optimism of group forecasts with that of individual forecasts:

$$OPTIMISM_{i,j,t}=\rho_0+\rho_1 GROUP_{i,j,t}+\rho_2 FAGE_{i,j,t}+\rho_3 FREQ_{i,j,t}+\rho_4 NIND_{i,j,t}+\rho_5 BSIZE_{i,j,t}$$
$$+\rho_6 IEXP_{i,j,t}+\sigma_{i,j,t} \quad (3)$$

In the above model, OPTIMISM refers to analyst i's forecast optimism for firm j in fiscal year t, and is calculated as the forecast error (analyst i's annual earnings forecast for firm j in fiscal year t minus the actual amount for firm j in fiscal year t) of analyst i following firm j in fiscal year t minus the minimum forecast error for those analysts who follow firm j in fiscal year t, with this difference divided by the range of forecast errors for those analysts who follow firm j in fiscal year t. All the other variables are defined the same as in the above section.

Table 8 presents results from estimating the above Equation (3). In column (1), the forecast optimism of group forecasts is compared with that of individual forecasts in general. The coefficient on the GROUP dummy variable is significantly negative (-0.007, p-value = 0.088), indicating that analyst groups make less optimistic earnings forecasts than individual analysts. In column (2), group forecasts are evaluated against individual forecasts made by members comprising groups in terms of forecast optimism. The coefficient on the GROUP variable is significant and negative (-0.009, p-value = 0.039), implying that individual analysts tend to issue more optimistic earnings forecasts when they are forecasting solo than when they are forecasting together with their colleagues in groups. In addition, the results show that analysts who have longer forecast horizons and less industry forecasting experience, issue more frequent earnings forecasts, and work for larger broker houses, tend to make more optimistic earnings forecasts. To sum up, we find that analyst groups provide less optimistic forecasts than individual analysts, consistent with previous results that analyst groups make more accurate forecasts than individual analysts.

[Insert Table 8 here]

4.5 Market Reactions to Analysts' Forecast Revisions

We further examine the market reactions to forecast revisions made by analyst groups versus individual analysts by estimating the following model:

$$CAR_{i,j,t}=\delta_0+\delta_1 REVP_{i,j,t}+\delta_2 GROUP_{i,j,t}+\delta_3 REVP_{i,j,t}\times GROUP_{i,j,t}+\delta_4 TIMELINESS_{i,j,t}$$
$$+\delta_5 REVP_{i,j,t}\times TIMELINESS_{i,j,t}+\sum_m \varphi_m Controls_{i,j,t}+\sum_m \gamma_m REVP_{i,j,t}\times Controls_{i,j,t}+\omega_{i,j,t} \quad (4)$$

In the above model, CAR is the 3-day cumulative market-adjusted stock return of firm j surrounding analyst i's forecast revision for firm j in fiscal year t. REVP refers to analyst i's forecast revision for firm j in fiscal year t, calculated as analyst i's earnings forecast of interest

minus analyst i's immediately preceding earnings forecast for firm j in fiscal year t, with this difference divided by firm j's stock price 10 trading days before the release of the forecast of interest. GROUP, TIMELINESS, and the control variables are defined as in the Appendix.

Table 9 presents results from estimating the above Equation (4). From column (1) to column (4), we consistently document significantly positive coefficients on REVP, suggesting that investors are responding to forecast revisions made by analysts in the short window of (-1, +1). However, we do not find significant coefficients on the interaction term between REVP and GROUP, indicating that investors do not react more strongly to forecast revisions made by analyst groups than to those made by individual analysts. Probably it is because analyst groups do not make timelier forecasts than individual analysts.

[Insert Table 9 here]

4.6 Group Members versus Individuals Affiliated with No Group

To further examine how forming a group impacts group members in their forecasting performances, we compare solo forecasts made by group members with those made by analysts who only forecast individually. We estimate the following models for forecast accuracy and timeliness, respectively:

$$\begin{aligned} ACCURACY_{i,j,t}=&\alpha_0+\alpha_1 MEM_{i,j,t}+\alpha_2 FAGE_{i,j,t}+\alpha_3 FREQ_{i,j,t}+\alpha_4 NIND_{i,j,t} \\ &+\alpha_5 BSIZE_{i,j,t}+\alpha_6 IEXP_{i,j,t}+\varepsilon_{i,j,t} \end{aligned} \quad (5)$$

$$\begin{aligned} TIMELINESS_{i,j,t}=&\alpha_0+\alpha_1 MEM_{i,j,t}+\alpha_2 FAGE_{i,j,t}+\alpha_3 FREQ_{i,j,t}+\alpha_4 NIND_{i,j,t} \\ &+\alpha_5 BSIZE_{i,j,t}+\alpha_6 IEXP_{i,j,t}+\varepsilon_{i,j,t} \end{aligned} \quad (6)$$

In the above models, MEM is a dummy variable that equals 1 if analyst i corresponds to a name field containing only one name, i.e., an individual, and this individual forecasts both by himself and as a member of a group. MEM equals 0 if analyst i corresponds to a name field

containing only one name, i.e., an individual, and this individual only forecasts by himself. All the other variables are defined the same as in the above.

Panel A, Table 10 presents results from estimating the above Equation (5) to compare the forecast accuracy of group members when making solo forecasts with that of individual analysts who only forecast on their own. The coefficient on MEM is positive but insignificant (0.004, p-value = 0.333), implying that compared to analysts who only make earnings forecasts individually, group members do not make more accurate forecasts when forecasting by themselves. Panel B, Table 10 shows results from estimating the above Equation (6) to examine the forecast timeliness of group members when forecasting individually versus that of individual analysts who only forecast on their own. The coefficient on MEM is significantly negative (-0.017, p-value < 0.001), indicating that when working by themselves group members make less timely forecasts than their counterparts who only provide solo forecasts. Thus the above results suggest that when group members are working together their forecast accuracy and timeliness as a whole improve.

[Insert Table 10 here]

4.7 Firm Characteristics that Attract Groups Following

The existence of analyst groups indicates that individual analysts may form into groups to meet certain market research demand. We examine what firm characteristics may cause analyst groups to follow by estimating the following model:

$$\text{Prob}\left[\text{GFIRM}_{j,t}=1\right]=\vartheta[\pi_0+\pi_1\text{ZSCORE}_{j,t}+\pi_2\text{SIZE}_{j,t}+\pi_3\text{INST}_{j,t}+\pi_4\text{FOLLOW}_{j,t}] \quad (7)$$

In the above model, GFIRM is a dummy variable that equals 1 if firm j in fiscal year t is followed by a group and equals 0 otherwise. ZSCORE refers to the Altman (1968) z-score for firm j in fiscal year t. This score is decreasing in the probability of bankruptcy. SIZE is the

natural logarithm of firm j's beginning-of-the-year market value in fiscal year t. INST is defined as the percentage of shares held by institutional investors. FOLLOW represents the number of independent analysts who follow firm j in fiscal year t.

Table 11 presents results from estimating the above Equation (7) to study the determinants of group-followed firm-years. The significant and positive coefficients on the independent variables illustrate that analyst groups are more likely to follow firms in financial distress, larger firms, firms with higher institutional ownership, and firms followed by a greater number of analysts in general. The findings are consistent with the argument that analysts work together in groups when making earnings forecasts is more challenging (as the forecasted firm is in financial difficulty) or that analysts organize into groups to gain an edge over their peers when there is more competition among analysts.

[Insert Table 11 here]

V. CONCLUSION

Using Chinese data on sell-side analysts, we examine whether analyst groups outperform individual analysts in providing earnings forecasts. We find that analyst groups make more accurate forecasts than individual analysts while analyst groups do not issue less timely forecasts than individual analysts. In addition, the effect of forming groups on forecast accuracy other than timeliness is more salient when the forecasted firm is larger, has higher institutional ownership, and is followed by more analysts. Furthermore, group forecasts are less optimistic than individual forecasts. A comparison between forecasts made by group members individually and forecasts made by individual analysts affiliated with no group indicates that working in groups benefits group members by enhancing their forecast accuracy and timeliness. Finally, the

likelihood that analyst groups cover a given firm increases with bankruptcy risk, firm size, institutional ownership, and the number of analysts following.

This study has several implications. First, when analysts are working in groups, they tend to forecast more accurately while their group forecasts are not less timely than individual forecasts. Thus analysts' teamwork helps improve their performance (at least for forecast accuracy). Second, group forecasts are more accurate than individual forecasts, especially when there is increased competition among analysts. This implies that analysts realize that working together in groups helps better compete with their peers. In practice, broker houses may encourage the formation of analyst groups in order to maintain competitive on the market. Finally, the archival methods adopted in the paper enable large-sample tests of predictions based on psychological theories and may extend the horizon of future research.

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Appendix
Definition of Variables

ACCURACY	Analyst i's forecast accuracy for firm j in year t, calculated as the maximum absolute forecast error for analysts who follow firm j in year t minus the absolute forecast error of analyst i following firm j in year t, with this difference divided by the range of absolute forecast errors for analysts who follow firm j in year t.
BETA	The slope coefficient obtained from a firm-specific regression of the firm's daily stock return on the value-weighted market index daily stock return over the period of the 100 trading days ending 10 trading days prior to the release of the revised forecast.
BSIZE	Analyst i's brokerage house size, calculated as the number of analysts employed by the brokerage house which employs analyst i following firm j in year t minus the minimum number of analysts employed by the brokerage houses which employ analysts following firm j in year t, with this difference divided by the range of the numbers of analysts employed by the brokerage houses which employ analysts following firm j in year t.
CAR	The 3-day cumulative market-adjusted stock return of firm j surrounding analyst i's forecast revision for firm j in year t.
FAGE	Analyst i's forecast age, calculated as the number of days from the forecast date to the earnings announcement date for analyst i following firm j in year t minus the minimum forecast horizon for analysts who follow firm j in year t, with this difference divided by the range of forecast horizons for analysts who follow firm j in year t.
FOLLOW	The number of independent analysts who follow firm j in year t.
FREQ	Analyst i's forecast frequency, calculated as the number of firm j forecasts made by analyst i following firm j in year t minus the minimum number of firm j forecasts made by analysts who follow firm j in year t, with this difference divided by the range of the numbers of firm j forecasts made by analysts who follow firm j in year t.
GFIRM	Dummy variable that equals 1 if firm j in year t is followed by a group and equals 0 otherwise.
GROUP	Dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names (a group) and 0 if analyst i corresponds to a name field containing only one name (an individual).
IEXP	Analyst i's industry forecasting experience, calculated as the number of prior forecasting years for analyst i following firm j's industry in year t minus the minimum number of prior forecasting years for analysts who follow firm j's industry in year t, with this difference divided by the range of the numbers of prior forecasting years for analysts who follow firm j's industry in year t.
INST	The percentage of shares held by institutional investors.
MEM	Dummy variable that equals 1 if analyst i corresponds to a name field containing only one name, i.e., an individual, and this individual forecasts both by himself and as a member of a group. *MEM* equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual, and this individual only forecasts by himself.
MTB	Market-to-book ratio, calculated as firm j's beginning-of-the-year market value divided by beginning-of-the-year total equities in year t.
NIND	The number of industries followed by analyst i, calculated as the number of industries followed by analyst i following firm j in year t minus the minimum number of industries followed by analysts who follow firm j in year t, with this difference divided by the range of the numbers of industries followed by analysts who follow firm j in year t.
OPTIMISM	Analyst i's forecast optimism for firm j in year t, calculated as the forecast error (analyst i's forecast for firm j in year t minus the actual amount for firm j in year t) of analyst i following firm j in year t minus the minimum forecast error for analysts who follow firm j in year t, with this difference divided by the range of forecast errors for analysts who follow firm j in year t.
REVP	Analyst i's forecast revision for firm j in year t, calculated as analyst i's earnings forecast of interest minus analyst i's immediately preceding earnings forecast for firm j in year t, with this difference divided by firm j's stock price 10 trading days before the release of the forecast of interest.
SIZE	The natural logarithm of firm j's beginning-of-the-year market value in year t.

(continued on the next page)

Appendix
Definition of Variables – Continued

TIMELINESS	Analyst i's forecast timeliness for firm j in year t, calculated as the number of days between the immediately preceding forecast and the forecast of interest divided by the number of days between the forecast of interest and the immediately succeeding forecast. This variable is standardized as the timeliness of analyst i following firm j in year t minus the minimum timeliness for analysts who follow firm j in year t, with this difference divided by the range of timeliness for analysts who follow firm j in year t.
ZSCORE	The Altman (1968) z-score for firm j in year t. This score is decreasing in the probability of bankruptcy.

Table 1 Groups vs. individuals: Comparison of analyst-year level forecast characteristics

	Group-years n = 9,226		Individual-years n = 10,909		Tests of differences	
Variables	(1)	(2)	(3)	(4)	(1) – (3)	(2) – (4)
	Mean	Median	Mean	Median	T-Test	Wilcoxon Test
ACCURACY	0.498	0.462	0.412	0.352	0.086***	0.110***
TIMELINESS	0.080	0.032	0.065	0.030	0.015***	0.002**
FAGE	0.516	0.514	0.490	0.476	0.026***	0.038***
FREQ	0.112	0.000	0.203	0.120	-0.091***	-0.120***
NIND	0.078	0.000	0.189	0.117	-0.111***	-0.117***
BSIZE	0.539	0.532	0.395	0.367	0.144***	0.165***
IEXP	0.169	0.158	0.291	0.250	-0.122***	-0.092***

Note: This table reports means and medians for the analyst-year relative descriptive statistics. *Group* is an indicator variable that equals 1 if analyst i corresponds to a name field containing at least two different names and 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. The other variables are defined in the Appendix. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 2 Forecast characteristics: Pearson and Spearman correlations

Variables	*ACCURACY*	*TIMELINESS*	*GROUP*	*FAGE*	*FREQ*	*NIND*	*BSIZE*	*IEXP*
ACCURACY		0.158***	0.157***	-0.321***	-0.591***	-0.264***	-0.048***	-0.389***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
TIMELINESS	0.126***		0.059***	0.112***	-0.215***	-0.086***	-0.011	-0.053***
	(<0.001)		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.149)	(<0.001)
GROUP	0.157***	0.016**		0.045***	-0.210***	-0.278***	0.243***	-0.293***
	(<0.001)	(0.032)		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
FAGE	-0.303***	0.086***	0.040***		-0.097***	-0.057***	0.025***	0.449***
	(<0.001)	(<0.001)	(<0.001)		(<0.001)	(<0.001)	(<0.001)	(<0.001)
FREQ	-0.671***	-0.134***	-0.225***	-0.107***		0.362***	0.067***	0.256***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(<0.001)	(<0.001)	(<0.001)
NIND	-0.306***	-0.062***	-0.289***	-0.048***	0.486***		-0.088***	0.132***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(<0.001)	(<0.001)
BSIZE	-0.070***	-0.057***	0.245***	0.026***	0.072***	-0.076***		0.115***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(<0.001)
IEXP	-0.437***	-0.035***	-0.265***	0.533***	0.280***	0.178***	0.112***	
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	

Note: The Pearson (Spearman rank) correlations of the analyst-year standardized variables are above (below) the diagonal. The two-tailed p-values are in parentheses below the correlations. All the variables are defined in the Appendix. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3 Groups versus individuals: Earnings forecast accuracy

$$ACCURACY_{i,j,t} = \alpha_0 + \alpha_1 GROUP_{i,j,t} + \alpha_2 FAGE_{i,j,t} + \alpha_3 FREQ_{i,j,t} + \alpha_4 NIND_{i,j,t} + \alpha_5 BSIZE_{i,j,t} + \alpha_6 IEXP_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

Variables	(1) Groups versus individual analysts n = 325,418	(2) Groups versus group members n = 286,407
INTERCEPT	0.935***	0.933***
	(<0.001)	(<0.001)
GROUP	0.008**	0.010***
	(0.011)	(0.006)
FAGE	-0.504***	-0.508***
	(<0.001)	(<0.001)
FREQ	-0.035***	-0.037***
	(<0.001)	(<0.001)
NIND	-0.036***	-0.032***
	(<0.001)	(<0.001)
BSIZE	-0.020***	-0.017***
	(<0.001)	(<0.001)
IEXP	0.038***	0.040***
	(<0.001)	(<0.001)
Adjusted R^2	26.24%	26.48%
F-value	4,731.50***	4,046.42***

Note: This table presents results from estimating the above Equation (1) to evaluate the earnings forecast accuracy of analyst groups versus individual analysts. In the group versus individual analysts sample, *GROUP* is a dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names and equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. In the groups versus group members sample, an individual forecasts both by himself (analyst i corresponds to a name field containing only his name, i.e., *GROUP*=0) and as a member of a group (analyst i corresponds to a name field containing his name and other individuals' names, i.e., *GROUP*=1). All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 4 Groups versus individuals: Earnings forecast timeliness

$$\text{TIMELINESS}_{i,j,t} = \beta_0 + \beta_1 \text{GROUP}_{i,j,t} + \beta_2 \text{FAGE}_{i,j,t} + \beta_3 \text{FREQ}_{i,j,t} + \beta_4 \text{NIND}_{i,j,t} + \beta_5 \text{BSIZE}_{i,j,t} + \beta_6 \text{IEXP}_{i,j,t} + \mu_{i,j,t} \quad (2)$$

Variables	(1) Groups versus individual analysts n = 291,350	(2) Groups versus group members n = 257,551
INTERCEPT	0.095***	0.090***
	(<0.001)	(<0.001)
GROUP	0.002	0.003
	(0.503)	(0.304)
FAGE	0.026***	0.026***
	(<0.001)	(<0.001)
FREQ	-0.013***	-0.013***
	(<0.001)	(<0.001)
NIND	0.027***	0.026***
	(<0.001)	(<0.001)
BSIZE	0.016***	0.022***
	(<0.001)	(<0.001)
IEXP	-0.025***	-0.022***
	(<0.001)	(<0.001)
Adjusted R^2	0.29%	0.30%
F-value	29.30***	28.46***

Note: This table presents results from estimating the above Equation (2) to evaluate the earnings forecast timeliness of analyst groups versus individual analysts. In the group versus individual analysts sample, *GROUP* is a dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names and equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. In the groups versus group members sample, an individual forecasts both by himself (analyst i corresponds to a name field containing only his name, i.e., *GROUP*=0) and as a member of a group (analyst i corresponds to a name field containing his name and other individuals' names, i.e., *GROUP*=1). All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5 Groups versus individuals: Partitioned by the size of forecasted firms
Panel A: Earnings forecast accuracy

$$ACCURACY_{i,j,t} = \alpha_0 + \alpha_1 GROUP_{i,j,t} + \alpha_2 FAGE_{i,j,t} + \alpha_3 FREQ_{i,j,t} + \alpha_4 NIND_{i,j,t} + \alpha_5 BSIZE_{i,j,t} + \alpha_6 IEXP_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

	Groups versus individual analysts		Groups versus group members	
Variables	(1) Large	(2) Small	(3) Large	(4) Small
	n = 154,105	n = 154,129	n = 135,657	n = 135,587
INTERCEPT	0.929***	0.944***	0.928***	0.941***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	0.015***	0.003	0.015***	0.005
	(0.001)	(0.387)	(0.002)	(0.208)
FAGE	-0.455***	-0.569***	-0.457***	-0.573***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
FREQ	-0.028***	-0.036***	-0.034***	-0.037***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
NIND	-0.031***	-0.027***	-0.027***	-0.024***
	(<0.001)	(<0.001)	(0.001)	(<0.001)
BSIZE	-0.023***	-0.025***	-0.018***	-0.022***
	(<0.001)	(<0.001)	(0.005)	(<0.001)
IEXP	0.042***	0.033***	0.041***	0.038***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Adjusted R^2	21.33%	32.52%	21.56%	32.77%
F-value	1,743.94***	3,656.72***	1,507.13***	3,122.06***

(to be continued)

(Continued)

Panel B: Earnings forecast timeliness

$$TIMELINESS_{i,j,t} = \beta_0 + \beta_1 GROUP_{i,j,t} + \beta_2 FAGE_{i,j,t} + \beta_3 FREQ_{i,j,t} + \beta_4 NIND_{i,j,t} + \beta_5 BSIZE_{i,j,t} + \beta_6 IEXP_{i,j,t} + \mu_{i,j,t} \quad (2)$$

	Groups versus individual analysts		Groups versus group members	
Variables	(1) Large	(2) Small	(3) Large	(4) Small
	n = 138,893	n = 138,917	n = 122,853	n = 122,683
INTERCEPT	0.093***	0.100***	0.088***	0.094***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	0.000	0.003	0.002	0.004
	(0.994)	(0.273)	(0.548)	(0.193)
FAGE	0.000	0.026***	-0.001	0.026***
	(0.944)	(<0.001)	(0.809)	(<0.001)
FREQ	-0.010***	-0.016***	-0.010***	-0.015***
	(<0.001)	(<0.001)	(0.001)	(<0.001)
NIND	0.016***	0.025***	0.016**	0.022***
	(0.007)	(0.001)	(0.010)	(0.003)
BSIZE	0.010**	0.019***	0.015***	0.027***
	(0.039)	(<0.001)	(0.005)	(<0.001)
IEXP	-0.005	-0.021***	-0.002	-0.018***
	(0.316)	(<0.001)	(0.692)	(0.001)
Adjusted R^2	0.07%	0.28%	0.08%	0.30%
F-value	3.89***	22.26***	3.79***	23.25***

Note: Panel A presents results from estimating the above Equation (1) to evaluate the earnings forecast accuracy of analyst groups versus individual analysts for large and small firms, respectively. Panel B presents results from estimating the above Equation (2) to evaluate the earnings forecast timeliness of analyst groups versus individual analysts for large and small firms, respectively. We use the median value of the size of forecasted firms to divide the original sample into the large and small sub-samples. In the groups versus individual analysts sample, *GROUP* is a dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names and equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. In the groups versus group members sample, an individual forecasts both by himself (analyst i corresponds to a name field containing only his name, i.e., *GROUP*=0) and as a member of a group (analyst i corresponds to a name field containing his name and other individuals' names, i.e., *GROUP*=1). All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 6 Groups versus individuals: Partitioned by the percentage of shares held by institutional investors
Panel A: Earnings forecast accuracy

$$ACCURACY_{i,j,t} = \alpha_0 + \alpha_1 GROUP_{i,j,t} + \alpha_2 FAGE_{i,j,t} + \alpha_3 FREQ_{i,j,t} + \alpha_4 NIND_{i,j,t} + \alpha_5 BSIZE_{i,j,t} + \alpha_6 IEXP_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

	Groups versus individual analysts		Groups versus group members	
Variables	(1) High	(2) Low	(3) High	(4) Low
	n = 159,661	n = 159,663	n = 140,730	n = 140,590
INTERCEPT	0.934***	0.921***	0.934***	0.917***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	0.012***	0.003	0.012***	0.006
	(0.004)	(0.434)	(0.005)	(0.183)
FAGE	-0.489***	-0.492***	-0.492***	-0.496***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
FREQ	-0.032***	-0.037***	-0.036***	-0.038***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
NIND	-0.024***	-0.037***	-0.020***	-0.033***
	(<0.001)	(<0.001)	(0.003)	(<0.001)
BSIZE	-0.021***	-0.018***	-0.017***	-0.015***
	(<0.001)	(<0.001)	(0.006)	(0.005)
IEXP	0.032***	0.033***	0.031***	0.038***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Adjusted R^2	22.88%	24.14%	23.16%	24.36%
F-value	1,882.11***	3,104.48***	1,680.18***	2,666.72***

(to be continued)

(Continued)

Panel B: Earnings forecast timeliness

$$TIMELINESS_{i,j,t} = \beta_0 + \beta_1 GROUP_{i,j,t} + \beta_2 FAGE_{i,j,t} + \beta_3 FREQ_{i,j,t} + \beta_4 NIND_{i,j,t} + \beta_5 BSIZE_{i,j,t} + \beta_6 IEXP_{i,j,t} + \mu_{i,j,t} \quad (2)$$

	Groups versus individual analysts		Groups versus group members	
Variables	(1) High	(2) Low	(3) High	(4) Low
	n = 143,546	n = 143,482	n = 126,995	n = 126,932
INTERCEPT	0.098***	0.102***	0.091***	0.099***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	0.002	0.002	0.004*	0.002
	(0.336)	(0.503)	(0.097)	(0.527)
FAGE	-0.007***	0.030***	-0.007**	0.031***
	(0.009)	(<0.001)	(0.019)	(<0.001)
FREQ	-0.011***	-0.016***	-0.010***	-0.016***
	(<0.001)	(<0.001)	(0.001)	(<0.001)
NIND	0.018***	0.030***	0.020***	0.026***
	(0.002)	(<0.001)	(0.001)	(0.003)
BSIZE	0.011**	0.019***	0.017***	0.025***
	(0.020)	(0.001)	(0.001)	(<0.001)
IEXP	-0.007	-0.033***	-0.003	-0.030***
	(0.174)	(<0.001)	(0.528)	(<0.001)
Adjusted R^2	0.10%	0.38%	0.12%	0.37%
F-value	13.03***	8.34***	7.78***	23.24***

Note: Panel A presents results from estimating the above Equation (1) to evaluate the earnings forecast accuracy of analyst groups versus individual analysts for firms with high and low institutional ownership, respectively. Panel B presents results from estimating the above Equation (2) to evaluate the earnings forecast timeliness of analyst groups versus individual analysts for firms with high and low institutional ownership, respectively. We use the median value of the percentage of shares held by institutional investors to divide the original sample into the high and low sub-samples. In the groups versus individual analysts sample, *GROUP* is a dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names and equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. In the groups versus group members sample, an individual forecasts both by himself (analyst i corresponds to a name field containing only his name, i.e., *GROUP*=0) and as a member of a group (analyst i corresponds to a name field containing his name and other individuals' names, i.e., *GROUP*=1). All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 7 Groups versus individuals: Partitioned by the number of analysts following
Panel A: Earnings forecast accuracy

$$ACCURACY_{i,j,t} = \alpha_0 + \alpha_1 GROUP_{i,j,t} + \alpha_2 FAGE_{i,j,t} + \alpha_3 FREQ_{i,j,t} + \alpha_4 NIND_{i,j,t} + \alpha_5 BSIZE_{i,j,t} + \alpha_6 IEXP_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

	Groups versus individual analysts		Groups versus group members	
Variables	(1) More	(2) Less	(3) More	(4) Less
	n = 165,206	n = 160,212	n = 144,493	n = 141,914
INTERCEPT	0.950***	0.892***	0.952***	0.889***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	0.014***	-0.001	0.013***	0.002
	(0.001)	(0.749)	(0.002)	(0.620)
FAGE	-0.480***	-0.499***	-0.487***	-0.500***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
FREQ	-0.019***	-0.036***	-0.021***	-0.038***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
NIND	-0.015*	-0.005	-0.016*	0.001
	(0.051)	(0.324)	(0.059)	(0.806)
BSIZE	-0.009	-0.010**	-0.006	-0.007
	(0.145)	(0.025)	(0.337)	(0.141)
IEXP	0.023***	-0.002	0.024***	-0.001
	(0.001)	(0.691)	(0.002)	(0.893)
Adjusted R^2	25.48%	26.19%	26.18%	26.25%
F-value	2,018.96***	3,503.68***	1,807.79***	3,022.41***

(to be continued)

(Continued)

Panel B: Earnings forecast timeliness

$$TIMELINESS_{i,j,t} = \beta_0 + \beta_1 GROUP_{i,j,t} + \beta_2 FAGE_{i,j,t} + \beta_3 FREQ_{i,j,t} + \beta_4 NIND_{i,j,t} + \beta_5 BSIZE_{i,j,t} + \beta_6 IEXP_{i,j,t} + \mu_{i,j,t} \quad (2)$$

	Groups versus individual analysts		Groups versus group members	
Variables	(1) More	(2) Less	(3) More	(4) Less
	n = 146,238	n = 145,112	n = 128,855	n = 128,696
INTERCEPT	0.090***	0.110***	0.087***	0.103***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	-0.001	0.005	0.000	0.006
	(0.762)	(0.150)	(0.942)	(0.102)
FAGE	-0.002	0.038***	-0.004	0.041***
	(0.338)	(<0.001)	(0.114)	(<0.001)
FREQ	-0.010***	-0.019***	-0.010***	-0.019***
	(<0.001)	(<0.001)	(0.001)	(<0.001)
NIND	0.009	0.022***	0.008	0.021***
	(0.150)	(0.001)	(0.219)	(0.002)
BSIZE	0.014***	0.011**	0.019***	0.018***
	(0.007)	(0.042)	(<0.001)	(0.003)
IEXP	-0.004	-0.026***	-0.001	-0.023***
	(0.438)	(<0.001)	(0.869)	(<0.001)
Adjusted R^2	0.06%	0.39%	0.08%	0.43%
F-value	3.95***	29.03***	4.92***	30.66***

Note: Panel A presents results from estimating the above Equation (1) to evaluate the earnings forecast accuracy of analyst groups versus individual analysts for firms with more and fewer analysts following, respectively. Panel B presents results from estimating the above Equation (2) to evaluate the earnings forecast timeliness of analyst groups versus individual analysts for firms with more and fewer analysts following, respectively. We use the median value of the number of analysts following to divide the original sample into the more and fewer sub-samples. In the groups versus individual analysts sample, *GROUP* is a dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names and equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. In the groups versus group members sample, an individual forecasts both by himself (analyst i corresponds to a name field containing only his name, i.e., *GROUP*=0) and as a member of a group (analyst i corresponds to a name field containing his name and other individuals' names, i.e., *GROUP*=1). All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 8 Groups versus individuals: Earnings forecast optimism

$$\text{OPTIMISM}_{i,j,t} = \rho_0 + \rho_1 \text{GROUP}_{i,j,t} + \rho_2 \text{FAGE}_{i,j,t} + \rho_3 \text{FREQ}_{i,j,t} + \rho_4 \text{NIND}_{i,j,t} + \rho_5 \text{BSIZE}_{i,j,t} + \rho_6 \text{IEXP}_{i,j,t} + \sigma_{i,j,t} \quad (3)$$

Variables	(1) Groups versus individual analysts n = 325,418	(2) Groups versus group members n = 286,407
INTERCEPT	0.220***	0.223***
	(<0.001)	(<0.001)
GROUP	-0.007*	-0.009**
	(0.088)	(0.039)
FAGE	0.357***	0.362***
	(<0.001)	(<0.001)
FREQ	0.039***	0.041***
	(<0.001)	(<0.001)
NIND	0.001	-0.002
	(0.848)	(0.775)
BSIZE	0.032***	0.027***
	(<0.001)	(<0.001)
IEXP	-0.018***	-0.019***
	(0.006)	(0.007)
Adjusted R^2	13.84%	14.14%
F-value	1,271.02***	1,104.08***

Note: Table 8 presents results from estimating the above Equation (3) to evaluate the earnings forecast optimism of analyst groups versus individual analysts. In the groups versus individual analysts sample, *GROUP* is a dummy variable that equals 1 if analyst i corresponds to a name field containing at least two different names and equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual. In the groups versus group members sample, an individual forecasts both by himself (analyst i corresponds to a name field containing only his name, i.e., *GROUP*=0) and as a member of a group (analyst i corresponds to a name field containing his name and other individuals' names, i.e., *GROUP*=1). All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 9 Groups versus individuals: Market reactions to analysts' forecast revisions

$$CAR_{i,j,t} = \delta_0 + \delta_1 REVP_{i,j,t} + \delta_2 GROUP_{i,j,t} + \delta_3 REVP_{i,j,t} \times GROUP_{i,j,t} + \delta_4 TIMELINESS_{i,j,t} + \delta_5 REVP_{i,j,t} \times TIMELINESS_{i,j,t} + \sum_m \varphi_m Controls_{i,j,t} + \sum_m \gamma_m REVP_{i,j,t} \times Controls_{i,j,t} + \omega_{i,j,t} \quad (4)$$

Variables	(1) Base Model n = 150,736	(2) Base+Timeliness n = 140,487	(3) Controls n = 145,929	(4) Controls+Timeliness n = 136,681
INTERCEPT	0.008***	0.009***	0.026***	0.026***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
REVP	0.193***	0.192***	0.686***	0.720***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
GROUP	0.002***	0.002***	0.001*	0.001*
	(0.001)	(0.001)	(0.086)	(0.070)
REVP×GROUP	0.037	0.045	0.025	0.034
	(0.200)	(0.113)	(0.419)	(0.270)
Timeliness				
TIMELINESS		-0.006***		-0.006***
		(<0.001)		(<0.001)
REVP×TIMELINESS		0.007		-0.008
		(0.862)		(0.844)
Forecast controls				
FAGE			0.004***	0.004***
			(<0.001)	(<0.001)
REVP×FAGE			0.153***	0.120***
			(<0.001)	(<0.001)
FREQ			0.002**	0.002**
			(0.016)	(0.025)
REVP×FREQ			0.092***	0.106***
			(0.004)	(0.001)
NIND			-0.001	-0.001
			(0.294)	(0.411)
REVP×NIND			-0.060	-0.056
			(0.152)	(0.196)
BSIZE			0.004***	0.004***
			(<0.001)	(<0.001)
REVP×BSIZE			0.035	0.047
			(0.390)	(0.262)
IEXP			-0.002	-0.002
			(0.110)	(0.109)
REVP×IEXP			-0.056	-0.051
			(0.281)	(0.342)
Firm controls				

MTB			0.001***	0.001***
			(<0.001)	(<0.001)
REVP×MTB			0.025**	0.026**
			(0.046)	(0.047)
SIZE			-0.001***	-0.001***
			(<0.001)	(<0.001)
REVP×SIZE			-0.026***	-0.024**
			(0.006)	(0.011)
BETA			-0.004***	-0.004***
			(<0.001)	(<0.001)
REVP×BETA			-0.095***	-0.093***
			(0.005)	(0.006)
FOLLOW			0.000	0.000
			(0.492)	(0.731)
REVP×FOLLOW			-0.027	-0.043*
			(0.201)	(0.057)
Adjusted R^2	0.60%	0.69%	1.09%	1.19%
F-value	109.41***	72.38***	28.20***	26.53***

Note: This table presents results from estimating the above Equation (4) to evaluate the market reactions to analyst groups' versus individual analysts' forecast revisions. The dependent variable, *CAR*, is the 3-day cumulative market-adjusted stock return of firm j surrounding analyst i's forecast revision for firm j in year t. All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. Continuous variables are winsorized at 1 and 99 percentiles. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 10 Group members versus individuals affiliated with no group
Panel A: Earnings forecast accuracy

$$ACCURACY_{i,j,t} = \alpha_0 + \alpha_1 MEM_{i,j,t} + \alpha_2 FAGE_{i,j,t} + \alpha_3 FREQ_{i,j,t} + \alpha_4 NIND_{i,j,t} + \alpha_5 BSIZE_{i,j,t} + \alpha_6 IEXP_{i,j,t} + \varepsilon_{i,j,t} \quad (5)$$

	(1)
Variables	Group members versus individuals affiliated with no group
	n = 229,195
INTERCEPT	0.932***
	(<0.001)
MEM	0.004
	(0.333)
FAGE	-0.499***
	(<0.001)
FREQ	-0.028***
	(<0.001)
NIND	-0.034***
	(<0.001)
BSIZE	-0.028***
	(<0.001)
IEXP	0.033***
	(<0.001)
Adjusted R^2	25.52%
F-value	3,290.43***

(to be continued)

(Continued)

Panel B: Earnings forecast timeliness

$$TIMELINESS_{i,j,t} = \beta_0 + \beta_1 MEM_{i,j,t} + \beta_2 FAGE_{i,j,t} + \beta_3 FREQ_{i,j,t} + \beta_4 NIND_{i,j,t} + \beta_5 BSIZE_{i,j,t} + \beta_6 IEXP_{i,j,t} + \mu_{i,j,t} \quad (6)$$

Variables	(1) Group members versus individuals affiliated with no group n = 202,811
INTERCEPT	0.109***
	(<0.001)
MEM	-0.017***
	(<0.001)
FAGE	0.020***
	(<0.001)
FREQ	-0.016***
	(<0.001)
NIND	0.025***
	(<0.001)
BSIZE	0.015***
	(0.004)
IEXP	-0.012***
	(0.004)
Adjusted R^2	0.30%
F-value	25.16***

Note: Panel A presents results from estimating the above Equation (5) to evaluate the earnings forecast accuracy of group members when making individual forecasts versus individual analysts who are affiliated with no group and only make forecasts by themselves. Panel B presents results from estimating the above Equation (6) to evaluate the earnings forecast timeliness of group members when making individual forecasts versus individual analysts who are affiliated with no group and only make forecasts by themselves. *MEM* is a dummy variable that equals 1 if analyst i corresponds to a name field containing only one name, i.e., an individual, and this individual forecasts both by himself and as a member of a group. *MEM* equals 0 if analyst i corresponds to a name field containing only one name, i.e., an individual, and this individual only forecasts by himself. All the other variables are defined in the Appendix. Coefficients are estimated from the OLS regression and p-values in parentheses below the coefficient estimates are based on standard errors adjusted for both heteroskedasticity and intra-analyst error correlation. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 11 Determinants of group-followed firm-years

$$\text{Prob}\left[\text{GFIRM}_{j,t} = 1\right] = \vartheta[\pi_0 + \pi_1 \text{ZSCORE}_{j,t} + \pi_2 \text{SIZE}_{j,t} + \pi_3 \text{INST}_{j,t} + \pi_4 \text{FOLLOW}_{j,t}] \quad (7)$$

Variables	n = 10,011
INTERCEPT	-6.936***
	(<0.001)
ZSCORE	0.258***
	(<0.001)
SIZE	0.152**
	(0.024)
INST	0.981***
	(<0.001)
FOLLOW	2.089***
	(<0.001)
Pseudo R^2	37.74%
LR-Chi-Square	4,743.51***

Note: This table presents results from estimating the above Equation (7) to evaluate the determinants of group-followed firm-years. The dependent variable, *GFIRM*, is a dummy variable that equals 1 if a firm-year is followed by at least a group and equals 0 otherwise. All the other variables are defined in the Appendix. Coefficients are estimated from the logistic regression adjusted for intra-firm error correlation and p-values are reported in parentheses below the coefficient estimates. Continuous variables are winsorized at 1 and 99 percentiles. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.