Are analyst teams' forecasts more accurate?[*]

Wen He
Accounting Cluster
UQ Business School
University of Queensland
wen.he@uq.edu.au

Andrew Jackson
School of Accounting
Business School
UNSW Sydney
a.b.jackson@unsw.edu.au

Chao Kevin Li
School of Accounting
Business School
UNSW Sydney
k.li@unsw.edu.au

Abstract

Using archival data of 106,264 analyst forecasts, we find forecasts by analyst teams are more accurate and less optimistically biased than forecasts by individual analysts. The finding supports the experimental evidence that groups outperform individuals in quantitative judgment tasks. We also find that analyst teams with a clear hierarchy outperform other teams, suggesting that a hierarchy facilitates group decision making. Finally, we show that investors understand the superior forecasts of analyst teams and respond more strongly to analyst teams' forecast revisions.

Key words: Groups; teamwork; group hierarchy; analyst earnings forecasts
JEL Classifications: M41

April 2017

[*] We thank … for helpful comments.

1. Introduction

Team work has become increasingly common in the modern corporate world, particularly for complex and important tasks. The judgment and decision making literature in accounting and auditing has long been investigating the group judgments of accountants and auditors (Trotman, Tan, & Ang, 2011; Trotman, Bauer, & Humphreys, 2015). A number of experimental studies have documented that groups outperform the average individual in quantitative judgment tasks such as forecasting.[1] Some studies even find that group judgments can be as accurate as the most accurate individual's judgments.[2] However, archival evidence on group performance is scarce. And surprisingly, the only archival study that examines financial analysts' earnings forecasts finds that analyst teams underperform individual analysts in terms of forecast accuracy (Brown & Hugon, 2009). The unexpected archival evidence raises questions about the generalizability of the results from experimental studies and the validity of theories of group judgment and decision making developed from experimental results.

In this study, we re-examine the performance of analyst teams compared to individual analysts using a large sample of analysts' earnings forecasts. This re-examination is important for at least two reasons. First, we provide out-of-sample evidence to either confirm or refute the findings in Brown & Hugon (2009) who examine analyst teams' performance from 1993 to 2005 in the U.S. One issue with Brown & Hugon (2009) is that their sample consists of only 1,645 annual observations for analyst teams but 26,770 annual observations for individual analysts, meaning that analyst teams' forecasts account for less than 6% of the sample. This small percentage of analyst teams does not seem to be consistent with the

[1] See, for example, Bonner, Sillito, & Baumann (2007), Henry (1993, 1995), Laughlin, Bonner, Miner, and Carnevale (1999), and Sniezek and Henry (1990).
[2] See, for example, Einhorn, Hogarth, & Klempner (1977), Laughlin, Gonzalez, & Sommer (2003), Sniezek and Henry (1989), and Uecker (1982).

observed prevalence of teamwork in the finance industry.[3] Another issue is that, while Brown & Hugon (2009) try to control for analyst and firm characteristics in their research design, the authors acknowledge and find that brokerage houses are more likely to assign analyst teams to firms that are difficult to forecast or pose a relatively larger forecasting task. This raises the question whether the underperformance of analyst teams reported in Brown & Hugon (2009) is driven by task difficulty and is confined to very difficult tasks. Second, experimental studies emphasize that group performance often depends on group structure such as hierarchy, which Brown & Hugon (2009) do not consider. We therefore believe that it is warranted to re-examine analyst teams' performance using archival data.

Our investigation is based on a large sample of 106,264 earnings forecasts issued by financial analysts in China. Over the sample period from 2004 to 2014, we document a steady increase in the percentage of forecasts issued by analyst teams. In recent years, over 40% of forecasts are made by analyst teams, and this percentage is above 50% in large brokerage houses. Multivariate analysis finds that large brokerage houses are more likely to have analyst teams and that analysts with more forecasting experience are more likely to work in a team. This evidence is consistent with the observed practice in the finance industry that large brokerage houses are likely to have economies of scale and assign a senior analyst to work with a junior analyst as part of the training program for junior analysts.

More importantly, we find analyst teams' earnings forecasts are more accurate than individual analysts' forecasts. Controlling for analyst and firm characteristics, we show that analyst teams' forecasts are 13% more accurate than the median individual analyst forecast. Analyst teams are also less optimistically biased, suggesting that working in a group helps to

[3] There could be two reasons for the small percentage of analyst teams in Brown & Hugon's (2009) sample. First, their sample period covers the 1990s when teamwork might not be the dominant form in analyst workplaces. Second, even though analysts work in teams, only one analyst (usually the senior one) signs the analyst report. In this regard, the evidence in Brown & Hugon (2009) indicates the differences between analyst reports signed by one analyst versus reports signed by multiple analysts.

mitigate individuals' cognitive bias or to constrain conflicts of interests that lead to biased forecasts. Furthermore, we use a difference-in-difference design to compare the earnings forecasts made by analysts who issued forecasts individually and then joined an analyst team to issue team forecasts for the same firm. We find a statistically significant improvement in forecast accuracy and a reduction in forecast optimism after an analyst joins a team. The evidence provides strong support for the experimental findings and various theories on the superior performance of groups.

Studies on organizational behaviour indicate that hierarchy within a team can be an effective way to coordinate team efforts and achieve team objectives (Gardner, 2010; Groysberg, Polzer, & Elfenbein, 2011; Overbeck, Correll, & Park, 2005). Consistent with this view, we find that analyst teams with a clear hierarchy are more accurate than analyst teams without a hierarchy. The results from the difference-in-difference design suggest that individual analysts joining a team with a hierarchy experience a significantly larger improvement in forecast accuracy than analysts joining a team without a hierarchy.

Finally, we find that analyst teams' earnings forecasts are less influenced by other analysts' forecasts, indicating that analyst teams are more independent and less likely to herd or hide in the crowd. Investors appear to understand the superiority of analyst teams and react more strongly to forecast revisions issued by analyst teams than to those issued by individual analysts.

Our study makes two contributions to the literature. First, we provide archival evidence supporting the experimental findings that groups outperform individuals in quantitative judgment tasks. Despite a large number of experimental studies on group judgment and decision making, archival evidence is very limited. The only archival study on analyst teams' performance finds unexpected evidence that analyst teams are less accurate than individuals (Brown & Hugon, 2009). Using a more recent sample and rigorous research design, we show that analyst teams are indeed more accurate than individuals. Our evidence thus lends important support to various theories explaining the superior performance of groups (e.g., Bonner et al., 2007; Einhorn et al., 1977; Henry, 1993, 1995; Laughlin et al., 1999, 2003; Schultze, Mojzisch, & Schulz-Hardt, 2012; Sniezek & Henry, 1989, 1990).

Second, we show that a hierarchy within analyst teams facilitates forecasting tasks and results in more accurate forecasts, consistent with prior experimental studies on team management and performance. Our evidence adds to the limited archival literature on the role of hierarchy in financial markets. He and Huang (2011) find that clarity of board hierarchy facilitates boardroom interactions and is positively associated with firms' performance. Lobo et al. (2017) show that in France where firms are required to be audited by two auditors, auditor teams consisting of one Big 4 auditor and one non-Big 4 auditor provide better audit quality than auditor teams with two Big 4 auditors. The authors argue that hierarchy in auditor teams is more likely to develop in teams with a Big 4 and non-Big 4 combination and this hierarchy leads to better audit quality. Overall, our study thus builds a link between experimental studies and archival studies and opens many opportunities to use archival data to verify experimental findings.

2. Hypothesis development

2.1 Forecast performance of analyst teams

A number of experimental studies have documented that groups outperform the average of individuals in quantitative judgment tasks (Bonner, Sillito, & Baumann, 2007; Henry 1993, 1995; Sniezek & Henry, 1990). In these experiments, participants are asked to first complete a series of quantitative judgment tasks individually and then work on the same tasks again in groups. Comparing the individual judgments with group judgments, experimental researchers find that the consensus estimates made by a group are usually more accurate than the average estimate made by individuals. This finding suggests that social interaction and/or interdependence may help improve group judgments, because without social interaction it seems reasonable to expect group members to simply average individuals' estimates to reach group consensus. The evidence that social interaction can improve group judgments in quantitative tasks also contrasts with prior findings of process loss in other types of group tasks due to the detrimental role of social interaction and social interdependence.[4]

Furthermore, Sniezek and Henry (1989, 1990) find that group estimates can be as accurate as the estimates made by the group members who were the most accurate in the past. Henry (1993, 1995) shows that groups are able to determine the most accurate group member through social interaction. These findings suggest that one reason that group estimates outperform the average estimate of individuals is the group's ability to identify experts or accurate judgments and to assign more weight to the expert or accurate judgments when forming group estimates.

More recently, Schultze, Mojzisch and Schultz-Hardt (2012) propose that groups' superior performance may be due to group-to-individual transfer through which group members become more accurate individually during group interactions. In their experiments, the accuracy of individual participants' estimates increases due to group interaction, resulting in high accuracy at the group level.

Prior research suggests that professionals can perform better in groups than as individuals because group work can make each group member more accountable and thus help mitigate the effect of cognitive bias. For example, a number of studies document that in

[4] See Hill (1982), Kerr & Tindale (2004) and Nijstad (2009) for a review of the related studies. Trotman, Bauer, & Humphreys (2015) review the auditing studies on process gain and loss in auditor group work.

the audit review process, increased accountability can mitigate preparers' biased use of audit evidence due to a recency bias (Kennedy, 1993) or a consistency or confirmation bias (Tan, 1995). Koonce et al. (1995) show accountability increases the amount of justification documented by preparers, implying an increased effort. Therefore, individuals in a group can become more accurate due to increased effort and reduced bias.

Based on the findings in experimental studies, we expect to find that analyst teams issue more accurate earnings forecasts than individual analysts. Our first hypothesis is stated below in alternative form:

H1: Analyst teams' forecasts are more accurate than individual analysts' forecasts.

Prior archival studies have documented that financial analysts often issue over-optimistic forecasts because of conflicts of interest and/or cognitive bias.[5] Analysts may want to appear to be more positive about firms' prospects in order to advance their career (Hong & Kubik, 2003), to curry favour with managers (Ke & Yu, 2006) or to win investment banking business from the managers (Michaely & Womack, 1999; O'Brien, McNichols, & Lin, 2005). In the absence of conflicts of interest, analysts may also suffer from cognitive bias that leads to over-optimistic forecasts (Kadous, Krische, & Sedor, 2006; Sedor, 2002).

We conjecture that group work may constrain analysts' conflicts of interest and optimism bias and lead to less optimistic forecasts. Working in a group implies that each group member has their reputation at stake and each has to rely on others to complete the forecasting task. Holding each other accountable thus requires each group member to invest more effort and work at their best level. Relative to individuals, groups are less likely to compromise their reputation and independence and succumb to conflicts of interest.[6] To the

[5] See Ramnath, Rock, & Shane (2008) and Beyer et al. (2010) for a review of the analyst literature.
[6] There are many reasons that group work can fail and result in process losses, such as the freeriding problem and non-cooperation. We argue that in the role of financial analyst, these problems are less likely to happen

extent that group work can mitigate individuals' cognitive bias, provoke more effort from individuals and better maintain independence, we expect to find that groups issue less optimistic earnings forecasts than individuals. We state our second hypothesis in alternative form as below:

H2: Analyst teams' forecasts are less optimistic than individual analysts' forecasts.

Prior studies also find that analysts are likely to herd, or issue forecasts that are too close to other analysts' forecasts in the market (Clement & Tse, 2005; Hong, Kubik, & Solomon, 2000). One reason for herding is analysts' career concerns. Issuing bold but inaccurate forecasts is likely to reduce analysts' reputation and impair future career advancement. Hiding in the crowd may be a safer strategy to secure jobs, particularly for young analysts and unskilled analysts who are not fully confident about the accuracy of their forecasts. Another reason is the information cascade in which value-relevant information gradually flows through different groups of analysts (Hirshleifer & Teoh, 2003). Analysts who receive the information later issue forecasts similar to those issued by analysts who get information earlier. We argue that analyst teams are less likely to herd for two reasons. First, working in a team implies that more analysts are collecting information and thus it is likely teams will receive information in a more timely manner than individuals. Consistent with this view, Brown & Hugon (2009) find team analysts' forecasts are timelier than individual analysts' forecasts. Second, since analyst teams put more effort into their work and issue more accurate forecasts, as we hypothesize, analyst teams are more confident about their forecasts than individuals. Therefore, analyst teams are more likely to issue their forecasts as they are, rather than being overly influenced by other analysts' forecasts. This argument leads to our third hypothesis stated in alternative form as follows:

---

because of strong competition among analysts from different brokers, and close monitoring by their clients including institutional investors. Furthermore, in China financial analysts are ranked by media based on their forecast accuracy. This motivates analysts to work harder to issue more accurate forecasts in general.

H3: Analyst teams are less likely to herd than individual analysts.

2.2 The role of hierarchy in a group

Many studies find that having a clear hierarchy facilitates group decision making and improves group performance. For example, Gardner (2010) uses survey data of 89 consulting and audit teams in the Big 4 auditors to show that when several team members perceive themselves as leaders of the team, team performance is poorer. Lobo et al. (2017) find that auditor pairs with a clear hierarchy (such as a Big 4 auditor combined with a non-Big 4 auditor) provide higher audit quality than auditor pairs with no such hierarchy (such as a Big 4 auditor combined with another Big 4 auditor). He & Huang (2011) document that manufacturing firms in the U.S. with a clear hierarchy in the board of directors have better operating performance in the future. In experimental auditing research, a large number of studies find that the review process involving a participant of a higher status (such as a senior or a manager) can improve the performance of preparers and overall audit quality.[7]

Based on these studies, we hypothesize that analyst teams with a clear hierarchy (such as teams with a senior analyst and a junior analyst) are more likely to issue more accurate and less optimistic forecasts than analyst teams without such a hierarchy (such as teams with two junior teams or groups with two senior analysts). Analyst teams with a clear hierarchy are also less likely to herd. We state our hypotheses in alternative form as follows:

H4a: Analyst teams with a clear hierarchy issue more accurate and less optimistic forecasts than analyst teams without a clear hierarchy.

H4b: Analyst teams with a clear hierarchy are less likely to herd than analyst teams without a clear hierarchy.

2.3 Market reaction to forecasts of analyst teams

[7] See Trotman, Bauer, & Humphrey (2015) for an excellent review of the literature on the audit review process.

Prior studies find that analyst forecast revisions contain value-relevant information and can cause stock price changes.[8] Furthermore, market reactions are related to the quality of analysts' forecasts. For example, analysts elected by institutional investors as All-Star Analysts are more accurate in their earnings forecasts and their forecast revisions receive stronger market reactions (Gleason & Lee, 2003; Stickel, 1992). Jegadeesh & Kim (2010) show that market reactions are stronger to analyst recommendations that are away from the consensus than those that are closer to consensus, suggesting that investors understand analysts' herding behaviour and react more strongly to those who do not herd. Based on these studies, we argue that, since analyst teams are more accurate and herd less, analyst teams' forecast revisions will receive stronger market reactions than individual analysts' forecast revisions. Furthermore, since analyst teams with a clear hierarchy perform better, we expect that the market reacts more strongly to forecast revisions issued by analyst teams with a clear hierarchy. We thus state our last hypotheses in alternative form as follows:

H5a: The market reacts more strongly to forecast revisions issued by analyst teams than those issued by individual analysts.

H5b: The market reacts more strongly to forecast revisions issued by analyst teams groups with a clear hierarchy than those issued by analyst teams groups without a clear hierarchy.

3. Data, sample and research design

3.1 Data and sample

We conduct our empirical tests using analyst forecasts in China where analysts sign off on their research reports. Therefore, for each report we are able to unambiguously identify individual analysts and analyst teams, and each analyst within a group. We collect data on

[8] See Ramnath, Rock, & Shane (2008) and Beyer et al. (2010) for a review of the analyst literature.

analyst forecasts and firms' accounting and price information from CSMAR, a widely used database for China research. Our sample starts in 2004 when analyst forecasts are available in CSMAR, and ends in 2014. To remove stale forecasts and to examine analyst forecast revisions, we require an analyst to issue at least two forecasts for a firm's annual earnings and we drop the forecast without a preceding forecast for our empirical tests. We also require a firm to be covered by more than one analyst so that we compare the forecasts for the same firm made by different analysts. These sample selection criteria leave 106,264 earnings forecasts issued for 10,002 firm-years.

Table 1 reports the distribution of analyst forecasts, firms and brokers across years. We find that, over time, there is an increase in the number of brokers and the number of firms receiving forecasts, consistent with the rapid growth in the brokerage industry in China in the past decade. With the increase in brokers, there is also a significant increase in the number of earnings forecasts issued by analysts.

Table 1 also reports the percentage of earnings forecasts that are issued by analyst teams. We find there is an upward trend in this percentage, suggesting that more and more analysts work in teams to issue earnings forecasts. In recent two years, over 40% of earnings forecasts are issued by analyst teams, compared with less than 10% in earlier years. We further break down brokers based on their size measured by the number of analysts working for the broker. We find that large brokers are more likely to issue forecasts by analyst teams. In the most recent two years, over 50% of forecasts in large brokers are issued by analyst teams. This is consistent with large brokers having the economies of scale and the capability to form groups among analysts.

[Insert Table 1 about here]

We note that the percentage of forecasts issued by analyst teams is much higher in China than that reported in Brown & Hugon (2009) in the U.S. This could be due to the difference in the sample period. Brown & Hugon (2009) examine the period from 1993 to 2005, while our sample period covers the period from 2004 to 2014. We would like to calculate the percentage of analyst teams in the U.S. in recent years. However, this is not possible as the major provider of analyst data in the U.S., the International Brokerage Estimation System (I/B/E/S), stopped providing researchers with the identification of analysts a few years ago. Researchers using I/B/E/S data are now unable to identify whether the forecasts are issued by individual analysts or analyst teams.

3.2 Regression models to test H1 and H2

H1 and H2 predict that analyst teams' forecasts are more accurate and less optimistic than individual analysts' forecasts. To test this prediction, we first conduct a univariate analysis by comparing the accuracy and optimism of forecasts made by analyst teams and individual analysts. To control for a number of factors associated with analyst forecasts, we conduct multivariate analyses and estimate the following regression models:

$$ACCURACY_{ijt}\,(PESSIMISM_{ijt}) = \alpha_0 + \beta_1 GROUP_{ijt} + X + e_{ijt} \qquad (1)$$

where $ACCURACY_{ijt}$ is -1 multiplied by the absolute value of the difference between actual earnings and analyst *i*'s earnings forecasts for firm *j* in year *t*, deflated by closing share prices of firm *j* two days before the forecast date. $PESSIMISM_{ijt}$ is analyst *i*'s actual earnings minus earnings forecast for firm *j* in year *t*, deflated by closing share prices of firm *j* two days before the forecast date. Larger values of *ACCURACY* indicate that the forecasts are more accurate, while large *PESSIMISM* suggests the forecast is less optimistic relative to the actual earnings. The variable of interest, $GROUP_{ijt}$, equals 1 if the forecast report issued by analyst *i* for firm *j* in year *t* is signed by more than one analyst, and 0 otherwise. H1 and H2 predict that $\beta_1 > 0$ in regressions, suggesting analyst teams' forecasts are more accurate and more pessimistic.

In the regressions, we include a set of control variables *X* that have been shown to be related to analyst forecasts. To control for analysts' workload, we include *NCOS*, the number of firms followed by the analyst(s), and *NINDUST*, the number of industries followed by the analyst(s). To control for resources and support provided by brokerage houses, we include *SIZE_BROKER*, the logarithm of one plus the number of analysts employed by a broker in one year. To control for analysts' experience in making forecasts, we include *EXP*, the number of years since the analyst's first forecast appeared in the database. For analyst teams, we use *EXP* of the least experienced analyst.[9] To control for the time lag between forecast date and earnings announcement date, we include *DAYSBEFORE*, the logarithm of one plus the number of days between a forecast date and the corresponding actual earnings announcement date. To control for firm characteristics, we include *SIZE_FIRM*, the logarithm of a firm's market value, and *MB*, the ratio of a firm's market value of equity to its book value of its equity. Finally, we further include firm-fixed effects to ensure the within-firm comparison so that we are comparing the forecasts for the same firm but from different types of analysts. We also include year-fixed effects to control for variations in forecasts driven by a specific year. Since one analyst or analyst teams can issue multiple forecasts, we adjust the standard errors for the clustering effect at the analyst level.

In addition to the above cross-sectional regression model, we also adopt a difference-in-difference approach to identify the effects of working in a group on analysts' forecasts. In particular, for each team of analysts we find the date when they initially form the team to issue forecasts for firm *i* and set this date as date 0. We truncate a time window of four years

[9] Alternatively, we use the *EXP* of the most experienced analyst or the average *EXP* of all analysts in the group. Our results remain unchanged using these alternative definitions of *EXP*.

([-3, +3]) surrounding date 0. We then compare the forecasts for firm *i* issued by the group in the two years after date 0 with the forecasts for firm *i* issued by individual group members in the two years before date 0. We call these forecasts treatment forecasts. Since we are comparing the forecasts for the same firms issued by the same analysts before and after they join a group, this comparison provides a cleaner test of the effect of group work. One concern for this comparison is that analysts may become more accurate over time as they gain forecasting experience so the improvement in forecasts may be driven by an increase in experience over time rather than joining a group. To address the effect of increased experience, we use as benchmarks the forecasts issued by the same analyst but individually for firms other than firm *i* in the same four-year window. Assuming that the increase in experience should have the same effect on benchmark forecasts, we can attribute any incremental improvement in forecasts relative to benchmark forecasts to the effect of the group work. Specifically, we estimate the following multivariate models using treatment forecasts and benchmark forecasts:

$$ACCURACY_{ijt}\,(PESSIMISM_{ijt}) = \alpha_0 + \beta_1\, JOINT + \beta_2 POST + \beta_3\, JOINT \times POST + X + e_{ijt} \quad (2)$$

where *JOINT* equals 1 for treatment forecasts, and 0 for benchmark forecasts, and *POST* equals 1 if the forecast is issued after date 0, and 0 otherwise. The variable of interest is the interaction term between *JOINT* and *POST*. In this model, *JOINT* captures the difference between treatment forecasts and benchmark forecasts in the two years before date 0 and *POST* captures changes in characteristics of benchmark forecasts around date 0. The interaction term captures the incremental changes in *ACCURACY* and *PESSIMISM* of treatment forecasts relative to that of benchmark forecasts. A positive β_3 would support H1 and H2 that analysts are more accurate and less optimistic after they join a group. We include the same set of control variables as those in Equation 1 to control for other factors related to analyst forecasts.

3.3 Regression models to test H3

H3 predicts that analyst teams are less likely to herd than individual analysts. Following prior studies (e.g., Clement & Tse, 2005), we use the degree of co-movement between an analyst's earning forecast revisions and prevailing consensus revisions to measure analysts' herding. The intuition of this measure is that an independent analyst will forecast based on their own information and thus co-move less with other analysts in the market. In contrast, a herding analyst will overly rely on the prevailing consensus and their forecast revisions will be too close to the consensus revisions. To test H3, we estimate the following multivariate regressions:

$$REV_{ijt} = \delta_0 + \delta_1 GROUP + \delta_2 CONSENSUS\_REV + \delta_3 GROUP \times CONSENSUS\_REV + X + e \qquad (3)$$

where REV_{ijt} represents analyst *i*'s forecast revision for firm *j* in year *t*, deflated by closing share prices two days before the forecast date. *CONSENSUS_REV* is the consensus forecast revisions, calculated as the average of forecast revisions by other analysts following firm *j* in year *t* and issued prior to analyst *i*'s forecast revision, and scaled by closing share prices two days before the forecast date. The coefficient δ_2 captures the degree to which an analyst's revision co-moves with the consensus revisions. The variable of interest is the interaction term whose coefficient δ_3 measures whether analyst teams' revisions co-move more or less with the consensus forecast revisions, compared with individual analysts' revisions. A negative δ_3 would provide support to H3, suggesting that analyst teams' forecasts are less dependent on consensus forecasts. In the regressions, we include the same set of control variables *X* as those in Equation 1.

3.4 Regression models to test H4a and H4b

H4a and H4b hypothesize that analyst teams with a clear hierarchy issue more accurate and less optimistic forecasts, and herd less, relative to analyst teams without a clear hierarchy. To measure the hierarchy in a team, we examine whether the analysts within a team have different years of forecasting experience. The intuition is that in Chinese culture hierarchy is often based on official positions, and for people with the same position, hierarchy is based on the length of experience. Although we cannot observe whether an analyst has a senior position, we note that analysts with senior positions usually have longer experience in brokerage houses. We thus measure the hierarchy within a group in two ways. First, we define two indicator variables, *HIERARCHY* and *FLAT*. *HIERARCHY* equals 1 for teams in which the senior analyst have at least three more years' experience than the junior analyst, and 0 otherwise.[10] *FLAT* takes a value of 1 for groups in which the analysts' experience does not differ by more than two years, and 0 otherwise. Second, we define *GAP* as the difference between the maximum and minimum length of experience within a group, where larger *GAP* indicates a clearer hierarchy within the group based on analysts' experience.

To test H4a, we re-estimate Equations 1 and 2 with *GROUP* and *JOINT* replaced with the measures of group hierarchy. Specifically, we estimate the following equations:

$$ACCURACY_{ijt}\,(PESSIMISM_{ijt}) = \alpha_0 + \beta_1 HIERARCHY_{ijt} + \beta_2 FLAT_{ijt} + X + e_{ijt} \tag{4a}$$

$$ACCURACY_{ijt}\,(PESSIMISM_{ijt}) = \alpha_0 + \beta_1 GAP_{ijt} + X + e_{ijt} \tag{4b}$$

In Equation 4a, we expect to find $\beta_1 > \beta_2$, suggesting that groups with a hierarchy are more accurate and less optimistic than groups with no hierarchy. Similarly, in Equation 4b, a positive β_1 would support H4a.

[10] In a robustness test, we define *HIERARCHY* as groups whose senior analysts have at least 4 or 5 more years' experience than junior analysts. We obtain essentially the same results. The majority of groups have two analysts. For groups with more than two analysts, we compare the most and the least experienced analysts. Excluding groups with more than two analysts from the sample does not change our results.

To test H4b that analyst teams with a hierarchy herd less than groups without a hierarchy, we re-estimate Equation 3 with *GROUP* replaced with measures of group hierarchy:

$$REV_{ijt}= \delta_0+\delta_1 HIERARCHY_{ijt}+ \delta_1 FLAT_{ijt} +\delta_3 CONSENSUS\_REV_{ijt}+$$
$$\delta_4 HIERARCHY_{ijt}\times CONSENSUS\_REV_{ijt}+ \delta_5 FLAT\times CONSENSUS\_REV_{ijt}+X+e_{ijt} \quad (4c)$$

$$REV_{ijt}= \delta_0+\delta_1 GAP_{ijt}+\delta_2 CONSENSUS\_REV_{ijt}+ \delta_3 GAP\times CONSENSUS\_REV_{ijt}+X+e_{ijt} \quad (4d)$$

We expect to find that in Equation 4c $\delta_4 < \delta_5$, indicating that groups with a hierarchy issue forecasts that co-move less with the consensus revisions, compared with groups without a hierarchy. Similarly, we expect to find a negative δ_3 in Equation 4d to support H4b.

3.5 Regression models to test H5a and H5b

H5a and H5b hypothesize that the market reacts more strongly to forecast revisions issued by analyst teams, and particularly by analyst teams with a hierarchy. To measure market reactions to analyst forecast revisions, we follow the literature to calculate *CAR*, the three-day cumulative market-adjusted returns surrounding forecast revision dates. We then estimate the following models to assess market reactions to analyst teams' forecast revisions relative to individual analysts' revisions:

$$CAR_{ijt}=\gamma_0+ \gamma_1 GROUP_{ijt}+ \gamma_2 REV_{ijt} + \gamma_3 GROUP_{ijt}\times REV_{ijt} +X+e_{ijt} \quad (5a)$$

$$CAR_{ijt}=\gamma_0+ \gamma_1 HIERARCHY_{ijt} + \gamma_2 FLAT_{ijt} + \gamma_3 REV_{ijt} + \gamma_4 HIERARCHY_{ijt}\times REV_{ijt} +$$
$$\gamma_5 FLAT_{ijt}\times REV_{ijt} +X+e_{ijt} \quad (5b)$$

$$CAR_{ijt}=\beta_0+ \beta_1 GAP_{ijt} + \beta_2 REV_{ijt} + \beta_3 GAP_{ijt} \times REV_{ijt}+X+e_{ijt} \quad (5c)$$

We expect to find in Equation 5a, the coefficient of *REV* to be positive based on prior findings that stock prices move in the same direction as analysts' forecast revisions. More importantly, we expect to find $\gamma_3 > 0$, suggesting that market reaction to analyst teams' forecast revisions is stronger. Equations 5b and 5c examine market reactions to forecast revisions issued by groups with and without a hierarchy. We expect $\gamma_4 > \gamma_3$ in Equation 5b and $\beta_3 > 0$ in Equation 5c to be supportive of H5b that the market reacts more strongly to forecast revisions issued by analyst teams with a hierarchy. Consistent with previous models, we include the same set of control variables *X* in the regressions.

4. Empirical results

4.1 Forecast accuracy and optimism

We start with a univariate analysis comparing the accuracy and pessimism of earnings forecasts issued by analyst teams and individual analysts. Table 2 reports the results. We find analyst teams' forecasts are more accurate than individual analysts' forecasts. Both the mean and the median of *ACCURACY* are significantly higher for analyst teams than for individual analysts. Analyst teams also have significantly larger *PESSIMISM*, suggesting that their forecasts are less optimistic than individual analysts' forecasts. *CAR* is larger for analyst teams, implying that the market reacts more strongly to analyst teams' forecasts. The result is consistent with our hypotheses that analyst teams are more accurate and less optimistically biased, and investors react more strongly to analyst teams' superior forecasts.

Table 2 also reveals that analyst teams are more common in large brokers. They cover less firms and industries, and the least experienced analyst in the group has significantly less experience than individual analysts. This evidence is consistent with the industry practice that large brokers have economies of scale and use teams to provide training for junior and inexperienced analysts.

[Insert Table 2 about here]

Table 3 reports the results from multivariate analysis of forecast accuracy and pessimism. In Models 1 and 2, we find that *GROUP* has positively and statistically significant coefficients, suggesting that analyst teams' forecasts are more accurate and less optimistic. The estimated effect of group work is also economically significant. The coefficients of *GROUP* are 0.0013 and 0.0012 in Models 1 and 2 respectively, suggesting that on average, analyst teams' forecasts are 13% more accurate and 41% less optimistic than the median individual analysts' forecasts.[11] The evidence is consistent with the univariate result in Table 2, but robust to various controls for firm and analyst characteristics.

In Models 3 and 4, we use a difference-in-difference approach to examine the changes in forecast accuracy and optimism for treatment firms after an individual analyst joins a group. This approach uses the same analysts' forecasts of other firms (benchmark firms) as a benchmark and helps to isolate the effect of group work on analyst forecasts for treatment firms.[12] We find that *JOINT* has an insignificant coefficient, suggesting that working individually the analysts issue forecasts of the same degree of accuracy and optimism for treatment firms and benchmark firms. The interaction term between *JOINT* and *POST* has a positive and statistically significant coefficient, implying that analysts' forecasts for treatment firms become more accurate and less pessimistic after the analysts begin working in a group. In Model 3, the interaction term has a coefficient of 0.0035, suggesting that analysts' forecasts become 35% more accurate after analysts join a group, given the median accuracy is 0.0100 for individual analysts. The evidence provides strong support to our H1 and H2.

[Insert Table 3 about here]

In Table 4, we examine the effect of hierarchy within analyst teams. Models 1 and 2 show that *HIERARCHY* has a positive and statistically significant coefficient, implying that

[11] Table 2 shows that the median forecast accuracy and pessimism is -0.0100 and -0.0029 for individual analysts' forecasts. We calculate the economic effects by dividing the estimated coefficients by the median forecast accuracy and pessimism for individual analysts' forecasts.

[12] Both treatment firms and benchmark firms are covered by the same analysts. However, analysts issue forecasts for treatment firms individually before joining a team and then issue forecasts for the same firm but working in a team. The same analysts issue forecasts for benchmark firms individually in the three years before and three years after they join a team.

analyst teams with a clear hierarchy issue more accurate and less optimistic forecasts than individual analysts. In both models, the coefficients of *FLAT* are positive, but not statistically significant, suggesting groups with no clear hierarchy do not outperform individual analysts in forecasting tasks. The F-test suggests that the coefficients of *HIERARCHY* is significantly larger than the coefficients of *FLAT* in both models, implying that analyst teams with a hierarchy outperform teams without a hierarchy. In Models 3 and 4, we find *GAP* has a positive and statistically significant coefficient, implying that larger difference in analyst experience is associated with better group performance in forecasting tasks. Overall, the results in Table 4 support H4a that analyst teams with a clear hierarchy issue more accurate and less optimistically biased earnings forecasts.

[Insert Table 4 about here]

4.2 Herding

H3 predicts that analyst teams are less likely to herd and their forecast revisions will co-move less with the outstanding forecasts of other analysts. We examine this hypothesis in Model 1, Table 5. First, we note that *CONSENSUS_REV* has a positive coefficient, consistent with the idea that analysts' forecast revisions are likely to contain a common component across all the analysts, either because of herding or responding to the same information. Furthermore, we note the interaction term between *GROUP* and *CONSENSUS_REV* has a negative and statistically significant coefficient, implying that analyst teams' forecast revisions are less associated with consensus revisions. The magnitude of the estimated coefficients suggests that the co-movement between analyst teams' forecast revisions and consensus revisions is about 20% less than the co-movement between individual analysts' revisions and consensus revisions. This evidence supports H3.

H4b predicts that relative to groups without a hierarchy, analyst teams with a clear hierarchy herd less. Models 2 and 3 in Table 5 test this prediction. In Model 2, we find the coefficient of the interaction term between *HIERARCHY* and *CONSENSUS_REV* is negative and statistically significant, suggesting that analyst teams with a clear hierarchy herd less. The coefficient of the interaction term between *FLAT* and *CONSENSUS_REV*, however, is negative but statistically insignificant, implying teams without a hierarchy do not herd less than individual analysts. The F-test shows that the coefficient of *HIERARCHY* × *CONSENSUS_REV* is statistically larger than the coefficient of *FLAT* × *CONSENSUS_REV*. In Model 3, the interaction term between *GAP* and *CONSENSUS_REV* is negative and statistically significant, suggesting that groups with a clear hierarchy tend to herd less and their forecasts are less dependent on consensus forecasts. The evidence in Models 2 and 3 provides strong support to H4b.

[Insert Table 5 about here]

4.3 Market reactions

In Table 6, we examine the market reactions to analyst teams' forecast revisions. We find in all models where dependent variables are *CAR*, the coefficients of *REV* are positive and statistically significant, consistent with prior findings that stock prices move in the same direction as analyst forecast revisions. More importantly, in Model 1 the coefficient of the interaction term between *GROUP* and *REV* is positive and statistically significant, supporting H5a that investors react more strongly to analyst teams' forecast revisions. The magnitude of the coefficients suggests that market reaction to analyst teams' forecast revisions is 24% (=0.0293÷0.1216) stronger than the reaction to individual analysts' revisions.

Models 2 and 3 in Table 6 examine the market reactions to forecast revisions issued by analyst teams with a hierarchy. We find that in Model 2 the interaction term between

HIERARCHY and *REV* has a positive and statistically significant coefficient, while the coefficient of *FLAT* × *REV* is not statistically significant. The F-test shows that the coefficient of *HIERARCHY* × *REV* is significantly larger than the coefficient of *FLAT* × *REV*, suggesting that the market reacts more strongly to analyst teams with a hierarchy than to teams without such a hierarchy. Model 3 shows that the interaction term between *GAP* and *REV* has a positive and statistically significant coefficient, implying that groups with a clear hierarchy attract more market reaction to their forecast revisions. Taken together, the results in Table 6 support H5a and H5b that investors react more strongly to superior forecasts issued by analyst teams, particularly by groups with a clear hierarchy.

[Insert Table 6 about here]

4.4 Additional tests

Finally, we examine analysts' decisions to work in a group to issue earnings forecasts. The common practice in brokerage houses suggests that large brokers and senior analysts are more likely to have analyst teams for two reasons. First, large brokers have economies of scale and it is easier for them to assign analysts into groups given their larger pool of analysts. Second, in the past decade a large number of new graduates have joined brokers to become junior analysts. Working in a group with a senior analyst is possibly the most effective way to provide on-job training for junior analysts. So senior analysts are more likely to be assigned to work in a group with a junior analyst, and this training practice is more common in large brokers where there are a sufficient number of senior analysts available to mentor and train junior analysts.

To provide empirical evidence on this industry practice, we use logistic models to estimate the probability of a forecast being issued by analyst teams. We include broker size (*SIZE_BROKER*), analyst experience (*MAX_EXP*) and the interaction term between these two variables as the main explanatory variables. We also include a number of firm characteristics in the regressions. The results are reported in Table 7. The results show that broker size is positively associated with group forecasts, consistent with large brokers having more analyst teams. Analyst experience is also positively associated with group forecasts, suggesting that senior analysts are more likely to work in a group. The interaction term has positive coefficients, suggesting senior analysts in large brokers are particularly more likely to work in a group. Firm characteristics, however, do not appear to be associated with the probability of the forecasts being issued by an analyst team. Overall the evidence is consistent with the observed industry practice.

5. Conclusion

A number of experimental studies have documented that groups outperform individuals in quantitative judgment tasks (Bonner, Sillito, & Baumann, 2007; Henry, 1993, 1995; Laughlin, Bonner, Miner, and Carnevale, 1999; and Sniezek and Henry, 1990). Based on experimental evidence, various theories have been proposed to explain the superior performance of groups (Bonner et al., 2007; Einhorn et al., 1977; Henry, 1993, 1995; Laughlin et al., 1999, 2003; Schultze, Mojzisch, & Schulz-Hardt, 2012; Sniezek & Henry, 1989, 1990). However, archival evidence on group performance is scarce, with one exception being Brown & Hugon (2009) who find that analyst teams issue less accurate earnings forecasts than individual analysts in the U.S.

In this study, we re-examine the forecasts of group and individual analysts using a large sample of 106,264 earnings forecasts in China from 2004 to 2014. Consistent with group work becoming more popular in professional services, we find an increasing number of forecasts issued by analyst teams and in recent years over 50% of forecasts are issued by groups. More importantly, we find that forecasts by analyst teams are more accurate and less optimistically biased than forecasts by individual analysts. Analyst teams are less likely to herd, relative to individual analysts. Investors appear to understand the superior forecasts issued by analyst teams and respond more strongly to teams' forecast revisions. Furthermore, we find that analyst teams with a clear hierarchy outperform teams without a hierarchy, while groups without a hierarchy do not outperform individual analysts.

Our archival evidence validates and supports prior findings on superior group performance in quantitative judgment tasks based on experiments. The results also provide support to theories explaining why groups outperform individuals. Furthermore, we provide archival evidence on the role of hierarchy in group performance. Consistent with prior findings in the management literature, our results suggest that a clear hierarchy may facilitate group decision making and lead to superior group performance on quantitative judgment tasks.

References

Beyer, A., Cohen, D. A., Lys, T. Z., & Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, *50*, 296–343.

Bonner, B. L., Sillito, S. D., & Baumann, M. R. (2007). Collective estimation: Accuracy, expertise, and extroversion as sources of intra-group influence. *Organizational Behavior and Human Decision Processes*, *103*, 121–133.

Brown, L., & Hugon, A. (2009). Team earnings forecasting. *Review of Accounting Studies*, *14*, 587–607.

Clement, M., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance*, *60*, 307–341.

Einhorn, H. J., Hogarth, R. M., & Klempner, E. (1977). Quality of group judgment. *Psychological Bulletin*, *84*, 158–172.

Gardner, H. K. (2010). Disagreement about the team's status hierarchy: An insidious obstacle to coordination and performance. Working Paper No 10-113, Harvard Business School.

Gleason, C., & Lee, C. (2003). Analyst forecast revisions and market price discovery. *The Accounting Review*, *78*, 193–225.

Groysberg, B., Polzer, J. T., & Elfenbein, H. A.. (2011). Too many cooks spoil the broth: How high status individuals decrease group effectiveness. *Organization Science, 22*(3), 722–37.

He, J., & Huang, Z., 2011. Board informal hierarchy and firm financial performance: Exploring a tacit structure guiding boardroom interactions. *Academy of Management Journal*, *54*, 1119–1139.

Henry, R. A. (1993). Group judgment accuracy: Reliability and validity of post discussion confidence judgments. *Organizational Behavior and Human Decision Process*, *56*, 11–27.

Henry, R. A. (1995). Improving group judgment accuracy: Information sharing and determining the best member. *Organizational Behavior and Human Decision Processes*, *62*, 190–197.

Hill, G. W. (1982). Group versus individual performance: Are N + 1 heads better than one? *Psychological Bulletin*, *91*, 517–539.

Hirshleifer, D., & Teoh, S. H. (2003). Herd behaviour and cascading in capital markets: a review and synthesis. *European Financial Management*, *9*, 25-66.

Hong, H., & Kubik, J. (2003). Analyzing the analysts: career concerns and biased earnings forecasts. *The Journal of Finance*, *58*, 313–351.

Hong, H., Kubik, J. D., & Solomon, A. (2000) Security analysts' career concerns and herding of earnings forecasts. *RAND Journal of Economics 31*, 121–144.

Jegadeesh, N., & Kim, W. (2010). Do analysts herd? An analysis of recommendations and market reactions. *Review of Financial Studies*, *23*, 901–937.

Kadous, K., Krische, S., & Sedor, L. (2006). Using counterexplanation to limit analysts' forecast optimism. *The Accounting Review*, *81*, 377–397.

Ke, B., & Yu, Y. (2006). The effect of issuing biased earnings forecasts on analysts' access to management and survival. *Journal of Accounting Research, 44*, 965–999.

Kennedy, J. (1993). Debiasing audit judgment with accountability: A framework and experimental results. *Journal of Accounting Research*, *31*(2), 231–245.

Kerr, N. L., & Tindale, R. S. (2004). Group performance and decision making. *Annual Review of Psychology*, *55*, 623–655.

Koonce, L., Anderson, U., & Marchant, G. (1995). Justification of decisions in auditing. *Journal of Accounting Research*, *33*(2), 369-384.

Laughlin, P. R., Bonner, B. L., Miner, A. G., & Carnevale, P. J. (1999). Frames of reference in quantity estimations by groups and individuals. *Organizational Behavior and Human Decision Processes*, *80*, 103–117.

Laughlin, P. R., Gonzalez, C. M., & Sommer, D. (2003). Quantity estimations by groups and individuals: Effects of known domain boundaries. *Group Dynamics: Theory, Research and Practice, 7*, 55–63.

Lobo, G. J., Paugam, L., Zhang, D., & Casta, J. F. (2017). The effect of joint auditor pair composition on audit quality: Evidence from impairment tests. *Contemporary Accounting Research*, *34*, 118–153.

Michaely, R., & Womack, K. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies*, *12*, 653−686.

Nijstad, B. A. (2009). *Group performance*. New York: Psychology Press.

O'Brien, P., Mcnichols, M., & Lin, H. (2005). Analyst impartiality and investment banking relationships. *Journal of Accounting Research, 43*, 623-650.

Overbeck, J. R., Correll, J., & Park, B. (2005). Internal status sorting in groups: The problem of too many stars. In Research on Managing Groups and Teams, Vol. 7, eds, Salas, E., 169-199: Emerald Group.

Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, *24*, 34–75.

Schultze, T., Mljzisch, A., & Schulz-Hardt, S. (2012). Why groups perform better than individuals at quantitative judgment tasks: Group-to-individual transfer as an alternative to differential weighting. *Organization Behavior and Human Decision Processes, 118*, 24-36.

Sedor, L. (2002). An explanation for unintentional optimism in analysts' earnings forecasts. *The Accounting Review*, *77*, 731–753.

Sniezek, J. A., & Henry, R. A. (1989). Accuracy and confidence in group judgment. *Organizational Behavior and Human Decision Processes*, *43*, 1–28.

Sniezek, J. A., & Henry, R. A. (1990). Revision, weighting and commitment in consensus group judgment. *Organizational Behavior and Human Decision Processes*, *45*, 66–84.

Stickel, S. (1991). Common stock returns surrounding earnings forecast revisions: More puzzling evidence. *The Accounting Review*, 66, 402–416.

Tan, H.-T. (1995). Effects of expectations, prior involvement, and review awareness on memory for audit evidence and judgment. *Journal of Accounting Research*, *33*(1), 113–135.

Trotman, K. T., Bauer, T. D., & Humphreys, K. A. (2015). Group judgment and decision making in auditing: Past and future research. *Accounting, Organizations and Society*, *47*, 56–72.

Trotman, K. T., Tan, H. C., & Ang, N. (2011). Fifty-year overview of judgment and decision-making research in accounting. *Accounting and Finance*, *51*, 278–360.

Uecker, W. C. (1982). The quality of group performance in simplified information evaluation. *Journal of Accounting Research*, *20*, 388–402.

Table 1 Sample distribution over time

This table reports the distribution of sample observations over time from 2004 to 2014. It reports the number of brokers, the number of analysts, the number of firms, and the number of forecasts each year in the sample period. It also shows the percentage of forecasts issued by analyst teams. We further partition the brokers into three groups, Small, Medium and Large, based on the number of analysts employed and report the percentage of forecasts issued by analyst teams for each group of brokers.

					Percentage of forecasts issued by teams			
Year	Brokers	Analysts	Firms	Forecasts	Overall	Small	Medium	Large
2004	55	140	165	311	3.86%	0.00%	4.22%	9.05%
2005	63	300	267	809	2.72%	1.30%	4.60%	8.11%
2006	47	279	332	1,063	5.08%	2.65%	21.08%	12.68%
2007	62	481	469	1,896	15.08%	13.50%	8.18%	30.59%
2008	72	945	743	6,751	20.20%	3.78%	12.78%	36.38%
2009	80	1,149	843	8,164	25.99%	6.71%	20.07%	39.72%
2010	84	1,418	1,187	10,928	28.87%	3.67%	16.18%	39.46%
2011	85	1,257	1,474	16,427	16.66%	1.93%	6.20%	26.71%
2012	84	1,578	1,548	20,156	25.49%	2.35%	6.54%	39.10%
2013	78	1,762	1,456	21,258	40.02%	5.44%	15.01%	51.88%
2014	77	1,704	1,518	18,501	47.35%	1.23%	23.35%	58.54%
Total		11,013	10,002	106,264				

Table 2 Descriptive statistics

This table reports the descriptive statistics for the sample. Variables are defined in Appendix 1. ***, ** and * indicate the difference is statistically significant at the 1%, 5% and 10% level respectively.

	Forecasts by analyst teams (N=32,156)			Forecasts by individual analysts (N=74,108)			Difference in mean	Difference in median
Variable	Mean	Median	Std Dev	Mean	Median	Std Dev		
ACCURACY	-0.0202	-0.0085	0.0345	-0.0236	-0.0100	0.0395	0.0034***	0.0015***
PESSIMISM	-0.0059	-0.0020	0.0356	-0.0085	-0.0029	0.0399	0.0026***	0.0009***
CAR	0.0094	0.0044	0.0475	0.0073	0.0032	0.0464	0.0021***	0.0012***
REV	-0.0034	0.0000	0.0225	-0.0047	0.0000	0.0263	0.0013***	0.0000***
CONSENSUS_REV	-0.0030	0.0000	0.0200	-0.0035	0.0000	0.0220	0.0005***	0.0000
NCOS	8.4365	7.0000	6.0560	14.2065	10.0000	15.3886	-5.7700***	-3.0000***
NINDUST	1.9018	2.0000	1.0649	2.6302	2.0000	1.9755	-0.7284***	0.0000***
SIZE_BROKERCD	55.7722	53.0000	22.1532	35.3636	32.0000	18.8325	20.4086***	21.0000***
EXP	0.4331	0.0000	0.7206	0.7888	0.0000	1.1572	-0.3557***	0.0000***
SIZE	15.9272	15.8199	1.3504	15.7342	15.5898	1.4086	0.1930***	0.2301***
MB	3.4425	2.7713	2.4262	3.4415	2.7507	2.4003	0.0010*	0.0206**
DAYSBEFORE	5.1601	5.3660	0.8357	5.2404	5.4250	0.7950	-0.0803***	-0.0590***

Table 3 Analyst teams' forecast accuracy and pessimism

This table reports the results from OLS regressions examining analyst teams' forecast accuracy and optimism. Models 1 and 2 estimate Equation 1, and Models 3 and 4 estimate Equation 2. Variables are defined in Appendix 1. In brackets are the t-statistics based on standard errors adjusted for the clustering effect at the analyst level. ***, ** and * indicate the estimated coefficients are statistically significant at the 1%, 5% and 10% level based on two-tailed tests.

Variables	(1) *ACCURACY*	(2) *PESSIMISM*	(3) *ACCURACY*	(4) *PESSIMISM*
GROUP	0.0013***	0.0012**		
	(2.84)	(2.52)		
JOINT			0.0001	-0.0001
			(0.27)	(-0.36)
POST			0.0003	0.0009
			(0.55)	(1.47)
JOINT × *POST*			0.0020***	0.0017**
			(2.67)	(1.96)
NCOS	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.73)	(-0.54)	(-1.40)	(-1.34)
NINDUST	0.0001	-0.0000	0.0003	0.0001
	(0.64)	(-0.11)	(1.48)	(0.41)
SIZE_BROKERCD	0.0000	0.0000	0.0000	0.0000
	(0.16)	(0.62)	(0.33)	(0.19)
GEXP	-0.0004**	-0.0005**	-0.0001	-0.0002*
	(-2.05)	(-2.22)	(-1.29)	(-1.69)
SIZE	0.0153***	-0.0013***	0.0151***	-0.0016**
	(27.55)	(-2.65)	(20.47)	(-2.00)
MB	-0.0002	0.0013***	-0.0001	0.0012***
	(-1.31)	(8.41)	(-0.31)	(5.20)
DAYSBEFORE	-0.0072***	-0.0047***	-0.0076***	-0.0051***
	(-37.85)	(-25.37)	(-30.62)	(-18.21)
Year Fixed Effects	YES	YES	YES	YES
Brokerage Fixed Effects	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES
Observations	106,264	106,264	56,281	56,281
R-squared	0.426	0.278	0.471	0.329

Table 4 The effect of hierarchy in analyst teams' forecast accuracy and optimism

This table reports the results from OLS regressions examining the effect of hierarchy on analyst teams' forecast accuracy and optimism. Models 1 and 2 estimate Equation 4a, and Models 3 and 4 estimate Equation 4b. Variables are defined in Appendix 1. In brackets are the t-statistics based on standard errors adjusted for the clustering effect at the analyst level. ***, ** and * indicate the estimated coefficients are statistically significant at the 1%, 5% and 10% level based on two-tailed tests.

Variables	(1) *ACCURACY*	(2) *PESSIMISM*	(3) *ACCURACY*	(4) *PESSIMISM*
HIERARCHY (β_1)	0.0017***	0.0021***		
	(2.88)	(3.50)		
FLAT (β_2)	0.0009	0.0003		
	(1.64)	(0.56)		
GAP			0.0003***	0.0003***
			(3.20)	(3.89)
NCOS	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.76)	(-0.60)	(-0.82)	(-0.55)
NINDUST	0.0001	-0.0000	0.0001	-0.0000
	(0.65)	(-0.08)	(0.61)	(-0.12)
SIZE_BROKERCD	0.0000	0.0000	0.0000	0.0000
	(0.16)	(0.62)	(0.21)	(0.52)
MAX_GEXP1	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(-1.97)	(-2.07)	(-2.05)	(-2.01)
SIZE	0.0153***	-0.0013***	0.0153***	-0.0013***
	(27.66)	(-2.66)	(27.60)	(-2.66)
MB	-0.0002	0.0013***	-0.0002	0.0013***
	(-1.32)	(8.39)	(-1.32)	(8.40)
DAYSBEFORE	-0.0072***	-0.0047***	-0.0072***	-0.0047***
	(-37.87)	(-25.30)	(-37.82)	(-25.27)
Constant	-0.2318***	0.0299***	-0.2316***	0.0299***
	(-25.21)	(3.57)	(-25.12)	(3.55)
F-test: $\beta_1 > \beta_2$	1.58*	6.54***		
Year Fixed Effects	YES	YES	YES	YES
Brokerage Fixed Effects	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES
Observations	106,264	106,264	106,264	106,264
R-squared	0.426	0.278	0.426	0.278

Table 5 Analyst herding

This table reports the results from OLS regressions examining the co-movement between analysts' forecast revisions and consensus forecast revisions. Model 1 estimates Equation 3, and Models 2 and 3 estimate Equations 4c and 4d, respectively. Variables are defined in Appendix 1. In brackets are the t-statistics based on standard errors adjusted for the clustering effect at the analyst level. ***, ** and * indicate the estimated coefficients are statistically significant at the 1%, 5% and 10% level based on two-tailed tests.

Variable	(1) *REV*	(2) *REV*	(3) *REV*
CONSENSUS_REV	0.4013***	0.4016***	0.3989***
	(27.15)	(27.16)	(28.97)
GROUP	0.0003		
	(1.29)		
GROUP × *CONSENSUS_REV*	-0.0792***		
	(-3.37)		
HIERARCHY		0.0008***	
		(2.82)	
FLAT		-0.0002	
		(-0.63)	
HIERARCHY × *CONSENSUS_REV* (β_1)		-0.1177***	
		(-4.15)	
FLAT × *CONSENSUS_REV* (β_2)		-0.0426	
		(-1.44)	
GAP			0.0001***
			(3.26)
GAP × *CONSENSUS_REV*			-0.0197***
			(-4.32)
NCOS	0.0000**	0.0000**	0.0000**
	(2.20)	(2.12)	(2.27)
NINDUST	-0.0001	-0.0001	-0.0001
	(-1.43)	(-1.38)	(-1.45)
SIZE_BROKERCD	-0.0000	-0.0000	-0.0000
	(-1.30)	(-1.33)	(-1.55)
MAX_GEXP	-0.0001	-0.0001	-0.0001
	(-0.73)	(-1.14)	(-1.15)
SIZE	0.0029***	0.0029***	0.0029***
	(9.53)	(9.58)	(9.59)
MB	0.0004***	0.0004***	0.0004***
	(5.10)	(5.09)	(5.13)
BETW_REV	-0.0022***	-0.0022***	-0.0022***
	(-20.40)	(-20.45)	(-20.42)
DAYSBEFORE	0.0002	0.0002*	0.0002*
	(1.63)	(1.80)	(1.86)
Constant	-0.0423***	-0.0424***	-0.0425***
	(-8.00)	(-8.06)	(-8.08)
F-test: $\beta_1 > \beta_2$		4.57***	
Year Fixed Effects	YES	YES	YES
Brokerage Fixed Effects	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
Observations	66,336	66,336	66,336
R-squared	0.224	0.224	0.224

Table 6 Market reaction to analyst teams' forecast revisions

This table reports the results from OLS regressions examining market reactions to analysts' forecast revisions. Models 1, 2 and 3 estimate Equation 5a, 5b and 5c, respectively. Variables are defined in Appendix 1. In brackets are the t-statistics based on standard errors adjusted for the clustering effect at the analyst level. ***, ** and * indicate the estimated coefficients are statistically significant at the 1%, 5% and 10% level based on two-tailed tests.

Variables	(1) *CAR*	(2) *CAR*	(3) *CAR*
REV	0.1216***	0.1216***	0.1181***
	(14.26)	(14.26)	(14.69)
GROUP	-0.0003		
	(-0.76)		
GROUP × REV	0.0293**		
	(2.05)		
HIERARCHY		-0.0001	
		(-0.14)	
FLAT		-0.0005	
		(-1.08)	
HIERARCHY×REV (β_1)		0.0659***	
		(3.35)	
FLAT × REV (β_2)		0.0006	
		(0.04)	
GAP			-0.0000
			(-0.38)
GAP × REV			0.0131***
			(4.08)
SIZE_FIRM	-0.0012***	-0.0012***	-0.0012***
	(-4.44)	(-4.45)	(-4.45)
MB	0.0015***	0.0015***	0.0015***
	(9.57)	(9.57)	(9.57)
SIZE_BROKER	0.0000	0.0000	0.0000
	(0.55)	(0.55)	(0.52)
NCOS	-0.0001***	-0.0001***	-0.0001***
	(-4.99)	(-4.98)	(-4.97)
NINDUST	0.0002	0.0002	0.0002
	(1.19)	(1.18)	(1.19)
MAX_GEXP	-0.0000	-0.0000	-0.0000
	(-0.19)	(-0.33)	(-0.08)
BETW_REV	-0.0011***	-0.0011***	-0.0011***
	(-5.69)	(-5.68)	(-5.66)
DAYSBEFORE	-0.0028***	-0.0028***	-0.0028***
	(-7.01)	(-7.00)	(-7.00)
Constant	0.0410***	0.0411***	0.0409***
	(7.53)	(7.56)	(7.51)
F-test: $\beta_1 > \beta_2$		7.42***	
Year Fixed Effects	YES	YES	YES
Brokerage Fixed Effects	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
Observations	106,264	106,264	106,264
R-squared	0.027	0.027	0.027

Table 7 Determinants of group analyst forecasts

This table reports the results from logistic regressions estimating the probability that an earnings forecast is issued by a group of analysts. Variables are defined in Appendix 1. In brackets are the t-statistics based on standard errors adjusted for the clustering effect at the broker level. ***, ** and * indicate the estimated coefficients are statistically significant at the 1%, 5% and 10% level based on two-tailed tests.

Variables	(1) *GROUP*	(2) *GROUP*	(3) *GROUP*	(4) *GROUP*	(5) *GROUP*
SIZE_BROKER	0.0067***	0.0045***	0.0045***	0.0045***	0.0046***
	(10.61)	(7.64)	(7.70)	(7.67)	(7.79)
MAX_EXP	0.0448***	0.0253***	0.0253***	0.0249***	0.0260***
	(11.53)	(3.23)	(3.24)	(3.11)	(3.20)
SIZE_BROKER ×*MAX_EXP*		0.0005***	0.0005***	0.0005***	0.0005***
		(3.17)	(3.20)	(3.17)	(3.03)
SIZE	0.0013	0.0011	0.0011	0.0017	0.0024
	(0.38)	(0.33)	(0.32)	(0.48)	(0.67)
MB	0.0020	0.0019	0.0020	0.0014	0.0020
	(1.58)	(1.50)	(1.49)	(0.95)	(1.12)
STD_RET			-0.0790	-0.0518	-0.0690
			(-1.08)	(-0.73)	(-0.73)
FIRM_JOINT				0.0228*	0.0207
				(1.78)	(1.54)
IND_JOINT				0.0492***	0.0493***
				(2.89)	(2.76)
RET					0.0107
					(1.28)
ROA					-0.1320***
					(-2.72)
G_SALES					0.0105
					(1.30)
Constant	-0.1670**	-0.0798	-0.0722	-0.1228**	-0.1323**
	(-2.61)	(-1.43)	(-1.26)	(-2.07)	(-2.18)
Year Fixed Effects	YES	YES	YES	YES	YES
Firm Fixed Effects	broker	broker	broker	broker	broker
Observations	55,443	55,443	53,176	48,239	44,275
R-squared	0.247	0.250	0.253	0.251	0.252

Appendix 1: Variable definitions

Variables	Definitions
ACCURACY	-1 multiplied by the absolute value of the difference between actual earnings for firm *j* in year *t* and analyst *i*'s earnings forecasts for the same firm year, deflated by closing share prices two days before the forecast date.
PESSIMISM	The difference between actual earnings for firm *j* in year *t* and analyst *i*'s earnings forecasts for the same firm year, deflated by closing share prices two days before the forecast date.
CAR	3-day cumulative market-adjusted returns surrounding forecast release dates.
REV	Analyst *i*'s forecast revision for firm *j* in year *t*, deflated by closing share prices two days before the forecast date.
CONSENSUS_REV	The average of forecast revisions by other analysts who follow firm *j* in year *t*, prior to analyst *i*'s forecast revision, divided by closing share prices two days before the forecast date.
GROUP	Equals 1 if the forecast report is signed by more than one analyst, otherwise 0.
HIERARCHY	Equals 1 for analyst teams whose most experienced analyst has at least three more years' experience than the least experienced analyst, and 0 for other analyst teams.
FLAT	Equals 1 for analyst teams with *HIERARCHY* = 0, and 0 for other analyst teams.
GAP	Equals the difference between group member *GEXP*, 0 for single analyst.
NCOS	The number of firms followed by the analyst(s).
NINDUST	The number of industries followed by the analyst(s).
SIZE_BROKER	The logarithm of one plus the number of analysts employed by a brokerage in one year.
EXP	Number of years since an analyst's forecasts first appeared in the database. For analyst teams, we use the minimum.
MAX_EXP	The *EXP* of the most experienced analyst in a group.
SIZE	The logarithm of a firm's market value.
MB	Market value of equity deflated by the book value of its equity.
DAYSBEFORE	The logarithm of one plus the number of days between a forecast date and the corresponding actual earnings announcement date.
STD_RET	The daily price volatility for firm *i* in the preceding year.
RET	The cumulative market returns over the preceding year for firm *i*.
G_SALES	Sales growth in the preceding year.