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Do analyst teams issue higher quality forecasts? Evidence from analyst reports

Kathryn Brightbill
University of Iowa

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DO ANALYST TEAMS ISSUE HIGHER QUALITY FORECASTS?

EVIDENCE FROM ANALYST REPORTS

by

Kathryn Brightbill

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of the requirements for the Doctor of Philosophy
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Thesis Supervisor: Professor Cristi A. Gleason

Graduate College
The University of Iowa
Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Kathryn Brightbill

has been approved by the Examining Committee for
the thesis requirement for the Doctor of Philosophy degree
in Business Administration at the August 2018 graduation.

Thesis Committee: ____
Cristi A. Gleason, Thesis Supervisor

____
Daniel W. Collins

____
S. Paul Hribar

____
Mark Penno

____
Eean Crawford

To Ethan Brightbill

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ABSTRACT

Despite significant regulatory and academic interest in sell-side analyst forecasts and an extensive literature demonstrating the impact of teamwork in general, we lack evidence of the effect of teamwork on analyst forecasts. In 2005 analyst teams issued nearly three-fourths of analyst reports for a sample of 89 large, heavily followed companies. Over a twelve-year period 86 of those companies had more reports issued by analyst teams than by individual analysts. Using a hand-collected sample of more than 17,000 analyst reports, I document that forecasts issued by analyst teams systematically differ from the forecasts of individual analysts in ways predicted by team literature. I find that prior to the year 2000 analyst teams issue forecasts that are less accurate and more biased than forecasts issued by individual analysts. Beginning in 2000, the relative benefit of analyst teamwork strengthens, consistent with changes due to Regulation Fair Disclosure, brokerage closures, and other regulatory interventions. In addition I find that, within company-year, team-issued forecasts are less pessimistically biased but not less optimistically biased than the forecasts issued by individual analysts. Lastly, the benefits of teamwork vary with the size of the team and over the life of the team, following an inverted u-shaped pattern. My results inform regulators as they consider factors that impact analyst forecast accuracy and bias.

PUBLIC ABSTRACT

Despite significant regulatory and academic interest in sell-side analyst forecasts and an extensive literature demonstrating the impact of teamwork in general, we lack evidence of the effect of teamwork on analyst forecasts. In 2005 analyst teams issued nearly three-fourths of analyst reports for a sample of 89 large, heavily followed companies. Over a twelve-year period 86 of those companies had more reports issued by analyst teams than by individual analysts. Using a hand-collected sample of more than 17,000 analyst reports, I document that forecasts issued by analyst teams systematically differ from the forecasts of individual analysts in ways predicted by team literature. I find that prior to the year 2000 analyst teams issue forecasts that are less accurate and more biased than forecasts issued by individual analysts. Beginning in 2000, the relative benefit of analyst teamwork strengthens, consistent with changes due to Regulation Fair Disclosure, brokerage closures, and other regulatory interventions. In addition I find that, within company-year, team-issued forecasts are less pessimistically biased but not less optimistically biased than the forecasts issued by individual analysts. Lastly, the benefits of teamwork vary with the size of the team and over the life of the team, following an inverted u-shaped pattern. My results inform regulators as they consider factors that impact analyst forecast accuracy and bias.

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CHAPTER 1. INTRODUCTION

"Many hands make light the work." (John Heywood)

When people work in teams they produce output that fundamentally differs from when they work alone, as demonstrated by an extensive literature in both psychology and management operations. Yet despite this evidence, and significant regulatory and academic interest in sell-side analyst forecasts, we lack an understanding of the effects of working in teams on analyst forecasts (Brown & Hugon, 2009). Analyst teams issue more reports than individual analysts, comprising more than two thirds of my sample. In addition, forecasts issued by analyst teams elicit a stronger market reaction than forecasts issued by individual analysts (Brown and Hugon, 2009). The broader team literature documents that teams are prone to free-riding (Webb, 1989, Albanese & Fleet 1985, Williams et al. 1991), perform better at abstract problem solving (Shaw, 1932), and are less adept at creative tasks (Dillion et al. 1972), all of which arguably affect analyst forecast quality. Furthermore, some analysts remain in the same team for years. Extended team tenure of this nature may lead to a deterioration in the quality of forecasts if members lose the ability to engage in productive debates (e.g., Tjosvold, 1982, Tjosvold & Field, 1983). Excepting Brown and Hugon (2009) evidence on this prominent feature of the forecasting environment has been hindered by a lack of machine-readable data.[1] I overcome this limitation by hand-collecting a sample of forecasts from over 17,000 analyst reports. Using the team literature as a guide, I predict and find that analyst teams issue forecasts that systematically differ from the

[1] A concurrent paper by Fang and Hope (2018) uses a similar dataset of approximately 50,000 analyst reports to identify analyst teams across all firms and explores the properties of their forecasts, including accuracy, frequency of reports, and team diversity. My paper explores the impact of analyst teams on forecast quality during an earlier time period and considers the effect of team tenure and team size on forecast quality. Our papers agree that analyst teams issue higher quality forecasts, but disagree on the impact of team size on forecast accuracy.

forecasts of their individual peers and that these differences are moderated by measurable characteristics of analyst teams.

Analyst teams are widespread and play a significant role in information intermediation to the market. Over a twelve year period from 1994-2005, analyst teams issued more than seventy percent of reports for a sample of 89 large, heavily followed companies. The percentage of reports issued by teams and the number of analyst teams both increased from 1995 to 2005, from 62 to 73 percent of reports and from 82 to 278 teams.[2] The increase in teams and team reports may be attributable to rising demand for access to analysts (Bagnoli and Watts, 2008), in response to a changing information environment (Amato, 2012; Li, 2008), or it may reflect brokerage closures and consolidations in later years (e.g., Hong & Kacperczyk, 2010; Kelly & Ljungqvist, 2012). Regardless of the precipitating factors, analyst teams are abundant and have increased over time. Given that teams systematically differ from their individual counterparts, understanding how working in teams affects analyst outputs contributes meaningfully to our understanding of the analyst forecasting environment.

Knowing whether and under what circumstances analyst teams issue higher quality forecasts provides new insights relevant to regulators and researchers. One objective of Regulation Fair Disclosure (Reg FD), promulgated in 2000, was to reduce bias in analyst forecasts. Thus, regulators should be interested in whether analyst teams issue less biased forecasts than individual analysts. As Abarbanell and Bushee (1997; 1998) demonstrate, less sophisticated investors may be misled by biased forecasts. If teams issue less biased forecasts, some investors may be better off relying on reports issued by teams more than

[2] Over the same time period, analyst forecasts became less accurate on average.

those issued by individual analysts. Furthermore, the lead analysts of teams have approximately 2.5 more years of experience than individual analysts, which offers an alternative explanation for the association between absolute forecast errors and analyst experience documented in prior research.

Motivated by the team literature, I develop three hypotheses on the impact of teamwork on the quality of analyst forecasts. First, I predict that analyst teams issue higher quality forecasts than their individual peers. This prediction is in line with the broader literature on teams but is contrary to results reported by Brown and Hugon (2009) who find that analyst teams issue less accurate forecasts. My prediction rests upon research that finds teams perform abstract reasoning tasks better than individuals (Laughlin et al., 1968; Johnson et al., 1978; Shaw 1932), but perform worse on creative or majority rules tasks (Dillon et al., 1972; Harari & Graham, 1975; Kerr & MacCoun, 1996).[3] Teams also reach solutions to challenging problems more quickly than individuals, especially in high ability teams (Shaw & Ashton, 1976). The benefits of working in teams occurs despite free-riding, which reduces beneficial the effects of teamwork (Steiner, 1972).[4] The net effect of teamwork on analyst forecast quality should be positive, as forecasting is not a creative process and the small size of analyst teams reduces the likelihood of free-riding.

Second, I predict that analyst team forecast quality follows an inverted u-shape over the life of the team, where quality increases up to a point before peaking and declining. It takes time for teams to reap the benefit of shared knowledge (Berman, Down and Hill,

[3]Abstract reasoning refers to the ability to detect patterns and is sometimes taken as a measure of fluid intelligence (Sternberg, 2008). Importantly, creativity and fluid intelligence may be correlated (Nusbaum & Silvia, 2011). The tendency for groups to outperform individuals on abstract reasoning tasks and not creative tasks may depend upon the manner in which creativity is measured (quantity vs. quality of output).

[4] Latané et al. (1979) note that social-loafing, distinct from free-riding, can also occur outside of teams. Whether it occurs within teams is dependent upon a number of factors including the observability of other team members efforts.

2002; Moreland & Thompson, 2006) yet teams that have worked together for extended periods may experience a decline in the quality of their output, as the ability to constructively disagree with one another declines (e.g., Tjosvold, 1982; Tjosvold & Field, 1983) and teams become isolated from external feedback (Katz, 1982). Thus analyst team forecast quality should increase as members recognize their specific roles, but should eventually decline as the team fails to incorporate novel outside input or members become complacent in their interactions.

Lastly, because of disagreement in prior research on the impact of team size on team performance, I offer the (null) hypothesis that analyst team size is not associated with the quality of team forecasts. Webb (1989) finds that free-riding is less likely to be observed in teams of two individuals, while Amason and Sapienza (1997) note that difficulties resolving interpersonal conflict rise with the number of members in a team. However, these authors also state that larger teams have access to greater and more diverse cognitive resources. Martz et al. (1992) even find that team size has no impact on performance. Thus the impact of team size on the quality of analyst forecasts is an empirical one.

To test my hypotheses and determine the effect of teamwork on forecast quality, I must accurately identify analyst teams. Machine-readable data on analyst teams is not readily available, as team reports are often listed in databases under only the lead analyst's name. Hence, I hand-collect team data to form a sample of more than 17,000 analyst reports from ThomsonOne. From these reports, I record the analyst forecasts, the name of individual team members, and the report dates to calculate team size and team tenure. These data allow me to investigate whether analyst teams issue more accurate or less biased forecasts than individual analysts, and the degree to which team characteristics impact forecast quality.

I test my three predictions across the full sample, within company-year, and within analyst. My full sample regression provides insight on the average impact of teamwork on forecast quality, but does not perfectly control for the tendency of analyst teams to follow different types of companies than individual analysts, nor does it control for potential differences in ability between the analysts who work in teams and those who work alone. To address the tendency for analyst teams to follow different types of companies, and because companies can change types over time,[5] I also compare the forecasts of teams to the forecasts of individual analysts within the same company-year. Finally, to address potential differences in ability between analysts in teams and individual analysts, I compare the forecasts of lead analysts to their forecasts when they issue reports alone.

I find that analyst teams issue more accurate forecasts than individual analysts, but this effect is largely driven by the later years of my sample. After 2000, brokerage closures and regulatory changes appear to shift the relative benefits of analyst teamwork on forecast quality. While analyst teams issue forecasts of consistent quality throughout my sample period, individual analysts begin to issue less accurate, more biased forecasts after 2000. Furthermore, relative to individual analysts, I find that analyst teams issue less pessimistically biased but not less optimistically biased[6] one-year-ahead earnings-per-share (EPS) forecasts within the same company-year. Overall, analyst teams issue

[5] For instance, Apple nearly failed in 1996 prior to Steve Jobs' return yet from 2010 to 2012 profits nearly tripled. In the former case Apple is a company in decline, while in the latter case Apple is a growth company.
[6] That is, when analyst teams issue pessimistic forecasts, those forecasts tend to be less pessimistic (closer to 0 error) than pessimistic forecasts issued by individual analysts in the same company-year. When analyst teams issue optimistic forecasts, those forecasts are equally optimistic relative to the forecasts issued by individual analysts in the same company year. Thus, teams issue less pessimistically but not less optimistically biased forecasts.

optimistic forecasts less frequently and on average exhibit smaller optimistic biases. Consequently, I conclude that analyst teams issue higher quality forecasts than individual analysts.

I also find that team characteristics are associated with the quality of forecasts issued by teams. A team that has been together one year has on average a scaled forecast bias that is 17% more optimistic than a team producing its first forecast, yet teams in the third quintile of tenure issue the least biased forecasts. When team size is a statistically significant factor, it generally appears to be detrimental to forecast quality. I find that each additional team member is associated with an increase in (and more optimistic) forecast errors.

Finally, in robustness tests, I document that analyst team forecasts exhibit smaller bias than the forecasts of individual analysts at long horizons, but virtually identical pessimistic errors at short horizons. Given that prior research implies that short-horizon pessimism is linked to catering to management (Richardson et al., 2004), the tendency for analyst teams to exhibit pessimism at short horizons suggests that analyst teams may need to cater to management, perhaps to acquire business for an analysts' brokerage. Taken together, my results reveal systematic differences in the quality of forecasts issued by analyst teams and individual analysts.

My paper complements prior work by Brown and Hugon (2009) that used the I/B/E/S broker translation file to classify analyst teams. They find that forecasts listed as being issued by an analyst team on I/B/E/S are less accurate, on average, than forecasts listed under an individual analyst on I/B/E/S and attribute this to the tendency for teams to follow large companies and companies in distress. They also find that analyst teams issue more timely forecasts, and that forecasts issued by analyst teams elicit a stronger market response. However, as a result of how team forecasts are entered into I/B/E/S, a majority of analyst team reports are listed under only the lead analyst's name.

In contrast, using hand-collected research reports from ThomsonOne to identify teams, I find that analyst teams issue *more* accurate forecasts than individual peers, especially in the post-2000 period. I document that differences in forecast quality are not likely to be explained by the tendency for analyst teams to follow different types of companies.[7] My research also demonstrates that analyst teams issue less pessimistically (but not less optimistically) biased forecasts within company-year, a distinction of particular importance to regulators given prior research connecting overly optimistic forecasts to perverse financial market incentives (Bradshaw et al., 2003). Because of the quality of my data, I am also able to link the quality of forecasts issued by teams to team characteristics, specifically the length of time an analyst team has worked together and the number of members in the analyst team. In doing so, I demonstrate that simply controlling for analyst teams may be insufficient; analyst teams, and their forecast quality, are not static. Lastly, my results highlight differences in the walk-down pattern of forecasts and the relative frequency of optimistic and pessimistic forecasts issued by analyst teams.

My research also contributes to the team literature, as the sell-side analyst reporting environment provides a powerful, large-sample setting to examine the impact of teams in a professional, real-world setting. Team research typically uses experiments or field research to identify differences between teams and individuals, which can be attributed to the difficulty in gathering broad, team-based archival data. This constraint is not present in

[7]Specifically, the benefits of teamwork do not appear to be attributable to either the tendency for teams to follow different types of companies or to higher ability analysts opting into lead analyst positions.

my study, and thus I document that much of the experimentally captured effects of working in teams translates into verifiable real-world consequences.

CHAPTER 2. MOTIVATION

2.1 The Effects of Teamwork

In 1951, Asch asked a series of participants to engage in a simple task: identify the shortest of three lines of clearly differing lengths. When working alone, subjects were able to identify the shortest line nearly 100% of the time. However, when put into teams of confederates told to choose the wrong answer, nearly one third of participants *went along* with the incorrect team answer, a phenomenon known as 'groupthink.' Asch's experiments were among the first to convincingly demonstrate the disparity between a person's behaviors when alone and when in a team.

Following the Asch experiments thousands of papers were published in the managerial and psychology literature investigating the impact of teamwork on behavior and production. The psychology literature focuses on uncovering instances where team biases differ from individual biases,[8] while the managerial literature emphasizes factors that influence team performance. My study draws from both literatures and explores how the length of time an analyst team has worked together (team tenure) and the number of members in an analyst team (team size) impact forecast quality. I focus on these team characteristics because team tenure and size are associated with team performance in prior literature. These characteristics are also more readily measurable within my analyst data than other team characteristics like leadership style or incentive structures.[9] I use extant research on teamwork to motivate hypotheses about the impact of teamwork and team characteristics on the quality of analyst forecasts in Section 3.

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[8] Kugler et al. (2012) provides a thorough background of the effect of teamwork on rationality.
[9] Unobservable factors, like the leadership style of the lead analyst, recognition for work within the teams, and lead vs. team incentives, may also impact team performance.

In general, teamwork enhances performance for tasks that require learning or abstract reasoning (Laughlin et al., 1968; Johnson et al., 1978; Shaw 1932; Taylor & Faust, 1952). Working in teams enables members to catch one another's errors in tasks that have a defined correct solution, like forecasting EPS for a company (Shaw, 1932). Teams are also better at jointly processing information from several senses; teams can connect visual, auditory, and tactile information more readily than can individuals (Laughlin et al., 1968). In the context of sell-side analysts, analyst teams are likely to be more accurate than an individual analyst when deciphering information delivered via a conference call or an in-person meeting

Working in teams is not universally beneficial; teamwork is detrimental for tasks that involve creativity or for which a majority-rules decision-making process is involved (Dillon et al., 1972; Harari & Graham, 1975; Kerr & MacCoun, 1996).[10] Dillon et al. (1972) document that individuals generate a larger number of solutions to real-life problems. This outcome is reiterated in Harari and Graham (1975), who show that teams produce significantly fewer ideas when brainstorming than do comparable nominal groups of individuals, especially when "[team members] have a genuine concern about the outcome" of the brainstorming session. If the forecasting process were creative in nature, analyst teams would be likely to issue lower quality forecasts than individual analysts.

Teams also reach solutions to challenging problems more quickly than individuals, especially in high ability teams (Shaw & Ashton, 1976). In disjunctive tasks – tasks which require an either-or decision among group members – groups perform as well as or better than predicted based upon the ability of the members of the group (Shaw & Ashton, 1976).

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[10] See Hill (1982) for an early review of studies on team vs. individual efficacy.

Thus teams appear to benefit not only from the relative ability of their members, but also from an 'assembly bonus' effect in which the act of working together stimulates stronger performance in its members. Given that analyst teams are comprised of multiple highly skilled individuals, often experts in different industries, analyst teams should be particularly liable to benefit from an 'assembly bonus.'

Despite teams' ability to quickly and accurately solve complex problems, teams are often less productive than the sum of their parts. Steiner (1972) finds that individuals working in teams underperform relative to when the same individuals work alone; the subjects engage in free-riding. Although the output of a team is greater than the output of an individual, especially on the type of additive task (rope-pulling) considered in Steiner (1972), the efficiency loss caused by free-riding implies that individual work may be preferable to teamwork when the benefits of teamwork are sufficiently small or when individual work satisfies consumer demand. Whether a team performs better than an individual depends not only on the task at hand, but also on factors like the length of time a team has worked together (tenure) and the number of members in the team (size). Analyst teams, therefore, are likely to issue higher quality forecasts in general, but their forecast quality should differ depending on team characteristics like team tenure and team size.

Team performance improves as team members gain experience working with one another (Berman et al., 2002; Moreland & Thomson, 2006; Tuckman, 1965). Berman et al (2002) predict that this improvement results from the stock of intangible information called 'tacit knowledge' which results from interactions between team members over time. Similarly, teams do not immediately reap the benefits of 'transactive memory,' the tendency for teams to assign roles and proficiencies amongst their members (Moreland &

Thomson, 2006). This stream of research suggests team performance increases monotonically with time.

However, when considering teams who have worked together for longer durations (more than one year), field research finds that the quality of team output declines as 'constructive controversy' drops in frequency or intensity.[11] Constructive controversy, the willingness to intellectually engage and disagree with teammates, has been linked to the quality of team output (e.g., Tjosvold 1982, Tjosvold & Field, 1983). Katz (1982) argues that newcomers improve innovation, as the longevity of teams comes with a tendency to ignore or become isolated from external critical feedback. Long-lasting teams may also experience 'knowledge ossification', in which the value of tacit knowledge begins to decay (Berman et al., 2002). This latter research suggests team performance declines monotonically over time. Combined, these streams of research suggest that analyst team forecasting performance follows an inverted u-shaped pattern over the life of the team, where performance increases up to a point, peaks, and then declines.

The number of members in an analyst team is also likely to impact forecast quality. Webb (1989) finds that free-riding is less likely to be observed in teams of two individuals because team members effectively monitor one another and appropriately assign blame for shirking. The likelihood of divergent goals, coordination difficulties, and challenges resolving interpersonal conflict also rise with the number of members in a team (Blau, 1970; Shaw & Harkey, 1976, Amason & Sapienza, 1997). Free-riding and team conflict suggest that smaller analyst teams will issue higher quality forecasts.

[11] Prior research often focuses on teams created for an experiment which disband when the experiment ends. Field research provides insight on teams who work together over longer durations. However, given the expense of field research, these are often limited to several months to slightly more than one year. Archival research can help bridge the gap in examining long-lasting teams.

On the other hand, larger teams have access to greater and more diverse cognitive resources that may be more beneficial in highly uncertain environments or on challenging tasks (Kozlowski & Bell, 2003). For instance, Halebjian and Finkelstein (1993) find that companies with large top management teams are more profitable, but only in turbulent industries in which teams have some measure of discretion. In a meta-analysis of 27 studies, Dalton et al. (1999) find a positive association between board size and company performance. In contrast, Martz et al. (1992) find that team size has no impact on performance. Given divergent results on the impact of team size on team performance, it is an empirical question which effect will dominate in the sell-side analyst setting.

Team research typically uses experiments and field research to detect differences between teams and individuals, which results from the difficulty in gathering broad, team-based archival data. Sell-side analyst reporting provides a powerful, large-sample setting to examine the impact of teams in a professional, real-world setting.

2.2 Analyst Forecasts and the Increase in Analyst Teams

Analyst forecasts and recommendations inform investors and move market prices (Fried & Givoly, 1982; O'Brien, 1988; Philbrick & Ricks, 1991; Givoly et al. 1979; Lys & Sohn, 1990; Francis et al., 1997) and can enhance market liquidity (Roulstone, 2003). Less sophisticated market participants are often unable to fully unravel the effects of analyst bias (Abarbanell & Bushee, 1997; 1998) which has prompted regulatory efforts to reduce analyst bias, including Reg FD (promulgated in October of 2000) and SEC rules that require analysts to disclose potential conflicts of interest (2002).[12] Given this attention to

[12]The intent of this regulation was partially to reduce analysts' catering to management, evidenced by a decline in short horizon forecast pessimism.

reducing bias, the effect of teamwork on analyst forecast quality should be of interest to regulators.

Notwithstanding the external interest in reducing bias, the internal purpose of analyst teams might not be to improve the quality of the analyst report. As Bagnoli et al. (2008) document, investor preferences captured in *Institutional Investor* shift in the late 1990s toward analysts providing 'accessibility and responsiveness' and 'timely calls and visits' (2008, Table 1). Thus brokerage houses could use analyst teams to meet changing market expectations. Alternatively, analyst teams may function as a training ground for new or inexperienced analysts. In either case, any effect on the properties of forecasts is secondary to changes in the frequency of reports or other analyst services.

Brokerage closures and consolidations are also likely to influence the effect of teamwork on the quality of analyst forecasts (e.g., Hong & Kacperczyk, 2010). While brokerage closures happen periodically, Kelly and Ljungqvist (2012) document a significant cluster of 20 such closures or mergers that occur between 2000 and 2005, the latter years of my sample. These closures increase the supply of experienced analysts. To the extent that additional coverage is not needed by the surviving brokerage houses, these analysts may be placed in teams, potentially leading to a greater number of high ability teams with higher quality forecasts after 2000. I control for time periods before and after 2000 in my empirical tests to account for this possibility.

Additionally, analysts may be assigned to teams in response to a changing information environment: the length of annual reports has nearly doubled over the last twenty years (Amato, 2012), annual report readability has declined (Li, 2008), and global operations have expanded.[13] Given that analysts are subject to limited attention (Dong & Heo, 2014), teamwork could provide an alternative to issuing a deteriorating product.

Teamwork may also improve analysts' information acquisition for companies that cross industry barriers or for companies that are in emerging industries. It is also possible that the increase in analyst teams may reflect a change in the number, size, or complexity of publicly traded companies, rather than a demand for analyst teams in general. Regardless of which factors have prompted the near ubiquity of analyst teams, teams are likely to issue forecasts that statistically differ from forecasts issued by individual analysts in predictable ways.

2.3 Analysts Team Reports

Analyst teams are comprised of a lead, second, and in some cases, a third, fourth, or fifth analyst. Both analysts issuing reports as part of a team and analysts issuing reports alone usually have access to research assistants who aid in collecting information and running models of EPS.[14] When issuing a report, the lead analysts' name is listed first followed by other members in the team. This ordering reflects the importance of the lead analyst: the lead analyst usually has the most experience and often has a well-defined reputation.

Analyst reports reflect the collaboration and discussion of expert members of the team and thus the process of issuing a report may be classified as a 'divisible, optimizing'

[13]Increased length of annual reports suggests either that companies have become more complex or that deciphering information about companies has become more challenging. Analysts may not rely on annual reports for significant incremental information in their forecasting process, but changes in annual reports likely reflect the information environment of the company.
[14]Research assistants typically have not undergone formal testing to become an analyst. Thus, analyst teams are teams of experts with similar levels of ability, while analysts who issue reports individually work with others who are less experienced and less knowledgeable than themselves.

task,[15] in which individual members contribute according to their unique abilities towards the production of a high quality output (Steiner, 1972). Anecdotally, team reports are primarily generated by the second third and fourth analysts on the team, though this structure is likely to vary by team, brokerage house, and over time. The lead analyst may play a role in developing the forecast and report or may simply verify the quality of the work of the other analysts on the team. Regardless of the role the lead analyst plays, however, all analysts in a team are held responsible for the report and all analysts typically share in the bonus pool, though not necessarily equally. Because all analysts on a team share responsibility for the quality of analyst reports, prior literature suggests working in a team is likely to provide analysts some protection from negative career outcomes. I describe the hypothesized effects of teamwork on the quality of analyst forecasts in the next section.

[15]Steiner (1972) classifies tasks into their components (divisible vs unitary), focus (maximizing vs optimizing), and interdependence, which relates to how inputs from team members are combined. Although the first two pieces of the Steiner taxonomy can readily be applied to the analyst reporting task, the last – interdependence – is unobservable and is likely to vary across teams and across time.

CHAPTER 3. HYPOTHESIS DEVELOPMENT

3.1 Teams vs. Individual Analysts: Absolute Forecast Errors and Bias

I argue that analyst teams will issue higher quality forecasts than individual analysts, consistent with findings in prior literature that teams exhibit faster problem-solving speed, enhanced learning, and improved abstract reasoning (Shaw, 1932; Laughlin et al., 1968; Johnson et al., 1978).[16] Higher quality forecasts are also consistent with analyst teams more readily incorporating soft information found in company-related news (Bradshaw et al., 2015).

The magnitude of absolute forecast error and forecast bias capture forecast quality.[17] Exploring forecast bias (i.e., signed forecast error) and absolute forecast error separately provides a more nuanced understanding of the factors which moderate the beneficial effects of teams, as prior research documents incentives for analysts to bias their forecasts but does not similarly document incentives to provide inaccurate forecasts (Lim, 2001). Given my prediction that analyst teams issue higher quality forecasts, my first set of hypotheses are as follows:

H1a *Analyst teams issue forecasts with smaller absolute forecast errors than individual analysts.*

H1b *Analyst teams issue less biased forecasts than individual analysts.*

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[16]Alternatively, analyst teams may issue more timely forecasts. This possibility, however, works against my findings as analysts issuing forecasts in a 'more timely' fashion have less time to impound information into their forecasts.

[17]Janakiraman et al. (2007) illustrate that the days between an analysts first forecast declined following Reg FD, while Bandyopadhyay et al. (1995) document that analyst forecasts become more informative of their stock recommendation as the forecast horizon shortens. Numerous other papers explore the impact of forecast horizon on forecast quality, as well as appropriate controls for forecast horizon. Thus for the purposes of my paper I do not consider forecast horizon as a measure of quality in itself, but do include horizon as a control when possible in all of my tests.

While I predict that analyst teams issue higher quality forecasts than individual analysts, there are reasons to expect the opposite, or even no, relationship between working in teams and forecast quality. If brokerages prefer that analysts work in teams only to meet investor demands for accessibility, then teamwork may have no statistically distinguishable impact on forecast bias or absolute forecast error, absent spill-over effects. If analyst teams function as a training ground for new analysts, the time and effort associated with training is likely to negatively impact forecast quality. These factors, among others, suggest that analyst teams issue forecasts of equal or lower quality than their individual peers.

3.2 Team Factors: Size and Tenure

My first set of hypotheses consider the effect of teamwork on the quality of analyst forecasts in general. However, the team literature suggests the benefits of teamwork vary along a number of characteristics, such as the length of time a team has worked together (tenure) and number of members in a team (size). Hence, my second and third hypotheses focus on the size and tenure of analyst teams, respectively. Given the disagreement in the literature on the impact of team size on performance,[18] I state my second hypothesis in the null form.

H2 *There is no relationship between the size of an analyst team and the quality of forecasts issued by that team.*

Finding a positive relation between analyst team size and the quality of forecasts is consistent with larger teams' access to more diverse cognitive resources (Amason & Sapienza, 1997). In the analyst setting, larger teams are more likely to have analysts with

[18]It is possible that the benefits associated with team size should also follow an inverted u-shape with respect to forecast quality. However, the size of analyst teams typically varies from 2-4 members, reducing the likelihood that such an effect could be observed in the analyst setting.

differing industry expertise (Kadan et al., 2012). Alternatively, a negative association between team size and forecast quality is consistent with increased free-riding and coordination difficulties of larger teams (Blau, 1970, Webb, 1989).

Finally, I predict that team tenure, or the length of time a team has worked together, has a non-monotonic impact on the quality of forecasts issued by analyst teams. New teams should issue lower quality forecasts than teams that have matured, up to a point of maximum forecast quality, after which the quality of forecasts issued by analyst teams should decline. My third and final hypothesis is as follows:

H3 *The quality of forecasts issued by teams increases for a period of time, peaks, and then declines.*

CHAPTER 4. DATA COLLECTION

4.1 Sample

In their 2009 paper, Brown and Hugon identify analyst teams using the broker translation file, and corroborate the efficacy of this strategy by contacting I/B/E/S directly. From the description of their verification process:

> *"[T]he information pertaining to classification of analyst teams originates from brokerage firm spreadsheets, proprietary I/B/E/S software used by brokerage firms, and I/B/E/S employees who examine research reports. In addition, we contacted a small sample of analyst team members via email to verify that they had worked with the other team member included in the coding."*

Through my hand-collection process I find that the majority of reports issued by analyst teams in my sample are mis-identified in the broker translation file as having been issued by individual analysts. When analyst reports are correctly identified on I/B/E/S as having been issued by a team, the members of the team are frequently incorrect or members of the team listed on the hard copy of the analyst report are omitted. Although these errors are common, I do not claim that they indicate a failure on the part of I/B/E/S, in part because of the numerous ways through which team identification enters the I/B/E/S database.

As accurate data on analyst teams and their characteristics is not readily available, I hand-collect data specific to my research objectives. Analyst reports are drawn from ThomsonOne for 89 companies from 1994-2005, as analyst reports on ThomsonOne are rare before 1994. My initial data collection ends in 2005. In order to calculate analyst experience, I connect analyst reports to I/B/E/S. I draw companies from the Technology (GICS Group 4510), Transportation (2030), and Retail (2550) industries because a plurality of analysts self-identify as following one or more of these industries (Brown et al., 2015). I require that companies have a following of at least 5 analysts and at least 10 team reports.[19] Among the 854 companies that meet these criteria, I randomly select 30 companies from each industry without replacement.

I download team and individual analyst reports from ThomsonOne, excluding reports with the label ‘note,’ as these often do not include an explicit EPS estimate.[20] I limit my search to reports issued from brokerage houses to ensure that differences between individual and team forecasts are attributable to the team environment rather than to employment in a brokerage house per se, as Jacob et al. (2008) find that the incentives in a non-brokerage environment substantially differ from incentives present in brokerage houses.

I collect five items from each analyst report: the names of the analysts on the report,[21] the number of analysts in the team, the date of the report, the brokerage house, and the EPS estimate. Notably, many reports that are listed as ‘individual’ reports on ThomsonOne are actually issued by teams according to the names on the report. However, the converse is not true: almost no team reports are listed as being individually-issued. Reports issued on the same day result in two data points when the same-day reports differ from one another. I exclude unreadable reports, reports with no associated names, and

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[19]The requirement of ‘at least ten analyst team reports’ resulted in an exclusion of three companies from the initial data collection process.

[20]In order for a report to be classified as a ‘note,’ ThomsonOne requires that the term ‘note’ appears in the title of the report as found in the search engine. This causes some notes to be included in the search and retrieval process. However, I maintain the requirement that I only include reports with EPS estimates in my sample.

[21]For the most part, names are located on the first page of the analyst report. In some cases only the lead analyst is listed on the front page while the remaining team members are listed at or near the end of the report. Typically the location of the names of team/individual analysts was brokerage specific, reducing the likelihood that significant errors are introduced in the coding process.

credit rating reports from my sample. This hand-collection process results in 12,557 team data points and 4,915 individual data points, for a total of 17,472 analyst reports. Of these, 6,612 are forecast reiterations.

I match the actual EPS outcome for each company as found in I/B/E/S to the split-adjusted EPS found on the analyst reports to calculate absolute forecast error and forecast bias. I match on 8-digit CUSIP, forecast date, and fiscal year in both I/B/E/S and my data set. This reduces my sample size to approximately 9,000 observations (631 company years). I match analyst codes from the 2005 translation file to the lead or individual analyst on a report to calculate analyst experience. In most cases, team reports are entered into I/B/E/S under only the lead analyst's name. This suggests that using I/B/E/S identifiers to control for teams suffers misclassification error. I also collect data from the Compustat Historical Segment and Fundamentals Annual files to calculate the number of segments and market-to-book ratio of companies followed by analysts.

I note several caveats about my data selection and interpretation. First, it is possible that analyst teams actually issue all reports, while only some reports include the names of the team members involved. This is unlikely, given the substantial variation in the number of names included on reports of the same format, from the same brokerage house, and in short succession. It seems reasonable to assume that reports are at least marginally informative about who is involved in their making. This caveat also works against my finding any significant differences between team and individual analyst forecasts. In addition, while I find an increase in analyst teams over time, this increase could be specific to analysts and/or brokerages included in the ThomsonOne database or to my sample. Finally, while I label reports that list only one analyst as having been issued by an ‘individual,’ no analyst truly works alone: most analysts have research assistants and work in an environment where other analysts are present. Thus my hypothesis and results document the effect of structured teams of documented experts, rather than the effect of working with or around others in general. This definition of working in teams aligns with prior field research.

4.2 Sample Statistics

My sample consists of team and individual reports for a total of 89 companies in the Technology, Retail, and Transportation industries, for which I provide descriptive statistics in Table 1, Panel A. In all three industries, analyst teams issue at least 72% of report observations. However, all companies in the pooled sample have a following of both team and individual analysts. The minimum frequency of team report observations for a company in any industry is 20%, while the maximum frequency for any company is 97%. The trend for analyst team following is irrespective of company market-to-book ratio, suggesting that although analyst teams may be more likely to follow distressed companies, more factors than company distress precipitate team following.[22] The most experienced analysts follow the Transportation industry, at an average of 11.58 years, compared to 10.86 years in the Retail industry and 9.24 years in the Technology industry. The most experienced analyst in my sample has more than 23 years of experience. As in Abarbanell and Lehavy (2003), the forecast errors are skewed by highly optimistic forecasts (max scaled forecast errors – not tabulated).

[22]Market-to-book ratio is also a proxy for growth and sensitivity to risk, among other constructs. Within the non-winsorized sample, my extreme MTB observations reflect the bursting of the internet bubble. After winsorization the minimum and maximum MTB values are within expected norms. Thus my results are not driven by extreme values. I do not restrict my sample on stock price, but all of my companies are large and heavily followed.

(Insert Table 1 about here)

Panel B of Table 1 shows that the number of teams in my sample exceeds the number of individual analysts in all years. However, I define an analyst team as a unique, order-specific combination of analysts listed on a report because of the importance of the lead analyst. This means that if two analysts work together on a report and the order of their names changes, I treat each ordering as a unique team. From this definition, a random ordering of team member names would cause an artificial inflation in the team count if analyst teams increase in size over time.[23] To account for this possibility I also compare the number of unique lead analysts to individual analysts (untabulated). Even with this more restrictive requirement, I find that teams outnumber individual analysts and that the frequency of team observations increases over the sample period.

Table 1 Panel C documents sample statistics for analyst teams and individual analysts. Most teams are comprised of two members and remain together close to one year (across all companies).[24] Although the average tenure of analyst teams is short, the measure is deflated by analyst teams who only remain together for a single report, which is captured as a team tenure of zero days. The average earnings forecast bias of analyst team forecasts is approximately two-thirds of the magnitude of individual analyst forecasts. I also observe a greater dispersion of individual analyst forecasts than team forecasts, suggesting that one potential benefit of teamwork is a reduction of extreme forecasts. Lead analysts have, on average, about 11.58 years of experience to individual analysts' 8.84. At the 90th percentile,

[23] A team of size 2 has 2 possible combinations, while a team of size 3 has 6 possible combinations. Thus if the order of team names is random and teams increase in size, this definition could lead to artificially high team counts. This idiosyncrasy does not inflate team forecast observations.

[24] Prior literature accepts a classification of two as a 'team.' From Baker et al. (2006): "a *team* consists of two or more individuals, who have specific roles, perform interdependent tasks, are adaptable, and share a common goal". I adopt this definition for my main tests, but acknowledge other definitions exist (e.g. Marschak, 1955). Tests of cross-sectional differences in team size address alternative definitions of a team.

the experience of lead analysts and individual analysts differs by less than one and a half years.

Table 1, Panel D shows the Pearson correlation coefficients for my team and control variables. Although Brown and Hugon (2009) find that teams are more likely to follow distressed or larger companies, analyst teams and analyst team size are uncorrelated or only marginally correlated with MTB and number of segments in my sample. This indicates my empirical results are less likely to be driven by unrelated company variables. Teams are weakly associated with issuing forecasts earlier in the horizon, as are larger teams. The length of time a team has worked together does not appear to be associated with a tendency to issue forecasts earlier or later in the forecast horizon. The experience of lead analysts is positively associated with team tenure, suggesting teams with more senior lead analysts are likely to work together for longer periods of time.

CHAPTER 5. RESEARCH METHODS AND RESULTS

5.1 Measuring Absolute Forecast Error and Forecast Bias

While absolute forecast error captures the inaccuracy of analyst forecasts, forecast bias (i.e., signed forecast error) reflects the tendency for forecast errors to be signed in a particular direction. Two forecast errors of $0.05 and -$0.05 have equal absolute forecast error, but the former represents a forecast $0.10 cents more optimistic than the latter, and $0.05 cents more optimistic than reported EPS. Despite the close connection between absolute forecast errors and bias, forecast bias is likely to be driven by adverse incentives that differ between analyst teams and individual analysts (Lim, 2001). For this reason, I use both absolute forecast errors and forecast bias to capture forecast quality.[25]

Following prior literature, I measure forecast bias (i.e., signed forecast error), as the difference between the analyst forecast at time *t* and the actual EPS announced by the company on the earnings announcement date, scaled by the end of period price and multiplied by 100:

$$Bias = FE_t = \frac{Forecast_t - EPS}{Price} * 100$$

This definition means negative errors are interpreted as 'pessimistically biased' while positive errors are interpreted as 'optimistically biased.' Absolute forecast errors are the absolute value of the forecast error at the time of the forecast ($|FE|$).[26]

[25]Prior research has documented that the market may not be concerned with forecast bias so long as that bias is consistent over time (Hilary and Hsu, 2013). However, other authors have noted that less sophisticated market participants do not always unravel the effects of bias (Abarbanell & Bushee, 1997; 1998). Thus, while some market participants may be less impacted by forecast bias, I argue that bias is nevertheless an important characteristic of forecast quality.

[26]As Lim (2001) has noted, analysts may follow a quadratic loss function, in which case the absolute forecast error may not accurately capture forecast accuracy. In untabulated results I find the qualitative aspects of my findings remain unchanged using squared, rather than absolute, forecast errors.

5.2 Measuring Team Size and Tenure

Team size is measured as the number of unique analyst names appearing on the analyst report. In most cases analyst names appear on the first page of the report. However, in some circumstances (e.g., Lehman Brothers), only the lead analysts' name is present on the first page while team member names appear elsewhere. Names in the general text of the report are excluded. For Investext team reports on ThomsonOne that only show the lead analyst's name, I treat the team size as two.[27] Such reports are almost exclusively isolated to 1994 and make up an insignificant portion of my sample. My inferences are unchanged by excluding reports from 1994 from my analyses.

The order of names on the analyst reports is significant, and thus I record analyst names in my data set in the same order that they appear on the report. Lead analyst names (usually labeled as lead) are almost exclusively the first name listed, which reflects the importance of the lead analyst. By capturing the order of team names on a given report I am better able to control for the effect of analyst ability and experience in my empirical tests.

I calculate analyst team tenure as the difference between the date of an analyst team report and the date the team first appears in my data:

$$Tenure = Report\ Date - \ Initial\ Team\ Report\ Date$$

I measure tenure at across all companies in my data set and also at the individual company level. The length of time a team (2 to 4 analysts) has worked together, independent of which companies they follow, captures the effect of the development of both transactive and tacit memory. Team tenure across all companies is thus likely to

[27]These represent fewer than 50 reports in total.

illustrate the effect of specializing roles within teams on forecast quality. However, the length of time a team has worked together across companies may not capture instances where team member roles vary with the company being followed. Thus tenure is explicitly defined as either:

1. The number of days a team (set of 2 to 4 analysts) has worked together, independent of company followed, within my sample.
2. The number of days a team (set of 2 to 4 analysts) has worked together on the same company within my sample.

Because the lead and second analyst of a team tend to be more persistent than the third and fourth members, the above definitions may underestimate the tenures of larger teams. To address this concern I use additional definitions of tenure that reflect only the lead and second analyst:

3. The number of days the lead and second analyst worked together, independent of company followed, within my sample.
4. The number of days the lead and second analyst worked together on the same company within my sample.

5.3 Empirical Tests and Results

In all of my tests, I first examine the effect of working in teams, excluding tenure and size variables, to determine whether the forecasts of analyst teams statistically differ from the forecasts of individual analysts. I then examine the extent to which team tenure and team size impact the absolute error and bias of analyst team forecasts.

5.3.1 Full Sample Linear Regression of Team Characteristics

My first set of equations capture the degree to which absolute forecast error and bias are related to team size and tenure using my entire sample (analyst and company subscripts omitted for brevity):

$$|FE_t| = \beta_0 + \beta_1 Team + \beta_2 TeamSize + \beta_3 TeamTenure$$

$$+\beta_4 TeamTenureSq + Controls + e \text{ [1a]}$$

$$FE_t = \beta_0 + \beta_1 Team + \beta_2 TeamSize + \beta_3 TeamTenure$$

$$+\beta_4 TeamTenureSq + Controls + e \text{ [1b]}$$

β_1 captures the effect of working in a team, while β_2 measures the effect of team size. β_3 captures tenure. Because I expect a non-linear relationship between analyst team tenure and forecast quality, I also include the square of team tenure. I draw controls from Hutton (2005), including market-to-book ratio (MTB) and number of segments (Num_Seg). I also control for analyst experience. Lastly, I include a control for the number of days prior to the earnings announcement that a forecast is issued because analyst teams and individual analysts may issue forecasts at different times during the fiscal year.[28] I do not include controls for the number of analysts following the company, as every company in my sample is required to have a following of at least 5 analysts. Additionally, I do not include institutional ownership as a control given recent evidence that institutional ownership data may be unreliable during my sample period (WRDS, 2017). I include year and industry fixed effects, and cluster errors at the company level.

[28]Brown and Hugon (2009) measure 'forecast age' as days prior to the earnings announcement that a forecast is made, scaled by the range of forecasts issued in the same year. Their measure captures the relative timeliness of forecasts, while my measure of forecast horizon is explicitly intended to control for differences in the information available at the time of the forecast.

Given the widespread brokerage closures in the early 2000s (Kelly & Ljungqvist, 2012), the Global Analyst Research Settlements, and other regulatory interventions, the information environment of later years in my sample is likely to significantly differ from the information environment of earlier years.[29] In particular, brokerage closures may have allowed for the creation of high ability teams, while Reg FD may incrementally benefit analyst teams, as teams possess an enhanced ability to adapt to a changing information environment. To control for these changes around the turn of the century, I include a post-2000 indicator variable, as well as an interaction term between the team forecast and post-2000 indicator variables.

5.3.2 Full Sample Results: The Effect of Teamwork on Absolute Forecast Error

Table 2 reports the full sample differences in absolute forecast error between forecasts issued by analyst teams and forecasts issued by individual analysts. In the main effects column I observe that analyst teams appear to issue forecasts with statistically greater absolute forecast error than their individual peers given the positive coefficient on the team indicator, and controlling for market-to-book, the number of company segments, forecast horizon, and experience. However, the absolute forecast error of analyst team forecasts is lower than individual forecasts in the post-2000 period, as captured by the negative coefficient on the interaction of the team and post-2000 indicator variables. I confirm that the net effect of teamwork is a reduction in absolute forecast errors by running the same regression absent the post-2000 indicator variables (untabulated). On average

[29] Reg FD prohibited managers from selectively disclosing material company-specific information to market participants unless the information was shared to all market participants equally. In addition, the Sarbanes Oxley act, implemented in 2002, was likely to have influenced the post-2000 information environment by requiring companies to disclose enhanced financial statements and holding managers responsible for the contents of annual reports. In the latter case, it is likely that enhanced disclosures may have decreased the benefits of analyst teamwork.

analyst teams issue forecasts that have statistically smaller forecast errors than the forecasts issued by individual analysts over my entire sample period. These results support hypothesis H1a: analyst teams issue forecasts with smaller absolute forecast errors.

(Insert Table 2 about here)

Columns (1) through (4) of Table 2, which include only forecasts issued by analyst teams, capture the effect of team size and tenure on the absolute forecast errors of analyst teams. Unlike in the main effects column, the post-2000 indicator variable is not significant under any specification. This indicates that after the year 2000 individuals began to issue *less accurate* forecasts, rather than teams improving their accuracy in the post-2000 period. In all cases, neither team tenure nor its squared term are statistically significant. Thus Table 2 does not support that forecast quality is initially increasing and then decreasing in team tenure, regardless of the measure of tenure (H3). However, team size is statistically positively correlated with absolute forecast error in all columns: larger teams issue less accurate forecasts. Each additional team member is associated with a 6.9% - 8.8% increase in the magnitude of forecast error (0.0868/1.3292 and 0.1072/1.2200). Thus I conclude that team size is negatively associated with forecast quality.

The results in Table 2 illustrate that analyst teams issue forecasts that are higher quality than the forecasts issued by individual analysts, and the differences in forecast quality vary with the sample period under consideration. Thus, failure to consider analyst team membership in extant literature may result in either over- or under-estimation of the effects of incentives on analysts, depending on the time period studied. For instance, prior literature regarding Regulation Fair Disclosure suggests that analysts found a method to circumvent the requirement that managers not provide selective access to analysts, as forecast errors decrease in magnitude shortly after its implementation. These same results may instead reflect the concomitant shift in the number of analyst teams and their increased relative accuracy in the post-2000 time period.

5.3.3 Full Sample Results: The Effect of Teamwork on Forecast Bias

Although the results in Table 2 document that analyst teams issue forecasts with larger absolute forecast errors prior to 2000 and smaller post-2000 than their individual peers, Table 2 does not provide insight on whether the bias of forecasts issued by analyst teams differs from the bias of forecasts issued by individual analysts. Lim (2001) notes that analysts have incentives to trade statistically biased forecasts for inside information from management. These incentives are likely to differ between individual analysts and analyst teams. Analyst teams may not rely on management for access to inside information as much as individual analysts given that analyst teams possess superior ability to collect and interpret alternative sources of information. At the same time, both analyst teams and individuals are likely to be subject to pressure to generate business for their brokerage houses. Thus, I explore the bias of analyst team forecasts in Table 3.

(Insert Table 3 about here)

Table 3 reports the differences in forecast bias between forecasts issued by analyst teams and forecasts issued by individual analysts. In Table 3, the negative coefficient on the team indicator variable in the main effects column indicates that analyst teams issue forecasts that are less optimistically biased than their individual peers. A smaller degree of optimism in analyst team forecasts may indicate that analyst teams follow companies for whom the prospect is bleak, or that analyst teams are better able to unravel long-horizon optimism. Unlike in Table 2, neither the post-2000 indicator variable nor the interaction term is statistically significant in the main effects column.

I document the effect of team variables on the quality of analyst team forecasts in columns (1) through (4), in which only team forecasts are included. Team tenure is positively associated with forecast bias, for all measures of tenure, while tenure squared is negatively associated with forecast bias. Because analyst teams are on average more pessimistic than individual analysts, these jointly indicate that forecast bias decreases in magnitude initially (pessimism decreases) followed by an eventual decline (pessimism increases), in line with my predictions in H3. Moreover, I document a positive and significant coefficient for team size in columns (1) and (2), indicating that larger teams issue more optimistic forecasts than smaller teams. In conjunction with Table 2, larger teams issue forecasts that are more optimistic and that are less accurate than smaller teams. Hence, I reject H2 (null) and conclude that team size is negatively associated with forecast quality.

The results in Table 2 suggest that analyst teams issue forecasts that are less optimistically biased, where this reduced optimism is moderated by both the length of time the team has worked together and the size of the analyst team. Hence, when researchers consider factors that reduce forecast optimism, they must also consider the impact of working in teams. However, it is possible that the results found in Tables 2 and 3 reflect a tendency for analyst teams to follow different companies than individual analysts, as purported by Brown and Hugon (2009). If, for instance, analyst teams follow larger companies for whom the information environment is more complete, then the smaller absolute forecast errors I observe in analyst team forecasts may result from the information environment of the company rather than the impact of teamwork. Secondly, if analyst teams follow companies for whom prospects are bleak, analyst team forecasts will have a greater tendency to be pessimistic. I consider these possibilities in my next set of tests.

5.3.4 Within-Company Analysis of Forecast Quality

Equations [1a] and [1b] employ the standard controls for the analysts' information environment found in prior literature, but they are unable to perfectly control for the possibility that analyst teams follow different companies than individual analysts follow. If analyst teams and individual analysts follow different types of companies, or the same company in different life-cycle stages (as found in Brown and Hugon 2009), then the results of regression [1a] and [1b] could capture the effect of endogenous differences in company characteristics on forecast quality rather than the effect of teamwork.

To better control for unobservable company effects, I also test my first set of hypotheses using within company-year samples in a first differences test. I measure the difference in absolute forecast errors as the difference in the *average* absolute error of forecasts issued by analyst teams and the average absolute error of forecasts issued by individual analysts for the same company in the same year. In this way, I capture whether analyst teams or individual analysts issue forecasts with smaller absolute error in the same company-year. Differences in the absolute error of forecasts issued by teams and individual analysts are calculated as follows:

$$|FE_t|\ \mathrm{Diff}_{withincompany} = \frac{\Sigma\,|FE|_{Team}}{\#\,Teams} - \frac{\Sigma\,|\mathrm{FE}|_{\mathrm{Individual}}}{\#\,Solo}$$

This process cannot be used to calculate the difference between the bias of forecasts issued by analyst teams and forecasts issued by individual analysts, however, as forecast bias is a *signed* measure. To calculate the difference in forecast bias between team and individual analysts, only biases of the same sign can reasonably be compared—optimistic team forecasts vs. optimistic individual forecasts and pessimistic team forecasts vs. pessimistic individual forecasts.[30]

$$FE_t \text{ Diff}_{withincompany} = \frac{\Sigma FE_{Team}}{\# \, Teams} - \frac{\Sigma \text{FE}_{\text{Individual}}}{\# \, Solo}$$

$$\text{where } [\Sigma FE_{Team} and \Sigma \text{FE}_{\text{Individual}}] > 0 \text{ (optimistic)}$$

or

$$FE_t \text{ Diff}_{withincompany} = \frac{\Sigma FE_{solo}}{\# \, Solo} - \frac{\Sigma \text{FE}_{\text{teams}}}{\# \, Team}$$

$$\text{Where } [\Sigma FE_{Team} \; and \Sigma \text{FE}_{\text{Individual}}] < 0 \text{ (pessimistic)}$$

By definition, when both team and individual forecasts are greater than zero (optimistic), a negative FE_t $\text{Diff}_{withincompany}$ indicates that team forecasts on average have a smaller magnitude of *optimistic* bias than individual forecasts. When both team and individual forecasts are less than zero (pessimistic), a negative FE_t $\text{Diff}_{withincompany}$ would indicate that teams issue forecasts that have a smaller magnitude of *pessimistic* bias than do individual analysts. This setup ensures that negative coefficients on a variable can be interpreted as being correlated with a reduced magnitude of bias. I include an indicator variable for optimism when both team and individual forecasts are optimistic, to preclude the possibility that any difference in forecast bias is contingent on forecasts being optimistic/pessimistic. My second (within-company) regressions are as follows:

$$|FE_t| \text{ Diff}_{withincompany} = \beta_0 + Controls + e \text{ [2a]}$$

[30] My objective is to determine what factors impact the magnitude of analyst team forecast bias. Comparing average forecasts that are in disagreement may allow me to determine which forecasts are more 'optimistic', but not whether these forecasts have a smaller magnitude of forecast bias. That is, when comparing two pessimistic forecasts, one is always more 'optimistic' than the other, but is simultaneously less biased. In untabulated tests I do not require forecasts of the same sign for comparison and find the main results on the intercept are unchanged.

$$FE_t \text{ Diff}_{withincompany} = \beta_0 + Controls + e \text{ [2b]}$$

The dependent variable in equations [2a] and [2b] captures the difference in the average forecast errors of analyst teams and the average forecast errors of individual analysts. In equation [2a] and [2b], the intercept captures the average degree to which forecasts issued by analyst teams are less biased or have smaller forecast error. Given that companies are held constant in this test by construction, controls instead capture the differences between analyst teams and individual analysts that are unrelated to my research question but are related to forecast quality. For this reason, I control for the difference in analyst experience, where I measure experience as the difference in days between the report date and the date of the first appearance of the lead/individual analyst code on I/B/E/S.[31] In addition, I include an indicator variable for the post-2000 period as these comparisons are within company-year. I delete observations where only one team or individual forecast is issued per company-year to reduce the likelihood that outliers drive my results.

Although I control for the tendency of analyst teams to follow different types of companies than individual analysts, I do not observe the brokerage-level decision making process which results in analyst teams being assigned to follow some companies and not others. As a result, this test does not control for selection. However prior literature notes that the analyst forecasting process is largely unobservable (Ramnath et al., 2008; Bradshaw 2011; Brown et al. 2015), and this test controls for two determinants of analyst teamwork that are likely to impact the reasonability of my inferences (Brown and Hugon, 2009).

[31]This definition has the potential to under-estimate the experience of analysts, as many analysts participate in team reports but are not included in I/B/E/S files. Unfortunately, there are few alternative methods of capturing analyst experience.

5.3.5 Within-Analyst Analysis of Forecast Quality

Analysts who work in teams may also differ in ability or type from analysts who work alone (e.g. Jacob et al. 1999; Clement et al. 2007). As analysts become more competent they may be more likely to be assigned as leads to analyst teams. Alternatively, the most able analysts may find no need to work in teams, although this latter possibility works against finding differences in forecast quality between teams and individual analysts.

To control for the possibility that differences in analyst ability or type influence my findings I compare the forecasts of analysts who work as the lead in a team to the forecasts issued when the same analyst issues reports alone. A within-analyst design controls for analyst ability and type but reintroduces company effects specific to the first equations ([1a] and [1b]) as analysts who issue reports as part of a team and also issue reports individually tend not to do so for the same company in the same year.

$$|FE|\ \mathrm{Diff}_{analysttoself} = \beta_0 + Controls + e \text{ [3a]}$$

$$FE\ Diff_{analysttoself} = \beta_0 + Controls + e \text{ [3b]}$$

In equations [3a] and [3b] the dependent variable is the difference in the average forecast error of analyst teams less the average forecast error of individual analysts, where the lead analyst of the team and the individual analyst are the same individual. My controls address the difference in the companies an analyst follows when providing forecasts as an individual and when providing forecasts as the lead of a team. I return to company-specific controls that mirror the controls used in the first regression [1a] and [1b]. Controls in [3a] and [3b] are the differences in market-to-book ratio and the difference in the number of company segments. I also control for differences in analyst experience, since assignment as a lead analyst may reflect career advancement and for differences in the days prior to an earnings announcement that forecasts are issued. I do not include an indicator variable for the post-2000 period because the dependent variable is the difference in mean of an analysts' individual and team forecast errors across the entire sample period.

5.3.6 Within-Company Regression Results

As both team forecasts and individual forecasts are averaged, the number of observations in the second regression is significantly reduced, from 7,462 analyst forecasts to 303 company-years.

(Insert Table 4 about here)

Table 4 reports the differences in the average absolute and signed forecast error of analyst teams and individual analysts, within company-year (left) and within-analyst (right). The absolute forecast error column of the within-company set in Table 4 shows that, consistent with my full sample results, teams issue forecasts with statistically reduced absolute forecast errors in the post-2000 period. In an untabulated F-test, the net effect of teamwork on absolute forecast error is one of reduction: analyst teams issue forecasts with smaller absolute forecast errors, even controlling for the tendency of analyst teams to follow different companies than individual analysts.

In the forecast bias column of my within-company tests I observe that analyst teams issue statistically less pessimistic forecasts than individual analysts in the post-2000 period, even controlling for the tendency of analyst teams to follow different types of companies or the same companies in different life stages. Specifically, analyst teams issue forecasts (within company-year) that are similarly biased to the forecasts issued by individual analysts prior to 2000. Because these results reflect a first differences test they cannot clarify whether analyst teams issued less biased, more accurate forecasts after 2000 or whether individual analysts began to issue forecasts that were more biased and less accurate.

5.3.7 Within-Analyst Regression Results

Table 4 also reports the difference in the absolute forecast error between analysts when they issue forecasts as the lead member of a team and when the same analyst issues forecasts alone. I find that when an analyst issues a forecast as the lead of a team, they issue forecasts that have insignificantly different absolute forecast error compared to when the same analyst issues forecasts alone. This may reflect that the team environment functions as a training ground for new analysts. Alternatively, if analysts who work alone request a team member when the analyst faces significant uncertainty, then the lack of results are likely to reflect teamwork offsetting the negative effects of uncertainty. Similarly, results in Table 4 may reflect challenges associated with mentorship in analyst teams. Unfortunately, absent the capacity to separate company and year specific effects from analyst ability, the results in Table 4 must be interpreted with caution.

The final column of Table 4 captures the difference in bias between the forecasts of analysts when they issue forecasts as the lead member of a team than when they issue forecasts alone. As with absolute forecast error, forecast bias does not significantly differ when an analyst issues forecasts as the lead of a team than when the same analyst issues alone. Because the within-analyst tests did not reveal statistically significant results, I cannot rule out that analyst ability at least partly drives the higher forecast quality of analyst teams. However, it is unlikely that analyst ability changes with the length of time a team has worked together or with the size of an analyst team, leaving inferences regarding analyst team characteristics unchanged.

5.4 The Walk-Down in Forecast Bias of Teams and Individual Analysts

In addition to examining the magnitude and frequency of forecast bias, prior literature has also considered the trend of forecast bias over the forecast horizon (Richardson et al., 2004). In figure 2 I examine whether the walk-down pattern observed by Richardson et al. (2004) is attenuated for forecasts issued by analyst teams. Following Richardson et al. (2004), I graph the median forecast error for teams and individuals in a side-by-side comparison. As teams and individuals could forecast at different times during the year, I also evaluate the average horizon at which team and individual forecasts are generated. I find that individual analysts issue more reports around earning announcements while teams issue reports smoothly across the earnings horizon. These differences are not statistically significant.

(Insert Figure 2 about here)

In Figure 2, I observe that analyst team forecasts exhibit a smaller magnitude of forecast bias at long horizons, consistent with theories that suggest forecast bias is influenced by information and uncertainty (Brightbill et al., 2017). By three months prior to the earnings announcement date, the median forecast error of reports issued by teams and individual analysts are virtually identical. Given prior literature that suggests short horizon pessimism is evidence of catering to management (Richardson et al., 2004), the results documented in Figure 2 suggest that teams may not be immune to incentives to cater.

5.5 Team Tenure and Forecast Quality: An Inverted U-Shaped Relation

I base my third hypothesis - that the quality of forecasts issued by analyst teams follows an inverted u-shaped over team tenure - on prior research that documents a non-linear relationship between the quality of team and the length of time a team has worked together. In Table 3, the significance and sign of the coefficients on the tenure (positive) and tenure-squared (negative) provided a statistical test of this hypothesis. From these I conclude that forecast bias follows an inverted u-shaped pattern over time, but absolute forecast errors (Table 2) do not. I illustrate this in Figure 3:

(Insert Figure 3 about here)

In Figure 3, I illustrate the relationship between team tenure and the forecast bias of analyst teams. Consistent with my hypothesis, I find that analyst teams are the most biased in the first and fifth quintiles of team tenure.[32] However, teams do not appear to follow the same trend in calendar time. Teams of two years appear to be the most biased, while teams of one and three years provide less biased forecasts. However, analyst teams are, on average, pessimistic. Thus the calendar time trend illustrates that analyst teams become less pessimistic over time, to a point of minimum pessimism, and then increase in pessimism again. This suggests that team tenure is an important factor to consider when evaluating the quality of forecasts issued by analyst teams.

5.6 Robustness Tests

In addition to my main tests documenting the impact of working in teams on the quality of analyst forecasts, I run a battery of robustness tests to support the validity of my

[32]The change in bias from the third to fourth quintile, while dramatic, is not unexpected given my hypothesis. However, the magnitude may reflect in part that 'quintile' of tenure collects one fifth of all analyst-team observations, and thus covers a different length of time than quintiles 1, 2, 3, and 5.

conclusions. In all cases my results are robust to the exclusion of observations from 1994, during which my tenure variable may be artificially deflated, to clustering by industry rather than company (where applicable), to the exclusion of industry and year fixed effects (where applicable), and to the exclusion of my post-2000 indicator variables (where applicable).

5.6.1 Percent Frequency of Optimistic Forecasts

Although my within-company and within-analyst tests on the effect of teamwork on forecast bias highlighted whether analyst teams issued statistically less biased forecasts, my tests did not shed light on the relative frequency of issuing optimistic or pessimistic forecasts.

Table 5 reports the effect of working in teams on the frequency of issuing optimistic forecasts (% of optimistic forecasts). In the full-sample column I find that analysts issue optimistic forecasts approximately 59% of the time, an effect attenuated by working in a team. Analyst teams issue optimistic forecasts only 53% of the time, or approximately ten percent less frequently than individual analysts. In conjunction with my prior results, I conclude that analyst teams issue forecasts with a smaller magnitude of optimism in part through an increase in the frequency of pessimistic forecasts. However, the within-company column demonstrates that this result is not due exclusively to the tendency for analyst teams to follow different companies or companies for whom the prospect is bleak; analyst teams issue less frequent optimistic forecasts even for the same company in the same year. Further, this trend is irrespective of time period, and does not appear to be driven by the tendency for pessimistic analysts to work in teams (within-analyst column).

5.6.2 Effect of Teamwork on Last Forecast in Period

As a final test, I explore whether analyst teams continue to issue more accurate or less biased forecasts even as the earnings announcement nears. In Table 6 I examine whether the final forecast issued by analyst teams are less biased or have a smaller magnitude of error than the last forecast issued by individual analysts. Similar to prior results, I find that analyst teams issue final forecasts that have a smaller magnitude of error than individual analysts, but only in the post-2000 period. In untabulated tests, analyst teams are no more accurate than individual analysts by the last forecast of the horizon in the full sample. Analyst teams are equally biased by the last forecast of the horizon. Jointly, these results indicate that the forecast benefits associated with analysts working in a team are largely observed at longer horizons.

5.7 Discussion

My results are consistent with theory and evidence from the team literature: analyst teams issue forecasts that systematically differ from those issued by individual analysts. However, the interpretation of my results is subject to several caveats. First, although I attempt to control for the tendency of analyst teams to follow different kinds of companies than individual analysts, I do not observe the team-making process and thus do not perfectly control for why brokerages select teams to follow some companies and not others. Secondly, although I attribute forecast differences to 'teamwork,' these differences may result either from the cooperative nature of teams or from the tendency for larger numbers of people to be more accurate than individuals. That is, it is possible that averaging the forecasts of individual analysts might approach the accuracy of teams. Thus I do not conclude it is the act of engaging in teamwork *per se* that drives my results. Despite this, my primary objective is to document the differences between analyst team forecasts and individual forecasts, as these differences have largely not been controlled for in prior literature. Lastly, as the majority of analyst teams in my sample are comprised of only two analysts, my results with respect to team size should be interpreted cautiously.

I also make no claim as to whether working in teams is objectively ‘better’ – either for the respective analysts or for the market as a whole. Given that analysts work in teams and individually within the same brokerage houses, for the same companies, and across time, it is probable that working individually is at least sometimes preferable to working in teams. If analyst teams were exclusively better then individual analysts should not be present in my sample in equilibrium.

CHAPTER 6. CONCLUSION

Prior literature has largely ignored the presence and consequences of analyst teams, with the exception of Brown and Hugon (2009). In part, the lack of researcher interest may stem from a belief that analyst teams are comparatively rare. Using a hand collected sample of more than 17,000 analyst reports I document that analyst teams are common, that the use of analyst teams has increased more than four-fold from the mid-1990s to the mid-2000s, and that the increase in analyst teams occurred for a sample of large, heavily followed companies. By the end of my sample, analyst team observations outnumber individual observations nearly three to one.

As Bagnoli et al. (2008) document, investor preferences in *Institutional Investor* shift toward analysts providing 'accessibility and responsiveness' and 'timely calls and visits' by the late 1990s. Brokerage houses may encourage working in teams to meet these changing market expectations. If this is the case, then any effect on the properties of forecasts would be secondary to changes in the frequency of reports or other unobservable analyst characteristics. Thus teamwork plausibly has no impact on the error or bias of analyst forecasts absent unintended spill-over. Instead, I document that forecasts issued by analyst teams vary in predictable and statistically significant ways from the forecasts issued by individual analysts.

I find that analyst teams issue more accurate forecasts than individual analysts, but this effect is largely driven by the post 2000 period. After 2000, brokerage closures and regulatory changes appear to shift the relative benefits of analyst teamwork on forecast quality. Furthermore, relative to individual analysts, I find that analyst teams issue less pessimistically biased, but not less optimistically biased,[33] one-year-ahead earnings-per-share (EPS) forecasts within the same company-year. Overall, analyst teams issue optimistic forecasts less frequently and on average exhibit smaller optimistic biases. I conclude that analyst teams issue forecasts of higher quality than the forecasts issued by individual analysts.

I also find that team characteristics are associated with the quality of forecasts issued by teams. A team that has been together one year has a scaled forecast bias that is 17% more optimistic on average than a team producing its first forecast. At the same time, teams in the third quintile of tenure are the least biased. Thus brokerage houses might benefit from periodically rearranging team assignments. When team size is a statistically significant factor, it generally appears to be detrimental to forecast quality. I find that each additional team member is associated with an increase in the magnitude of forecast error and optimistic bias. Both the length of time an analyst team has worked together and the number of members in an analyst team impact the quality of the forecasts issued by that team.

I also document that analyst team forecasts exhibit smaller bias than the forecasts of individual analysts at long horizons, but virtually identical pessimistic errors at short horizons. Given that prior research suggests that short-horizon pessimism is linked to catering to management (Richardson et al., 2004), the tendency for teams to exhibit pessimism at short horizons suggests teams may not be immune to catering to management, perhaps because incentives to acquire business for analysts' brokerage house is present

[33]That is, when analyst teams issue pessimistic forecasts, those forecasts tend to be less pessimistic (closer to 0 error) than pessimistic forecasts issued by individual analysts in the same company-year. When analyst teams issue optimistic forecasts, those forecasts are equally optimistic relative to individual analysts in the same company year. Thus, teams issue less pessimistically but not less optimistically biased forecasts.

irrespective of analysts working in teams. Analyst teams also issue optimistic forecasts less frequently than individual analysts, even controlling for the tendency of analyst teams to follow different types of companies. By the last forecast of the horizon, analyst teams do not issue higher quality forecasts than individual analysts, suggesting the benefits of team work are better observed at long horizons. Taken together, my results reveal systematic differences in the quality of forecasts issued by analyst teams and individual analysts.

Finally, my research contributes to the team literature, as the sell-side analyst reporting environment provides a powerful, large-sample setting to examine the impact of teams in a professional, real-world setting. Team research typically uses experiments or field research to identify differences between teams and individuals, which can be attributed to the difficulty in gathering broad, team-based data in archival settings. This constraint is not present in my study, and thus I document that much of the experimentally captured effects of working in teams translates into verifiable real-world consequences.

My results provide insight into the differences between forecasts issued by analyst teams and forecasts issued by individual analysts. However, teamwork is likely to impact not only forecasts but also a number of other research products important to the market. Future research on analyst teams could document whether analyst teams provide more profitable buy/sell recommendations, whether analysts in teams appear to be protected from adverse career outcomes, whether working in analyst teams explains disagreement in the literature on the contribution of analyst experience to forecast quality, and whether analysts who work in teams are able to benefit from the transactive memory of their teams even for companies on which they forecast individually. Further, my research documents the output of analyst teams without insight into the 'black box' of how or why analyst teams are formed. Future research should consider the determinants of forming analyst teams.

APPENDIX A. TABLES

Table A1.A Descriptive Statistics by Industry

Panel A: Selected sample statistics for companies in the Transportation, Retail, and technology industries.

Transportation (2030)				
Variable	Mean	25th Pctl	Median	75th Pctl
Market to Book	1.80	1.25	1.98	3.20
Percent Team	0.80	0.77	0.81	0.88
Scaled Forecast Error	0.45	-0.28	0.05	0.99
Abs Forecast Error	1.35	0.16	0.55	1.73
Experience	4228	2541	4877	6076

Retail (2550)				
Variable	Mean	25th Pctl	Median	75th Pctl
Market to Book	3.06	1.75	2.49	3.64
Percent Team	0.72	0.63	0.75	0.80
Scaled Forecast Error	0.57	-0.29	0.45	1.07
Abs Forecast Error	1.20	0.35	0.72	1.38
Experience	3963	1741	4497	5559

Technology (4510)				
Variable	Mean	25th Pctl	Median	75th Pctl
Market to Book	6.24	2.31	3.97	7.59
Percent Team	0.73	0.69	0.72	0.88
Scaled Forecast Error	0.61	-0.27	0.00	0.94
Abs Forecast Error	1.27	0.14	0.46	1.46
Experience	3371	1390	3359	5237

Descriptive statistics for 89 companies in the Retail, Technology, and Transportation industries from 1994-2005. The 'percent team' statistic documents that between 70 and 80 percent of all reports are issued by teams for each industry in my sample. MTB, Scaled Forecast Error, and Absolute Forecast Error are measured as described in the appendix. As in Abarbanell and Lehavy (2003), forecast errors are skewed by highly optimistic forecasts. Analysts in the transportation industry have the most experience (measured in days), on average, while those in technology have the least experience.

Table A1.B Frequency of Team and Individual Observations

Panel B: The frequency of unique analyst teams and individual analysts by year.

Year	Team	Individual	Total	% Team	% Ind
1994	61	63	124	49.19%	50.81%
1995	82	44	126	65.08%	34.92%
1996	108	66	174	62.07%	37.93%
1997	135	85	220	61.36%	38.64%
1998	174	102	276	63.04%	36.96%
1999	201	111	312	64.42%	35.58%
2000	224	103	327	68.50%	31.50%
2001	222	96	318	69.81%	30.19%
2002	278	79	357	77.87%	22.13%
2003	264	76	340	77.65%	22.35%
2004	295	108	403	73.20%	26.80%
2005	278	105	383	72.58%	27.42%

The frequency of unique analyst teams and indivual analysts by year from 1994-2005 for a sample of 89 large, heavily followed companies in the Retail, Technology, and Transportation industries. A unique team is defined as the unique order specific combination of two or more analysts listed on one report.

Table A1.C Team and Individual Sample Statistics

Table 1 Cont'd

Panel C: Mean, standard deviation, 10^{th} and 90^{th} percentile statistics for analyst teams and individual analysts.

	Team				Individual			
Variable	10th Pctl	90th Pctl	Mean	Std Dev	10th Pctl	90th Pctl	Mean	Std Dev
Team Size	2	3	2.30	0.52				
Tenure (Full Team) Across Companies	0	585	255.07	285.46				
Tenure (Full Team) Within Company	0	517	213.52	247.39				
Tenure (Lead/2nd) Across Companies	0	735	323.55	329.61				
Tenure (Lead/2nd) Within Company	0	626	261.39	285.53				
MTB	1.18	7.38	3.60	10.39	1.22	7.09	3.36	14.99
FE	-0.96	2.31	0.46	1.88	-0.80	3.08	0.71	2.17
|FE|	0.06	3.25	1.22	1.69	0.06	3.52	1.35	1.99
Analyst Experience (Days)	861	6783	4227.3	2176.71	350	6279	3226	2223.43

Scaled forecast errors are defined as the difference between the actual yearly EPS and the analyst forecast, divided by end of period price. Team tenure is as defined in the appendix. Tenure and analyst experience are measured in days. Analyst team size is measured as the number of analyst names identified on an analyst report. Analyst teams are usually composed of two members and work together on average slightly less than one year. The lead analysts of teams are more experienced than individual analysts (4096 days vs 3214 days), and analyst teams issue forecasts with smaller optimistic forecast errors (0.46 vs 0.71). Both analyst teams and individual analysts follow firms with similar MTB.

Table A1.D Pearson Correlation Coefficients

Panel D: Pearson Correlation Coefficients

Variable	Team		Size		Tenure		Tenure^2		MTB		Number of Segments		Experience		Post 2000		Post 2000 x Team		Days Before EA
Team	1.00																		
Size	0.83	***	1.00																
Tenure	0.46	***	0.29	***	1.00														
Tenure Sq	0.10	***	0.02	*	0.71	***	1.00												
MTB	0.00		-0.02	*	-0.06	***	-0.04	***	1.00										
# Segments	-0.02	**	-0.01		0.02	**	0.06	***	-0.01		1.00								
Experience	0.21	***	0.20	***	0.20	***	0.11	***	-0.01		0.00		1.00						
Post 2000	0.14	***	0.21	***	0.13	***	0.04	***	-0.10	***	0.06	***	0.13	***	1.00				
Post 2000 x Team	0.69	***	0.65	***	0.38	***	0.09	***	-0.07	***	0.03	***	0.21	***	0.66	***	1.00		
Days Before EA	0.05	***	0.05	***	0.01		-0.01		0.07	***	-0.02	*	0.01		-0.02		0.03	***	1.00

Pearson Correlation coefficients for team and control variables. Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and hand-collected from ThomsonOne Analyst Reports. Although Brown and Hugon (2009) find that teams are more likely to follow distressed or larger firms, in my sample both presence in a team and team size are either uncorrelated or only marginally correlated with MTB and number of segments. This provides support for presence in teams - rather than firm variables - driving my results. Teams are weakly associated with issuing forecasts earlier in the horizon, as are larger teams. The length of time a team has worked together does not appear to be associated with tendencies to issue earlier or later in the forecast horizon. The experience of lead analysts is positively associated with team tenure, suggesting teams with more senior lead analysts are likely to work together for longer periods.

Table A2 Full Sample Regression of Absolute Forecast Errors

Full Sample linear regression of scaled forecast errors on team characteristics including size and tenure.

$$|FE| = \beta_0 + \beta_1 Team + \beta_2 TeamSize + \beta_3 TeamTenure + \beta_4 TeamTenureSq + controls + e$$

Variable	Main	Full Team (1)	Full Team (2)	Lead/2nd (3)	Lead/2nd (4)
Intercept	1.1430 ***	1.3292 ***	1.2562 ***	1.3186 ***	1.2200 ***
	(10.80)	(7.77)	(7.52)	(7.85)	(7.37)
Team	0.2260 ***				
	(3.04)				
Team Size		0.0868 *	0.0866 *	0.1082 **	0.1072 **
		(1.69)	(1.70)	(2.09)	(2.09)
Tenure		0.0000	-0.0001	-0.0001	-0.0001
		(-0.22)	(-0.93)	(-0.93)	(-0.82)
Tenure Squared		-0.0001	0.0000	-0.0001	0.0000
		(-0.77)	(0.08)	(-0.82)	(-0.04)
Post 2000	0.4214 ***	-0.0990	-0.0296	-0.1056	-0.0355
	(3.52)	(-0.70)	(-0.21)	(-0.74)	(-0.25)
Post 2000 x Team	-0.3614 ***				
	(-3.87)				
MTB	-0.0498 ***	-0.0564 ***	-0.0549 ***	-0.0565 ***	-0.0547 ***
	(-11.25)	(-13.88)	(-10.12)	(-10.15)	(-9.96)
# Segments	-0.0011	-0.0138	-0.0120	-0.0147 *	-0.0129
	(-0.15)	(-1.59)	(-1.39)	(-1.68)	(-1.48)
Days Prior	-0.0033 ***	-0.0030 ***	-0.0030 ***	-0.0030 ***	-0.0030 ***
	(-17.90)	(-13.88)	(-13.94)	(-13.74)	(-13.80)
Experience	0.0000 ***	0.0000	0.0000	0.0000	0.0000 ***
	(-5.38)	(-0.91)	(-1.13)	(-0.75)	(-1.15)
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
N	7462	4832	4897	4798	4865
R2	0.1120	0.1116	0.1089	0.1132	0.1095

Scaled forecast errors are defined as the difference between the actual yearly EPS and the analyst forecast, divided by end of period price and multiplied by 100. Scaled forecast errors are winsorized at the 1st and 99th percentiles. Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and hand-collected from ThomsonOne Analyst Reports. The (Main) column captures the main team effect in the full cross-section: Teams issue forecasts with greater errors prior to 2000, but post 2000 this effect is reversed. Columns (1)-(4), which include only team forecasts, illustrate that only team size is correlated with forecast errors. In all specifications an additional team member is associated with an increase in the magnitude of forecast errors. Year and Industry fixed effects are included in all columns. Errors are clustered at the firm level (GVKEY).

Table A3 Full Sample Regression of Scaled Forecast Bias

Full sample linear regression of the scaled forecast bias on team characteristics, including size and tenure.

$$FE = \beta_0 + \beta_1 Team + \beta_2 TeamSize + \beta_3 TeamTenure + \beta_4 TeamTenureSq + controls + e$$

Variable	Main	Full Team (1)	Full Team (2)	Lead/2nd (3)	Lead/2nd (4)
Intercept	0.1843	-0.4059 **	-0.3949 **	-0.3192	-0.3285 *
	(1.55)	(-2.01)	(-2.03)	(-1.61)	(-1.71)
Team	-0.1912 **				
	(-2.29)				
Team Size		0.1245 **	0.1212 **	0.0730	0.0758
		(2.25)	(2.21)	(1.32)	(1.39)
Tenure		0.0005 ***	0.0006 ***	0.0005 ***	0.0007 ***
		(3.53)	(3.49)	(3.75)	(4.21)
Tenure Squared		-0.0003 ***	-0.0004 *	-0.0003 ***	-0.0005 ***
		(-3.02)	(-1.92)	(-3.23)	(-2.77)
Post 2000	-0.0972	-0.2568	-0.2329	-0.2600	-0.2289
	(-0.72)	(-1.49)	(-1.37)	(-1.50)	(-1.34)
Post 2000 x Team	0.0225				
	(0.22)				
MTB	-0.0460 ***	-0.0440 ***	-0.0437 ***	-0.0440 ***	-0.0437 ***
	(-9.76)	(-7.81)	(-7.83)	(-7.75)	(-7.80)
# Segments	-0.0004	-0.0090	-0.0094	-0.0093	-0.0100
	(-0.04)	(-0.88)	(-0.93)	(-0.90)	(-0.98)
Days Prior	-0.0028 ***	-0.0023 ***	-0.0023 ***	-0.0023 ***	-0.0023 ***
	(-14.15)	(-9.45)	(-9.54)	(-9.35)	(-9.42)
Experience	0.0000	0.0000	0.0000	0.0000	0.0000
	(-0.13)	(-0.81)	(-0.94)	(-0.70)	(-0.84)
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
N	7462	4832	4897	4798	4865
R2	0.0639	0.0598	0.0594	0.0601	0.0605

Scaled forecast errors are defined as the difference between the actual yearly EPS and the analyst forecast, divided by end of period price and multiplied by 100. Scaled forecast errors are winsorized at the 1st and 99th percentiles. Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and hand-collected from ThomsonOne Analyst Reports. The (Main) column captures the main team effect: Team forecasts are less optimistically biased than individual analyst forecasts. Columns (1)-(4), which include only forecasts issued by teams, document that additional team members, as captured by size, are associated with an increase in the magnitude of team forecast optimism. This effect only holds true when considering the tenure of the entire team, suggesting that teams with stable lead and second analysts perform consistently regardless of team size. The negative coefficient on all tenure squared variables, in conjunction with positive tenure coefficients, illustrate that the bias found in team forecasts follows an inverted u-shape pattern. Year and Industry fixed effects are included in all columns. Errors are clustered at the firm level (GVKEY).

Table A4 Within-Analyst and Within-Company Regressions

Regression of the differences in average absolute and signed scaled forecast errors between teams and individual analysts within company year and within-analyst on differences in team characteristics including size and tenure.

	Within Company				Within Analyst			
Variable	|FE|		FE		|FE|		FE	
Intercept	-0.0032		0.0255		0.0926		-0.1495	
	(-0.03)		(0.16)		(0.47)		(-0.59)	
Post 2000	-0.3591	***	-0.6026	***				
	(-2.71)		(-3.55)					
Optimistic			0.1067				-0.2096	
			(0.58)				(-0.21)	
MTB					-0.0677		0.0286	
					(-1.61)		(0.68)	
Number Seg					-0.1208		-0.0745	
					(01.11)		(1.10)	
Days Prior	-0.0043	***	-0.002		-0.0039	*	0.0015	
	(-4.85)		(-1.46)		(-1.94)		(0.74)	
Experience	0.0000		0.0000		0.0003		0.0003	
	(0.72)		(-0.12)		(1.10)		(1.10)	
Industry FE	Y		Y		N		N	
Year FE	N		N		N		N	
N	303		303		155		155	
R2	0.1627		0.0565		0.0544		0.0216	

Scaled forecast errors are defined as the difference between the actual yearly EPS and the analyst forecast, divided by end of period price. Differences in errors are defined as the difference between the average error for teams and individual analysts within a firm-year and for the same analyst for the within-analyst tests. Scaled forecast errors are winsorized at the 1st and 99th percentiles. Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and hand-collected from ThomsonOne Analyst Reports. The within-company tests illustrate that, within the same company year, analyst teams issed more accurate, less biased forecasts but only in the post-2000 period. The within-analyst tests capture that, controlling for the ability of the lead analayst, analyst teams do no issue forecasts that are differently biased or more or less accurate than forecasts issued by the lead analyst alone.

Table A5 Percent Frequency of Optimist Forecasts by Teams

Regressions of the percent frequency of optimistic forecasts by analysts on team characteristics, including size and tenure, and comparing the difference in absolute forecast error within company-year, and within-analyst.

Variable	Full Sample	Team Only	Within Company	Within Analyst
Intercept	0.5883 ***	0.5459 ***	-0.1340 ***	-0.0394
	(37.48)	(21.20)	(-5.36)	(-1.06)
Team	-0.0592 ***			
	(-5.67)			
Team Size		0.0107 *		
		(1.68)		
Tenure		0.0000		
		(1.10)		
Tenure Squared		-0.0001 ***		
		(-5.45)		
Post 2000	0.0202	-0.0110	0.0483	
	(1.28)	(-0.56)	(1.61)	
Post 2000 x Team	-0.0059			
	(-0.47)			
MTB	-0.0050 ***	-0.0063 ***		0.0032
	(-7.43)	(-7.53)		(0.32)
# Segments	-0.0028 ***	-0.0052 ***		0.0243
	(-2.87)	(-4.36)		(1.03)
Days Prior	0.0000	0.0000	-0.0003	-0.0001
	(0.88)	(0.53)	(-1.48)	(-0.14)
Experience	0.0000	0.0000	0.0000	0.0000
	(-1.06)	(0.73)	(0.37)	(-0.53)
Industry FE	Y	Y	Y	N
Year FE	Y	Y	N	N
N	6942	4558	274	106
R2	0.1055	0.1174	0.0437	0.0121

Percent optimistic forecast errors are defined as the number of positive forecast errors by analyst (team) divided by the total number of forecasts for the same analyst (team). Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and hand-collected from ThomsonOne Analyst Reports. The 'Full Sample' column, which includes both team and individual forecasts, captures the main team effect: teams issue fewer optimistic forecasts than individual analysts. The 'Team Only' column includes only team forecasts, captures tenure as defined in the appendix, and shows that larger teams issue more optimistic forecasts than smaller teams. 'Within-Company' regresses the difference between the average percentage of optimistic forecast errors of solo analysts and analyst teams within the same company in the same year, while 'Within-Analyst' regresses the difference between in percent optimistic forecast errors of a lead analyst working alone and the same analyst working in a team.Within-Company, I find that analyst teams issue less optimistic forecasts on average. I do not find that the percentage of optimistic forecast errors of lead-analysts in a team differ from the forecasts of the same analyst working alone.

Table A6 Regression of Errors of Last Forecast of Fiscal Year

Regressions of the scaled absolute forecast error and bias on team characteristics, including size and tenure, for the last forecasts made in a given fiscal year.

	FE				|FE|			
Variable	Full		Team Only		Full		Team Only	
Intercept	0.6348	***	0.2248		1.4488	***	1.5932	***
	(3.10)		(0.56)		(7.58)		(4.22)	
Team	-0.1422				0.3066	**		
	(-1.03)				(2.37)			
Team Size			0.0212				0.0756	
			(0.17)				(0.64)	
Tenure			0.0001				-0.0004	
			(0.32)				(-1.14)	
Tenure Squared			0.0006				0.0005	
			(1.38)				(1.26)	
Post 2000	-0.2448		-0.2512		0.8844	***	0.5538	**
	(-1.08)		(-0.86)		(4.19)		(2.02)	
Post 2000 x Team	-0.0602				-0.4395	**		
	(-0.33)				(-2.57)			
MTB	-0.0427	***	-0.0365	***	-0.0466	***	-0.0525	**
	(-4.56)		(-2.88)		(-5.32)		(-4.40)	
# Segments	0.0006		-0.0143		0.0114		-0.0031	
	(-0.39)		(-0.66)		(0.71)		(-0.15)	
Experience	0.0000		0.0000		-0.0001	***	0.0000	
	(0.38)		(-0.05)		(-2.97)		(-0.65)	
Industry FE	Y		Y		Y		Y	
Year FE	Y		Y		Y		Y	
N	1922		1062		1922		1062	
R2	0.039		0.058		0.0733		0.0845	

Data is derived from the I/B/E/S summary and detail files, Compustat Historical Segment and Fundamental Annual files, and hand-collected from ThomsonOne Analyst Reports. The 'Full Sample' column, which includes both team and solo forecasts, captures the main team effect. The 'Team Only' column includes only team forecasts, captures tenure as defined in the appendix, and illustrates that team characteristics do not moderate absolute or signed forecast error in the last forecast issued before an earnings announcement. The full sample columns, which capture the main effect of teamwork on forecast error and bias in the last forecast of the horizon, show that teams are not differently biased in the last forecast of the horizon but do issue forecasts with smaller forecast error in the post-2000 period.

APPENDIX B. FIGURES

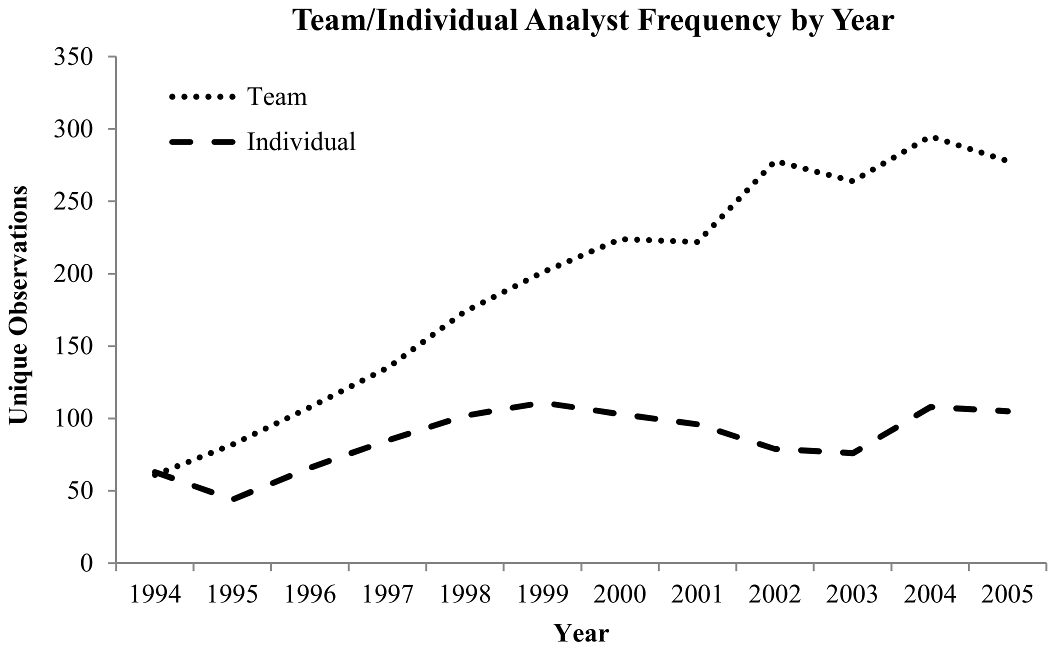

Figure B1 Panel A Team/Individual Analyst Frequency by Year

The number of unique team and individual analyst observations in each year from 1994-2005. Unique team observations are defined as unique order-specific combinations of two or more analysts. This graph captures an increase in the frequency of analyst teams over the sample period. In no period do teams comprise less than half of the observations for sample companies, regardless of how team is defined.

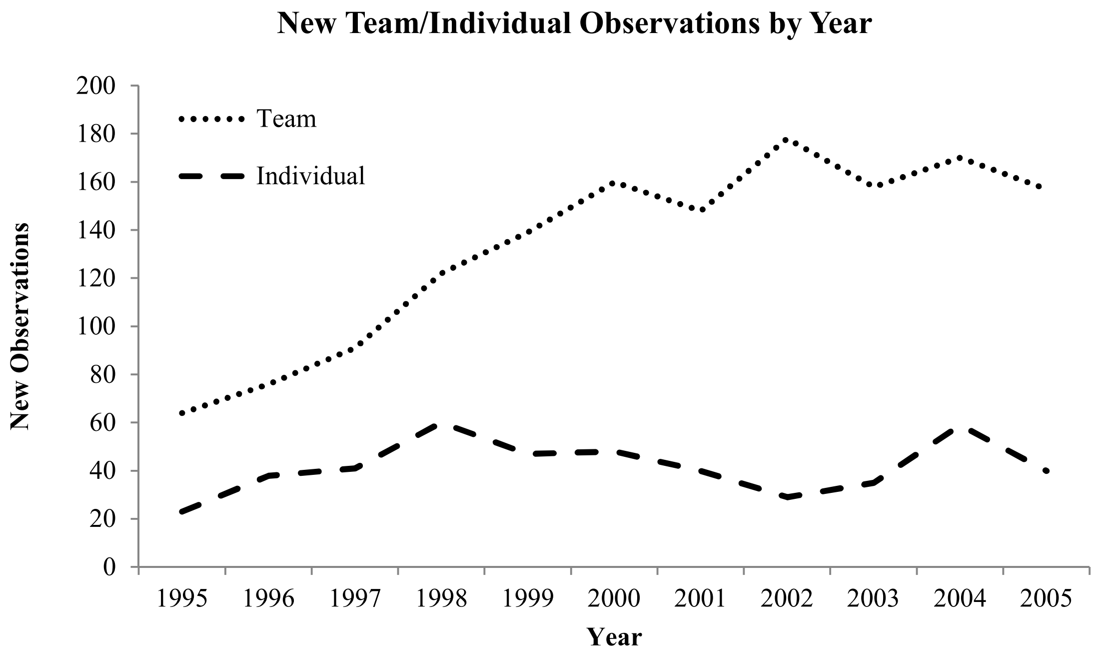

Figure B1 Panel B New Team/Individual Observations by Year

New unique observations of analyst teams and individual analysts by year, where unique observations are as defined in Figure B1 Panel A. The increase in the number of analyst teams appears to reflect an increase in the number of new teams rather than differential attrition rates.

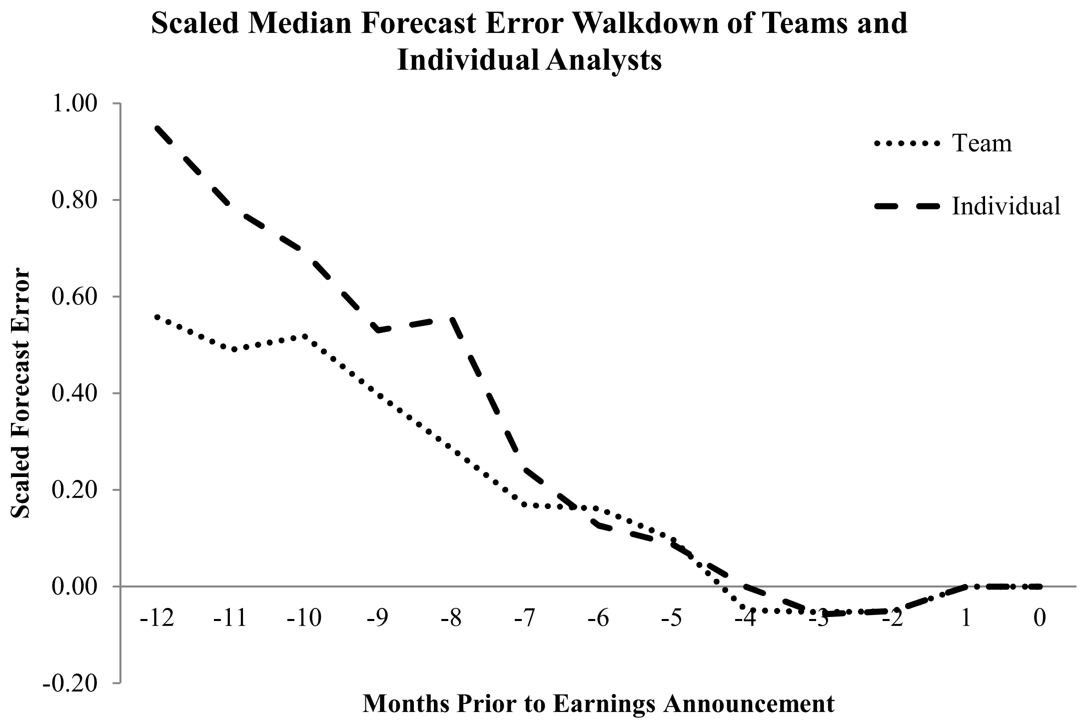

Figure B2 Scaled Median Forecast Error Walkdown of Teams and Individual Analysts

Median scaled forecast error for both forecasts issued by analyst team and individual analysts of year-ahead EPS forecasts. At long horizons analyst teams issue forecasts that are less biased than the forecasts issued by individual analysts. However, at short horizons the median bias of forecasts issued by analyst teams is virtually identical to the bias in individually issued forecasts.

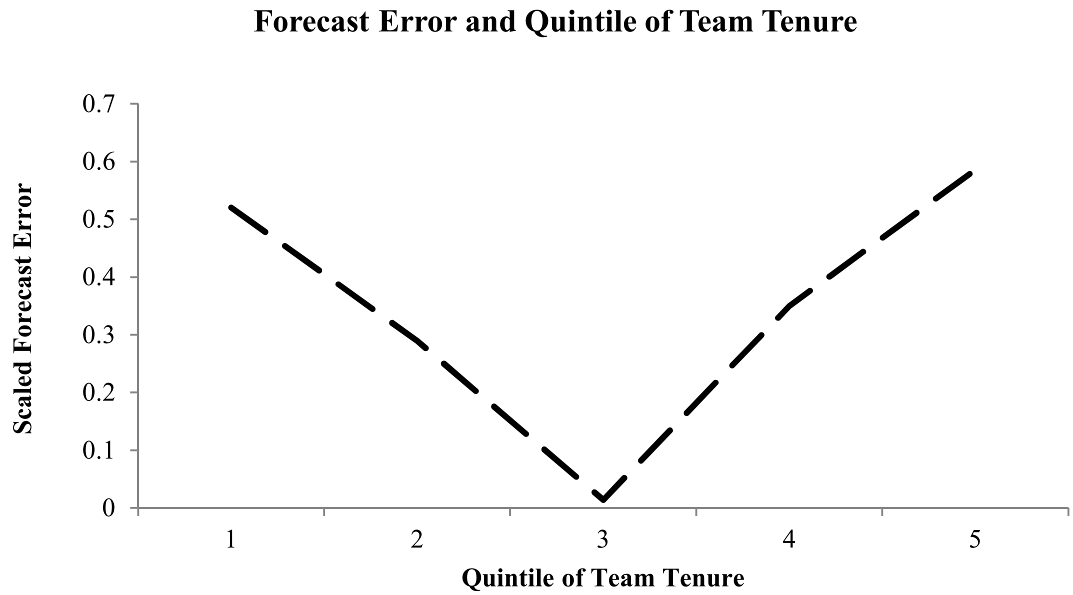

Figure B3 Panel A Forecast Error and Quintile of Team Tenure

The scaled forecast error (bias) of analyst teams by quintile of team tenure, where a quintile contains one fifth of all team report observations. Thus each quintile encompasses a different duration of tenure. Teams of the shortest (1^{st} quintile) and longest (5^{th} quintile) tenures appear to be more biased than teams of intermediate tenure.

Forecast Error and Years of Team Tenure

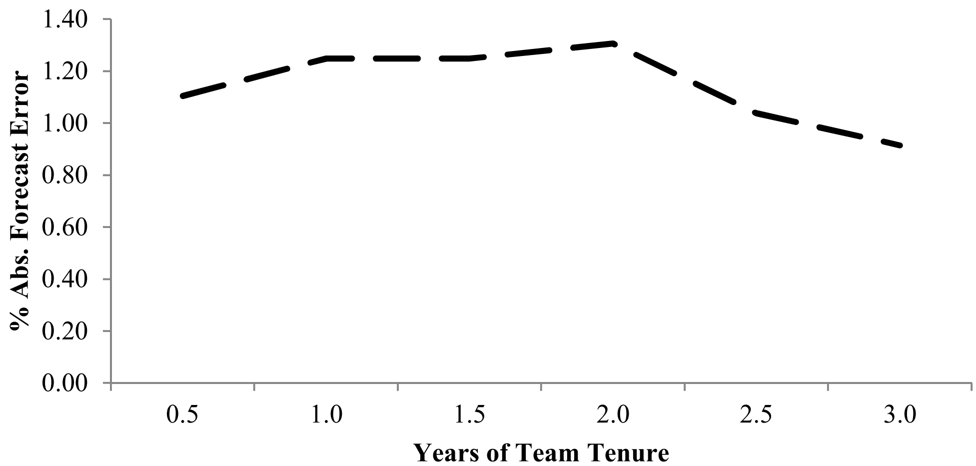

Figure B3 Panel B Forecast Error and Years of Team Tenure

Forecast error (bias) of analyst teams with tenure of 0.5 to 3.0 years. While forecasts issued by analyst teams in the third quintile of tenure (Figure B3 Panel A) exhibit lower forecast error than in the first and fifth quintile, the same pattern is not true over calendar time. Instead, the error of forecasts issued by teams increases from 0.5 to 2.0 years, after which the errors decline again.

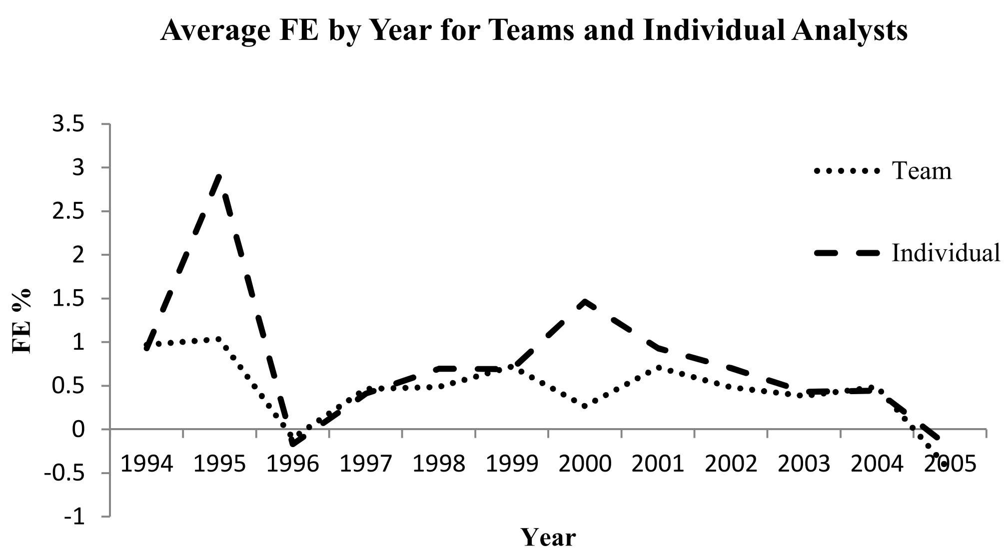

Figure B4 Panel A Average FE by Year for Teams and Individual Analysts

Forecast error (bias) of analyst teams and individual analysts by year over the entire sample period from 1994-2005. While individual analysts and analyst teams differ markedly in forecast bias in 1995, teams generally do not issue less biased forecasts than individual analysts prior to 2000. Following 2000, analyst teams issue less biased forecasts.

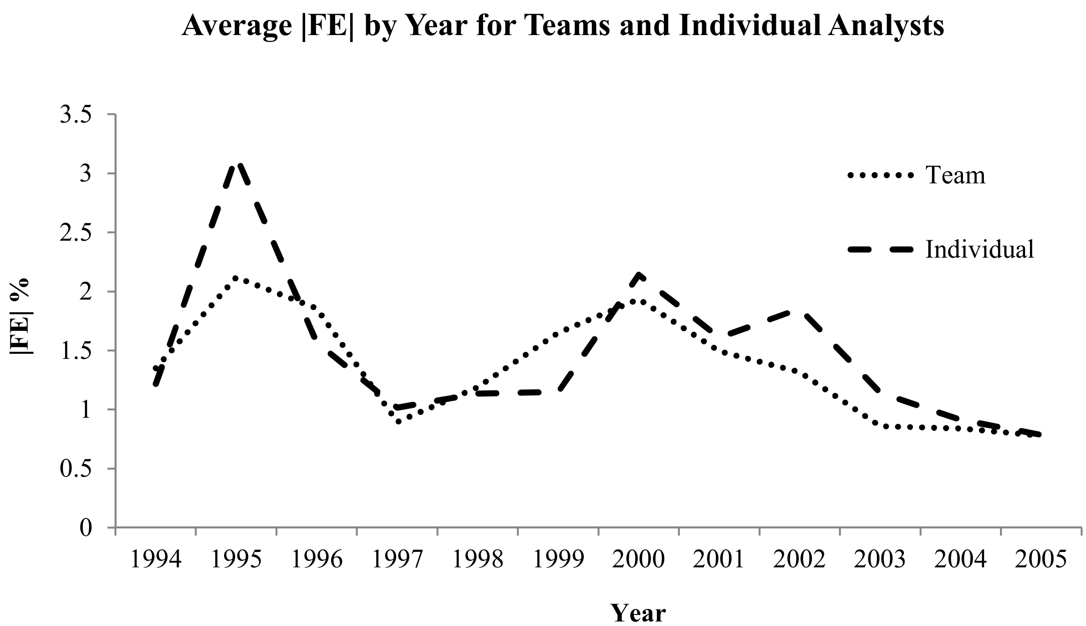

Figure B4 Panel B Average |FE| by Year for Teams and Individual Analysts

Absolute Forecast error of analyst teams and individual analysts by year over the entire sample period from 1994-2005. While individual analysts and analyst teams differ markedly in absolute forecast error in 1995, teams generally do not perform better than individual analysts prior to 2000. Following 2000, analyst teams issue forecasts with smaller absolute forecast errors.

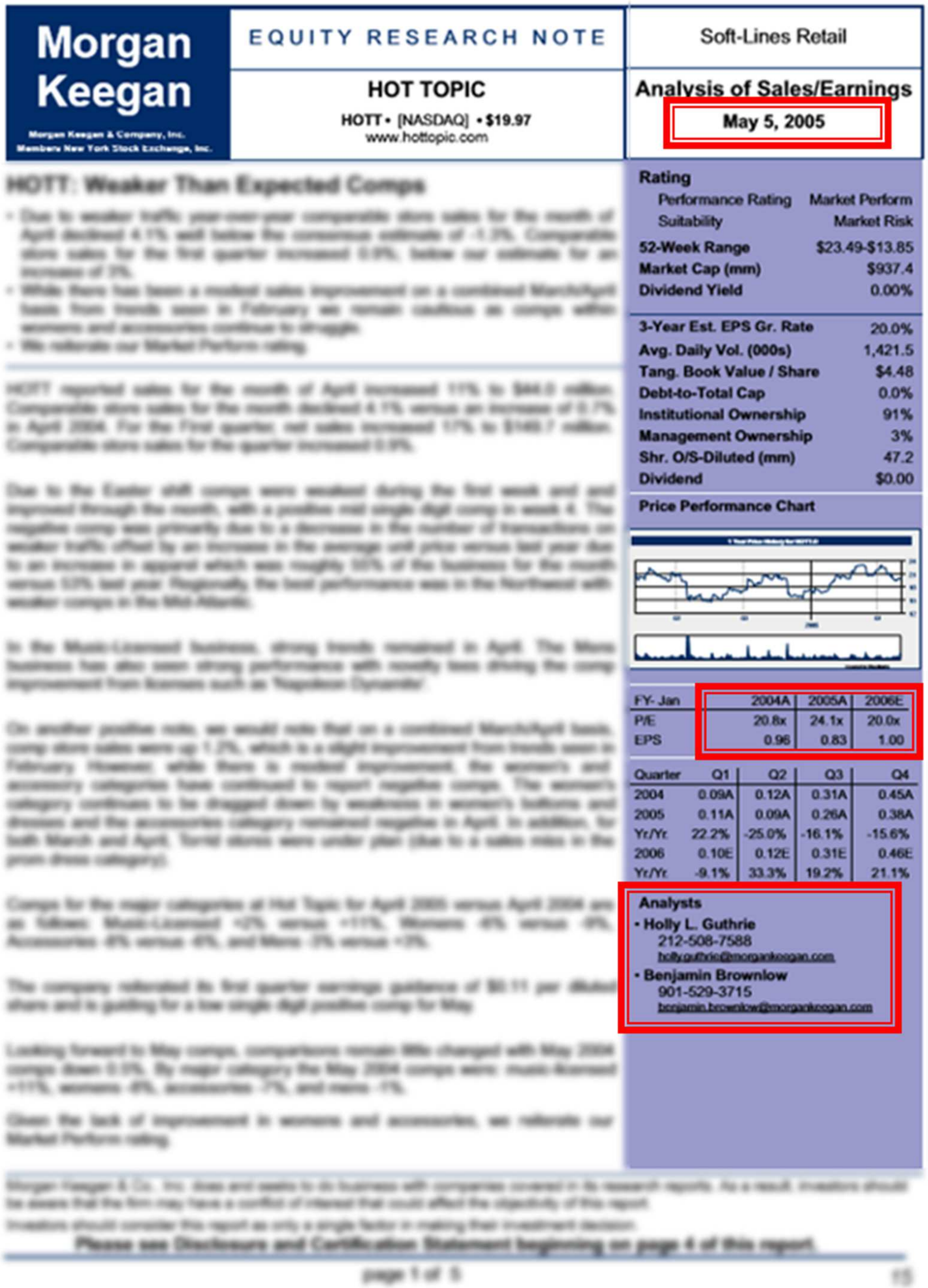

Figure B5 Example Analyst Report

An example of a report issued by a team of analysts working at Morgan Keegan. Red boxes highlight where the EPS forecast, team member names, and date of the report can be located. The position of these items on a report differs by brokerage house and across time, but are generally found on the first page of the analyst report.

APPENDIX C. VARIABLE DEFINITIONS

Forecast Quality Measures:	
FE	The difference between the analyst forecast at time *t* and the actual EPS announced by the company on the earnings announcement date, scaled by end of period price and multiplied by 100. $$FE = \frac{Forecast - \text{EPS}}{Price} * 100$$
$\lvert FE \rvert$	The absolute difference between the analyst forecast at time *t* and the actual EPS announced by the company on the earnings announcement date, scaled by end of period price and multiplied by 100. $$\lvert FE \rvert = \left\lvert \frac{Forecast - \text{EPS}}{Price} \right\rvert * 100$$
FE Diff	The difference between the average forecast error of teams and the forecast error of individual analysts, where the signs of the average forecast errors match. This definition means that a negative coefficient on a variable is associated with a decrease in forecast bias. $$\text{FE Diff} = \frac{\Sigma FE_{Team}}{\# Teams} - \frac{\Sigma \text{FE}_{\text{Individual}}}{\# Solo}$$ $$\text{where}[\Sigma FE_{Team} and \Sigma \text{FE}_{\text{Individual}}] < 0 \text{ (pessimistic)}$$ or $$\text{FE Diff} = \frac{\Sigma FE_{solo}}{\# Solo} - \frac{\Sigma \text{FE}_{\text{teams}}}{\# Team}$$ $$\text{where } [\Sigma FE_{Team} \text{ } and \text{ } \Sigma \text{FE}_{\text{Individual}}] > 0 \text{ (optimistic)}$$
$\lvert FE \rvert$ *Diff*	The difference between the average absolute forecast error of teams and the average absolute forecast error of individual analysts. $$\lvert \text{FE} \rvert \text{Diff} = \frac{\Sigma \lvert FE \rvert_{Team}}{\# Teams} - \frac{\Sigma \lvert \text{FE} \rvert_{\text{Individual}}}{\# Solo}$$

Team Characteristic Measures:	
Team	An indicator variable equal to 1 when an analyst team issues the report and zero when an individual analyst issues the report.
Tenure (1)	The length of time a full team (set of 2 to 4 analysts) has worked together within my sample, independent of company followed.
Tenure (2)	The length of time a full team (set of 2 to 4 analysts) has worked together on the same company in my sample.
Tenure (3)	The length of time the lead and second analyst have worked together in my sample, independent of company.
Tenure (4)	The length of time the lead and second analyst have worked together on the same company in my sample.
Team Size	The number of analysts listed in the team on a team report.
Experience	The difference in days between the report date and when the lead (individual) analyst first appeared in I/B/E/S.
Optimistic	An indicator variable equal to 1 when both the average team forecast error and average individual forecast error are optimistic and equal to zero when both are pessimistic.
Company Level Measures:	
MTB	Following standard measurement of market-to-book ratio: $$MTB = prcc\_f * \frac{csho}{ceq}$$ Where prcc_f is the price at the close of the fiscal year, csho is common shares outstanding, and ceq is common equity. Data is collected from the Compustat Fundamentals Annual file.
Number of Segments	Calculated by counting the number of unique segments found in a specific company-year, according to the Compustat Historical Segments file.

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