Social Comparisons with Peers and Analyst Forecast Accuracy

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Abstract

Financial analysts interact with their peers in various contexts. While prior research typically characterizes analyst relationships as purely competitive, we use a multiple-method approach drawing on social comparison theory to show that these relationships likely are more nuanced than previously understood. We argue that social comparison can enhance self-evaluation and therefore motivate effort, contributing to improved performance. Using peer analyst coverage overlaps for other firms in the focal analyst's portfolio to measure social comparison, we find that greater social comparisons are associated with more accurate forecasts. Importantly, social comparisons are also associated with various proxies of analyst effort, consistent with our theory. Cross-sectionally, overlaps of firms with greater importance and a longer history of being covered by the analyst have stronger effects, consistent with better knowledge of peers increasing the value of social comparisons. We conduct various analyses to rule out two alternative explanations based on competition and information-sharing among peers. Finally, we conduct 12 semi-structured interviews with analysts to offer rich descriptive evidence to provide context for our findings and test the assumptions of social comparison theory. Findings from these interviews support the notion that peer comparisons among analysts are an important element of the institutional environment and suggest areas for future research.

Keywords: social comparison; peers; analysts; forecast accuracy; earnings forecast

JEL codes: G14, G24

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1. Introduction

Financial analysts are one of the most important information intermediaries in capital markets (see Beyer, Cohen, Lys, and Walther 2010). Their information production and dissemination have critical implications for price discovery and market efficiency (e.g., Kelly and Ljungqvist 2012). In the past three decades, a long line of literature has studied the determinants of analyst forecasting performance. In addition to individual characteristics such as ability (e.g., Mikhail, Walther, and Willis 1997; Clement 1999) and conflicts of interest (e.g., Das, Levine, and Sivaramakrishnan 1998; Michaely and Womack 1999; Jackson 2005), the literature has also examined how interpersonal dynamics affect analyst behavior (e.g., Lys and Soo 1995; Hong and Kacperczyk 2010). While this research typically characterizes analyst relationships as purely competitive, research in social psychology suggests these relationships are more nuanced than previously understood. In this paper, we shed light on analyst peer dynamics by using a multi-method approach drawing on social comparison theory (Festinger 1954; Gerber, Wheeler, and Suls 2018). In particular, we use both archival and interview methods to examine whether and how social comparisons with peer analysts affect forecast accuracy.

Analysts are exposed to their peers through a variety of channels, all of which provide opportunities for peer comparisons. Most firms are covered by multiple analysts from different brokers, and institutional features such as the ranking of All-star analysts likely create incentives to pay attention to peers' research. In addition, industry-focused and firm-sponsored events such as analyst days present opportunities for analysts to interact with peers. While competitive pressures can motivate comparisons with peers, research in social psychology suggests that other reasons motivate these comparisons as well. One specific theory for why peers matter for noncompetition reasons is social comparison theory, which describes how individuals evaluate their abilities or opinions in comparison to similar others (Festinger 1954). As a fundamental social psychological process, social comparison is an important driver of human behavior and has been shown to impact professionals in capital markets (Hannan, Krishnan, and Newman 2008; Tafkov 2013; Kuselias, Lauck, and Williams 2021).

Yet, it is ex-ante unclear how social comparisons affect analyst performance. On the one hand, social comparison can improve analysts' performance through improved self-evaluation. People have an innate drive to evaluate themselves. When objective measures are unavailable or noisy, as is often the case, it can be difficult to identify how greater effort translates to better outcomes, making self-evaluation difficult. In these cases, people tend to engage in social comparison, which helps them gain clarity about their abilities and progress by providing reference points. Accurate self-evaluation can increase effort to perform better in at least two ways. One, it enables individuals to discern the relationship between effort levels and outcome differences, and diminishes uncertainty about whether greater effort increases the probability of further advancement (Bonner and Sprinkle 2002; Thomas 2016). Two, it can increase effort through emotional reactions. Through accurate self-assessment, individuals can recognize their progress and achievement, which induce positive affect that motivates them to set higher goals and exert additional effort (Ilies and Judge 2005).

On the other hand, social comparison can cause distraction and thus impair performance (Baron 1986). Peer analysts could direct analysts' attention away from their task and towards their peers' forecasts. If analysts are preoccupied with comparing themselves to others, they will have less energy and time to devote to collecting and processing information, thereby decreasing their forecasting performance. In addition, if peer comparisons feature high-performing peers, ensuing unfavorable comparisons could have a demotivating effect. As a result, the "on average" relation between social comparison and analyst forecasting performance remains an empirical question.

It is empirically challenging to capture the impact of social comparison on sell-side analysts' performance, primarily due to the fact that social comparison is inherently intertwined with competition and information sharing. To mitigate the impact of these two alternative effects, we construct our social comparison measure not based on peers' coverage overlaps for the *current* firm (i.e., where competition and information sharing are most relevant), but based on peers' coverage overlaps for *other* firms in the focal analyst's portfolio. Specifically, for a focal analyst i following firm j, peer coverage overlaps are calculated as the total number of times other firms in the focal analyst's portfolio (i.e., firms in analyst i's portfolio except for firm j) are jointly covered by peers (i.e., analysts who also cover firm j). We provide a numeric example in Appendix A.

Following the vast prior literature, we evaluate analyst performance based on their forecast accuracy (e.g., Clement 1999; Hong, Kubik, and Solomon 2000; Harford, Jiang, Wang, and Xie 2019). We test how social comparisons affect the focal analyst's forecast accuracy for the focal firm using analyst forecast data over the period 1994–2017. The results show that analysts with greater peer overlaps issue more accurate earnings forecasts after controlling for a variety of analyst and firm characteristics and year, analyst, and firm fixed effects. A one-standard-deviation increase in peer overlaps is associated with an increase in forecast accuracy of 4.5%. We also utilize brokerage closure/merger events to address the potential endogeneity caused by omitted analyst characteristics and document similar results. Our results are consistent with increased opportunities for comparisons with peers improving analysts' forecast accuracy.

Our theory of social comparisons posits that better analyst performance is related to analysts devoting greater effort. We conduct several additional analyses based on analyst outputs to shed light on this mechanism. Specifically, we find that higher peer overlaps are associated with more frequent and timely earnings forecasts and a higher likelihood of issuing supplementary sales forecasts, supporting our theory that social comparison leads to greater effort by analysts.

Next, we explore cross-sectional variation in the effect of peers' overlap on forecast accuracy, given that peer comparison on different sets of firms may provide varying degrees of usefulness for self-evaluation. As analysts have limited time and resources, they tend to focus on covered firms that are more important to their careers (Harford et al. 2019) and to develop a deeper understanding of peers covering these firms. Therefore, we predict that peer comparisons with analysts covering these important firms are more useful for analysts' self-evaluation and thus motivate improved performance. Using firm size, trading volume, and institutional ownership to identify firms' relative importance, we find that overlaps of relatively more important firms have a greater positive effect on forecast accuracy. We also test whether overlaps on other firms covered longer by an analyst have incremental effects. As the number of years of coverage increases, analysts likely build stronger relationships with peer analysts and gain more knowledge of them, improving the informativeness of peer comparisons. We find that overlaps on other firms with a longer coverage history have a greater positive effect on forecast accuracy.

After documenting the main and cross-sectional analyses, we address two alternative explanations based on competition and information-sharing among peers. It is worth noting that our main analysis mitigates the impact of those two alternatives by constructing our social comparison measure based on peers' coverage overlaps for *other* firms (rather than the *current* firm) in the focal analyst's portfolio. Nevertheless, we conduct a few additional tests to address each alternative explanation. Regarding the competition story, our results continue to hold when we focus on social comparisons with inferior-performing peers, who matter less for competition but still matter for social comparison. Our results are robust to controlling for analyst following, a commonly-used proxy for competition, or when we use an alternative measure of overlap based solely on peer analysts who do not follow the current firm and therefore cannot be considered competitors for the focal firm. For the information-sharing story, our inferences remain the same when we focus on social comparisons with peers in industries other than the focal firm's industry. A similar pattern of results obtains when we focus on superior versus inferior peers, or bold versus herding peers, again inconsistent with the information-sharing explanation.

Finally, we conduct semi-structured interviews with analysts to provide context for our findings and test the assumptions of social comparison theory. Evidence from these interviews confirms that (1) our measure is consistent with how analysts define their peers, (2) analysts pay attention to and compare themselves with their peers, (3) analysts use peers for self-evaluation, and (4) peers increase analysts' motivation. While our archival evidence is consistent with social comparison theory, our interviews reveal that other factors, such as building personal relationships, may also be at play, providing additional support for the notion that peer dynamics are more nuanced than prior literature suggests and indicating opportunities for future research on analyst peer dynamics.

Our study contributes to the literature on the determinants of analyst forecast accuracy and answers Bradshaw, Ertimur, and O'Brien's (2017) call for research on behavioral factors as potential drivers of the quality of forecasts. Recent research has documented that analyst forecast accuracy deteriorates when analysts' judgments are impaired by psychological factors such as decision fatigue (Hirshleifer, Levi, Lourie, and Teoh 2019), motivated reasoning (Bradshaw, Lee, and Peterson 2016), and environment-induced pessimism (Lo and Wu 2018; Li, Luo, and Soderstrom 2020; Dong, Fisman, Wang, and Xu 2021). We add to this line of literature by identifying a prevalent but previously unexplored psychological phenomenon—social comparison—that improves the quality of analyst research.

Our study also contributes to an emerging stream of research investigating how social comparisons by capital market participants affect their decision-making quality. The accounting literature has explicitly or implicitly incorporated social comparison theory to examine the effect on the performance of employees and auditors (Hannan et al. 2008; Kadous, Leiby, and Peecher 2013; Tafkov 2013; Wang 2017; Kuselias et al. 2021). We extend the analysis to sell-side analysts and provide new insights by showing how social comparisons drive greater effort and improved analyst performance.

Our study is also related to the literature on the relationship between the composition of analyst portfolios and forecasting behavior. This line of research finds that within an analyst's portfolio, firms' relative importance, concurrent earnings announcements, and product market competition affect analyst effort and coverage decisions (Harford et al. 2019; Driskill, Kirk, and Tucker 2020; Hsu, Li, Ma, and Phillips 2020). Our study extends this literature by showing that other firms in an analyst's portfolio provide opportunities for peer comparisons, which have positive effects on forecast accuracy for the current firm.

2. Literature review and hypothesis development

2.1. Behavioral and psychological factors and analyst performance

A growing body of research in accounting and finance draws on psychology theories to analyze analyst behavior (Bradshaw et al. 2016; Lo and Wu 2018; Hirshleifer et al. 2019; Dong et al. 2021). Bradshaw et al. (2017) call for more research into behavioral and psychological factors affecting analyst performance. Recently, a growing number of studies have devoted attention to the role of these factors in explaining the observed forecast bias. Applying motivated reasoning theory, Bradshaw et al. (2016) attribute the within-year walkdown of analyst forecasts to a combined effect of forecast difficulty and incentives to curry favor with managers. Using survey data on trust in analysts' countries of origin, Bhagwat and Liu (2020) find that more trusting analysts react faster to information from outside sources such as management guidance and earnings announcements. Lo and Wu (2018) examine the association between seasonal affective disorder and analyst performance, finding evidence that analysts' quarterly earnings forecasts are more pessimistic, less precise, and more asymmetrically bold in the fall because diminished sunlight causes depression and irritability. Hirshleifer et al. (2019) study the effect of decision fatigue on analyst forecasts. They document that forecast accuracy declines as the number of forecasts that analysts have already issued increases throughout a day, consistent with the evidence in psychology literature that judgments and decisions made under fatigue tend to rely more on heuristics. These studies mainly focus on how individual analysts' behaviors are affected by psychological factors, while largely ignoring the role of interpersonal dynamics, such as social comparisons.

2.2. Peer dynamics among financial analysts

While behavioral research on analysts largely focuses on individual characteristics, there is reason to expect that peer relationships are relevant to understanding the behavior of analysts. The overwhelming majority of firms in the US equity market are covered by more than one analyst, and prior literature has examined the role of peer dynamics among analysts from different brokers covering the same firm.[1] These studies can be broadly classified into two groups.

[1] While we define peers in this paper as those analysts covering the same company from different brokers, a separate stream of literature focuses on the dynamics among analysts from the same broker who are covering different companies (e.g., Hwang, Liberti, and Sturgess 2019; Do and Zhang 2020; Huang, Lin, and Zang 2022; Phua, Tham, and Wei 2023; Chen, Mayew, and Yan 2024).

The first group explores how competitive dynamics influence analysts' behaviors and forecast accuracy. For example, Lys and Soo (1995) find that forecast accuracy increases with analyst following, arguing that competition drives analysts to produce more precise forecasts. Hong and Kacperczyk (2010) utilize mergers of brokerage houses and find that competition reduces forecast optimism bias. At the industry level, Merkley, Michaely, and Pacelli (2017) show that competition (measured by the number of analysts covering an industry) is positively associated with forecast quality.[2]

The second group documents the herding behavior of financial analysts, where analysts align their forecasts with the consensus. For example, research has found that analysts often issue forecasts and stock recommendations similar to those previously issued by others (Trueman 1994; Welch 2000). Examining the motivations for herding, Hong et al. (2000) find that inexperienced analysts are more likely to herd, partly due to career concerns, and are more likely to be terminated for bold forecasts. Clement and Tse (2005) find that herding behavior is negatively associated with analysts' prior accuracy, the size of their brokerage, and their experience, but positively associated with the number of industries they follow.

For both streams of literature, the focus is largely on analysts' motivation to "win" or "avoid losing" against their peers.[3] Although competitive pressures are prevalent, research in social psychology finds that even in competitive settings, peer dynamics are complex and multifaceted, suggesting that peer relationships are more nuanced than previously understood.

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[2] Relatedly, Banerjee (2021) proposes a model where competition impairs forecast informativeness when prior uncertainty about the economic state is high; otherwise, it enhances informativeness.

[3] One notable exception is Merkley, Michaely, and Pacelli (2020), which find that increases in analyst cultural diversity positively affect the quality of the consensus earnings forecast, suggesting that analysts learn from their diverse peers.

2.3. Social comparison

People tend to engage in social comparison to evaluate their own status and abilities. Social comparison theory predicts that people are propelled by an innate drive to compare themselves with others whom they consider to be similar to themselves on some attributes (Festinger 1954). Studies have examined the role of social comparison in various aspects of life, such as health, appearance, compensation, and awards (Gerrard, Gibbons, Lane, and Stock 2005; Tiggemann and McGill 2004; Ridge, Aime, and White 2015; Shi, Zhang, and Hoskisson 2017), and identified other underlying motives for social comparison, including self-improvement and self-enhancement (Wills 1981; Wood 1989). The evidence in the social psychology literature suggests that social comparison is a common social phenomenon, and that information derived from social comparisons assists people in evaluating and improving their performance (Gibbons, Blanton, Gerrard, Buunk, and Eggleston 2000; Huguet, Dumas, Monteil, and Genestoux 2001; Gerrard et al. 2005).

In the accounting and management literature, the effect of social comparisons on effort and performance has been tested with experimental and archival methods in the contexts of relative performance evaluation (Hannan et al. 2008; Tafkov 2013; Wang 2017), auditing (Kadous et al. 2013; Kuselias et al. 2021), investing (Shi et al. 2017), pay disparity (Aime, Hill, and Ridge 2020), and pay transparency (Schuhmacher, Towry, and Zureich 2022). For example, Hannan et al. (2008) and Tafkov (2013) show that social comparisons inherent in relative performance information improve the performance of employees compensated under individual performance-based contracts due to their desire to maintain a positive self-image, and that this effect is more pronounced when relative performance information is public.

2.4. Hypothesis development

While people have an innate drive to evaluate their opinions and abilities (Festinger 1954), this evaluation can be difficult, particularly when objective bases for self-evaluation are unavailable or noisy, as is often the case for analyst forecasts. To elaborate, without a vivid point of comparison, it is difficult to assess whether a given difference between the forecasted and actual earnings is small or large. Perhaps more importantly, while greater effort can increase the accuracy of analysts' forecasts, forecasting is inherently uncertain and external factors other than analyst effort can affect accuracy.

When faced with uncertainty, people tend to compare themselves with others whom they consider to be similar on some attributes. Social comparison helps people gain clarity about their opinions, abilities, and progress by providing reference points against which to evaluate their outcomes. For financial analysts, comparing with their peers can alleviate two of the challenges in self-evaluation. One, the presence of other reference points reveals "where I stand" in the sell-side industry and thus helps evaluate the relative magnitude of forecast error. Two, to the extent that factors in the environment (unrelated to effort) affect forecast accuracy, peers' forecasts will also be affected by these factors. As a result, social comparisons facilitate the isolation of how effort translates into outcomes.

Accurate self-evaluation enables individuals to discern the relationship between effort and outcomes, helping them realize the degree to which progress can be achieved through working harder. When individuals are unable to see the link between their effort and outcomes, they likely perceive more effort as harder to justify. More accurate self-evaluations through social comparison can encourage continued effort by diminishing the uncertainty about whether and how increased effort increases the probability of further advancement (Bonner and Sprinkle 2002; Thomas 2016).

Similarly, the expectancy theory of motivation suggests that individuals are motivated toward goals if they believe that greater effort will lead to better performance (Vroom 1964).

Accurate self-assessments can also increase effort through emotional reactions. Through accurate self-assessment, individuals can recognize their progress and achievement, which induce positive affect that, in turn, motivates them to set higher goals and exert additional effort (Ilies and Judge 2005). In increasing perceived self-efficacy, positive affect can also lead to persistence in effort in the face of challenges and resilience against setbacks (Bandura 1997; Pajares 1997; Zimmerman 2000). These arguments suggest that social comparison leads to more accurate self-evaluation, which motivates individuals to increase effort and improve performance. Thus, we provide the following hypothesis:

H1: Social comparison is positively associated with analyst performance.

However, this hypothesis is not without tension, because social comparison may cause distraction and thus impair performance (Baron 1986). Peer analysts may divert analysts' attention away from their primary task of generating accurate forecasts and instead shift their focus towards the forecasts made by their peers. Such behavior would undermine the quality of their forecasts by reducing effort in gathering and analyzing information that is crucial for accurate forecasts. Further, if peer comparisons are focused on higher-performing peers, it is possible that negative affect from unfavorable comparisons could be demotivating. As a result, the relationship between social comparison and analyst performance remains an open empirical question.

3. Variables and Data

3.1 Measuring social comparison

It is empirically challenging to isolate the effects of social comparison in the context of analysts' peer dynamics, as the presence of peers may also affect analyst performance through competition and information sharing. A top priority in our empirical strategy is to circumvent those alternative effects (see more in Section 4.5). Most importantly, we recognize that these alternative channels are most relevant for peers who are also forecasting the current firm, because incentives to outperform those overlapping peers and the information flows among them are a very salient issue, as we confirm in our interviews with analysts (see details in Section 5).

To mitigate the effects of those alternative channels, we construct our social comparison measure (*OVERLAP*) not based on peer overlaps on the current firm, but based on peer overlaps on *other* firms covered by the focal analyst. $OVERLAP_{ijt}$ captures the extent to which analyst *i*'s portfolio overlaps with portfolios of peer analysts who cover firm *j* jointly with analyst *i* in year *t*. Specifically, $OVERLAP_{ijt}$ is the total number of times other firms (i.e., firms in analyst *i*'s portfolio except for firm *j*) are also covered by peers. While a large number of analysts covering the current firm would be indicative of heavy competition or frequent information-sharing, $OVERLAP_{ijt}$ could still equal zero if analyst *i* does not overlap with peer analysts on other firms. We use a hypothetical example in Appendix A to illustrate how to calculate $OVERLAP_{ijt}$.[4]

In this way, competition and information sharing become less relevant because we measure peer overlaps in covering other firms but measure performance in forecasting the current firm, creating a disconnect between these alternative effects and performance. By contrast, social comparison is still very relevant because observing peers who overlap in other firms can still help the focal analyst improve self-evaluation.

3.2. Other variables

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[4] We note that because actual comparisons cannot be directly observed, we rely on coverage overlaps as a proxy for social comparisons. Our measure is designed to capture both an analyst's opportunities for comparisons (the number of overlapping analysts who could represent peers) as well as the expected usefulness of these peers (represented by the number of overlaps with each peer). Thus, although an analyst may have many peers that they could compare themselves to, our assumption is not that they are comparing themself with every peer.

We measure analyst performance based on analysts' forecast accuracy, consistent with the literature (e.g., Clement 1999; Hong et al. 2000; Harford et al. 2019). Specifically, we calculate $ACCURACY_{ijt}$ by scaling absolute forecast errors (*AFE*) to fall between 0 and 1, with higher values indicating higher accuracy. *AFE* is the absolute difference between analyst *i*'s earnings per share (EPS) forecast for firm *j* and the actual EPS of firm *j*. We test our hypothesis by estimating the following equation:

$$ACCURACY_{ijt} = \beta_1 OVERLAP_{ijt} + Controls + FEs + \varepsilon_{ijt} \quad (1)$$

We include analysts' firm-specific (*FEXP*) and general experience (*GEXP*) to control for analysts' ability, brokerage size (*BSIZE*) to control for brokerage resources, the number of firms (*NFIRM*) and two-digit SICs (*NIND*) an analyst covers to account for portfolio complexity, and forecast frequency (*FREQ*) to control for analyst effort (Clement 1999; Jacob, Lys, and Neale 1999). Following Clement and Tse (2003), we scale all analyst variables to fall between 0 and 1 to control for firm-year differences. A high value of the scaled variable indicates that an analyst scores high on a characteristic relative to other analysts following the same firm in that year. Finally, we control for several firm characteristics, including firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*), profitability (*ROA*), and analyst following (*FOLLOW*), as prior literature shows they influence firm information environment and forecast difficulty, thereby affecting forecast accuracy (Bhushan 1989; Lys and Soo 1995; Lang and Lundholm 1996; Hutton, Lee, and Shu 2012; Jennings 2019).[5] The inclusion of analyst following, a common proxy for competition, is particularly noteworthy, as it helps us to isolate the effect of social comparison as

[5] It is important to note that while *ACCURACY* is scaled within each firm-year to fall between 0 and 1, we do not "standardize" it to create the same distribution. As a result, these firm characteristics can still help us to control for differences in the mean and variance in *ACCURACY* across different firm-years. For example, it is possible that larger firms might have overall more accurate forecasts and/or more concentrated distributions of forecast accuracy than smaller firms. Including these variables, consistent with prior literature, can help increase the power of our tests. Nevertheless, we confirm that all our findings are unaffected by excluding those firm-level controls (untabulated).

distinct from competition (see more detailed discussion in Section 4.5.1). Appendix B provides detailed definitions of variables. We also include year, analyst, and firm fixed effects in the regression to control for time trends, time-invariant analyst and firm characteristics. Firm-level variables are winsorized at the 1st and 99th percentiles.

3.3. Data and sample

We obtain data on analyst forecasts from the Institutional Broker's Estimate System (I/B/E/S) over the period 1994–2017. We choose 1994 as the starting year because forecasts were delivered to I/B/E/S only in batches before 1994, leading to inaccurate dates assigned to forecasts in the database before 1994 (Hilary and Hsu 2013). Stock price data is from the Center for Research in Security Prices (CRSP), and firm characteristics data is from Compustat. Consistent with prior studies, we focus on one-year ahead EPS forecasts and consider the latest forecast before the earnings announcement. We remove analysts coded as anonymous by I/B/E/S because it is not possible to identify these analysts and compute their coverage overlaps. Our baseline sample consists of 525,128 analyst-firm-year observations, including 11,825 analysts issuing forecasts on 8,339 unique firms.

Panel A of Table 1 provides descriptive statistics for key variables (raw values) used in this study. The mean value of *AFE* is 0.184. The mean value of *OVERLAP* is 72.534. For analyst characteristics, a typical analyst has 4.6 years of firm-specific experience and 12.0 years of general experience, issues 4.4 earnings forecasts for the firm-year pair, and covers 18.5 firms and 4.4 industries each year. The statistics of analyst characteristics are comparable to other studies on financial analysts. Panel B reports descriptive statistics for scaled variables. Panel C reports Pearson correlations. The Pearson correlation between *OVERLAP* and *ACCURACY* is +0.089, providing preliminary evidence that supports our hypothesis H1.

4. Results

4.1. Baseline results

We investigate the effect of peer overlaps on forecast accuracy and report the results in Table 2. In column (1), we estimate equation (1) excluding *OVERLAP*, allowing for a comparison with the prior research and confirming that the coefficients on analyst characteristics are similar to prior literature (Clement 1999; Jacob et al. 1999).[6] In columns (2) and (3), we include *OVERLAP* in the regression and find that its coefficients are positive and significant at the 1% level, indicating that peer overlaps are positively correlated with forecast accuracy. In terms of economic significance, for a one-standard-deviation increase in *OVERLAP*, forecast accuracy increases by 0.031, or 4.5% of mean *ACCURACY* (column 3).[7] Relatedly, it is worth noting that the R^2 increases from 0.037 in column (1) to 0.044 in column (2), highlighting the incremental explanatory power *OVERLAP* has on *ACCURACY.* Taken together, those results provide strong support to our main hypothesis H1.

We conduct a battery of robustness analyses. First, as social comparison theory indicates that people tend to compare with similar others, an analyst is more likely to compare themselves to a peer whose portfolio is more similar to her portfolio. Also, as an analyst who issues the first forecast in a year (i.e., the "first-mover") provides the first reference point for others, the "first-mover" is more likely to be chosen as the main comparison referent. We find that our inferences remain the same when we construct overlaps between an analyst and a peer who has the most similar portfolio and overlaps between an analyst and the "first-mover." Second, we remove

[6] It is worth noting that the coefficient on *FOLLOW* is significantly positive across three columns, suggesting that analyst competition may enhance forecast accuracy. In untabulated analyses, we find analyst accuracy is highest for the subsample with above-median *OVERLAP* and above-median *FOLLOW.* Importantly, we confirm that our results are robust even when we focus on the subsample with below-median *FOLLOW*, further mitigating the concern that our result is driven by competition. We provide more detailed discussion on a competition-based alternative explanation in Section 4.5.1.

[7] Specifically, 0.098 (the coefficient on *OVERLAP*) * 0.317 (standard deviation of *OVERLAP*) / 0.692 (i.e., the mean of *ACCURACY*).

analysts only overlapping on the focal firm when we calculate an analyst's relative performance to ensure that our results are not driven by this subset of analysts, and find our inferences are unchanged. Third, we use All-star status as an alternative proxy for analyst performance and find our inferences remain. An advantage of All-star status is that it is observable across comparison groups and is not scaled within a given firm-year. Fourth, our inferences are robust to conducting the main analyses at the analyst-year level by calculating the average forecast accuracy and the average overlap for all the firms covered by an analyst in a year.

4.2. Brokerage mergers/closures as exogenous shocks to peers' overlaps

One potential concern with our findings is that omitted analyst characteristics may drive our results. For example, analysts with strong social skills may engage in greater social comparisons as their broad social connections frequently expose them to social comparisons, and strong social skills may help analysts improve access to management information and thus lead to better performance. We use brokerage mergers and closures to address this concern.[8] If peer analysts' portfolios overlap with a dropped analyst's portfolio before the merger/closure, there should be a decrease in coverage overlaps of peer analysts after the merger/closure because of the loss of the dropped analyst's coverage for previously jointly covered firms, and the decrease in coverage overlaps is exogenous to analyst characteristics.

We utilize brokerage mergers/closures from 1994 to 2008 (Hong and Kacperczyk 2010; Kelly and Ljungqvist 2012).[9] We define the year when the mergers/closures took place as year *t* and use

[8] Brokerage mergers and closures are due to decreases in revenue from trading, market-making, and investment banking business. For brokerage mergers, a firm that was covered by both brokers before the merger should experience a drop in coverage because one of the two analysts is fired or reassigned to another firm after the merger. Similarly, firms should lose analyst coverage because of brokerage closures.

[9] To identify firms for which analyst coverage was terminated due to brokerage mergers/closures, we closely follow the steps used by Kelly and Ljungqvist (2012) and Li and You (2015). Specifically, for mergers, we identify firms that were covered by both the acquirer and target before the merger and by the acquirer after the merger. For closures, we identify firms that were covered by the affected broker before the closure. For each peer analyst (i.e., analysts who cover a firm jointly with the dropped analyst before the merger/closure), we calculate coverage overlaps with the

a two-year window around the merger/closure (year *t-1* and *t*). We keep the latest forecast of each analyst for each year and require the latest forecast in year *t* to be issued after the event date. The dependent variable is the change in forecast accuracy from year *t-1* to *t*. The independent variable, $OVERLAP\_DROP_{ijt}$, is defined as coverage overlaps between analyst *i* and the dropped analyst before the merger/closure. Regression results are reported in Table 3. The coefficient on *OVERLAP_DROP* is statistically significant, and the sign is consistent with expectation (coefficient = -0.002, *t*-stat = -2.25), suggesting an exogenous decrease in peer overlaps is associated with reduced forecast accuracy.

4.3. Peer overlaps and analyst effort

Social comparison theory suggests that comparisons with peers enhance an analyst's self-evaluation, which motivates them to put more effort into information acquisition and production, thereby contributing to better performance. In our interviews, analysts frequently mention comparisons with peers as "motivating" (see Section 5 for more details). To shed light on effort as a mechanism, we test whether social comparison is associated with analyst outputs that arguably capture greater effort. Following prior studies (Jacob et al. 1999; Harford et al. 2019), we first use earnings forecast frequency (*FREQ*) as a proxy for analyst effort. As prior research suggests that forecast timeliness is associated with higher analyst ability and effort (Cooper, Day, and Lewis 2001; Merkley et al. 2017), our second measure is forecast timeliness (*TIMELINESS*). The last measure captures whether an analyst issues sales forecasts in a year (*SALEFORECAST*) (Lang, Pinto, and Sul 2024). Ertimur, Mayew, and Stubben (2011) find that analysts seeking to build reputations and improve career outcomes are more likely to issue disaggregated earnings forecasts,

dropped analyst before the merger/closure. We remove terminations that do not trigger decreases in coverage overlaps of any peer analysts. The final sample includes 22 mergers and 21 closures and 3,550 exogenous terminations.

signaling greater effort.[10] The results in Table 4 indicate that analysts with higher peer overlaps devote more effort to their research by issuing more frequent and timely earnings forecasts and providing disaggregated earnings forecasts.

4.4. Cross-sectional tests

4.4.1. Firms' relative importance and the effect of peers' overlap

We next investigate the cross-sectional variation in the effect of peer overlaps on forecast accuracy given that peer comparison on different sets of firms may provide varying degrees of usefulness for self-evaluation. We consider whether overlaps of relatively more important firms are associated with a greater improvement in forecasts. As analysts' time, attention, and resources are limited, they tend to selectively allocate their effort to firms that are relatively more important to their careers (Harford et al. 2019). Thus, we expect that analysts will pay closer attention to and have greater knowledge of their peers on these firms, increasing the usefulness of peer comparisons and leading to increased effort and improved performance.

To examine this conjecture, we follow Harford et al. (2019) and use firm size, trading volume, and institutional ownership to construct measures that capture firms' relative importance in an analyst's portfolio.[11] To measure a firm's relative importance to analyst *i*, we first classify a firm as more (less) important to analyst *i* if the firm's size/trading volume/institutional ownership is in the top (bottom) quartile of all firms covered by analyst *i*.[12] We next separately calculate overlaps

[10] *FREQ* is defined as the number of annual earnings forecasts issued by an analyst for a firm, scaled to fall between 0 and 1. *TIMELINESS* is defined as the number of days between the prior year's earnings announcement and the first forecast issued by the analyst this year, multiplied by -1 and scaled to fall between 0 and 1. *SALEFORECAST* equals 1 if an analyst issues a sales forecast for a firm, and 0 otherwise.

[11] Firm size is the market capitalization at the end of year *t*-1. Trading volume is determined as the average daily trading volume over year *t*-1. Institutional ownership is the percent of a firm's common shares held by institutional investors at the end of year *t*-1.

[12] We require that each analyst cover at least four firms each year in order to rank firms into quartiles based on firm size/trading volume/institutional ownership. Our results are similar when we use median values to identify firms' relative importance.

of more important firms (*OVERLAP_HIGH*) and less important firms (*OVERLAP_LOW*) for analyst *i*, and scale them to fall between 0 and 1. We replace *OVERLAP* in equation (1) with *OVERLAP_HIGH* and *OVERLAP_LOW*. Columns (1) through (6) of Table 5 show the results. Consistent with expectations, we find that overlaps of firms of higher importance exert a greater positive influence on forecast accuracy compared to overlaps of firms of lower importance.

4.4.2. Analysts' firm-specific experience and the effect of peers' overlap

Next, we test whether overlaps of other firms covered longer by an analyst have incremental effects. As an analyst covers a firm for more years, she likely gains more knowledge of her peers and builds stronger connections with them, increasing the potential value of peer comparisons. Thus, we predict that overlaps of firms in which analysts have more experience have a greater positive effect on analyst forecasts.

We classify firms as being covered longer (shorter) by an analyst if the analyst's firm-specific experience (*FEXP*) in this firm is in the top (bottom) quartile of all firms covered by the analyst. Then, we separately calculate overlaps of firms with a longer/shorter history of being covered and convert them to scaled values (*OVERLAP_HIGH* and *OVERLAP_LOW*). We examine their respective effects on forecast accuracy. Results in Table 6 show that overlaps of firms with a longer history of being covered have a greater positive effect on forecast accuracy compared to overlaps of firms with a shorter history of being covered.

4.5. Alternative explanations

As mentioned previously, interaction with peers could potentially lead to different effects, such as competition and information sharing, both of which represent potential alternative explanations for our findings. In our interviews, analysts largely indicate that peers are not purely seen as competitors, but acknowledge competition as an element of analyst peer dynamics (see

Section 5 for more details). While our research design of focusing on coverage overlaps on *other* firms (rather than on the *current* firm) helps to mitigate those concerns, in this subsection, we provide further arguments and evidence to show that those two alternative explanations are unlikely to explain our findings.

4.5.1 Competition as an alternative explanation

In addition to controlling for the effect of competition in our regressions by including analyst following as a proxy for the level of competition, we conduct several additional analyses to address competition as an alternative explanation. First, while social comparison and competition can both motivate analysts to increase their effort, they are conceptually different. Competition is inherently associated with a rivalry or contest emphasizing the goal of outperforming others such that the pursuit of rewards associated with outperforming others motivates individuals to exert more effort. In contrast, social comparison is not necessarily motivated by success at the expense of others, but rather focuses on improving self-evaluation, which motivates effort and consequently improves performance. As a result, inferior peers can be as helpful as other peers in facilitating the focal analyst's self-evaluation through social comparison, but they do not offer as much incentive for the focal analyst to outperform in competition. In fact, the lack of challenge can even dampen the drive to compete (Jackson and Csikszentmihalyi 1999). Therefore, we focus on the comparison between an analyst and the peer with the lowest forecast accuracy in the previous year among all analysts following the focal firm, and calculate coverage overlaps with the inferior peer accordingly. In column (1) of Panel A of Table 7, we find a positive association between coverage overlaps with the inferior peer and forecast accuracy and the association does not differ regardless of whether the overlap is with inferior or superior peers. This finding alleviates concerns about the confounding effect of competition.

Second, to further isolate social comparisons from competition, we use an alternative measure of overlap. For overlaps of analyst i on firm j, we first exclude analysts who also cover firm j in the market, and then count the total number of times other firms in analyst i's portfolio are covered by the remaining analysts. This measure is less subject to the confounding effect of competition as it is based solely on analysts who do not follow the focal firm. In column (2) of Panel A of Table 7, we find that our main results continue to hold using this alternative measure.

4.5.2 The information acquisition explanation

Another concern is that coverage overlaps could capture potential learning of specific information from peers. To rule out this alternative explanation, we conduct several additional analyses. First, as industry knowledge has been consistently ranked as the most important characteristic of analysts by the buy-side (Brown, Call, Clement, and Sharp 2015; Bradley, Gokkaya, and Liu 2017), we exclude the potential information acquisition within an industry to test the robustness of our results. We reconstruct *OVERLAP* by counting overlaps of other firms in industries different from the current firm's industry and show results in Panel B of Table 7. Our inferences remain the same, supporting the social comparison interpretation.

Second, we compare the effect of overlaps with superior peers to that of overlaps with inferior peers. Analysts can obtain more information from peers who have superior performance than those who have inferior performance. Therefore, if our results are explained by learning of specific information, we would expect overlaps with superior peers to have a stronger effect on forecast accuracy. In contrast, though, similar effects obtain when focusing on overlaps with peers who have the highest and lowest forecast performance in the previous year (column (1) of Table 7, Panel A), inconsistent with the information acquisition effect. Third, we compare the effect of overlaps with bold peers to that of overlaps with herding peers. Prior studies show that bold forecasts provide new information and reflect analysts' private information and herding forecasts may simply reflect uninformed mimicry from other analysts (Gleason and Lee 2003; Clement and Tse 2005). Thus, analysts are more likely to gain information from bold forecasters than herding forecasters. We recalculate overlaps between an analyst and the herding (bold) peer, i.e., the analyst who has the highest (lowest) fraction of herding forecasts for the current firm in the previous year. Panel C of Table 7 shows that overlaps with bold and herding peers have similar effects. Together, our additional analyses suggest that information acquisition cannot fully explain our findings.

5. Semi-Structured Interviews

While our findings are consistent with social comparison theory, we acknowledge that this theory rests on several assumptions which are difficult to examine archivally. Therefore, we conduct a series of semi-structured interviews with sell-side financial analysts to provide additional context for our findings, examine the assumptions of our theory, and identify additional peer effects to motivate future research.

We interview twelve analysts using a set of prepared questions (Appendix C) designed to elicit insights about who analysts consider their peers, their relationships with these peers, and the role of peer comparisons in self-evaluation. In addition, we ask about the factors that motivate analysts in their work as well as other potential factors that may contribute to our archival findings. Following a semi-structured approach, interviewers deviate from the script to allow interviewees to provide additional details for their responses. Interviews are approximately 30 minutes in length and are conducted by two members of the research team. To allow participants to be candid in their responses, we assure anonymity and remove personally identifying information, including names of individuals and organizations, from transcriptions of the interviews. Below, we describe themes in responses and include representative quotes, including an identifier for the participant number and the question to which the participant was responding.[13]

5.1. Analyst peers

Consistent with our empirical measure, analysts generally define their peers as other sell-side analysts covering the same firms and industries.

> *It's just the sell-side analysts at the other firms, and you have sort of different tiers of firms, but I would say mostly was the sell-side analysts. But it would be also in your industry, right? So I was covering [Industry A], so I wouldn't say the [Industry B] analyst at some other firm was necessarily a peer.* [11-2]

> *Analysts covering the same stocks as I was. We didn't all cover exactly the same stocks. So the people who covered the same [Industry A] stocks were my peers. The people who covered the same [Industry B] stocks were my peers. But those weren't necessarily the same group of people.* [3-2]

Analysts indicated that peers are often met through firm-led events like analyst days, industry conferences, and earnings calls.

> *We see each other at industry conferences and company specific conferences. I know most of my peers in that regard.* [2-2]

> *We'd go to conferences together and be in the rooms with management teams asking questions. I pretty much, over a number of months when I first started, could figure out who among my peer group I thought really understood the business and might be a competitor to me, and who I really didn't think understood it.* [7-2]

> *Many of them I actually grew up with in the sector, meaning that we once upon a time started out as junior analysts. So we would see each other at conferences. Of course, when you're the junior guy, you're not really doing much of the talking, so you go have drinks somewhere.* [9-2]

In describing relationships with peers, some describe a largely competitive dynamic, consistent with prior research.

> *I did see them purely as my competitors, I mean, there's a handful of guys that they'll come to my house, know my wife, kids, and vice versa. But everyone else is like, "Hey, how are you? Good to see you."* [9-3]

[13] As an example, the identifier [3-1] represents a quote from the third analyst we interviewed responding to Question 1 in our list of prepared questions.

I wouldn't have been friendly with them just because we were competitors. And I definitely wouldn't have shared information with them ever. Let's see. I'm assuming the word antagonistic is maybe too strong. But it's like finance. It's very competitive. So I wouldn't be antagonistic. I wouldn't be out to get anybody, but I just wouldn't share anything. [3-3]

However, most respondents indicated that they did not view peers purely as competitors, describing relationships with other analysts ranging from professional acquaintances to close friends.

I don't know about lifelong friends. That's probably too strong a word in any case, but close in like a very select few cases when they were people with whom I've had experience in the past, all of those who worked at a company I'd worked at before, and I got to know very well outside of that name. See them at cocktail parties, see them at industry events. You know, have dialogue with them that way. I've probably got Christmas cards from one or 2, and you know, out of 15 to 18. So let's say professional, and that's about it. [5-2]

It's more just like you can speak the same language and learn things from one another. I think there are lots of advantages to having good relationships, because it's such a small universe on the sell-side and buy-side. [4-4]

I wouldn't characterize it as acrimonious. It was actually quite friendly. And then we'd go on these analyst days, which means that you know it's somebody who you've known for many years, and it's like, "Oh hey, we're all going to Argentina for a week to do an investor event. Let's have dinner. Let's get drinks." Very friendly, very collegial. [8-2]

Although there was some variation in how analysts described the nature of their relationships with peers, respondents overwhelmingly agreed that they pay attention to their peers, particularly high-performing peers.

There's definitely some that have the best reputation in the sector or whatever, and I think you try to be more like them in a way. Not with your call, but with your process. [1-2]

It depends on the analyst. So there were always the analysts who I like. Generally, I respect all of my peers, because I know the job was kind of shitty. You know. It can be very long hours, etc. But I kinda know who to look at, especially when I'd been covering the same space for so much time. [8-3]

You would have a sense of where does everyone fit and who's kind of the best, and who's maybe not the best but for whatever reason they're still around or have been able to have a job for a while. And I think you get a pretty good sense of who everyone is, and what their skills are. And yeah, how you need to level up to get to that point. [12-2]

Respondents indicate that paying attention to other analysts, particularly ones that are high-performing and those with unique perspectives, provides informational benefits.

> *Definitely there were people that stood out on each call as recognizable that you were waiting, you wanted to see what they were gonna ask about on the call.* [1-5]

> *I was a very vigorous reader of other analysts' research over time. It got to be pretty stale, but I was always looking for sort of like an understanding of how all the peers, you know, kind of, like put together their understanding of the industry. And you know, if they have it had any unique data points that they relied on over and over and over.* [5-5]

> *I tend to look at those guys who are outliers. right? Because everyone else is kind of speaking the same language, saying the same thing. But there are sometimes outliers who are, you know, going against the mainstream consensus, and sometimes they're right. Sometimes they're wrong. If you're right, you're a hero. If you're not, you're just hot garbage, but it's always beneficial to see the different viewpoints.* [6-5]

A common sentiment among the analysts we interview is that knowledge of their peers, both the quality of their work and their unique perspectives, is important.

> *When I listen to other people in the conference call and the questions that they ask, I can judge somewhat what they're thinking based on the time series of how they've asked questions before.* [3-6]

> *If I were covering a stock, and I didn't know any of the analysts, and I was looking at what their estimates are, I'm not gonna really care because I don't know if they're good or not.* [4-6]

> *If you have peers, you know them. You know they're qualified. You know their strength. And you know they're just as good as you are. So you kind of believe that whatever that group thinks is close to reality, whereas when you're covering a company that's covered by a bunch of unknown people, you don't know that, right?* [6-6]

> *I'll probably evaluate my estimates based off of the peers that I know versus those that I didn't and didn't respect, right? Because I know that these guys are doing the work. So my number being different than theirs is gonna require more scrutiny, like "what am I missing?"* [9-6]

In addition to meeting peers at industry events and hearing them on earnings calls, many respondents indicated that they read others' work, though some expressed concerns about being influenced by these viewpoints.

Not every single other analyst, but certainly like the key ones. You would want to know what they were forecasting and what they were writing about. [3-3]

All clients have access to reports, and clients can share that report with whomever they want. Although they're not supposed to. But they're not gonna get prosecuted for doing so. [6-3]

I don't want their perspective on what facts are to influence my perspective. But if there are facts that they are looking at that I haven't thought about, I need to be aware of those and incorporate that into my thought process, because that could influence my perspective. [10-4]

Responses above broadly confirm several assumptions of our test of social comparison theory. First, they indicate that analysts consider their peer set to include other analysts covering similar firms and industries, suggesting that our measure of coverage overlaps is a reasonable proxy for the extent of peer relationships. Second, they confirm that analysts pay attention to their peers, a necessary condition for social comparisons. Responses also suggest that relationships with peers are not purely competitive, supporting our assertion that peer dynamics among analysts are more nuanced than previously understood.

5.2. Comparisons with peers

In the previous section, analysts confirmed that they pay attention to their peers, an important assumption of social comparison theory. Asked directly about whether analysts compare themselves to their peers, respondents overwhelmingly indicate that these comparisons are common. Consistent with social comparison theory, many describe self-evaluation as a motivation for comparing themselves to peers.

I do definitely compare myself to peers. I think that while I do try to assess myself in a vacuum, you find some relative amount of self-scoring, self-worth, etc. in comparison with others. So the answer is yes, I do. And I think it's mostly on the basis, as I perceive, of quality of analyses and work. And mostly it's looking at my peers. And if someone develops a really interesting idea and does the like work to justify the analysis to justify it, I like that. And I compare myself against that. [2-4]

> *I started as a sell-side analyst when I was 23, and I was a leading analyst by the time I was 25, so I was quite young, and so I think I looked up to a lot of people around me, and I viewed them as a bar for me to move towards. And so for me, it was more of like a measuring stick or an aspirational goal.* [4-4]

> *It was something that everyone who was a covering analyst just sort of had as like part of their nature in a lot of ways. You know, it's like your nature to analyze companies. But also you want to analyze your results against your peers.* [5-4]

> *I compare myself to my peers. Yeah. […] That was one way of measuring how I was doing relative to them into in terms of call volumes, page views, research report, views, etc. And then, you know, using various investor surveys. Comparing myself – how many votes I would get, or where I get ranked relative to the other people who are in the same space covering the same space. You know, it really was just a way of measuring my performance.* [8-4]

> *You always want to benchmark, especially against those you respected and viewed as the best. I wanted to see where I stacked up to some of the people that had the more stellar reputation and just great institution knowledge in the sector. Right? So you take a page out of certain people's playbooks and you see what's best practices out there, what works and what doesn't. And you kind of make your own thing and build your own franchise that way. So yeah, I definitely try to benchmark myself against those I view to be really good researchers.* [9-4]

Many respondents note that peer comparisons are particularly useful for self-evaluation in that they account for unexpected events, with several mentioning the COVID-19 pandemic. These responses are consistent with the predictions of social comparison theory in that unpredictable events can blur the relationship between effort and accuracy, but peer comparisons can help account for random factors.

> *Sometimes it felt as though more work went into situations where I ended up getting an estimate far off the mark, because you know, you do a lot of research, and you miss a very key point. And then the results end up being away from what you thought at the same time.* […] *Sometimes it's sort of enough for the results to sort of speak themselves. But picture being on the sell side during COVID and having to forecast something like, you know, a global trading company. You did a lot of work on this one company, but oops, COVID. You didn't think of that. Sorry.* [5-1]

> *There are black swan events and unforeseen events that nobody really could have predicted. And so, there's no like blame or yeah, there is an element of "everyone's just acting on what is known or what we can kind of see in front of us."* [12-5]

> *I think it's a lot less demotivating if you're wrong with everybody else, that's for sure, and I think you can't blame your lack of effort or maybe less so because you're like, "well you know, we thought we had it right, but clearly everybody thought they had it right." So that definitely would play a role in keeping your spirits higher.* [1-6]

Some analysts indicate that they compare themselves to their peers for reputational reasons or because of institutional analyst rankings.

> *So, ranking is one thing. Who seems to have the closer relationships with managers or with firms, and that might be something I could see based on who gets to take the company on the roadshow to go see the clients.* [3-3]

> *You have to, because there is a lot of ranking. So, for instance, in the EPS proximity rankings. It wasn't done on an absolute basis across the industry. It was weighted compared to other analysts. Not just my peers, but a broader distribution, and companies of a similar type.* [5-4]

> *I wanted to be considered one of the best analysts. And so I did compare myself to the guys that I thought you know did the best work and also wanted to compare myself to the what the guys were doing that were getting votes above me, what they were doing different than I was doing.* [7-4]

Another common motivation for comparisons with peers is the need to understand what others are doing in order to produce differentiated work.

> *Reading their research reports, for instance. kind of gives you insight as to how close you are to them in terms of the viewpoints, or how different you are. And how you know potentially how you can differentiate. So it's a good benchmark.* [6-5]

> *You need to write differentiated research. And how do you get differentiated research? Well, you have to know what everybody else is doing. So you know, that was one way of measuring it.* [8-5]

5.3. Responses to comparisons with peers

After establishing that analysts regularly compare themselves to their peers, we examine how analysts respond to these comparisons. In particular, respondents describe reactions to being outperformed by peers.

> *If they perform an analysis that I'm working on that gets to market first, I'm upset. I'm envious. But if I do it first, I don't care what they're thinking so much. I only care at that point about what my clients are thinking.* [2-4]

There's guys who go to a hedge fund and then come back to sell side, and they're generally like, they want their model to nail every number. So I think for one of them, if they saw someone else getting it right, and they were getting it wrong. They'd probably be inclined to switch things up, and that probably applied to an extent to me as well. [4-5]

You might look into what they were doing versus you. What does their team look like? Where were their resources like? And how would how do I match it? What am I missing that this person seems to be getting done pretty well? [11-4]

While some respondents indicated frustration when being outperformed, they also described the unfavorable comparison as motivating. Analysts suggested that outperformance motivated them to work harder, develop stronger relationships with management teams, and think creatively.

I just tried harder. I might, if somebody is outperforming me, I guess I'll go back to the "how do I need to work harder or smarter to try and come up with the better recommendations and analysis and insights?" […] *How do I come up with a different research idea? The idea that nobody else is… how do you do that? You just try to think creatively and think in different places. So like sometimes, being a research analyst was like that. Who else can I talk to? Where else can I look? What else can I read?* [3-3]

I felt like some of the guys have been doing it longer than I had, developed closer relationships with the management teams than I had. So I had to work harder to develop this relationship because you know, you could learn things that aren't insider information, but if you're listening, paying attention to what the senior management's telling you, you can pick up some things. But you need to have a pretty close relationship with them to find out, you know, if their outlook on some aspect of their business is changed. You can just tell by the tone of the way they're talking about it, but it takes some time and experience to learn that. But I can think of a number of instances where I went to a meeting and learned something that I felt like my peers didn't pick up on. I know that probably sounds pretty strange, but there are a number of instances I can point to where that happened. [7-3]

Although some of the responses to outperformance could be viewed as consistent with competition, multiple respondents described motivational effects even when those peers were not their direct competitors.

I had to find a way to distinguish my research from a much bigger shop like JP Morgan. Wells Fargo had like 10 people right? And they cover 60 stocks. I'm covering 25 with a team of 3. So with this small platform that I have, how can I still shine relative to those that have more resources? So I was proud of being able to kind of still be a name that people listen to. [9-1]

But you might look at that and see that as demotivating that this one person's II number one every single year, and it's impossible to break into it, or you can see it as an opportunity. How do I get better? Maybe I can't beat that because I don't have that infrastructure around me. But maybe I can get to an honorable mention or something. And so still motivating to get to do the best you can do. [11-4]

Collectively, our interviews with sell-side analysts provide support for the assumptions of social comparison theory and provide additional understanding of peer dynamics among analysts. Responses confirm that analysts compare themselves to their peers for a variety of reasons, including self-evaluation. Respondents also suggest that peer analysts are not purely viewed as competitors, suggesting that these relationships are more nuanced than previously understood.

6. Conclusion

Comparisons with others can facilitate self-evaluations and improve performance. Drawing on social comparison theory, we use a multi-method approach to examine how social comparisons with peers improve the quality of analyst research. We test the impact of social comparisons on forecast accuracy using coverage overlaps between the focal analyst and peers to capture the extent of social comparisons faced by the focal analyst. Using a large sample of analyst forecasts over the period 1994–2017, we find that higher overlaps are associated with higher forecast accuracy. We then show greater effort following a greater extent of social comparisons. We also document cross-sectional variations in the effect—overlaps of other firms with higher relative importance and a longer history of being covered generate larger positive effects on forecast accuracy. Finally, we conduct a series of semi-structured interviews with sell-side analysts, which provide additional context for our findings, support our theoretical assumptions, and shed new light on peer dynamics among analysts.

This study has important implications for understanding analyst behavior and the broader functioning of the capital markets. By demonstrating that social comparisons with peers enhance analysts' self-evaluation and forecasting accuracy, this study highlights the productive role of peer dynamics beyond traditional competitive frameworks. The results suggest that institutional settings that increase analysts' exposure to their peers—such as industry conferences or cross-firm coverage—may foster more effortful and accurate information production. Furthermore, our findings encourage reconsideration of how sell-side analysts are evaluated and motivated, emphasizing the value of constructive peer interactions. For regulators and brokerage firms, recognizing the influence of social comparison can help inform policies that support transparency, collaboration, and professional development within the analyst community.

This paper has a few important limitations. First, although we construct our social comparison measure to minimize confounding effects from competition and information-sharing, disentangling these mechanisms empirically remains inherently challenging. Second, our archival analysis relies on coverage overlaps as a proxy for social comparison, which may not fully capture the richness or directionality of interpersonal interactions among analysts. Third, although our interviews provide valuable qualitative support for the theoretical framework, they are based on a limited sample of analysts and may not generalize across all sectors or geographies. Lastly, our study focuses on U.S. sell-side analysts, which may limit the applicability of our findings to other institutional contexts with different norms or structures of analyst behavior. Future research can explore other aspects of analyst peer dynamics and their consequences in capital markets.

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Appendix A: An Example Demonstrating the Computation of *OVERLAP*

Firm *f1* is followed by analysts A, B, C, D

Analyst A follows *f1, f2, f3*

Analyst B follows *f1, f3, f4*

Analyst C follows *f1, f3, f4, f5*

Analyst D follows *f1, f5, f6, f7*

$OVERLAP_{A, f1}$ = Overlaps of *f2* + Overlaps of *f3* = 0 + 2 = 2

$OVERLAP_{B, f1}$ = Overlaps of *f3* + Overlaps of *f4* = 2 + 1 = 3

$OVERLAP_{C, f1}$ = Overlaps of *f3* + Overlaps of *f4* + Overlaps of *f5* = 2 + 1 + 1 = 4

$OVERLAP_{D, f1}$ = Overlaps of *f5* + Overlaps of *f6* + Overlaps of *f7* = 1 + 0 + 0 = 1

$OVERLAP_{ijt}$ captures the extent to which analyst *i*'s portfolio overlaps with portfolios of peer analysts who jointly cover firm *j* with analyst *i* in year *t*. Specifically, $OVERLAP_{ijt}$ is the total number of times other firms (i.e., firms in analyst *i*'s portfolio except for firm *j*) are also covered by peers. We use a hypothetical example to illustrate how to calculate $OVERLAP_{ijt}$. As firm *f1* is followed by analysts A, B, C, and D, these four analysts are considered peers due to the joint coverage of *f1*. Analysts A, B, C, D cover {*f2*, *f3*}, {*f3*, *f4*}, {*f3*, *f4*, *f5*}, {*f5*, *f6*, *f7*} except for *f1*, respectively. $OVERLAP_{A, f1}$ measures the number of times other firms covered by A (i.e., *f2* and *f3*) overlap with firms covered by peers. Thus, $OVERLAP_{A, f1}$ is equal to the number of overlapping times of *f2* plus the number of overlapping times of *f3*. As *f2* is only covered by A and *f3* is covered by B and C except for A, $OVERLAP_{A, f1}$ = 0 + 2 = 2. Using the same method, we also calculate $OVERLAP_{B, f1}$, $OVERLAP_{C, f1}$, and $OVERLAP_{D, f1}$.

Appendix B: Variable Definition

Variable	Description
Analyst-firm-year level variables:	
$ACCURACY_{ijt}$	Analyst *i*'s relative forecast accuracy for firm *j* in year *t*, calculated as the highest absolute forecast error (*AFE*) for all analysts following firm *j* in year *t* minus *AFE* of analyst *i* for firm *j* scaled by the range of *AFE* for analysts following firm *j* in year *t*. As a result, a higher value would indicate lower *AFE* and higher accuracy. See the equation below: $ACCURACY_{ijt} = [Max(AFE_{jt}) - AFE_{ijt}]/[Max(AFE_{jt}) - Min(AFE_{jt})]$, where $Max(AFE_{jt})$ and $Min(AFE_{jt})$ are maximum and minimum values of *AFE* for all analysts covering firm *j* in year *t*, respectively.
$OVERLAP_{ijt}$	The scaled peers' overlap for analyst *i* following firm *j* in year *t*. Overlaps are the total number of times other firms (i.e., firms in analyst *i*'s portfolio except for firm *j*) are also covered by peers (i.e., analysts who jointly cover firm *j* with analyst *i* in year *t*). The scaled value is calculated as overlaps for analyst *i* following firm *j* in year *t* minus the lowest overlaps for analysts following firm *j* in year *t*, scaled by the range of overlaps for analysts following firm *j* in year *t*. See the equation below: $Scaled\ Variable_{ijt} = [Raw\ Variable_{ijt} - Min(Variable_{jt})]/[Max(Variable_{jt}) - Min(Variable_{jt})]$, where $Max(Variable_{jt})$ and $Min(Variable_{jt})$ are maximum and minimum values of an analyst characteristic for all analysts covering firm *j* in year *t*, respectively. Analyst variables except *ACCURACY* are scaled using this equation.
$OVERLAP\_DROP_{ijt}$	Coverage overlaps between analyst *i* (i.e., an analyst who jointly covers firm *j* with the dropped analyst) and a dropped analyst one year before brokerage mergers/closures.
$OVERLAP\_HIGH_{ijt}$	The scaled overlaps of other firms with *higher* importance/a *longer* history of being covered. First, a firm is classified as *more* important if its size/trading volume/institutional ownership is in the top quartile of all firms covered by analyst *i*; a firm is classified as having a *longer* history of being covered by analyst *i* if analyst *i*'s firm-specific experience for this firm is in the top quartile of all firms covered by analyst *i*. Second, overlaps of other firms with higher importance/a longer history of being covered are calculated. Last, raw overlaps are scaled to lie between 0 and 1. Firm size is the market capitalization at the end of year *t*-1. Trading volume is determined as the average daily trading volume over year *t*-1. Institutional ownership is the percent of a firm's common shares held by institutional investors at the end of year *t*-1.
$OVERLAP\_LOW_{ijt}$	The scaled overlaps of other firms with *lower* importance/a *shorter* history of being covered. First, a firm is classified as *less* important if this firm's size/trading volume/institutional ownership is in the bottom quartile of all firms covered by analyst *i*; a firm is classified as having a *shorter* history of being covered by analyst *i* if analyst *i*'s firm-specific experience for this firm is in the bottom quartile of all firms covered by analyst *i*. Second, overlaps of other firms with *lower* importance/a *shorter* history of being covered are calculated. Last, raw overlaps are scaled to lie between 0 and 1.

$OVERLAP\_SuperiorPeer_{ijt}$	The scaled coverage overlaps between analyst *i* and one peer who has the highest forecast accuracy for all analysts following firm *j* in the previous year.
$OVERLAP\_InferiorPeer_{ijt}$	The scaled coverage overlaps between analyst *i* and one peer who has the lowest forecast accuracy for all analysts following firm *j* in the previous year.
$OVERLAP\_ExcludeFocal_{ijt}$	The scaled total number of times other firms in analyst *i*'s portfolio are covered by analysts who do not cover the focal firm *j*.
OVERLAP_Herding	The scaled coverage overlaps between an analyst and one peer who has the highest fraction of herding forecasts for the current firm in the previous year. Forecasts are considered herding if they fall between the analyst's prior forecast and the consensus forecast immediately before the forecast revision, and all other forecasts are considered bold.
OVERLAP_Bold	The scaled coverage overlaps between an analyst and one peer who has the lowest fraction of herding forecasts for the current firm in the previous year.
$SALEFORECAST_{ijt}$	Equals 1 if analyst *i* issues a sales forecast for firm *j* in year *t*, and 0 otherwise.
$TIMELINESS_{ijt}$	The scaled forecast timeliness, defined as the number of days between the prior year's earnings announcement and the first forecast issued by an analyst this year, multiplied by -1 and scaled to lie between 0 and 1.
$FEXP_{ijt}$	The scaled firm-specific experience, calculated as the number of years of firm-specific experience for analyst *i* following firm *j* in year *t* minus the lowest number of years of firm-specific experience for analysts following firm *j* in year *t*, scaled by the range of years of firm-specific experience for analysts following firm *j* in year *t*.
$GEXP_{ijt}$	The scaled general experience, calculated as the number of years of general experience for analyst *i* following firm *j* in year *t* minus the lowest number of years of general experience for analysts following firm *j* in year *t*, scaled by the range of years of general experience for analysts following firm *j* in year *t*.
$BSIZE_{ijt}$	The scaled brokerage house size, calculated as the percentile of the number of analysts employed by the brokerage employing analyst *i* following firm *j* in year *t* minus the lowest percentile of number of analysts employed by brokerages for analysts following firm *j* in year *t*, scaled by the range of brokerage size for analysts following firm *j* in year *t*.
$NFIRM_{ijt}$	The scaled number of firms covered by analyst *i*, calculated as the number of firms covered by analyst *i* following firm *j* in year *t* minus the lowest number of firms covered by analysts following firm *j* in year *t*, scaled by the range in the number of firms covered by analysts following firm *j* in year *t*.
$NIND_{ijt}$	The scaled number of industries covered by analyst *i*, calculated as the number of two-digit SICs covered by analyst *i* following firm *j* in year *t* minus the lowest number of industries covered by analysts following firm *j* in year *t*, scaled by the range in the number of industries covered by analysts following firm *j* in year *t*.
$FREQ_{ijt}$	Analyst *i*'s scaled forecast frequency for firm *j*, calculated as the number of forecasts for firm *j* by analyst *i* in year *t* minus the lowest number of firm-*j*

	forecasts of all analysts following firm *j* in year *t*, scaled by the range in the number of firm-*j* forecasts of all analysts following firm *j* in year *t*.
Firm-year level variables:	
$SIZE_{jt}$	Market capitalization of firm *j* at the end of year *t* (in \$ ten billion).
MTB_{jt}	Market value of equity divided by book value of equity for firm *j* in year *t*.
LEV_{jt}	Long-term debt divided by lagged total assets for firm *j* in year *t*.
ROA_{jt}	Net income before extraordinary items divided by lagged total assets for firm *j* in year *t*.
$FOLLOW_{jt}$	The number of analysts issuing forecasts for firm *j* in year *t*.

Appendix C: Prepared Questions for Semi-Structured Interviews

Question 1

What motivates you to do good work as an analyst, and how do you know if you've done good work?

Question 2

How would you define your peers?

Question 3

How would you describe your relationship with your peers? Do you see them purely as your competitors?

Question 4

Do you compare yourself to your peers and if so, why?

Question 5

Does having peer analysts impact how you assess your work?

Question 6

Our research shows that analysts make more accurate forecasts when they have more peer analysts. Why do you think this might be the case?

Table 1
Descriptive Statistics

This table presents descriptive statistics for the main variables. Panel A provides statistics for variables with raw values, Panel B provides statistics for scaled variables, and Panel C provides Pearson correlations. The boldface number in Panel C indicates significance at the 5% level. Variable definitions are provided in Appendix B.

Panel A: Raw values

Variable	N	Mean	Std. Dev	Q1	Median	Q3
AFE	525,128	0.184	0.393	0.020	0.060	0.160
OVERLAP	525,128	72.534	76.176	16.000	49.000	105.000
FEXP	525,128	4.556	4.365	2.000	3.000	6.000
GEXP	525,128	11.980	8.024	5.000	11.000	17.000
BSIZE	525,128	86.580	16.414	82.000	93.000	97.000
NFIRM	525,128	18.484	11.722	12.000	17.000	22.000
NIND	525,128	4.386	3.052	2.000	4.000	6.000
FREQ	525,128	4.361	2.711	3.000	4.000	6.000
SIZE	525,128	1.154	2.603	0.080	0.260	0.915
MTB	525,128	3.444	4.479	1.501	2.379	3.967
LEV	525,128	0.228	0.240	0.035	0.174	0.333
ROA	525,128	0.063	0.175	0.015	0.068	0.140
FOLLOW	525,128	17.487	10.155	9.000	16.000	24.000
SALEFORECAST	452,164	0.606	0.489	0.000	1.000	1.000
TIMELINESS	452,164	-41.528	62.971	-68.000	-6.000	-1.000

Panel B: Scaled values

Variable	N	Mean	Std. Dev	Q1	Median	Q3
ACCURACY	525,128	0.692	0.333	0.500	0.833	0.960
OVERLAP	525,128	0.547	0.317	0.300	0.576	0.813
FEXP	525,128	0.375	0.365	0.000	0.250	0.667
GEXP	525,128	0.493	0.360	0.148	0.455	0.857
BSIZE	525,128	0.735	0.317	0.611	0.878	0.970
NFIRM	525,128	0.426	0.303	0.182	0.375	0.632
NIND	525,128	0.370	0.324	0.100	0.300	0.571
FREQ	525,128	0.483	0.324	0.231	0.500	0.750
TIMELINESS	452,164	0.833	0.267	0.757	0.984	1.000

Panel C: Pearson correlation table

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	*ACCURACY*	1												
(2)	*OVERLAP*	**0.089**	1											
(3)	*FEXP*	**0.012**	**0.130**	1										
(4)	*GEXP*	**0.022**	**0.155**	**0.360**	1									
(5)	*BSIZE*	**0.057**	**0.206**	**-0.012**	**0.023**	1								
(6)	*NFIRM*	**-0.017**	**0.346**	**0.170**	**0.217**	**0.022**	1							
(7)	*NIND*	**-0.041**	**0.055**	**0.097**	**0.122**	**-0.109**	**0.533**	1						
(8)	*FREQ*	**0.021**	**0.098**	**0.203**	**0.039**	**0.052**	**0.099**	**0.047**	1					
(9)	*SIZE*	**0.075**	**0.012**	**-0.048**	**0.011**	**0.084**	**-0.066**	**-0.084**	**-0.060**	1				
(10)	*MTB*	**0.025**	**-0.007**	**-0.009**	**-0.012**	**0.027**	**-0.013**	**-0.016**	**-0.017**	**0.133**	1			
(11)	*LEV*	**-0.010**	**0.014**	**0.006**	**-0.006**	**0.020**	**0.014**	**0.003**	**-0.016**	**-0.050**	**-0.019**	1		
(12)	*ROA*	**0.041**	-0.001	**-0.015**	**0.041**	**0.034**	**-0.031**	**-0.023**	**-0.033**	**0.144**	**0.114**	**-0.093**	1	
(13)	*FOLLOW*	**0.182**	**-0.008**	**-0.091**	**-0.016**	**0.169**	**-0.123**	**-0.159**	**-0.097**	**0.449**	**0.134**	**-0.040**	**0.146**	1

Table 2
Peers' Overlap and Forecast Accuracy

This table presents regressions of forecast accuracy on peers' overlap. The dependent variable *ACCURACY* is the relative forecast accuracy. *OVERLAP* is the scaled overlaps, calculated as the total number of times other firms in an analyst's portfolio are also covered by peers. Variable definitions are provided in Appendix B. *t*-statistics are reported in parentheses and standard errors are clustered by analyst. All *p*-values are two-tailed. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

DV = *ACCURACY*	(1)	(2)	(3)
OVERLAP		**0.100*****	**0.098*****
		(36.73)	**(36.62)**
FEXP	0.015***	0.010***	-0.006***
	(7.52)	(5.41)	(-3.23)
GEXP	0.017***	0.011***	0.005
	(6.14)	(4.13)	(0.78)
BSIZE	0.024***	0.006**	0.000
	(8.29)	(2.03)	(0.04)
NFIRM	0.005	-0.036***	-0.042***
	(1.51)	(-10.55)	(-12.24)
NIND	-0.018***	-0.003	-0.011***
	(-6.61)	(-1.24)	(-3.72)
FREQ	0.034***	0.030***	-0.004**
	(15.60)	(13.60)	(-2.24)
SIZE	-0.001***	-0.002***	0.002***
	(-5.27)	(-6.48)	(4.23)
MTB	0.000	0.000	0.000
	(0.29)	(0.78)	(1.34)
LEV	-0.003	-0.003	0.010***
	(-0.94)	(-1.29)	(3.08)
ROA	0.029***	0.029***	0.028***
	(7.97)	(7.89)	(5.72)
FOLLOW	0.006***	0.006***	0.006***
	(80.39)	(81.94)	(43.94)
Year FE	N	N	Y
Analyst FE	N	N	Y
Firm FE	N	N	Y
Observations	525,128	525,128	525,128
R-squared	0.037	0.044	0.143

Table 3
Brokerage Mergers/Closures, Exogenous Decreases in Overlaps, and Forecast Accuracy

This table presents the effects of exogenous drops of overlaps on changes in forecast accuracy using brokerage mergers/closures as a quasi-natural experiment. *OVERLAP_DROP* is coverage overlaps between an analyst and the dropped analyst before the merger/closure. Δ*ACCURACY* is the change in forecast accuracy from year *t-1* to *t*. For control variables, changes are defined as the values in year *t* minus the values in year *t*-1. Variable definitions are provided in Appendix B. *t*-statistics are reported in parentheses and standard errors are clustered by analyst. All *p*-values are two-tailed. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

DV = Δ*ACCURACY*	(1)
OVERLAP_DROP	**-0.002****
	(-2.25)
Δ*BSIZE*	-0.001**
	(-2.31)
Δ*NFIRM*	0.001
	(0.61)
Δ*NIND*	0.004
	(1.40)
Δ*FREQ*	0.006***
	(5.23)
Δ*SIZE*	-0.005**
	(-2.50)
Δ*MTB*	-0.003***
	(-3.79)
Δ*LEV*	0.059**
	(2.20)
Δ*ROA*	0.615***
	(11.28)
Δ*FOLLOW*	0.002*
	(1.71)
Year FE	Y
Analyst FE	Y
Firm FE	Y
Observations	24,141
R-squared	0.548

Table 4
Peers' Overlap and Analyst Effort

This table presents regressions of analyst effort on overlaps. *FREQ* is the scaled earnings forecast frequency. *TIMELINESS* is the scaled forecast timeliness. *SALEFORECAST* is the indicator of whether an analyst issues a sales forecast for a firm in a year. *OVERLAP* is the scaled overlaps. Variable definitions are provided in Appendix B. *t*-statistics are reported in parentheses and standard errors are clustered by analyst. All *p*-values are two-tailed. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

DV =	*FREQ*	*TIMELINESS*	*SALEFORECAST*
	(1)	(2)	(3)
OVERLAP	**0.133*****	**0.007*****	**0.027*****
	(45.62)	**(3.42)**	**(7.43)**
FEXP	-0.020***	-0.009***	-0.008***
	(-9.52)	(-5.80)	(-3.00)
GEXP	-0.027***	-0.008	0.037***
	(-3.76)	(-1.49)	(2.98)
BSIZE	0.003	0.036***	0.026***
	(0.65)	(12.15)	(2.96)
NFIRM	-0.059***	0.012***	-0.008
	(-14.71)	(4.30)	(-1.21)
NIND	-0.005	0.007***	-0.002
	(-1.27)	(2.97)	(-0.38)
$FREQ_{t-1}$	0.055***	0.045***	-0.000
	(21.55)	(27.74)	(-0.15)
SIZE	0.000	-0.002***	-0.001
	(0.92)	(-6.03)	(-1.60)
MTB	0.001***	0.001***	0.000
	(4.39)	(4.68)	(1.55)
LEV	0.013***	0.014***	-0.005
	(3.64)	(5.16)	(-1.20)
ROA	0.014**	0.031***	-0.018***
	(2.37)	(7.94)	(-2.62)
FOLLOW	-0.001***	0.005***	0.001***
	(-9.42)	(40.85)	(5.22)
Year FE	Y	Y	Y
Analyst FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	452,164	452,164	452,164
R-squared	0.243	0.177	0.746

Table 5
Peers' Overlap and Forecast Accuracy: Conditional on Firms' Relative Importance

This table presents regressions of forecast accuracy on peers' overlap, conditional on firms' relative importance in an analyst's portfolio. The dependent variable *ACCURACY* is the relative forecast accuracy. *OVERLAP_HIGH*/*OVERLAP_LOW* is the scaled overlaps of other firms with *higher*/*lower* importance. Firm size/ trading volume/institutional ownership is used to identify firms' relative importance. Variable definitions are provided in Appendix B. *t*-statistics are reported in parentheses and standard errors are clustered by analyst. All *p*-values are two-tailed. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Firm size		Trading volume		Institutional ownership	
DV = *ACCURACY*	(1)	(2)	(3)	(4)	(5)	(6)
OVERLAP_LOW	**0.013*****	**0.014*****	**0.014*****	**0.017*****	**0.025*****	**0.024*****
	(5.51)	**(6.15)**	**(6.19)**	**(7.17)**	**(10.59)**	**(10.50)**
OVERLAP_HIGH	**0.068*****	**0.057*****	**0.064*****	**0.053*****	**0.051*****	**0.045*****
	(26.81)	**(23.45)**	**(24.88)**	**(21.21)**	**(20.73)**	**(19.34)**
FEXP	0.010***	-0.004*	0.010***	-0.003*	0.010***	-0.005**
	(4.77)	(-1.73)	(4.84)	(-1.71)	(4.70)	(-2.21)
GEXP	0.010***	0.002	0.010***	0.005	0.010***	0.004
	(3.53)	(0.35)	(3.40)	(0.69)	(3.54)	(0.58)
BSIZE	0.012***	0.004	0.011***	0.004	0.011***	0.005
	(3.53)	(1.15)	(3.50)	(1.15)	(3.48)	(1.22)
NFIRM	-0.035***	-0.040***	-0.033***	-0.038***	-0.032***	-0.039***
	(-9.57)	(-10.72)	(-9.17)	(-10.19)	(-8.61)	(-10.32)
NIND	-0.009***	-0.012***	-0.010***	-0.013***	-0.008***	-0.011***
	(-3.01)	(-3.75)	(-3.31)	(-3.88)	(-2.81)	(-3.40)
FREQ	0.030***	-0.003	0.031***	-0.003	0.031***	-0.003
	(12.46)	(-1.63)	(12.75)	(-1.34)	(12.78)	(-1.29)
SIZE	-0.002***	0.001**	-0.002***	0.001**	-0.002***	0.001**
	(-7.40)	(2.09)	(-7.77)	(2.10)	(-7.80)	(2.26)
MTB	-0.000	0.000	-0.000	0.000	-0.000	-0.000
	(-0.47)	(0.12)	(-0.48)	(0.18)	(-0.05)	(-0.07)
LEV	-0.005	0.009**	-0.005	0.009**	-0.005*	0.008**
	(-1.54)	(2.28)	(-1.59)	(2.29)	(-1.75)	(2.04)
ROA	0.022***	0.022***	0.022***	0.023***	0.022***	0.021***
	(5.54)	(4.05)	(5.65)	(4.24)	(5.42)	(3.94)
FOLLOW	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(72.31)	(39.64)	(72.42)	(39.65)	(73.09)	(39.65)
Year FE	N	Y	N	Y	N	Y
Analyst FE	N	Y	N	Y	N	Y
Firm FE	N	Y	N	Y	N	Y
Observations	430,620	430,620	430,305	430,305	430,253	430,253
R-squared	0.039	0.133	0.039	0.132	0.038	0.132
p-value of *OVERLAP_LOW= OVERLAP_HIGH*	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Table 6
Peers' Overlap and Forecast Accuracy: Conditional on Analysts' Firm-specific Experience

This table presents regressions of forecast accuracy on peers' overlap, conditional on the analyst's firm-specific experience. The dependent variable *ACCURACY* is the relative forecast accuracy. *OVERLAP_HIGH*/*OVERLAP_LOW* is the scaled overlaps of other firms with a *longer*/*shorter* history of being covered. Variable definitions are provided in Appendix B. *t*-statistics are reported in parentheses and standard errors are clustered by analyst. All *p*-values are two-tailed. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Firm-specific experience	
DV = *ACCURACY*	(1)	(2)
OVERLAP_LOW	**0.015*****	**0.016*****
	(6.07)	**(6.82)**
OVERLAP_HIGH	**0.033*****	**0.037*****
	(12.78)	**(14.52)**
FEXP	0.011***	-0.001
	(4.99)	(-0.39)
GEXP	0.010***	-0.033***
	(3.02)	(-4.07)
BSIZE	0.019***	0.013***
	(6.07)	(3.41)
NFIRM	-0.031***	-0.045***
	(-7.65)	(-10.54)
NIND	-0.010***	-0.008**
	(-3.12)	(-2.14)
FREQ	0.031***	0.005**
	(11.38)	(2.20)
SIZE	-0.001***	0.001*
	(-4.73)	(1.94)
MTB	-0.000*	-0.000
	(-1.80)	(-0.87)
LEV	-0.012***	0.002
	(-3.58)	(0.47)
ROA	0.015***	0.007
	(3.21)	(1.12)
FOLLOW	0.006***	0.006***
	(63.41)	(34.26)
Year FE	N	Y
Analyst FE	N	Y
Firm FE	N	Y
Observations	406,223	406,223
R-squared	0.030	0.111
p-value of *OVERLAP_LOW*= *OVERLAP_HIGH*	<0.01	<0.01

Table 7
Tests Addressing Alternative Explanations

This table presents tests addressing alternative explanations. The dependent variable *ACCURACY* is the relative forecast accuracy. In Panel A, *OVERLAP_InferiorPeer* (*OVERLAP_SuperiorPeer*) is the scaled coverage overlaps between an analyst and one peer who has the lowest (highest) forecast accuracy in the previous year. *OVERLAP_ExcludeFocal* is the scaled total number of times other firms in an analyst's portfolio are covered by analysts who do not cover the focal firm. In column (1) ((2)) of Panel B, *OVERLAP* is calculated as overlaps of firms in different two-digit SIC (four-digit GICS) relative to the current firm. In Panel C, *OVERLAP_Herding* (*OVERLAP_Bold*) is the scaled coverage overlaps between an analyst and one peer who has the highest (lowest) fraction of herding forecasts for the current firm in the previous year. *t*-statistics are reported in parentheses and standard errors are clustered by analyst. All *p*-values are two-tailed. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Additional tests addressing the alternative explanation based on competition

DV = *ACCURACY*	(1)	(2)
OVERLAP_SuperiorPeer	**0.027***** **(7.56)**	
OVERLAP_InferiorPeer	**0.028***** **(7.99)**	
OVERLAP_ExcludeFocal		**0.033***** **(10.16)**
FEXP	0.001 (0.16)	-0.003 (-1.57)
GEXP	-0.012 (-0.79)	0.005 (0.93)
BSIZE	0.010 (1.43)	0.007** (1.98)
NFIRM	-0.036*** (-5.25)	-0.032*** (-9.35)
NIND	-0.003 (-0.49)	-0.017*** (-5.75)
FREQ	-0.003 (-0.89)	-0.002 (-1.20)
SIZE	0.002* (1.74)	0.002*** (3.85)
MTB	0.001** (2.51)	0.000 (1.17)
LEV	0.010 (1.20)	0.010*** (2.96)
ROA	-0.009 (-0.70)	0.029*** (5.98)
FOLLOW	0.005*** (17.36)	0.006*** (44.46)
Year FE	Y	Y
Analyst FE	Y	Y
Firm FE	Y	Y
Observations	96,382	534,027
R-squared	0.242	0.140
p-value of *OVERLAP_SuperiorPeer* = *OVERLAP_InferiorPeer*	0.87	

Panel B: Additional tests addressing the alternative explanation based on information sharing by focusing on coverage overlaps of firms from different industries

Overlaps of firms from different	Two-digit SIC	Four-digit GICS
DV = *ACCURACY*	(1)	(2)
OVERLAP	**0.042*****	**0.021*****
	(18.15)	**(8.37)**
FEXP	-0.004**	-0.002
	(-2.08)	(-0.97)
GEXP	0.006	0.008
	(0.89)	(0.87)
BSIZE	0.004	-0.001
	(1.18)	(-0.31)
NFIRM	-0.029***	-0.024***
	(-8.21)	(-5.85)
NIND	-0.018***	-0.018***
	(-5.68)	(-4.66)
FREQ	-0.002	-0.007***
	(-0.96)	(-3.19)
SIZE	0.002***	0.003***
	(3.60)	(5.18)
MTB	0.000	0.000
	(0.76)	(0.69)
LEV	0.011***	0.014***
	(3.22)	(3.55)
ROA	0.031***	0.035***
	(5.95)	(5.48)
FOLLOW	0.005***	0.005***
	(40.46)	(31.06)
Year FE	Y	Y
Analyst FE	Y	Y
Firm FE	Y	Y
Observations	482,831	356,514
R-squared	0.143	0.155

Panel C: Additional tests addressing the alternative explanation based on information sharing by comparing overlaps with bold peers and with herding peers

DV = *ACCURACY*	(1)
OVERLAP_Herding	**0.030*** **
	(10.48)
OVERLAP_Bold	**0.035*** **
	(12.46)
FEXP	-0.002
	(-0.62)
GEXP	-0.020
	(-1.44)
BSIZE	-0.008
	(-1.25)
NFIRM	-0.038***
	(-6.13)
NIND	0.002
	(0.30)
FEXP	-0.002
	(-0.68)
SIZE	0.002***
	(3.11)
MTB	0.000
	(0.92)
LEV	0.006
	(0.82)
ROA	0.037***
	(3.31)
FOLLOW	0.005***
	(20.54)
Year FE	Y
Analyst FE	Y
Firm FE	Y
Observations	133,915
R-squared	0.200
p-value of *OVERLAP_Herding* = *OVERLAP_Bold*	0.21