Social Learning and Analyst Behavior*

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Abstract

This study examines whether sell-side equity analysts engage in "social learning" where their earnings forecasts are influenced by the forecasts and outcomes of other analysts associated with other firms (i.e., the "peers") in their respective portfolios. We find that analyst optimism is negatively correlated with the recent forecast errors among peers on other firms in the analyst portfolio. An analyst is also more likely to issue "bold" forecasts when similar forecasts were recently issued for other portfolio firms. Analysts learn more from their peers with similar personal characteristics. Overall, social learning is beneficial to analysts and improves their forecast accuracy.

Keywords: Sell-side equity analysts, social learning, forecast optimism, bold forecasts, in-group bias, forecast accuracy.

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1. Introduction

Sell-side equity analysts face a difficult prediction task, and they use information from multiple sources to improve their forecasting skill. As competition increases, analysts are likely to exploit alternative and proprietary data sources to gain a competitive advantage. Nevertheless, learning from publicly available information sources is likely to remain an important aspect of their forecasting behavior.

In this paper, we study whether sell-side equity analysts engage in "social learning" where their earnings forecasts for a certain firm (i.e., the "focal" firm) are influenced by the characteristics of forecasts of other analysts on *other* firms (i.e., the "peers") in their respective coverage portfolios (i.e., the set of firms covered by an analyst).[1] Specifically, we investigate whether heterogeneity in the composition of analyst coverage portfolios generates heterogeneity in peer exposure that differentially influences their information gathering activities and forecasting behavior.

Previous research shows that analysts pay attention to the opinions of other analysts about a firm they cover. In particular, their forecasts are influenced by strategic herding behavior, where analysts follow each other's forecasts and recommendations on the same firm (Trueman 1994, Graham 1999, Welch 2000). Such behavior can result from information cascades where an analyst infers information from other analysts' earnings estimates (Bikhchandani, Hirshleifer, and Welch 1992), as well as through strategic behavior where analysts may be afraid to deviate from the

[1] In the finance and economics literature, "social learning" refers to situations where agents learn from others in a way that is broader than pure informational herding (see, for example, Ellison and Fudenberg 1993, Moretti 2011, Kaustia and Rantala 2015). In our context, an analyst's forecast-specific "peers" represent the group of analysts who cover at least one *other* firm in the analyst portfolio. Consider an analyst i who covers a portfolio of firms $j = 1, 2, \ldots, N$. When we compute the peer forecast characteristics (such as optimism or boldness) associated with analyst i for a specific focal firm $j = J$, we only consider the forecasts of all other analysts who also cover the firms in the coverage portfolio of analyst i, *excluding* the focal firm $j = J$.

consensus due to career concerns (Hong, Kubik, and Solomon 2000). The ability to extract information from the current actions of others is likely to be an important source of analyst expertise (Clement, Hales, and Xue 2011).[2]

We extend this line of research and posit that sell-side equity analysts engage in social learning to improve their forecasting performance. Specifically, our main conjecture is that an analyst's earnings forecast for the focal firm is additionally influenced by the actions and opinions of peer analysts covering other portfolio firms. In particular, due to limited attention, an analyst is likely to pay more attention to the forecast errors and revisions of other analysts on other firms in her own portfolio and pay relatively less attention to similar information about other firms that are not part of her portfolio.[3]

In a frictionless world where all analyst forecasts are public information, if analyst forecasts for a certain firm contain information that is relevant for other firms, all analysts following those other firms should react to this information in the same way. Instead, we posit that there will be heterogeneity in the information set of analysts induced by the heterogeneity in the composition of their coverage portfolios. In particular, information about peer forecasts and errors within the coverage portfolio would be more accessible to an analyst and could provide the context within which she examines and issues a forecast on a certain firm in the portfolio.

For example, if the forecasts of other analysts on other firms have been systematically higher (lower) than actual earnings, an analyst may update his views about the focal firm and issue more pessimistic (optimistic) forecasts to correct for the perceived bias. Similarly, if other analysts make

[2] Additionally, analyst rankings that identify top analysts within the same industry sector provide an additional incentive to study what other analysts are saying in their reports. Performance in these rankings has a significant impact on analyst compensation (Stickel 1992, Michaely and Womack 1999, Hong, Kubik, and Solomon 2000).
[3] Most analysts specialize in covering related firms in a particular industry or industry group (Michaely and Womack 1999, Mikhail, Walther, and Willis 2004, Boni and Womack, 2006, Merkley, Michaely, and Pacelli, 2017, Kaustia and Rantala 2020). Industry-specific knowledge is also an important input into analysts' earnings forecasts (Piotroski and Roulstone 2004, Kadan, Madureira, Wang, and Zach 2012, Bradley, Gokkaya, and Liu, 2017).

many positive or negative forecast revisions that deviate from the consensus, an analyst may imitate the behavior and issue similar "bold" forecasts for the focal firm. Figure 1 illustrates this key idea graphically.

Based on our limited attention hypothesis, we further predict that analysts are likely to learn more effectively from peer analysts who share similar personal characteristics with them. This additional conjecture is partially motivated by the large body of psychology literature on in-group bias, which suggests that people are more likely to follow or interact with others who are more like them (e.g., McPherson, Smith-Lovin, and Cook 2001).

Our social learning hypothesis differs from the traditional informational herding behavior (Bikhchandani, Hirshleifer, and Welch 1992) in two ways. First, in the current learning context, analysts learn from peer forecasts on *other* firms, as opposed to learning from other analyst forecasts on the *same* firm. Second, analysts also learn from *past* outcomes (forecast errors) of their peers and do not only imitate their *current* forecasts.[4]

We start by analyzing the impact of past forecast errors of peers on analyst forecast optimism toward the focal firm. We estimate panel regressions using quarterly earnings forecasts, where the dependent variable is an analyst's relative optimism for the focal firm, as reflected by forecast error.[5] The main explanatory variable is the one-quarter lagged average forecast error of peer analysts. That is, if analyst i follows firms j, k, and l, we explain the forecast error of analyst i on firm j during quarter t using the average forecast error of other analysts on firms k and l during quarter $t-1$.[6]

[4] For theoretical models of social learning, see Ellison and Fudenberg (1993, 1995), Banerjee and Fudenberg (1995), and Cao, Han, and Hirshleifer (2011).

[5] Similar to the convention in the analyst literature, forecast error is calculated as the difference between the earnings per share (EPS) forecast and the actual EPS, scaled by the share price.

[6] We only include peer forecasts from the previous quarter to ensure that our findings on peer influence are not affected by the order in which firms announce their earnings for the same quarter. Thus, our analysis differs from previous

All optimism regression specifications include earnings announcement fixed effects, which control for any joint firm- and time-specific factors that affect the forecast errors of all analysts following the focal firm. This means that, effectively, we are comparing analysts who follow the focal firm against each other and the variation in the explanatory variable is based on differences in the coverage portfolio of those analysts. We also include firm-analyst fixed effects to control for an analyst's average optimism regarding the focal firm.

The forecast optimism results show that peer analysts' lagged average forecast error on other firms has a negative and statistically significant impact on an analyst's forecast error. The coefficient values range between –0.004 and –0.010, with *t*-values between –2.9 and –5.1. The analyst's previous forecast error on the focal firm is positive and statistically significant, with a coefficient estimate of 0.005 when included as an additional explanatory variable. This finding is consistent with the evidence in previous studies, which finds serial correlation in forecast errors of analysts (Abarbanell and Bernard 1992, Markov and Tamayo 2006, Hilary and Hsu 2006, Linnainmaa, Torous, and Yae 2016).

When we re-estimate these same regressions using an alternative forecast optimism measure where we measure analyst optimism based on his forecast relative to the consensus forecast, the results are very similar. The signs of the coefficient estimates from forecast optimism regressions indicate that analysts react to the mistakes of other analysts but do not necessarily learn from their own previous errors. In economic terms, the social learning effect captured by our coefficient estimates is on average 2% of the mean absolute deviation from the consensus forecast.

Next, we analyze whether past bold forecast revisions of peer analysts predict the likelihood that an analyst issues a bold forecast with the same sign for the focal firm. A bold forecast, as

papers that specifically focus on the information content in early announcers' earnings surprises (Ramnath 2002, Thomas and Zhang 2008).

defined by Clement and Tse (2005), is a forecast where an analyst deviates both from the consensus forecast and from his own previous forecast in the same direction. Clement and Tse (2005) show that bold forecasts are more accurate than other forecasts and appear to reflect relevant private information. We conjecture that analysts update their beliefs about the earnings of focal firms using peer analysts' bold forecasts for other firms because those bold forecasts may contain information relevant for the focal firm. These bold forecasts of peers deviate from the consensus and are likely to stand out. Consequently, they are more likely to capture an analyst's attention.

We estimate quarterly panel regressions separately for bold-positive and bold-negative forecasts. The dependent variable in these regressions is an indicator variable that takes the value of one when an analyst issues a bold forecast during an observation quarter and zero otherwise. The main explanatory variable is the percentage of peer analysts who issue a bold forecast with the same sign during the preceding quarter. We also include an indicator variable that takes the value of one if the analyst issues a bold forecast himself during the preceding quarter. All bold regression specifications include the same set of fixed effects as the forecast optimism regressions.

The bold regression estimates indicate that analysts imitate the boldness of their peers. The coefficient estimate for peer analysts' bold-positive forecasts in the baseline regression is 0.010 with a *t*-value of 2.8, and the corresponding coefficient on bold-negative forecasts is 0.017 with a *t*-value of 5.3. The bold forecasts of peers with a different sign do not statistically significantly explain bold-positive or bold-negative forecasts. In economic terms, these coefficient estimates imply that, relative to the unconditional probability of making a bold forecast, a one standard deviation change in the explanatory variable increases bold forecast probability by 3.3% when we consider bold-positive forecasts and by 4.2% when we focus on the set of bold-negative forecasts.

When learning from the forecasts of other analysts, an analyst could pay more attention to peer forecasts for firms similar to the focal firm, as those forecasts are likely to contain more relevant information than forecast errors on dissimilar firms. In addition, certain peers may attract greater analyst attention.

In the next set of tests, we analyze which peer analyst forecasts generate stronger social learning effects. Specifically, we extend our previous forecast error regression specification by adding interaction terms with different firm similarity measures, including average correlation in earnings and earnings growth, percentage of firms in the same 3-digit SIC industry, and percentage of firms located in the same state. We find that these interaction terms are statistically significant and negative, indicating that an analyst reacts more strongly to peer forecast errors when other portfolio firms are similar to the focal firm.

We also find that analysts react more strongly to peer forecast errors when peer analysts cover many of the same firms (i.e., have greater portfolio overlap) and have higher forecast accuracy. We estimate our previous forecast optimism regressions using two main explanatory variables based on separate peer forecast error averages for peers with above-median and below-median portfolio overlap. Alternatively, we consider peers with above-median and below-median forecast accuracy. We measure forecast accuracy using analysts' recent forecasts. We find that the coefficients on high-overlap and high-accuracy peer averages are more negative than the corresponding low-overlap and low-accuracy coefficient estimates.

We further investigate whether analysts are more likely to learn from peers who are similar in personal characteristics. For these tests, we use data on analyst ethnicity and gender, which are identified based on an analyst's full name. We re-estimate the forecast optimism regressions using two new explanatory variables: the average forecast error for similar peer analysts and the average forecast error for dissimilar peer analysts. The results show that only the coefficient estimate on similar peers forecast errors is statistically significant and economically meaningful.

In the last set of tests, we investigate how social learning is related to forecast accuracy. If analysts systematically underreact to relevant public information about related firms, learning based on peers' forecast errors can result in a relative improvement in forecast accuracy. In contrast, even when the forecast errors from related firms contain useful information, it is possible that analysts overreact to this easily accessible information when they update their forecasts, which can reduce forercast accuracy.[7]

We first analyze whether related firms' lagged forecast errors can predict a firm's consensus forecast error to establish whether there is useful information to be learned from peers' forecast errors. We estimate panel regressions explaining consensus forecast error with the lagged average consensus forecast error for firms within the same 3-digit SIC industry category or Fama-French industry category. These regressions include firm and time fixed effects and control for the firm's previous consensus forecast error. The coefficient estimate on same-industry average is statistically significant and positive. This evidence suggests that analysts as a group do not fully incorporate relevant information in the consensus forecast errors of related firms.

It is likely that analysts who incorporate this information more effectively are more accurate. In the next set of tests, we focus on individual analysts and examine whether social learning affects

[7] The previous literature finds evidence of both under-reaction and over-reaction by analysts. For example, Ramnath (2002) finds that the error in the earnings forecast of the first announcer in an industry is informative about the errors of subsequent announcers, but analysts do not fully incorporate the information in their revised earnings forecasts. Guan, Wong, and Zhang (2015) find that analysts who follow a supplier firm's customer provide more accurate earnings forecasts for the supplier firms. Previous studies also demonstrate that stock market overreacts to same-quarter earnings announcements of related firms in the same industry (Thomas and Zhang 2008) and within the customer-supplier network (Cheng and Eshleman 2014).

forecast accuracy. We compare the actual forecast errors of each analyst to her adjusted errors that reflect hypothetical forecast errors without accounting for peer influence.

We find that actual forecasts of individual analysts are more accurate than adjusted forecasts in 64% of cases. Further, the absolute errors of actual forecasts are significantly smaller. When we use proportional mean absolute forecast error relative to the average absolute forecast error of other analysts associated with the same earnings announcement event, the actual forecasts are on average 2.0% more accurate than the adjusted forecasts.

Altogether, these results suggest that social learning improves forecast accuracy. Consequently, analysts who do not engage in social learning are likely to miss relevant public information contained in the past forecast errors of their peers.

These findings contribute to several strands of analyst literature. Previous studies focus primarily on herding behavior among analysts following the *same* firm (Trueman 1994, Graham 1999, Hong, Kubik, and Solomon 2000, Welch 2000). Our findings extend this learning literature and demonstrate that analyst forecasts are also influenced by peers who follow *other* firms in the coverage portfolio of the analyst. Specifically, analysts learn about the bias in the ex-post forecast errors of their peers rather than imitate their ex-ante forecasts as in traditional herding models. Our finding that analysts are particularly likely to learn from peers with similar demographic characteristics suggests that social learning among analysts is unlikely to be strategic or fully rational.

Our results also link to studies that focus on analysts as information intermediaries. The observation that analysts update their forecasts based on information about other firms in their coverage portfolio suggests that the analyst coverage network across firms can be related to the propagation of information and shocks across firms. Further, our finding that analysts react more strongly to information from same-industry and same-state firms suggests that industry-specific and location-specific information can be transmitted through the coverage network of analysts.

In related work, Hilary and Shen (2013) show that analysts play a role in intra-industry information transfers. Other related studies show that shared analyst coverage is related to stock return co-movement (Hameed et al. 2015, Israelsen 2016, Ali and Hirshleifer 2020, Kaustia and Rantala 2020) and similarity in corporate decisions (Kaustia and Rantala 2015, Gomes, Gopalan, Leary, and Marset 2017). Our evidence of social learning where analysts learn from the information in the reports of peer analysts may be a partial determinant of these observed patterns.

Last, we demonstrate that the set of firms an analyst covers influences his forecasting behavior. Prior literature has largely studied individual forecasts in isolation without paying much attention to the composition of firm portfolios.[8] In a recent related paper, Harford, Jiang, Wang, and Xie (2018) find that analysts make more accurate earnings forecasts on more important firms within their coverage portfolios due to selective attention and effort. Whereas their study shows that other firms in the portfolio influence an analyst's forecasting behavior due to their relative importance within the portfolio, our study finds that portfolio firms also influence analyst forecasts through social learning.

The rest of the paper is organized as follows. In the next section, we summarize the related literature on analyst learning and outline the main testable hypotheses. Section 3 describes the data, and Section 4 presents our key evidence of social learning. Section 5 examines which peer analyst forecasts are more influential, and Section 6 analyzes the relation between social learning and forecast accuracy. We conclude in Section 7 with a summary.

[8] Previous studies have analyzed how coverage of related firms within the supply chain influences forecast accuracy. Guan, Wong, and Zhang (2015) find that analysts who follow a firm's suppliers or customers have better forecast accuracy than other analysts. Luo and Nagarajan (2015) further show that such analysts provide lower-quality forecasts for other firms in their portfolios.

2. Related Literature and Testable Hypotheses

Our key premise is that an analyst can benefit from the information contained in the forecasts of other analysts on other firms contained in the analyst portfolio. This conjecture builds upon a rich and growing literature on analyst learning. Early studies on consistency in forecast biases show that analyst forecast errors are serially correlated (Butler and Lang 1991, Mendenhall 1991, and Abarbanell and Bernard 1992). This positive autocorrelation implies that, statistically speaking, analysts do not fully learn from their own past mistakes.

The literature on forecast error predictability offers several explanations for the persistence in analyst-specific forecast biases, including agency considerations (Das, Levine, and Sivaramakrishnan 1998, Lim 2001), skewness-related optimization (Gu and Wu 2003), reputational effects of forecast consistency (Hilary and Hsu 2013), parameter uncertainty (Markov and Tamayo 2006), and uncertainty regarding the firm's earnings process (Linnainmaa, Torous, and Yae 2016). Together, the evidence from this literature suggests that the persistent analyst-specific biases in the forecasts are at least partially intentional as analysts are likely to position their forecasts strategically based on their personal expectations about realized earnings.

Beyond these strategic considerations, analyst behavior is likely to be affected by nonstrategic factors (Malmendier and Shanthikumar 2014). Consequently, forecast optimism of analysts could be negatively correlated with the forecast errors of peers even when analysts' own forecast errors are positively autocorrelated, i.e., analysts may not learn from their own past mistakes, but they could learn from their peers. Motivated by these findings, our first key conjecture is that analysts update the nonstrategic component of the earnings forecast using the forecast errors of their portfolio peers.

There are several pieces of information that analysts can potentially learn from their peers. First, peer analysts' average forecast errors on other related firms capture potential systematic time-varying biases shared by analysts covering the same firms. Several papers document that analysts are influenced by cognitive biases (DeBondt and Thaler 1990, Sedor 2002, Friesend and Weller 2006), and such non-intentional biases may be shared among analysts who generate forecasts on similar firms. Brown (1997) provides evidence on systematic differences in analysts' optimism bias across industries.

Besides information on shared biases, related portfolio firms' forecast errors can also reveal industry-specific, local, or supply chain-related information that may be relevant for future earnings. Since the forecasting behavior of analysts is likely to be influenced by time and resource constraints (Harford et al. 2018, Hirshleifer, Levi, Lourie, and Teoh 2019), information in the observed forecast errors of peers may be more accessible than self-collected information. Most recently, Parsons, Sabbatucci, and Titman (2020) posit that when an analyst simultaneously monitors two stocks, he or she is more likely to recognize common relevant sources of information.

Analysts can also learn the forecasting style of other analysts. In particular, some analysts issue bold forecasts where they deviate both from the consensus and from their own previous forecast. Deviating from the consensus forecast is risky for an analyst because of career concerns (Hong, Kubik, and Solomon 2000), but Clement and Tse (2005) demonstrate that bold forecasts can reveal private information. It is likely that analysts are aware of this potential link between boldness of forecasts and accuracy, and they try to mimic the forecasting style of bold analysts.

In particular, both bold-positive and bold-negative forecasts of peers may influence an analyst's willingness to issue similar forecasts as they may be perceived to contain information that is relevant to another related portfolio firm. Our second key conjecture examines this potential link. This form of learning from the boldness of forecasts of peers is distinct from herding behavior where analysts imitate each other's forecasts on the same firm.

In addition to testing these key conjectures, we examine whether the learning effect is stronger when analysts and peers have similar demographic attributes. This conjecture is motivated by research in social psychology, which suggests that people systematically adopt favorable opinions about members of their own group and might be indifferent or have lower opinions about members who are outside of their group (e.g., Tajfel 1982, Hewstone, Rubin, and Willis 2002). In a recent study, Jannati, Kumar, Niessen-Ruenzi, and Wolfers (2019) find that that equity analysts exhibit in-group bias and have less favorable opinions about firms that are not headed by CEOs of their own sociodemographic group. This type of in-group bias could influence analyst learning too.

3. Data and Summary Statistics

We begin by summarizing our main data sources. We also provide summary statistics for sample analysts and their coverage portfolios.

3.1. Data Sources

Our main data source is the quarterly earnings announcements and associated earnings forecasts from the Institutional Broker Estimates System (I/B/E/S) detail history file. Additionally, we use share price data from the Center for Research in Security Prices (CRSP) and financial statement and firm location data from Compustat. The sample covers the 1984-2017 period. We exclude analysts coded as anonymous because it is not possible to track their earnings forecasts across quarters. We also exclude firm-quarters where only one analyst provides a forecast and analysts who only follow a single firm because we cannot form the peer analyst variables for these observations. Consistent with prior studies, for each analyst, we only consider the latest forecast before the earnings announcement date.

To address potential errors and data quality concerns in I/B/E/S, we require that the date when an analyst forecast becomes effective (ACTDATS) is on or after the analyst forecast announcement date (ANNDATS). We eliminate observations where a forecast review date (REVDATS) precedes the forecast announcement date (ANNDATS).[9]

We also use data on analyst gender and ethnicity. These items are not available through I/B/E/S, but we define them based on the analyst name in the database. I/B/E/S provides the last name and the first initial of each analyst, and we augment this information with hand-collected name information from Kumar (2010). I/B/E/S stopped providing the names in 2007, which means that we are only able to identify these items for analysts who were in the data before 2008.

The name collection procedure is similar to Kumar (2010). First, we collect the full names of all-star analysts from the *Institutional Investor* magazine. The October issue of the magazine provides a list of all-star analysts with their full names and biographical information. Then, analyst registers from Nelson's directory of investment research and analyst directories available at Yahoo Finance and other financial websites are used to obtain the full names of non-all-star analysts. Last, searches of news articles on Factiva and Google are used to identify remaining analysts' full names. The search is performed using an analyst's last name and the name of the brokerage firm. If the search yields a gender-neutral first name, we read the article to identify the gender.

We determine analyst race/ethnicity based on the last names of analysts. We match each analyst's last name to ethnicity categories defined by the US Census Bureau. In 2016, the U.S. Census Bureau released a national database of self-reported surname-ethnicity mapping based on

[9] We perform robustness checks to ensure that our results are not driven by stale earnings forecasts issued long before the earnings announcement date.

around 295 million individuals with valid surnames in the 2010 Census.[10] Using this classification method, we divide analysts into four racial/ethnic groups: African American, Asian-Pacific Islander, Hispanic, and White.[11]

3.2. Measuring Forecast Optimism and Boldness

We compute the forecast optimism of analysts using the forecast error measure, which is defined as the difference between the earnings per share (EPS) forecast and the actual EPS in I/B/E/S. Following prior literature, we divide this difference with the share price of the firm ten trading days prior to the announcement date. Our measure captures optimism based on relative differences between analysts: Analysts with more positive forecast errors for the same earnings announcement are considered to be more optimistic.

As an alternative way to measure optimism, we use the difference between an analyst's earnings forecast and the consensus forecast divided by the share price. This measure captures the ex-ante optimism before the earnings announcement. We define the consensus forecast as the median forecast based on the latest analyst forecasts prior to the earnings announcement date. To reduce the influence of outliers, each year, we exclude analyst-firm observations where forecast optimism is in the 1% left and right tails of the distribution. We omit observations with stock prices below $10.

To identify bold forecasts, we use the measure proposed in Clement and Tse (2005).[12] Specifically, forecast revisions where the new forecast is both above the analyst's prior forecast and the consensus forecast immediately before the forecast revision are classified as bold-positive

[10] The data are available at https://www.census.gov/topics/population/genealogy/data/2010_surnames.html. See Comenetz (2016) for a description of the data set.
[11] We drop American Indian/Alaskan Native (AIAN) census group and observations with two or more races as defined by the Census Bureau because of low frequency.
[12] Clement and Tse (2005) show that bold forecasts are likely to be induced by new private information and they are associated with greater forecast accuracy.

forecasts and forecast revisions that are both below the analyst's prior forecast and the prevailing consensus are classified as bold-negative forecasts.

3.3. Summary Statistics

Table 1, Panel A provides descriptive statistics on the firm portfolios of individual analysts based on quarterly observations. The average analyst issues earnings forecasts on 7.6 different earnings announcements during a quarter. The portfolios have high industry concentration, and the median portfolio has firms from only two different Fama-French 49 industries and three different 3-Digit SIC industries. The median Herfindahl-Hirschman Index based on industry composition is 0.504 with 3-Digit SIC codes and 0.618 with Fama-French industries.

An important issue in our empirical strategy is the degree of overlap in the coverage portfolios of analysts following the same firms.[13] We measure portfolio similarity using the Szymkiewicz–Simpson overlap coefficient, which is defined as the interaction (number of same firms) between two firm portfolios divided by the number of firms in the smaller portfolio. We calculate the average overlap coefficient relative to all other analysts who follow the same firm for each firm-analyst observation. When calculating the coefficient for analyst *i* who follows firm *j,* we exclude firm *j* itself, i.e., the coefficient between two analysts following firm *j* is based on other firms in the two portfolios.

Table 1, Panel A shows that the average portfolio overlap is 34.1%, and the median is 32.4%. In other words, if two analysts follow the same firm, typically, about two-thirds of the firms in the rest of their portfolio are different. Importantly, the coefficient values show that there is significant

[13] Previous studies show that, besides industry, the composition of analysts' firm portfolios can also reflect other aspects of firm similarity such as geographic proximity (O'Brien and Tan 2015, Jennings, Lee, and Matsumoto 2017), supply chain relationships (Guan, Wong, and Zhang, 2010, Luo and Nagarajan 2015), and business model (Kaustia and Rantala 2020). Brown, Call, Clement, and Sharp (2015) report that 48% of analysts agree to the notion that "The similarity of the company with other companies you follow" is very important when considering whether to cover a particular firm.

non-overlapping coverage among analysts following the same firm, which provides considerable variation in our explanatory variables.

Table 1, Panel B reports statistics on analyst characteristics. We can identify the gender of 4,997 analysts, of which 749 are female (15.0%), and 4,248 are male (85.0%). We are also able to assign 4,701 analysts into race/ethnicity groups, of which 4,200 are classified as White (89.3%), 351 as Asian (7.5%), 91 as Hispanic (1.9%), and 54 as African American (1.2%). According to 2010 U.S. Census, the White population accounts for 72.4% of all people living in the U.S., while Asians, Hispanics, and African Americans represent 5.0%, 16.3%, and 12.6%, respectively. Our surname-based matches suggest that Hispanics and African Americans are relatively under-represented within the analyst population.

Table 2, Panel A reports the summary statistics for forecast error and forecast optimism measures. The values are multiplied by one hundred to enhance readability. Mean forecast error is –0.046 with a median of –0.044. Mean forecast optimism relative to consensus is –0.039, and the median is zero. These distributions are similar to those reported in prior studies (for example, Hong and Kubik 2003).

Table 2, Panel B shows summary statistics for bold-positive and bold-negative forecasts. On average, 8.4% of quarterly firm-analyst forecast observations are classified as bold-positive, and 14.4% are classified as bold-negative.[14]

[14] If an analyst makes multiple forecast revisions related to the same earnings announcement, we define a quarterly observation as bold when at least one of the revisions is classified as a bold forecast. We also conduct robustness checks where we defined bold forecasts only based on the most recent forecasts and the results are similar (see Section 4.5).

4. Main Empirical Results

In this section, we present our main empirical results. We test our key conjecture, which posits that information from other analysts' previous earnings forecasts on other portfolio firms influences an analyst's current forecasting behavior.

4.1. Sorting Results

We start by presenting unconditional decile statistics on the relation between our main dependent and explanatory variables. These statistics reveal the basic relation between the variables, although they do not control for firm-, time-, or analyst-specific factors.

We first sort analysts' earnings forecasts into deciles based on $PeerForecastErrors_{i,j,t-1}$, which measures other analysts' average forecast error on other firms analyst i follows in quarter t. These peer forecast errors are measured based on earnings announcements during the previous quarter, defined as a 3-month period ending 90 days before the earnings announcement. For example, if analyst i follows firms j, k, and l in quarter t, $PeerForecastErrors_{i,j,t-1}$ is calculated as other analysts' average forecast error on firms k and l during quarter t–1.

Figure 2 shows the average analyst optimism relative to the consensus forecast in each decile. Except for the first three deciles where forecast optimism does not vary much, optimism decreases monotonically with $PeerForecastErrors_{i,j,t-1}$. The decreasing pattern indicates that peer analysts' one-quarter lagged forecast errors on other portfolio firms are negatively correlated with relative forecast optimism. Average value for the relative optimism in the first decile is –0.033, whereas the optimism in the last decile is –0.055.

Figure 3 sorts earnings forecasts into deciles based on one-quarter lagged percentage of peer analysts issuing bold-positive and bold-negative forecasts on other portfolio firms. The decile statistics show the average percentage of analysts making a bold forecast with the same sign during an observation quarter. In both cases, the percentages increase monotonically across deciles, indicating that there is a positive correlation between analysts' bold forecasts and recent bold forecasts of peers on other firms in the portfolio. This pattern may reflect autocorrelation in bold forecasts. To account for this possibility, in the regression models, we use earnings announcement fixed effects to control for potential time-series effects.

4.2. Relative Optimism Regression Estimates

We estimate a series of regressions to examine the relation between the forecast errors of peer analysts and forecast optimism. The dependent variable in these regressions is analyst *i*'s relative forecast optimism on firm *j*'s earnings announcement in quarter *t*. Forecast optimism is measured either based on forecast error or relative to the consensus forecast. The main explanatory variable $PeerForecastErrors_{i,j,t-1}$ measures other analysts' average forecast error on other firms in the portfolio during the previous quarter, as defined earlier. The regression specifications additionally include the analyst's own average forecast error on other firms during the previous quarter ($OwnOtherForecastErrors_{i,j,t-1}$) as well as the analyst's own previous forecast error on the focal firm ($OwnPreviousForecastError_{i,j,t-1}$) as control variables.

All regression specifications include earnings announcement fixed effects, which control for all common firm- and time-specific factors that potentially affect the forecast errors of all analysts following a given firm. This means that we implicitly control for all firm characteristics and the average forecast error on the firm in the previous quarter. When these fixed effects are included, we are effectively comparing the forecast errors of all analysts following a certain firm against each other. We also include firm-analyst fixed effects to control for the analyst's own average forecast error on the firm. We cluster standard errors by earnings announcement.

Table 3 reports the estimates for these relative optimism panel regression specifications. In Panel A, the dependent variable is forecast error relative to actual earnings, and in Panel B, optimism is measured relative to the consensus forecast. We find that the main explanatory variable, $PeerForecastErrors_{i,j,t-1}$, has a negative and statistically significant estimate in all specifications. The coefficient values range between –0.004 and –0.010, and the *t*-values vary between –2.4 and –5.1. There is little difference between the results in Panels A and B. These coefficients imply that analysts adjust their optimism levels and issue less (more) optimistic forecasts if their peers were over-optimistic (over-pessimistic) in the last quarter.

To evaluate the economic significance of these estimates, we compare the implied forecast adjustment calculated as the coefficient value multiplied with $PeerForecastErrors_{i,j,t-1}$ to the average absolute deviation from the consensus forecast among the analysts covering the same earnings announcement. Analysts are known to pay attention to the deviation from the consensus forecast for signaling purposes and career concerns (Hong and Kubik 2000). Based on coefficient values in Column 3 of Panel A, on average, the implied forecast adjustment resulting from social learning corresponds to 2.0% of the deviation from the consensus.

Interestingly, coefficients on the analyst's own previous forecast error on the focal firm and on other firms in his portfolio have the opposite sign compared to peers' errors. They are positive and statistically significant. Serial correlation in analysts' forecast errors is consistent with findings in the previous literature (Abarbanell and Bernard 1992, Markov and Tamayo 2006, Hilary and Hsu 2006, Linnainmaa, Torous, and Yae 2016). Together, these optimism regression estimates suggest that analysts adjust their forecasts based on the observed errors of others, but they do not learn from their own past mistakes.

Examining the economic significance of these estimates, we find that the effect of a one standard deviation change in $PeerForecastErrors_{i,j,t-1}$ corresponds to 4.2% of the median absolute forecast error (see Panel A, Column 3). Another way to evaluate the economic significance of the peer effect is to compare the coefficient on $PeerForecastErrors_{i,j,t-1}$ to the coefficients on variables capturing the effect of the analyst's own previous forecasts on the focal firm ($OwnPreviousForecastError_{i,j,t-1}$) and on other firms ($OwnOtherForecastErrors_{i,j,t-1}$) during the previous quarter. Column 3 of Table 3 shows that the absolute value of $PeerForecastErrors_{i,j,t-1}$ (0.010 in both Panels) is at least as large as the coefficients on $OwnPreviousForecastError_{i,j,t-1}$ (0.005 in Panel A and 0.010 in Panel B) and on $OwnOtherForecastErrors_{i,j,t-1}$ (0.007 in both panels).

We also test whether the peer effect is large enough to cause changes in the relative optimism ranking of analysts following a certain firm. Analysts' forecast errors on the focal firm are usually highly correlated, but analysts may pay attention to their relative optimism ranking among peers. To examine this possibility, first, we calculate the optimism percentile rank of each analyst based on the percentage of other analysts whose forecast is below the analyst's own forecast.[15] We then recalculate the ranking based on a "corrected" forecast error, which is defined as actual forecast error minus $PeerForecastErrors_{i,j,t-1}$ multiplied with its coefficient in the baseline regression (Column 3 of Table 3, Panel A). This corrected forecast error indicates what the forecast error without the effect of peer errors should be based on the regression coefficient. When we compare the two rankings with each other, average absolute change in the percentile rank of an individual analyst is 7.4%, which shows that peer errors cause economically meaningful changes in analysts' relative positions.

[15] We calculate the ranking for all earnings announcements covered by at least ten analysts.

4.3. Alternative Specifications and Robustness Checks

Using market capitalization as one of the firm importance proxies, Harford et al. (2018) find that analysts allocate more effort to portfolio firms that are relatively more important to their careers. It is possible that other analysts' forecast errors on such firms also receive relatively more attention. Appendix Table 1 reports results from the regressions of Table 3 using a market-value weighted version of $PeerForecastErrors_{i,j,t-1}$. In this alternative specification, the peer errors from each portfolio firm are weighted with its end-of-quarter market value. We find that all the coefficients in Appendix Table A1 are more negative than the corresponding coefficients in Table 3, and the baseline coefficient (Panel A, Column 3) changes from –0.010 to –0.013. These results are consistent with the hypothesis that peer analysts covering more important firms receive relatively greater attention.

One potential concern related to our baseline results in Table 3 is that they may be affected by stale information from forecasts issued long before the earnings announcement date. For example, some of the recorded forecasts on the earnings announced in quarter t may have been issued even before the previous earnings announcement in quarter t–1. Analysts have the option to revise their forecast at any time, and even observations issued long before the announcement date may be equally valid if the analyst felt that no material information affecting the earnings estimate has surfaced after the forecast was issued. Nevertheless, use of old forecasts can be potentially problematic because the peer variable is based on forecast errors in quarter t–1.

To address this possibility, Appendix Table A2 reports results from regressions where we only include forecasts issued 15, 45, or 90 days before the earnings announcement date. We form both the dependent and independent variables using these forecasts. We again find that all coefficients on $PeerForecastErrors_{i,j,t-1}$ are statistically significant, with values ranging between –0.010 and –0.031. We lose a few observations, but the coefficients are even more negative than in Table 3.

The next test addresses potential data quality concerns. A documented data problem in the I/B/E/S database is that forecast dates recorded prior to the early 1990s sometimes differ from the actual forecast date by a few days (Cooper, Day, and Lewis 2001, Clement and Tse 2003). As a data quality check, Appendix Table A3 estimates the regressions of Table 3 using only post-1993 observations, and the results are very similar.

In another robustness test, we estimate placebo regressions where, instead of using analysts' actual firm portfolios, we form $PeerForecastErrors_{i,j,t-1}$ based on the same number of randomly selected firms among all firms with analysts during the same quarter. We calculate the peer forecast errors based on the analysts who cover the random firms and perform the random selection separately for each firm-analyst observation in the data. This analysis addresses potential concerns related to the possibility that some mechanical effect in the time-series correlation of forecast errors influences our results.

Appendix Table A4 provides results from placebo regression specifications that are identical to the specifications in Table 3 except that we cannot include $OwnOtherForecastErrors_{i,j,t-1}$ because the analyst does not personally cover the randomly selected firms. We find that the coefficients on $PeerForecastErrors_{i,j,t-1}$ are not statistically significant in any placebo regression specifications.

Finally, Appendix Table A5 performs the analyses in Table 3 using 1% winsorization instead of leaving out the top and bottom 1% of the variable values. The results are almost identical. We exclude extreme observations by default because IBES is known to suffer from occasional data errors that can create outliers.

4.4. Alternative Forms of Social Learning

Our testable definition of social learning is based exclusively on peer analysts' forecasts on other portfolio firms, but it is possible that analysts also learn from the past forecast errors of other analysts on the focal firm (i.e., the firm for which an analyst issues a forecast). In particular, if the forecast errors of other analysts on the focal firm are significantly more positive or negative than analysts' average errors on other comparable firms in the same quarter, analysts may adjust their next-quarter forecasts for the focal firm to account for the perceived bias.

Testing whether such a social learning effect exists is not straightforward because we cannot simply include other analysts' average lagged forecast error on the focal firm as an explanatory variable in our previous regression specifications. The previous specifications include earnings announcement fixed effects, which implicitly control for the effect of the average lagged forecast error among analysts. Further, there is almost no within-firm variation in other analysts' lagged errors because the average focal firm error in the previous quarter is simply the lagged mean error calculated excluding the analyst himself. The remaining within-firm variation only reflects analysts' own relative optimism before the previous earnings announcement.

To test whether there is also a social learning effect based on lagged forecast errors on the focal firm, we use a regression specification where we explain analysts' relative forecast optimism with variables based on across-firm variation in other analysts' one-quarter lagged forecast errors. We sort analysts into quartiles based on other analysts' average lagged forecast error within the same 3-digit SIC industry quarter. We conduct the sorting within the industry-quarter to ensure that we are not capturing industry-specific shocks and we deduct the analyst's own lagged forecast error from the average peer error when forming the quartiles to separate peer analyst-specific errors from systematic errors shared by all analysts.

We define analysts with high and low same-firm peer errors based on the top and bottom quartile of other analysts' average forecast error on the focal firm. If analysts adjust their forecasts to account for the perceived bias in other analysts' forecasts, the top quartile dummy coefficient should be negative, and the bottom quartile dummy coefficient should be positive. To compare the focal firm effect with our previous findings, we also form similar quartile dummies based on $PeerForecastErrors_{i,j,t-1}$ within the industry-quarter.

Table 4 reports results from regressions explaining forecast error and forecast optimism with the top and bottom quartile dummies for same-firm and other portfolio-firm peer errors. The coefficient values are multiplied by 100 to enhanced readability. As before, the regression specifications include earnings announcement fixed effects. The results show that analysts learn both from other analysts' errors on the focal firm and on other portfolio firms. Coefficients on high same-firm and other-firm peer errors are positive and statistically significant, and coefficients on low same-firm and other-firm peer errors are negative and statistically significant.

Based on the estimated coefficients, the focal firm learning effect is as strong as the portfolio learning effect. Column 4 of Panel A explains forecast error with all the four dummies and includes all control variables. The coefficient on the high same-firm error dummy is –0.0027 with a *t*-value of –5.35, and the coefficient on the low same-firm error dummy is 0.0025 with a *t*-value of 4.57. The corresponding coefficients based on peer errors on other portfolio firms are –0.0016 with a *t*-value of 4.57 and 0.0013 with a *t*-value of 2.83. Analysts' own previous forecast errors on the focal firm and other portfolio firms are deducted from the means when forming the peer error quartiles, and their coefficients are not statistically significant when included as additional control variables.

4.5. Bold Forecast Regression Estimates

In the next set of tests, we examine whether the boldness of peer analysts affect the propensity of an analyst to issue a bold forecast. We estimate quarterly panel OLS regressions where we explain the decision to issue a bold forecast in quarter *t*. We estimate these regressions separately with bold-positive and bold-negative forecasts so that the dependent variable takes the value one if an analyst issued a bold forecast during the quarter.

The main explanatory variables are $PeerBoldPos_{i,j,t-1}$ and $PeerBoldNeg_{i,j,t-1}$, which measure peer analysts' bold forecasts on other firms in the analyst's portfolio during the preceding quarter.[16] $PeerBoldPos_{i,j,t-1}$ is calculated as the percentage of peer analysts who issue at least one bold-positive forecast during the previous quarter, and $PeerBoldNeg_{i,j,t-1}$ is calculated similarly based on bold-negative forecasts. These averages are based on individual peer analyst-firm observations. We also include a dummy that takes the value one if the analyst himself issued a bold forecast in the previous quarter because repeated bold forecast revisions across multiple quarters are not common. These regressions include earnings announcement fixed effects and analyst-firm fixed effects, and we cluster standard errors by the earnings announcement.

The results in Table 5 show that analysts are more likely to issue bold-positive and bold-negative forecasts if many peer analysts have issued bold forecasts with the same sign during the previous quarter. In the regressions where the bold-positive forecast indicator is the dependent variable, the coefficients on $PeerBoldPos_{i,j,t-1}$ are between 0.008 and 0.010 with *t*-values between 2.3 and 2.8. In the corresponding regressions explaining bold-negative forecasts, $PeerBoldNeg_{i,j,t-1}$ has coefficient values between 0.015 and 0.017 with *t*-values between 4.8 and 5.3. These results suggest that peer imitation is somewhat stronger with negative forecasts. The coefficients in

[16] Our observation quarter for the dependent variable covers 90 days before the earnings announcement and we measure peers' bold forecasts 91-180 days prior to the earnings announcement date.

Column 3 further show that bold-negative forecasts do not predict analysts' bold-positive forecasts and vice versa.

We can interpret these estimates in economic terms. The unconditional probability of issuing a bold forecast in each quarter is 8.4% for bold-positive and 14.4% for bold-negative forecasts. Based on these coefficients, a one standard deviation increase in $PeerBoldPos_{i,j,t-1}$ increases the probability of issuing a positive bold forecast by 0.3 percentage points, and the corresponding increase with $PeerBoldNeg_{i,j,t-1}$ is 0.6 percentage points. These one standard deviation changes represent an increase of 3.3% and 4.2% relative to the unconditional probabilities.

To ensure our bold regression results are robust, we conduct a few additional tests. First, we examine the sensitivity of our results to stale forecasts. Analysts sometimes revise their forecasts several times before the earnings announcement, and some may even issue both bold-positive and bold-negative forecasts for the same firm within the same quarter. To ensure that our results are not driven by stale information, we also estimate the same bold regressions with an alternative specification where we only include bold forecasts based on the last forecast revision before the earnings announcement date. Appendix Table A6 reports results from the same regressions with this specification, and the coefficients on $PeerBoldPos_{i,j,t-1}$ and $PeerBoldNeg_{i,j,t-1}$ are very similar.

We also test whether peer analysts' forecast errors and bold forecasts are both statistically significantly related to analyst forecasts when included in the same regression. Appendix Table A7 shows that coefficients on $PeerForecastErrors_{i,j,t-1}$ and bold-negative forecasts of peers are negative and statistically significant in relative forecast optimism regressions. The bold-positive forecasts of peers have a positive coefficient estimate, but it is not statistically significant.

These bold forecast regression estimates complement our forecast error results by suggesting that analysts learn both from their peers' actions and outcomes. Clement and Tse (2005) show that bold forecasts are relatively more accurate, so there is a stronger reason to pay attention to them. Further, forecasts that deviate from both the consensus and the previous analyst forecast are more likely to capture other analysts' attention.

5. Which Peer Forecasts Are Most Influential?

When analysts learn from peers' forecast errors, some peer forecasts may be more influential than others. Analysts may knowingly pay more attention to forecasts that are perceived to be particularly relevant for the firm whose earnings they are forecasting, and their selective attention may also unknowingly focus on certain kinds of peers. The results in the previous section already show that analysts react more strongly to peer forecast errors on high market capitalization firms. In this section, we continue this investigation by analyzing which peer forecasts are associated with stronger learning effects.

5.1. Impact of Firm Characteristics

If analysts think that other related firms' errors contain relevant information for their earnings forecasts, it is likely that they react more strongly when the other firms are perceived to be similar or closely related in their characteristics. To test this possibility, we estimate regressions that additionally include interaction terms with similarity measures, including portfolio firms' earnings correlation, earnings growth correlation, the percentage of firms that are in the same 3-digit SIC industry, and the percentage of firms located in the same state. We analyze each of these interactions separately because the measures are overlapping.

We measure earnings correlation as adjusted R^2 from a regression that explains the focal firm's scaled earnings with the average earnings of other firms in the analyst's portfolio using observations from the previous 12 quarters. Earnings are defined as quarterly income before extraordinary items (IBQ) and the variable is scaled by total assets (ATQ). The data are from Compustat quarterly files.

We define earnings growth correlation in a similar way based on regressions using quarterly observations of earnings growth percentage relative to the previous quarter. These correlation measures are based on adjusted $R^{2,}$ and therefore, they do not capture the sign or magnitude of the regression coefficient. However, they reveal the extent to which related firms' earnings can explain the focal firm's earnings.

Table 6 shows that the coefficients on interaction terms with earnings correlation, earnings growth correlation, the percentage of firms in the same industry, and the percentage of firms located in the same state are all negative and statistically significant at the 10% or higher. Further, the original $PeerForecastErrors_{i,j,t-1}$ variable remains negative and statistically significant. These findings suggest that analysts react more strongly to the information in the forecast errors of other firms when those firms share similar characteristics.

These results can also be interpreted as evidence on what kind of information is being learned. They suggest that analysts' learning within their coverage network can capture information on both industry-specific and location-specific shocks. Since analysts function as information intermediaries, learning from peers can contribute to the intra-industry information transfers, as documented in Hilary and Shen (2013).

5.2. Impact of Peer Analyst Characteristics

If analysts selectively pay more attention to some peers than others when forming their forecasts, it is natural to assume that peer forecasts issued by analysts who are perceived as being more accurate may receive more attention because they would be considered more informative.

Further, peers who cover many of the firms in the analyst's portfolio or share similar personal characteristics may receive more attention due to familiarity bias.

Table 7 analyzes the effect of peer analyst portfolio overlap, accuracy, and all-star status by estimating regressions that are similar to our baseline forecast error regression in Column 3 of Table 3, Panel A. In these regressions, we replace $PeerForecastErrors_{i,j,t-1}$ with peer forecast error averages calculated based on subsamples of peer analysts. Columns 1 and 2 separate the forecast-specific peers of each analyst into high-overlap and low-overlap peers based on whether their portfolio overlap is above or below median. We measure portfolio overlap with the Szymkiewicz–Simpson coefficient reported in Table 1.

When we include peer averages for the two groups as separate explanatory variables, we find that analysts learn relatively more from peers whose portfolios are similar. The coefficient on high-overlap peers is –0.007, whereas the coefficient on low-overlap peers is –0.005. The corresponding *t*-values are –2.9 and –2.3, respectively.[17]

Columns 3 and 4 study whether analysts react more strongly to forecast errors of peers who are more accurate based on their recent forecast performance. We measure accuracy using adjusted R^2 from an analyst-specific regression where we explain realized earnings with the analyst's corresponding forecasts using all forecasts issued by the analyst during the previous four quarters. The adjusted R^2 value measures how well the analyst's forecasts can predict the realized earnings.

We divide analysts' forecast-specific peers into high-accuracy and low-accuracy peers based on whether their forecast R^2 is above or below median within the peer group. When we include both the high-accuracy and low-accuracy peer forecast error averages as separate explanatory

[17] In a separate analysis related to portfolio overlap, we find that the social learning effect also exists if we only consider peer analysts who do not cover the focal firm. When we calculate $PeerForecastErrors_{i,j,t-1}$ excluding peers who do not cover firm *i*, the coefficient estimate in the baseline regression (Column 3 of Table 3, Panel A) is –0.010 with *t*-value –3.9. It is identical to the coefficient we obtain when we define the variable using all peers.

variables in Column 4, only the high-accuracy peer average is negative and statistically significant. These coefficient estimates indicate that analysts are influenced more by peers with high relative forecast accuracy.

Columns 5 and 6 study whether peer analysts who are *Institutional Investor* all-stars in the latest ranking are more influential. On the one hand, it is likely that analysts pay more attention to all-star peers because of their status or perceived accuracy. On the other hand, since Hilary and Hsu (2013) find that analysts who display consistent forecast errors over time are more likely to be nominated as all-stars, it is likely that all-star forecast errors may be less informative about shared time-varying biases, potentially resulting in a weaker social learning effect. Interestingly, our results indicate that the all-star coefficient (–0.006) is slightly less negative than the non-all-star coefficient (–0.007), which is consistent with the latter hypothesis.

To analyze whether analysts are more likely to learn from peer analysts with the same gender or similar race/ethnicity, we re-estimate the forecast optimism regressions with two main explanatory variables that measure the average forecast error of peers on other firms. We calculate the peer averages separately for peers who are similar and dissimilar based on both race/ethnicity and gender ($SimilarPeerForecastErrors_{i,j,t-1}$ and $DissimilarPeerForecastErrors_{i,j,t-1}$). If analysts are more likely to learn from peers who are similar, the coefficient on $SimilarPeerForecastErrors_{i,j,t-1}$ should be more negative than the coefficient on $DissimilarPeerForecastErrors_{i,j,t-1}$.

Table 8, Panel A calculates these averages based on analysts with the same and different gender. We find that the coefficient estimate on $SimilarPeerForecastErrors_{i,j,t-1}$ is –0.011 with *t*-value –2.5 while the coefficient on $DissimilarPeerForecastErrors_{i,j,t-1}$ is statistically insignificant with coefficient value –0.004.

Most analysts in the sample are male, and one potential concern is that the coefficient on *SimilarPeerForecastErrors*$_{i,j,t-1}$ may be larger than the dissimilar peer coefficient even if both females and males react more to male peers' forecast errors. Separate subsample regressions with males and females show that this is not the case. The *SimilarPeerForecastErrors*$_{i,j,t-1}$ coefficient is –0.038 for males and –0.011 for females with *t*-values around –2.0. The corresponding *DissimilarPeerForecastErrors*$_{i,j,t-1}$ coefficients are 0.047 and –0.005 with *t*-values 1.918 and –1.583. These coefficient estimates are consistent with our conjecture and confirm that male analysts are more likely to learn from other male analysts and female analysts are more likely to learn from other female analysts.

In Table 8, Panel B, we measure similarity based on race/ethnicity using the four race/ethnicity categories described earlier. The coefficient on similar peers' forecast errors is –0.028 with *t*-value of –3.9, whereas the coefficient on dissimilar peers' average forecast error is positive and statistically insignificant. These coefficient estimates imply that analysts react more strongly to the forecast errors of peers with same race and ethnicity.

We also estimate subsample regressions based on the two largest ethnic groups. Whites constitute 89.3% of the sample, and Asians constitute 7.5%. Among Whites, the coefficient on similar peers' average error is negative and statistically significant (–0.031), and it is even larger than in the full sample. The dissimilar peer coefficient is positive and insignificant. However, among Asians, neither coefficient is statistically significant, but the similar peer coefficient is more negative than the dissimilar peer coefficient (–0.007 versus –0.004).

Altogether, these findings suggest that analysts are more likely to learn from peers who are similar. It is difficult to find any obvious rational explanation for this observation. If the forecast errors of some analysts are systematically more informative than others and all analysts are aware of it, we should observe that all analysts adjust their forecasts based on that same group. Instead, we observe that analysts' reaction depends on the similarity in personal characteristics. This finding is consistent with the previous psychological and sociological literature on homophilic social interactions documenting that people are more likely to interact with others who are similar (McPherson, Smith-Lovin, and Cook 2001).[18]

6. Social Learning and Forecast Accuracy

Our results so far indicate that analysts are influenced by the forecast errors of their peers. A natural follow-up question is whether these interactions improve or decrease their forecast accuracy. To test this conjecture, we first estimate whether there is useful information that can be learned by observing related firms' forecast errors during the previous quarter. If there is no value-relevant information in forecasts of peers, analysts should not be able to improve their forecast accuracy through peer interactions.

We estimate panel regressions where we explain a firm's quarterly consensus forecast error with one-quarter lagged average error among other firms in the same 3-digit SIC industry, Fama-French 49 industry, or among other firms headquartered in the same state. These firm groups may be relevant to the forecasting decisions of analysts because Table 1 shows that analyst portfolios have high industry concentration and the results in Table 6 indicate that analysts react more to the forecast errors of same-industry and same-state firms. The accuracy regression specifications control for the firm's own one-quarter lagged average error and include firm and time fixed effects. Standard errors are dual-clustered by quarter and firm.

[18] Jannati et al. (2019) provide evidence on the existence of in-group bias among security analysts. They find that male analysts have lower earnings forecasts and worse stock recommendations for firms headed by female CEOs than for firms headed by male CEOs. Their results are similar if in-groups are defined based on race/ethnicity or political attitudes.

Table 9 shows that forecast errors of firms in the same industry are statistically significant, with coefficient 0.050 and predict the consensus forecast during the next quarter. At least on this basis, forecast errors of firms in the same industry contain useful information for future firm-level forecasts. Their predictive power suggests that analysts overall are likely to underreact to this information. The coefficient on same-state firms is also positive, but it is not statistically significant.

To directly analyze whether learning from the forecast errors of peers improves forecast accuracy, we calculate a "raw" forecast error that measures what the forecast error without the peer effect would be according to our regression results and compare it to actual forecast errors. We calculate the raw forecast error as actual forecast error minus $PeerForecastErrors_{i,j,t-1}$ multiplied with its coefficient in Column 3 of Table 3, Panel A.

We find that the peer-influenced forecast is more accurate than the raw forecast in 64% of the cases, indicating that forecast adjustments based on the forecast errors of peers reduce an analyst's forecast errors in most cases. To estimate how the social learning effect influences forecast accuracy based on absolute forecast errors, we calculate the Proportional Mean Absolute Forecast Error (PMAFE) of individual forecasts using peer-influenced and raw forecasts. PMAFE has previously been used as an accuracy measure by Clement (1999) and Malloy (2005) among others. It is calculated as (absolute forecast error – average absolute forecast error) / average absolute forecast error, where the average is calculated based on all forecasts for the same earnings announcement. We find that, on average, PMAFE is 2.0% lower with peer-influenced forecasts, which indicates that learning from the forecast errors of peers improves forecast accuracy. The difference in means is statistically significant at the 1% level.

As an alternative way to estimate the relation with forecast accuracy, we estimate regressions to explain an analyst's PMAFE with the absolute value of $PeerForecastErrors_{i,j,t-1}$. The absolute value of $PeerForecastErrors_{i,j,t-1}$ is proportional to the magnitude of the analyst-level social learning effect captured in our previous analyses, and these regressions investigate whether the absolute average forecast errors of peers are correlated with forecast accuracy. The regressions include firm-analyst fixed effects.

The results reported in Table 10 show that all coefficients on $Abs(PeerForecastErrors_{i,j,t-1})$ are negative, indicating that large systematic peer errors are associated with smaller forecast errors, after accounting for the average forecast error among the analysts following the same firm. A one standard deviation change in $Abs(PeerForecastErrors_{i,j,t-1})$ is associated with a roughly 1% change in PMAFE. We have also included the squared value of $Abs(PeerForecastErrorrs_{i,j,t-1})$ as an additional explanatory value to test for potential non-linear effects, but this coefficient estimate is statistically insignificant.

One interpretation for these findings is that analysts overall underreact to information in the forecast errors of related firms. But analysts who cover related firms are able to capture this information more effectively. This interpretation is consistent with the evidence in Guan, Wong, and Zhang (2015), who demonstrate that analysts who follow a firm's suppliers or customers have better forecast accuracy than other analysts.

7. Summary and Conclusions

In a frictionless world, analysts' reactions to new public information coming from a different firm should not depend on whether they personally cover that firm or not. The findings of this paper are at odds with such a frictionless view. We find that analysts adjust their forecasts based on observed errors of other analysts on other portfolio firms. Analysts also learn from the actions of their peers and are more likely to issue bold forecasts when similar forecasts were recently issued for other portfolio firms. We further find that analysts are particularly likely to learn from peers who share similar personal characteristics, which indicates that selective attention is likely to play a role in the observed social learning behavior.

An interesting implication of our findings is that the composition of an analyst's firm portfolio may affect individual forecasts and even influence forecast accuracy. Very often, the earnings surprises and analyst reports of one firm in an analyst's portfolio may contain information that is relevant for forecasts on another firm. Analysts covering two related firms are more likely to spot such information, and our results suggest that analysts, on average, improve their forecast accuracy when they learn from their peers.

Our findings also shed light on the role of analysts as information intermediaries. An emerging literature shows that shared analyst coverage of firms is related to stock return comovement, the similarity in corporate decisions, and information spillovers (Hameed et al. 2015, Israelsen 2016, Gomes et al. 2017, Kaustia and Rantala 2019, Ali and Hirshleifer 2020). Social learning across firms within analyst coverage portfolios can be one mechanism behind information transfers within analyst coverage networks of firms.

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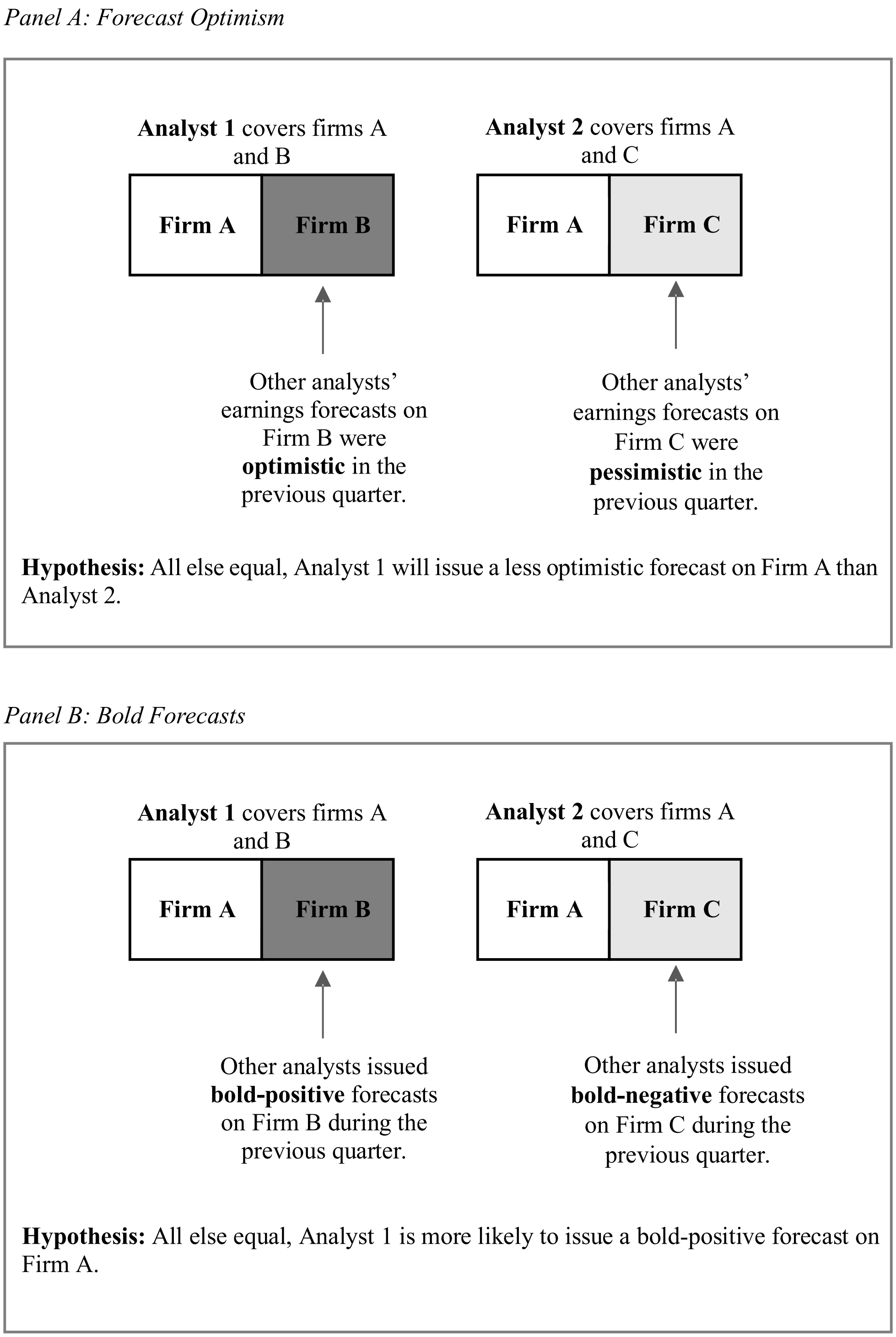

Figure 1
The Identification Strategy
This figure illustrates our identification strategy and the main testable hypotheses. Analyst 1 follows firms A and B, but not firm C. Analyst 2 follows firms A and C, but not firm B. In Panel A, we illustrate our first key hypothesis, which posits that, all else equal, Analyst 1's forecast on Firm A will be less optimistic than the forecast of Analyst 2. In Panel B, we illustrate our second key hypothesis, which posits that, all else equal, Analyst 1 is more likely to issue a bold-positive forecast on Firm A.

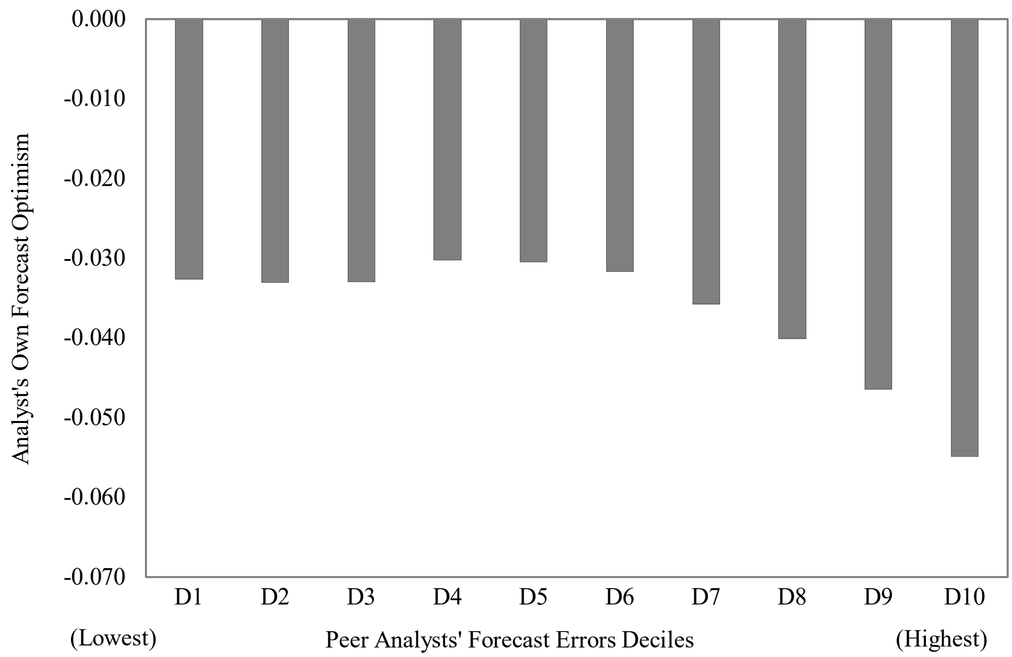

Figure 2
Unconditional Relation Between Analyst Forecast Optimism and Recent Forecast Errors of Peers on Other Firms in the Analyst Portfolio

This figure illustrates the relation between peer analysts' recent forecast errors on other firms in the analyst portfolio and the analyst's optimism relative to the consensus forecast. The sample consists of quarterly earnings forecasts in I/B/E/S between 1984 and 2017. Peer analysts are defined separately for each analyst-earning announcement observation, and they consist of other analysts following other firms in the analyst portfolio. Analysts are sorted into deciles based on peers' average forecast error on other firms in the analyst portfolio during the previous quarter. The bars show analysts' average optimism relative to the consensus for each decile. This average is calculated based on the most recent forecast issued before the earnings announcement. The forecast optimism values are multiplied by 100 for better presentation.

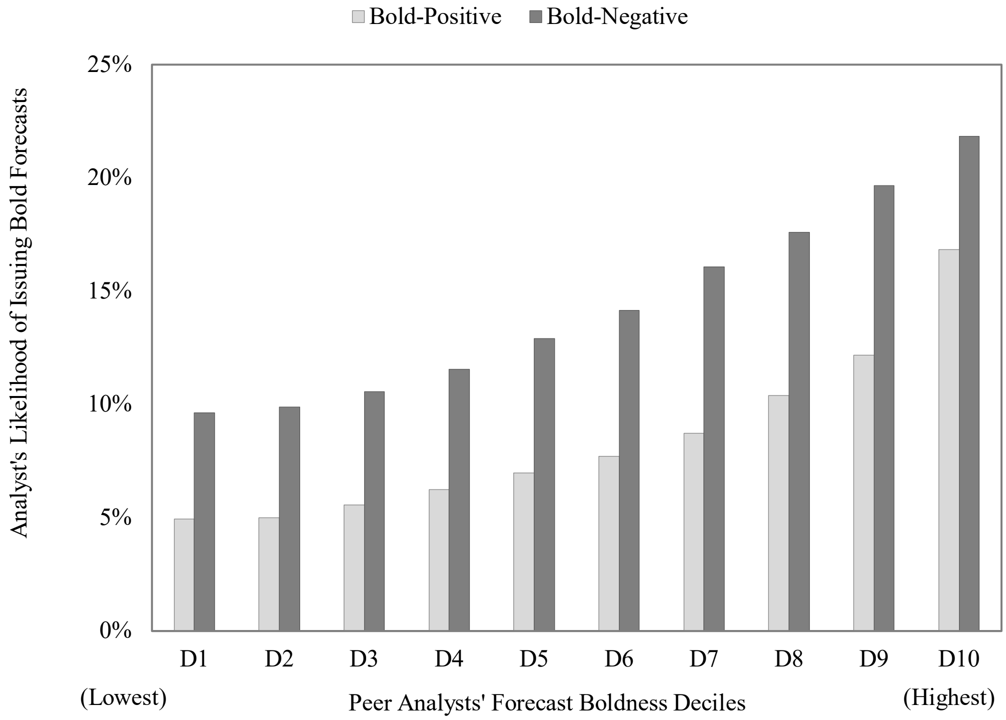

Figure 3
Unconditional Relation Between Bold Forecasts of Analysts and Recent Bold Forecasts of Peers on Other Firms in the Analyst Portfolio

This figure illustrates the relation between quarterly bold forecasts of analysts and peer analysts' recent bold forecasts with the same sign on other firms in the analyst portfolio. The sample consists of quarterly earnings forecasts in I/B/E/S between 1984 and 2017. Peer analysts are defined separately for each analyst-earning announcement observation, and they consist of other analysts following other firms in the analyst portfolio. Bold forecasts are defined as in Clement and Tse (2005), where they deviate positively or negatively both from the analyst's prior forecast and the consensus forecast immediately before the forecast revision. Analysts are sorted into deciles based on the percentage of peer analyst-firm observations in which the peer analyst issued a bold-positive or bold-negative forecast on other firms in the analyst portfolio during the previous quarter. The bars show the average quarterly percentage of analysts issuing a bold-positive or bold-negative forecast for each decile.

Table 1
Descriptive Statistics: Analyst Portfolios

This table provides descriptive sample statistics for analyst portfolios. The sample period is 1984 – 2017. Analyst data are from I/B/E/S Detail U.S. File. Industry codes are from Compustat (if available) and otherwise from CRSP. Detailed data criteria and variable specifications are discussed in Section 2. We exclude firm-quarters where only one analyst provides a forecast and analysts who only follow a single firm because we cannot form the peer analyst variables for these observations. Panel A characterizes analyst portfolios. The characteristics include the number of firms covered, the number of other analysts covering a firm in the portfolio, the number of different 3-Digit SIC and Fama-French 49 industries among the firms of the portfolio, and the coverage overlap percentage with other analysts following the same firm. The portfolio size and industry statistics are based on quarterly analyst observations, the number of other analysts covering a firm is based on quarterly firm observations, and the overlap statistics are based on quarterly analyst-firm observations. The portfolio overlap percentage between analyst *i* and another analyst is measured based on the Szymkiewicz−Simpson coefficient, defined as the interaction between the two portfolios divided by the number of firms in the smaller portfolio. The mean overlap percentage for analyst *i* following firm *j* is based on his portfolio overlap with all other analysts following firm *j* (the measured portfolios exclude firm *j* itself). Panel B provides statistics on sample analysts' gender and ethnicity based on the analyst's full name.

Panel A: Analyst Portfolios

	N	Mean	Std. Dev.	p25	Median	p75
Number of Firms Covered	308,759	7.6	5.8	3	6	11
Number of Other Analysts Covering a Firm	281,498	6.6	5.9	2	5	9
Number of Different SIC-3 Industries Covered	305,818	3.5	2.3	2	3	5
Number of Different FF49 Industries Covered	305,818	2.7	1.7	1	2	3
Coverage Overlap % with Other Analysts Following the Same Firm	2,255,362	34.1	23.6	15.0	32.4	50.3

Panel B: Analysts' Gender and Race/Ethnicity

Gender

N	% Male	% Female
4,997	85.0	15.0

Race/Ethnicity

N	% White	% Asian	% Hispanic	% African American
4,701	89.3	7.5	1.9	1.2

Table 2
Descriptive Statistics: Forecast Characteristics

This table provides descriptive sample statistics for analyst forecasts. The sample period is 1984 – 2017. Analyst and earnings forecast data are from I/B/E/S Detail U.S. File, and stock price data are from CRSP. Statistics on forecast optimism and bold forecasts are based on quarterly earnings forecasts. Detailed data criteria and variable specifications are discussed in Section 2. Panel A reports descriptive statistics on analysts' forecast errors and forecast optimism. $ForecastError_{i,j,t}$ is calculated as the analyst's forecast minus actual earnings per share and $Optimism_{i,j,t}$ is calculated as the analyst's own forecast minus the consensus forecast. Both values are scaled by share price 10 days before the earnings announcement date. $PeerForecastErrors_{i,j,t-1}$ is other analysts' average forecast error on other firms in the analyst portfolio during the previous quarter. All values are multiplied by 100 for better presentation. Panel B provides statistics on bold forecasts, defined as in Clement and Tse (2005). A bold-positive forecast is above the analyst's prior forecast and the consensus forecast immediately before the forecast revision, while a bold-negative forecast is below the analyst's prior forecast and the prevailing consensus. $BoldPos_{i,j,t}$ and $BoldNeg_{i,j,t}$ take the value one if the analyst issued a bold-positive or bold-negative forecast during an observation quarter. $PeerBoldPos_{i,j,t-1}$ and $PeerBoldNeg_{i,j,t-1}$ measure the percentage of positive or negative bold forecasts made by other analysts on other firms in the analyst portfolio during the previous quarter.

Panel A: Forecast Errors and Optimism (multiplied with 100)						
	N	Mean	St. Dev.	p25	Median	p75
$ForecastError_{i,j,t}$	1,164,488	–0.046	0.364	–0.161	–0.044	0.036
$Optimism_{i,j,t}$	1,164,488	–0.039	0.234	–0.073	0	0.041
$PeerForecastErrors_{i,j,t-1}$	1,164,488	–0.042	0.187	–0.123	–0.050	0.018
Panel B: Bold Forecasts						
	N	Mean	St. Dev.	p25	Median	p75
$BoldPos_{i,j,t}$	1,506,672	0.084	0.278	0	0	0
$BoldNeg_{i,j,t}$	1,506,672	0.144	0.351	0	0	0
$PeerBoldPos_{i,j,t-1}$ (%)	1,506,672	10.0%	11.1%	1.9%	6.5%	13.9%
$PeerBoldNeg_{i,j,t-1}$ (%)	1,506,672	16.3%	14.9%	4.7%	12.4%	24.4%

Table 3
Relative Optimism Regression Estimates

This table reports results from regressions explaining analysts' relative forecast optimism with peer analysts' past forecast errors on other firms in the analyst portfolio. The observations consist of analysts' quarterly earnings forecasts. In Panel A, the dependent variable is forecast error calculated as the analyst's forecast minus actual earnings per share, and in Panel B it is optimism calculated as the analyst's own forecast minus the consensus forecast. Both dependent variables are scaled by share price 10 days before the earnings announcement. The main explanatory variable is $PeerForecastErrors_{i,j,t-1}$, which measures other analysts' average forecast error on other firms in the analyst portfolio during the previous quarter. Other explanatory variables include $OwnPreviousForecastError_{i,j,t-1}$, which captures the analyst's own previous forecast error on the focal firm and $OwnOtherForecastErrors_{i,j,t-1}$, which is the analyst's own average forecast error on other firms in his portfolio during the previous quarter. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates			
	(1)	(2)	(3)
PeerForecastErrors$_{i,j,t-1}$	−0.004***	−0.004***	−0.010***
	(−2.894)	(−2.863)	(−5.113)
OwnPreviousForecastError$_{i,j,t-1}$		0.006***	0.005***
		(2.799)	(2.672)
OwnOtherForecastErrors$_{i,j,t-1}$			0.007***
			(4.637)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,164,488	1,164,488	1,164,488
Adj. R-squared	0.805	0.805	0.805
Panel B: Forecast Optimism Regression Estimates			
	(1)	(2)	(3)
PeerForecastErrors$_{i,j,t-1}$	−0.004**	−0.004**	−0.010***
	(−2.449)	(−2.395)	(−4.517)
OwnPreviousForecastError$_{i,j,t-1}$		0.011***	0.010***
		(5.029)	(4.910)
OwnOtherForecastErrors$_{i,j,t-1}$			0.007***
			(4.289)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,164,488	1,164,488	1,164,488
Adj. R-squared	0.468	0.468	0.468

Table 4
Forecast Error and Optimism Regression Estimates: Alternative Forms of Social Learning

This table reports results from regressions explaining analysts' relative forecast optimism with other analysts' past forecast errors on the focal firm and on other firms in the analyst's portfolio. The observations consist of analysts' quarterly earnings forecasts. In Panel A, the dependent variable is forecast error calculated as the analyst's forecast minus actual earnings per share, and in Panel B it is optimism calculated as the analyst's own forecast minus the consensus forecast. Both dependent variables are scaled by share price 10 days before the earnings announcement. $\mathit{HighSameFirmPeerErrors}_{i,j,t-1}$ and $\mathit{LowSameFirmPeerErrors}_{i,j,t-1}$ are dummy variables for observations where other analysts' one-quarter lagged average forecast error on the focal firm is in the top and bottom quartile within the same 3-digit SIC industry, respectively. The analyst's own forecast error is deducted from the values when defining the quartiles. $\mathit{HighOtherFirmPeerErrors}_{i,j,t-1}$ and $\mathit{LowOtherFirmPeerErrors}_{i,j,t-1}$ are formed similarly based on peer analysts' forecast errors on other portfolio firms, and the analyst's own average forecast error on those firms is deducted from the values when defining the quartiles. $\mathit{OwnPreviousForecastError}_{i,j,t-1}$ captures the analyst's own previous forecast error on the focal firm, and $\mathit{OwnOtherForecastErrors}_{i,j,t-1}$, is the analyst's own average forecast error on other firms in his portfolio during the previous quarter. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. Coefficient values are multiplied by one hundred to enhance readability. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)	(3)	(4)
$\text{HighSameFirmPeerError}_{i,j,t-1}$	–0.0027***		–0.0026***	–0.0027***
	(–5.72)		(–5.64)	(–5.35)
$\text{LowSameFirmPeerError}_{i,j,t-1}$	0.0024***		0.0023***	0.0025***
	(4.97)		(4.88)	(4.57)
$\text{HighOtherFirmPeerError}_{i,j,t-1}$		–0.0015***	–0.0015***	–0.00156***
		(–3.68)	(–3.51)	(–3.60)
$\text{LowOtherFirmPeerError}_{i,j,t-1}$		0.0012**	0.0012**	0.0013**
		(2.87)	(2.69)	(2.83)
$\text{OwnPreviousForecastError}_{i,j,t-1}$				–0.0775
				(–0.30)
$\text{OwnOtherForecastErrors}_{i,j,t-1}$				–0.0865
				(–0.66)
Earnings Announcement Fixed Effects	Yes	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes	Yes
N	1,142,610	1,142,610	1,142,610	1,142,610
Adj. R-squared	0.804	0.804	0.804	0.804

Panel B: Forecast Optimism Regression Estimates				
	(1)	(2)	(3)	(4)
HighSameFirmPeerError$_{i,j,t-1}$	–0.0030***		–0.0030***	–0.0022***
	(–6.13)		(–6.05)	(–4.12)
LowSameFirmPeerError$_{i,j,t-1}$	0.0031***		0.0030***	0.0023***
	(6.06)		(5.97)	(3.96)
HighOtherFirmPeerError$_{i,j,t-1}$		–0.0015***	–0.0014**	–0.0015**
		(–3.37)	(–3.17)	(–3.26)
LowOtherFirmPeerError$_{i,j,t-1}$		0.0016***	0.0015**	0.0016**
		(3.40)	(3.19)	(3.26)
OwnPreviousForecastError$_{i,j,t-1}$				0.5010
				(1.81)
OwnOtherForecastErrors$_{i,j,t-1}$				–0.0943
				(–0.67)
Earnings Announcement Fixed Effects	Yes	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes	Yes
N	1,142,610	1,142,610	1,142,610	1,142,610
Adj. R-squared	0.469	0.469	0.469	0.469

Table 5
Bold Forecast Regression Estimates

This table reports results from quarterly panel regressions explaining analysts' bold forecasts with peer analysts' bold forecasts on different firms in the analyst portfolio during the previous quarter. Peer analysts are defined separately for each analyst-earning announcement observation, and they consist of other analysts following other firms in the analyst portfolio. Bold forecasts, as defined by Clement and Tse (2005), deviate positively or negatively both from the analyst's prior forecast and the consensus forecast immediately before the forecast revision. Panel A reports results from regressions explaining bold-positive forecasts and Panel B from regressions explaining bold-negative forecasts. The dependent variable is binary and takes the value one if the analyst issued at least one positive (negative) bold forecast during a firm-quarter. The main explanatory variables, $PeerBoldPos_{i,j,t-1}$ and $PeerBoldNeg_{i,j,t-1}$, are defined as the percentage of peer analysts who issued at least one positive (negative) bold forecast during the previous quarter. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. $BoldPos_{i,j,t-1}$ and $BoldNeg_{i,j,t-1}$ are dummy variables that take the value of one if the analyst issued a positive or negative bold forecast for the focal firm during the previous quarter. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Bold-Positive Forecasts			
	(1)	(2)	(3)
$\text{PeerBoldPos}_{i,j,t-1}$	0.008**	0.009***	0.010***
	(2.343)	(2.621)	(2.829)
$\text{BoldPos}_{i,j,t-1}$		–0.054***	–0.054***
		(–35.382)	(–35.385)
$\text{PeerBoldNeg}_{i,j,t-1}$			0.003
			(1.282)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,506,672	1,506,672	1,506,672
Adj. R-squared	0.187	0.188	0.188

Panel B: Bold-Negative Forecasts			
	(1)	(2)	(3)
$\text{PeerBoldNeg}_{i,j,t-1}$	0.015***	0.016***	0.017***
	(4.759)	(5.227)	(5.329)
$\text{BoldNeg}_{i,j,t-1}$		–0.060***	–0.060***
		(–43.809)	(–43.810)
$\text{PeerBoldPos}_{i,j,t-1}$			0.004
			(0.856)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,506,672	1,506,672	1,506,672
Adj. R-squared	0.256	0.258	0.258

Table 6
Relative Optimism Regression Estimates: Portfolio Characteristics and Social Learning

This table reports relative forecast optimism estimates using extended regression specifications. Specifically, we consider variables interacted with peer analysts' past forecast errors on other firms in the analyst portfolio. The dependent variable is quarterly forecast error calculated as the analyst's forecast minus actual earnings per share, and it is scaled by share price 10 days before the earnings announcement. The explanatory variables include interactions with $PeerForecastErrors_{i,j,t-1}$, which measures other analysts' average forecast error on other firms in the analyst portfolio during the previous quarter. The interacted variables include $EarningsCorrelation_{i,j,t-1}$, which is defined as adjusted R^2 from a regression that explains the firm's earnings scaled by assets with the average earnings on other firms in the analyst portfolio using earnings from the previous 12 quarters. $EarningsGrowthCorrelation_{i,j,t-1}$ is measured similarly, except that the regression is based on quarterly observations of earnings growth relative to the preceding quarter. *% SIC-3PeerFirms*$_{i,j,t-1}$ measures the percentage of firms in the same 3-digit SIC industry, and *%Same-StatePeerFirms*$_{i,j,t-1}$ measures the percentage of firms headquartered in the same state according to Compustat. Unreported control variables include $OwnPreviousForecastError_{i,j,t-1}$ and $OwnOtherForecastErrors_{i,j,t-1}$, which are defined as in Table 3. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
PeerForecastErrors$_{i,j,t-1}$ × EarningsCorrelation$_{i,j,t-1}$	–0.049**			
	(–2.009)			
EarningsCorrelation$_{i,j,t-1}$	0.000			
	(0.733)			
PeerForecastErrors$_{i,j,t-1}$ × EarningsGrowthCorrelation$_{i,j,t-1}$		–0.097***		
		(–2.785)		
EarningsGrowthCorrelation$_{i,j,t-1}$		0.000		
		(0.174)		
PeerForecastErrors$_{i,j,t-1}$ × % SIC-3PeerFirms$_{i,j,t-1}$			–0.009**	
			(–2.106)	
%SIC-3PeerFirms$_{i,j,t-1}$			–0.000	
			(–0.591)	
PeerForecastErrors$_{i,j,t-1}$ × %Same-StatePeerFirms$_{i,j,t-1}$				–0.011*
				(–1.935)
%Same-StatePeerFirms$_{i,j,t-1}$				–0.000
				(–1.356)
PeerForecastErrors$_{i,j,t-1}$	–0.012***	–0.012***	–0.007***	–0.007***
	(–4.732)	(–5.055)	(–2.843)	(–3.261)
Earnings Announcement Fixed Effects	Yes	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes	Yes
N	867,732	867,765	1,160,690	1,073,742
Adj. R-squared	0.805	0.805	0.805	0.805

Table 7
Relative Optimism Regression Estimates: Peer Characteristics and Social Learning

This table reports results from quarterly panel regressions that examine how peer characteristics influences social learning. The dependent variable is forecast error calculated as the analyst's forecast minus actual earnings per share and it is scaled by share price 10 days before the earnings announcement. The main explanatory variables measure other analysts' average forecast error on other firms in the analyst portfolio during the previous quarter. The averages are calculated using various subgroups of peer analysts covering the other firms in an analyst's portfolio. *High-Overlap* and *Low-Overlap* $PeerForecastErrors_{i,j,t-1}$ are calculated based on analyst *i*'s forecast-specific peers whose Szymkiewicz–Simpson portfolio overlap coefficient is above and below median within the peer group. *High-Accuracy* and *Low-Accuracy* $PeerForecastErrors_{i,j,t-1}$ are calculated similarly based on analyst *i*'s peers with above median and below median forecast accuracy. We measure accuracy using adjusted R^2 from an analyst-specific regression that explains realized earnings with the analyst's corresponding earnings forecasts based on forecasts issued by the analyst during the previous four quarters. *All-Star* and *Non-All-Star* $PeerForecastErrors_{i,j,t-1}$ are calculated based on *Institutional Investor* all-star analysts. Unreported control variables include $OwnPreviousForecastError_{i,j,t-1}$ and $OwnOtherForecastErrors_{i,j,t-1}$, which are defined as in Table 3. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. t-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High-Overlap $PeerForecastErrors_{i,j,t-1}$	–0.008***	–0.007***				
	(–3.962)	(–2.941)				
Low-Overlap $PeerForecastErrors_{i,j,t-1}$		–0.005**				
		(–2.299)				
High-Accuracy $PeerForecastErrors_{i,j,t-1}$			–0.010***	–0.008***		
			(–5.373)	(–3.780)		
Low-Accuracy $PeerForecastErrors_{i,j,t-1}$				–0.003		
				(–1.613)		
All-Star $PeerForecastErrors_{i,j,t-1}$					–0.007***	–0.006***
					(–4.721)	(–3.250)
Non-All-Star $PeerForecastErrors_{i,j,t-1}$						–0.007**
						(–2.373)
Earnings Announcement Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	938,059	938,059	1,142,923	1,142,923	779,950	779,950
Adj. R-squared	0.805	0.805	0.804	0.804	0.797	0.797

Table 8
Relative Optimism Regression Estimates: Peer Similarity and Social Learning

This table reports results from quarterly panel regressions that examine the influence of analyst characteristics on social learning. The dependent variable is forecast error calculated as the analyst's forecast minus actual earnings per share, and it is scaled by share price 10 days before the earnings announcement. The main explanatory variables measure other analysts' average forecast error on other firms in the analyst portfolio during the previous quarter. $SimilarPeerForecastErrors_{i,j,t-1}$ is calculated based on other analysts with similar personal characteristics, and $DissimilarPeerForecastErrors_{i,j,t-1}$ is calculated based on other analysts with dissimilar personal characteristics. Panel A measures similarity based on gender and includes subsample regressions using only male and female analysts. Panel B measures similarity based on ethnicity and includes subsample regressions using only analysts classified as White and Asian. Other explanatory variables are defined as in Table 3. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Analyst Similarity Based on Gender

	Full Sample (1)	Male (2)	Female (3)
$SimilarPeerForecastErrors_{i,j,t-1}$	–0.011**	–0.038**	–0.011**
	(–2.497)	(–2.034)	(–2.020)
$DissimilarPeerForecastErrors_{i,j,t-1}$	–0.004	0.047*	–0.005
	(–1.309)	(1.918)	(–1.583)
$OwnPreviousForecastError_{i,j,t-1}$	–0.030***	–0.056**	–0.030***
	(–6.525)	(–2.367)	(–6.035)
$OwnOtherForecastErrors_{i,j,t-1}$	0.012***	–0.022	0.015***
	(3.163)	(–1.135)	(3.455)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	359,868	19,949	311,378
Adj. R-squared	0.761	0.746	0.760

Panel B: Analyst Similarity Based on Ethnicity

	Full Sample (1)	White (2)	Asian (3)
$SimilarPeerForecastErrors_{i,j,t-1}$	–0.028***	–0.031***	–0.007
	(–3.925)	(–3.565)	(–0.218)
$DissimilarPeerForecastErrors_{i,j,t-1}$	0.002	0.002	–0.004
	(0.433)	(0.381)	(–0.196)
$OwnPreviousForecastError_{i,j,t-1}$	–0.037***	–0.039***	0.020
	(–2.987)	(–2.999)	(0.446)
$OwnOtherForecastErrors_{i,j,t-1}$	0.011*	0.013*	–0.023
	(1.881)	(1.867)	(–0.857)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	261,394	242,040	7,938
Adj. R-squared	0.781	0.781	0.719

Table 9
Firm-Level Forecast Error Estimates

This table reports results from quarterly panel regressions explaining a firm's consensus forecast error with the average consensus errors among related firms during the previous quarter. The explanatory variables include average consensus forecast errors among other firms in the same 3-digit SIC and Fama-French 49 industry in quarter t–1 as well as the corresponding average among other firms headquartered in the same state. We additionally include the firm's previous forecast error as a control variable. The regressions include firm fixed effects and year-quarter fixed effects. The forecast errors are scaled by share price 10 days before the earnings announcement. The sample period is 1984-2017. t-statistics based on standard errors dual-clustered by the firm and year-quarter are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
Average SIC-3 Consensus Forecast Errors$_{t-1}$	0.050***		
	(13.828)		
Average FF49 Consensus Forecast Errors$_{t-1}$		0.052***	
		(14.234)	
Average Same-State Consensus Forecast Errors$_{t-1}$			0.002
			(1.423)
The Firm's Consensus Forecast Error in t–1	0.179***	0.182***	0.191***
	(27.929)	(29.095)	(28.651)
Year-Quarter Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
N	274,106	289,765	265,605
Adj. R-squared	0.139	0.138	0.137

Table 10
Forecast Accuracy Regression Estimates

This table reports results from regressions explaining Proportional Mean Absolute Forecast Error (PMAFE) in quarterly earnings forecasts. The dependent variable, PMAFE, is defined as (absolute forecast error – average absolute forecast error) / average absolute forecast error, where the average is calculated based on all forecasts for the same earnings announcement. Forecast error is calculated as the analyst's forecast minus actual earnings per share, and it is scaled by share price 10 days before the earnings announcement. The explanatory variables are absolute values of $PeerForecastErrors_{i,j,t-1}$, $OwnPreviousForecastError_{i,j,t-1}$, and $OwnOtherForecastErrors_{i,j,t-1}$, which are defined as in Table 3. Column 3 also includes the squared value of abs($PeerForecastErrors_{i,j,t-1}$). $PeerForecastErrors_{i,j,t-1}$, measures other analysts' average forecast error on other firms in the analyst portfolio during the previous quarter, $OwnPreviousForecastError_{i,j,t-1}$, captures the analyst's own previous forecast error on the focal firm, and $OwnOtherForecastErrors_{i,j,t-1}$, is the analyst's own average forecast error on other firms in his portfolio during the previous quarter. All regressions include firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	Regressions Explaining Proportional Mean Absolute Forecast Error		
	(1)	(2)	(3)
Abs(PeerForecastErrors$_{i,j,t-1}$)	–0.800**	–2.605***	–3.168***
	(–2.492)	(–5.512)	(–3.483)
Abs(PeerForecastErrors$_{i,j,t-1}$)^2			45.266
			(0.728)
Abs(OwnPreviousForecastError$_{i,j,t-1}$)		–2.262***	–2.259***
		(–12.850)	(–12.825)
Abs(OwnOtherForecastErrors$_{i,j,t-1}$)		2.545***	2.578***
		(6.377)	(6.408)
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1305873	1305873	1305873
Adj. R-squared	0.052	0.052	0.052

Appendix

Table A1
Forecast Error and Optimism Regression Estimates using Value-Weighted Peer Forecast Errors

This table reports results from the regression specifications displayed in Table 3 using value-weighted peer forecast errors. In this Table, the main explanatory variable is $Value\text{-}WeightedPeerForecastErrors_{i,j,t-1}$, which measures market-value weighted average forecast error of other analysts on other firms in the analyst portfolio during the previous quarter. The value-weighting is conducted using end-of-quarter market values measured as share price times shares outstanding. Share price data are from CRSP, and shares outstanding are from Compustat. $Value\text{-}WeightedOwnOtherForecastErrors_{i,j,t-1}$, is calculated similarly based on the analyst's own average forecast error on other firms in his portfolio during the previous quarter. All other variables are defined as in Table 3. Panel A reports results from regressions explaining forecast errors, and Panel B reports results from regressions explaining forecast optimism relative to the consensus forecast. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)	(3)
Value-WeightedPeerForecastErrors$_{i,j,t-1}$	–0.007***	–0.007***	–0.013***
	(–3.851)	(–3.822)	(–5.593)
OwnPreviousForecastError$_{i,j,t-1}$		0.006***	0.006***
		(3.224)	(3.098)
Value-WeightedOwnOtherForecastErrors$_{i,j,t-1}$			0.008***
			(4.317)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,164,488	1,164,488	1,164,488
Adj. R-squared	0.805	0.805	0.805

Panel B: Forecast Optimism Regression Estimates

	(1)	(2)	(3)
Value-WeightedPeerForecastErrors$_{i,j,t-1}$	–0.006***	–0.006***	–0.012***
	(–3.477)	(–3.430)	(–5.148)
OwnPreviousForecastError$_{i,j,t-1}$		0.011***	0.011***
		(5.368)	(5.248)
Value-WeightedOwnOtherForecastErrors$_{i,j,t-1}$			0.008***
			(4.102)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,164,488	1,164,488	1,164,488
Adj. R-squared	0.467	0.467	0.467

Table A2
Forecast Error and Optimism Regression Estimates using Alternative Window for Analyst Forecasts

This table reports results from regressions explaining analyst's relative forecast optimism with peer analysts' past forecast error using alternative time window cutoffs for analyst forecasts. The observations consist of analysts' quarterly earnings forecasts. Columns (1), (2), and (3) report results based on analyst forecasts that were issued within time windows of 15, 45, and 90 days prior to the earnings announcement, respectively. The same time window is also used when forming the explanatory variables. In Panel A, the dependent variable is forecast error, and Panel B it is forecast optimism relative to the consensus. All variables are defined as in Table 3. All regressions include earnings announcement fixed effects as well as firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)	(3)
$\text{PeerForecastErrors}_{i,j,t-1}$ [d–15, d–1]	–0.025**		
	(–2.022)		
$\text{PeerForecastErrors}_{i,j,t-1}$ [d–45, d–1]		–0.031***	
		(–3.242)	
$\text{PeerForecastErrors}_{i,j,t-1}$ [d–90, d–1]			–0.011***
			(–4.455)
$\text{OwnPreviousForecastError}_{i,j,t-1}$	0.037	–0.123**	–0.008***
	(0.840)	(–2.263)	(–3.051)
$\text{OwnOtherForecastErrors}_{i,j,t-1}$	–0.006	0.007	0.007***
	(–0.846)	(1.092)	(3.998)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	24,256	183,928	693,961
Adj. R-squared	0.863	0.804	0.788

Panel B: Forecast Optimism Regression Estimates

	(1)	(2)	(3)
$\text{PeerForecastErrors}_{i,j,t-1}$ [d–15, d–1]	–0.026*		
	(–1.920)		
$\text{PeerForecastErrors}_{i,j,t-1}$ [d–45, d–1]		–0.028***	
		(–2.779)	
$\text{PeerForecastErrors}_{i,j,t-1}$ [d–90, d–1]			–0.010***
			(–3.738)
$\text{OwnPreviousForecastError}_{i,j,t-1}$	0.037	–0.134**	–0.004
	(0.826)	(–2.339)	(–1.304)
$\text{OwnOtherForecastErrors}_{i,j,t-1}$	–0.008	0.006	0.006***
	(–1.090)	(0.891)	(3.380)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	24,256	183,928	693,961
Adj. R-squared	0.704	0.674	0.531

Table A3
Baseline Regression Estimates Excluding Pre-1994 Observations

This table reports results from the regression specifications displayed in Table 3, excluding pre-1994 observations. Cooper, Day, and Lewis (2001) and Clement and Tse (2003) report that I/B/E/S forecast dates in the 1980s and early 1990s sometimes differ from the actual forecast date by a few days. These subsample regressions function as a robustness check accounting for possible forecast timing errors in the data. Panel A reports results from regressions explaining forecast errors, and Panel B reports results from regressions explaining forecast optimism relative to the consensus forecast. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)	(3)
$PeerForecastErrors_{i,j,t-1}$	–0.004***	–0.004***	–0.013***
	(–2.716)	(–2.660)	(–5.935)
$OwnPreviousForecastError_{i,j,t-1}$		0.009***	0.009***
		(4.479)	(4.316)
$OwnOtherForecastErrors_{i,j,t-1}$			0.010***
			(6.317)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,087,786	1,087,786	1,087,786
Adj. R-squared	0.798	0.798	0.798

Panel B: Forecast Optimism Regression Estimates

	(1)	(2)	(3)
$PeerForecastErrors_{i,j,t-1}$	–0.004**	–0.004**	–0.012***
	(–2.225)	(–2.143)	(–5.325)
$OwnPreviousForecastError_{i,j,t-1}$		0.015***	0.014***
		(6.605)	(6.449)
$OwnOtherForecastErrors_{i,j,t-1}$			0.010***
			(5.982)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,087,786	1,087,786	1,087,786
Adj. R-squared	0.478	0.479	0.479

Table A4
Placebo Regression Estimates

This table reports results from regressions explaining analyst's relative forecast optimism with peer analysts' past forecast errors on a placebo group of related firms. Instead of defining peer analysts as other analysts who follow other firms in the analyst portfolio, we define them based on a placebo portfolio with the same number of randomly selected firms. The random selection is conducted separately for each firm-analyst observation, and we select the firms among all other sample firms that have analysts during the same quarter. The observations consist of analysts' quarterly earnings forecasts. In Panel A, the dependent variable is forecast error calculated as the analyst forecast minus actual earnings per share, and in Panel B it is optimism calculated as the analyst's own forecast minus the consensus forecast. Both dependent variables are scaled by share price 10 days before the earnings announcement. The main explanatory variable is $PlaceboPeerForecastErrors_{i,j,t-1}$, which measures other analysts' average forecast error on the firms in the placebo portfolio during the previous quarter. The other explanatory variable is $OwnPreviousForecastError_{i,j,t-1}$, which captures the analyst's own previous forecast error on the focal firm. All regressions include earnings announcement fixed effects and firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)
PlaceboPeerForecastErrors$_{i,j,t-1}$	–0.001	–0.001
	(–0.923)	(–0.922)
OwnPreviousForecastError$_{i,j,t-1}$		0.010***
		(4.805)
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes
N	1,034,486	1,034,486
Adj. R-squared	0.806	0.806

Panel B: Forecast Optimism Regression Estimates

	(1)	(2)
PlaceboPeerForecastErrors$_{i,j,t-1}$	–0.001	–0.001
	(–1.027)	(–1.025)
OwnPreviousForecastError$_{i,j,t-1}$		0.016***
		(6.977)
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes
N	1,034,486	1,034,486
Adj. R-squared	0.467	0.467

Table A5
Forecast Error and Optimism Regression Estimates with Alternative Treatment of Outliers

This table reports results from the regression specifications displayed in Tables 3 with variables winsorized at top and bottom 1% of their distributions. In Panel A, the dependent variable is forecast error, and Panel B it is forecast optimism relative to the consensus. All variables are defined as in Table 3. All regressions include earnings announcement fixed effects as well as firm-analyst fixed effects. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)	(3)
PeerForecastErrors$_{i,j,t-1}$	–0.007***	–0.007***	–0.015***
	(–3.357)	(–3.392)	(–5.611)
OwnPreviousForecastError$_{i,j,t-1}$		–0.007**	–0.007**
		(–2.273)	(–2.390)
OwnOtherForecastErrors$_{i,j,t-1}$			0.010***
			(4.732)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,257,452	1,257,452	1,257,452
Adj. R-squared	0.779	0.779	0.779

Panel B: Forecast Optimism Regression Estimates

	(1)	(2)	(3)
PeerForecastErrors$_{i,j,t-1}$	–0.008***	–0.007***	–0.015***
	(–3.952)	(–3.884)	(–5.587)
OwnPreviousForecastError$_{i,j,t-1}$		0.014***	0.013***
		(5.050)	(4.939)
OwnOtherForecastErrors$_{i,j,t-1}$			0.008***
			(4.197)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,257,452	1,257,452	1,257,452
Adj. R-squared	0.468	0.468	0.468

Table A6
Bold Regression Estimates using Alternative Measures of Bold Forecasts

This table reports results from the regressions of Table 4 using an alternative definition for bold forecasts. In this table, we only include the most recent forecast revision when defining bold forecasts in the dependent and independent variables. Otherwise, the regressions and variable definitions are identical to Table 4. Panel A reports results from regressions explaining bold-positive forecasts and Panel B from regressions explaining bold-negative forecasts. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Bold-Positive Forecasts

	(1)	(2)	(3)
$PeerBoldPos_{i,j,t-1}$	0.010***	0.011***	0.013***
	(2.767)	(2.993)	(3.470)
$BoldPos_{i,j,t-1}$		–0.062***	–0.062***
		(–39.833)	(–39.838)
$PeerBoldNeg_{i,j,t-1}$			0.005**
			(2.193)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,506,672	1,506,672	1,506,672
Adj. R-squared	0.177	0.180	0.180

Panel B: Bold-Negative Forecasts

	(1)	(2)	(3)
$PeerBoldNeg_{i,j,t-1}$	0.013***	0.014***	0.016***
	(4.042)	(4.515)	(4.861)
$BoldNeg_{i,j,t-1}$		–0.066***	–0.066***
		(–48.884)	(–48.885)
$PeerBoldPos_{i,j,t-1}$			0.008*
			(1.824)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,506,672	1,506,672	1,506,672
Adj. R-squared	0.245	0.247	0.247

Table A7

Explaining Relative Optimism using Peer Analysts' Past Forecast Errors and Bold Forecasts

This table reports results from regressions explaining analysts' relative forecast optimism with both peer analysts' past forecast errors and bold forecasts. In Panel A, the dependent variable is forecast error calculated as the analyst's forecast minus actual earnings per share, and in Panel B it is optimism calculated as the analyst's own forecast minus the consensus forecast. Both dependent variables are scaled by share price 10 days before the earnings announcement. All variables are defined in Tables 3 and 4. *t*-statistics based on standard errors clustered by earnings announcement are reported below the coefficients. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Forecast Error Regression Estimates

	(1)	(2)	(3)
$PeerForecastErrors_{i,j,t-1}$	–0.013***	–0.012***	–0.012***
	(–4.584)	(–4.399)	(–4.387)
$OwnPreviousForecastError_{i,j,t-1}$	–0.005*	–0.005*	–0.005*
	(–1.809)	(–1.810)	(–1.810)
$OwnOtherForecastErrors_{i,j,t-1}$	0.009***	0.009***	0.009***
	(4.334)	(4.317)	(4.316)
$PeerBoldPos_{i,j,t-1}$	0.000		0.000
	(0.944)		(0.201)
$PeerBoldNeg_{i,j,t-1}$		–0.000***	–0.000***
		(–3.346)	(–3.246)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,164,488	1,164,488	1,164,488
Adj. R-squared	0.750	0.750	0.750

Panel B: Forecast Optimism Regression Estimates

	(1)	(2)	(3)
$PeerForecastErrors_{i,j,t-1}$	–0.010***	–0.009***	–0.009***
	(–2.913)	(–2.762)	(–2.763)
$OwnPreviousForecastError_{i,j,t-1}$	–0.000	–0.000	–0.000
	(–0.068)	(–0.069)	(–0.069)
$OwnOtherForecastErrors_{i,j,t-1}$	0.007***	0.007***	0.007***
	(2.806)	(2.790)	(2.791)
$PeerBoldPos_{i,j,t-1}$	0.000		0.000
	(0.551)		(0.021)
$PeerBoldNeg_{i,j,t-1}$		–0.000**	–0.000**
		(–2.489)	(–2.350)
Earnings Announcement Fixed Effects	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes
N	1,164,488	1,164,488	1,164,488
Adj. R-squared	0.776	0.776	0.776