THE ACCOUNTING REVIEW
Vol. 99, No. 6
November 2024
pp. 129–156

American Accounting Association
DOI: 10.2308/TAR-2023-0117

Classifying Forecasts

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ABSTRACT: We employ a novel machine learning technique to classify analysts' forecast revisions into five types based on how the revision weighs publicly available signals. We label these forecast types as quant, sundry, contrarian, herder, and independent forecasts. Our tests reveal that a greater diversity of forecast types within the consensus is associated with increased consensus dispersion and improved consensus accuracy. Additionally, consensus diversity is associated with an improved information environment for firms, as reflected in reduced earnings announcement information asymmetry and volatility, higher earnings response coefficients, and faster price formation. Our study sheds light on how analysts revise their forecasts and documents capital market benefits associated with different analyst forecasting approaches.

Keywords: analyst forecasts; financial signals; forecast diversity; consensus accuracy; machine learning.

I. INTRODUCTION

An extensive literature examines properties of analyst earnings forecasts, such as accuracy, dispersion, and bias (Lys and Sohn 1990; Das, Levine, and Sivaramakrishnan 1998). This literature primarily focuses on how specific analyst characteristics (e.g., experience and specialization), resource availability (e.g., brokerage size), and incentives (e.g., investment banking spillover) influence the forecasts. Far less attention has been given to *how* analysts construct their forecasts or to associated market consequences related to the particular forecasting approach employed. The observed variation in analyst forecasts is striking when we consider that analysts have access to the same public information and suggests there may be different classifications or "types" of earnings forecasts, each of which considers and weighs public and private signals differently. Our objective is to empirically classify analyst earnings forecast revisions into types based on how the revision weighs public information. We then examine whether the diversity of forecast types reflected in the consensus has capital markets implications.

Our study is motivated by research suggesting analysts approach the research task in different ways. For example, Ertimur, Mayew, and Stubben (2011) and Mauler (2019) suggest that analysts engage in different levels of disaggregation

We thank David Veenman (editor), two anonymous reviewers, Brian Bratten, Kimball Chapman, Nargess Golshan, Bin Ke (discussant), Xikai Chen (discussant), Charley Irons, Tyler Kleppe, Ken Merkley, Joe Pacelli, Jeri Seidman, Quinn Swanquist, Jake Thornock, Ke Wang (discussant), Haifeng You, Julia Yu, and workshop participants at Brigham Young University, Georgia Institute of Technology, University of Kentucky, University of Virginia, the 2022 Conference on Financial Economics and Accounting (CFEA), the 2022 Hong Kong University of Science and Technology (HKUST) Research Symposium, and the 2023 University of Technology Sydney (UTS) Australian Summer Accounting Conference for helpful comments and suggestions. The authors of this publication have no conflicts of interest related to this research.

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Supplemental material is available online, as linked in the text.

Editor's note: Accepted by David Veenman, under the Senior Editorship of W. Robert Knechel.

Submitted: February 2023
Accepted: May 2024
Early Access: June 2024

in developing their forecasts. Survey responses in Brown, Call, Clement, and Sharp (2015) indicate that analysts place different weights on common research inputs. Furthermore, Brown et al. (2015) suggest that analysts have different levels of access to private information from managers and highlight that private information is a key input into the forecasting process. If there is indeed variation in how forecasts are constructed, then the extent to which a particular forecast contributes to a firm's information environment is likely to vary based on its type or method of construction. That is, different types of forecasts may complement one another, resulting in an improved information environment (Da and Huang 2020). Alternatively, greater diversity of forecast types may cloud the information environment, adversely impacting a firm's information environment.

Classifying forecast revisions into distinct groups is not straightforward, because we only observe the output of the forecasting process, not the method used to generate the forecast. To address this challenge, we use clusterwise linear regression (hereafter, CLR) to shuffle forecast revisions of quarterly earnings into various groups based on how the revision appears to incorporate and weigh public information.[1] Unlike prior research, our focus is on forecast revisions (the output) and not on the forecasters themselves (the analysts). Our focus on outputs allows for the possibility that analysts vary their use of a particular forecast type across covered firms, over time, or both.

To model individual analyst revisions, we examine 148 public signals across four categories of public information that analysts may consider when they revise their forecasts: (1) firm fundamentals, (2) valuation multiples, (3) momentum-based signals, and (4) forecast herding indicators. We estimate 1,000 regressions using random subsets of these 148 signals and use recursive feature elimination with cross-validation (RFECV) to identify three representative variables for each of the four categories. We then regress individual analyst revisions on these 12 representative variables. Although we expect these 12 variables will reasonably capture the public information analysts are likely to consider, we also expect that differences among the forecast types will reflect differences in analysts' access to private information.

Like many unsupervised machine learning techniques, CLR requires a researcher to specify the number of unique groups (k) or, in our setting, the unique number of forecast revision types. Our implementation estimates k separate weighted least squares regressions, where each observation is assigned a weight for each regression such that observation weights sum to 1. These regressions are iteratively estimated, and observation weights are reassigned based on each observation's k regression residuals. Our procedure translates larger residuals into smaller weights (and *vice versa*) for the next round of estimation. This process continues until weights stabilize. We classify revisions into a particular type based on their largest regression weight. Our diagnostics indicate that there are five unique types of forecast revisions,[2] which we label based on the weights assigned to specific categories of public signals. The labels include *Quant Forecasts* (give more weight to fundamental signals), *Sundry Forecasts* (lack a discernable pattern of weights), *Contrarian Forecasts* (give negative weight to other analyst signals), *Herder Forecasts* (give more weight to other analyst signals), and *Independent Forecasts* (do not give much weight to public signals).[3]

Our first test examines whether our method identifies revision classifications that vary in terms of accuracy. We do this by examining how the consensus forecast accuracy varies with coverage by each of the five forecast types identified. Our estimates suggest that adding a revision from any of the forecast classifications within a quarter is associated with a significant increase in consensus accuracy, consistent with prior research suggesting forecast accuracy increases with analyst following. However, the magnitude of the improvement in consensus forecast accuracy varies considerably depending on the type of forecast that is added. For example, adding an *Independent Forecast* has four times more impact than adding a *Quant Forecast*. This test provides initial evidence that the CLR procedure effectively groups forecasts into meaningful classifications that contribute differently to the quality of the consensus.

Next, we conduct tests to understand how diversity in coverage from various forecast types impacts the information environment of the firm. To do so, we develop measures that capture the diversity of opinion reflected in the different forecast types included in the consensus, which we refer to as consensus diversity. We measure consensus diversity in two ways. First, we define "consensus coverage" as the number of unique forecast revision types in a firm's consensus in a firm-quarter. This measure is analogous to "analyst following," except we are counting unique forecast types included in the consensus rather than unique analysts included in the consensus. Second, we develop a measure of "consensus

[1] We develop our own implementation of CLR, which is very similar to the model outlined in Späth (1979). In different settings, Larcker and Richardson (2004) and Allen, Larson, and Sloan (2013) both employ latent class mixture models, which are conceptually similar to CLR.

[2] We actually identify six forecast types, but one type captures outlier revisions (less than 1 percent of total forecasts), which we exclude from our analyses. Additionally, we note that the labels we assign are subjective and based on the variables we chose for the clustering procedure.

[3] We estimate the CLR using a pooled sample between 2010 and 2017. For model training, we use one-quarter-ahead forecast revisions issued within five days after the earnings announcement (e.g., the Q3 analyst forecast issued after the Q2 earnings announcement), which roughly holds constant forecast horizon and public information available to the analysts. The R^2 values within the five predominant forecast classifications identified by the CLR average nearly 80 percent, which is more than double the explanatory power of the pooled regression model.

balance," which captures how evenly forecast revisions are distributed among the different types in the consensus. This measure is derived from variation in the number of analysts contributing forecast revisions from each of the five types. We test whether these measures are incremental to a traditional measure of general analyst coverage in explaining the firm's information environment.

We begin by examining whether consensus diversity is incremental to analyst coverage in explaining consensus analyst forecast dispersion and consensus forecast accuracy. Our evidence indicates that both proxies for consensus diversity are positively associated with consensus forecast dispersion, which is intuitive because different forecasting processes likely lead to different forecasts. However, we also find that both proxies are *positively* associated with consensus forecast accuracy. For the median firm in our sample, our estimates indicate that adding a forecast from a new type corresponds to an increase in consensus accuracy that is 44 percent larger than adding a forecast from a type that is already included in the consensus. This finding is consistent with research suggesting that independence among social media forecasters in a crowdsourced setting yields a more accurate consensus forecast (Da and Huang 2020).

We next examine whether consensus diversity relates to three capital market outcomes at the earnings announcement (EA) for the period forecasted, including trading characteristics (bid-ask spread and volatility), returns (absolute returns and earnings response coefficients), and price formation (intraperiod price efficiency and jump ratio). Our expectations for these three market tests are as follows. First, prior research suggests information asymmetry temporarily but substantially increases at EAs because certain investors can more quickly process and respond to earnings news (Kim and Verrecchia 1994; Lee, Mucklow, and Ready 1993; Amiram, Owens, and Rozenbaum 2016). If greater consensus diversity before the EA creates a richer information environment for all investors, then this should mitigate the information advantage of sophisticated investors. Consistent with this argument, we find that both abnormal bid-ask spreads (a proxy for information asymmetry) and the change in volatility (reflective of investor uncertainty and disagreement) at the EA are negatively associated with both proxies for consensus diversity.

Second, if firms with more diverse consensus forecasts have a higher quality earnings expectation metric, this should increase investors' ability to interpret deviations from expectations, thereby increasing the market reaction to earnings as measured by the firm's earnings response coefficient (ERC). Consistent with this argument, we find that ERCs are positively associated with both measures of consensus diversity. We also examine the magnitude of EA returns under the premise that a more diverse set of forecast types reduces the information content of the EA because the market has a higher quality earnings expectation, but we fail to find evidence to support this argument.

Third, if consensus diversity creates a higher quality information environment for investors, we expect faster price formation following EAs. We use two measures of the speed of price formation, intraperiod timeliness (IPE) and the jump ratio, and find some evidence with both measures suggesting higher consensus diversity is associated with a more efficient price response. Overall, our capital market tests suggest that there are benefits associated with a firm having greater forecast type diversity in its coverage.

Finally, we evaluate the extent to which forecast types vary within an analyst both in the cross-section and over time. When we examine the distribution of forecast type within an analyst at a given quarter (i.e., whether analysts use multiple forecast types in a quarter), we find little evidence that analysts adopt a particular style. For example, our tests reveal that, when analysts cover three firms in a quarter, only 6.7 percent issue all three forecasts with a single type. We also find that analysts' use of a particular forecast type is not very persistent for an analyst-firm combination, suggesting that most analysts use a variety of forecast types over time.[4,5]

We contribute to the growing literature in accounting, finance, and economics that examines the benefits of diversity among groups of experts when drawing consensus. Most relevant to our paper, Merkley, Michaely, and Pacelli (2020) find that cultural diversity among the analyst coverage of a firm is associated with higher forecast quality, in part because such diversity leads to more diverse opinions. Merkley et al. (2020) primarily focus on diversity measured at the analyst level (i.e., the human level). We extend this line of research by identifying and exploring the market outcomes of diversity at the *forecast revision* level (i.e., the output level), which is subject to change over time both across firms and within a given analyst.

We also contribute to research examining the determinants of analyst consensus dispersion and accuracy. Consistent with conventional wisdom, this literature suggests the quality of a firm's information environment is increasing in the number of analysts covering the firm. Our evidence suggests this characterization is incomplete. Our tests

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[4] We also confirm that use of any particular forecast type is not simply time period or industry specific. Specifically, the distribution of forecast types across both time and industry is relatively stable.

[5] One implication of this result is that individual analyst accuracy for a given firm is unlikely to be persistent over time. We verify this is the case in our data using two tests. First, we rank analysts covering a firm by accuracy in a given quarter and regress this rank on analyst-firm fixed effects. Those fixed effects explain only 5.6 percent of the variation in this variable. Second, we compare a regression of forecast accuracy on firm fixed effects with one using crossed firm-analyst fixed effects. The increase in R^2 from adding the fixed effects is only marginal.

reveal a more nuanced view that the relation between a firm's information environment and its following depends on the types of forecasts issued, implying that differences in the forecasting process can have important implications for firms' information environments. We also provide new evidence to this literature that suggests some analyst outputs are likely influenced by or related to those issued by their peers. For example, prior research identifies forecasts that appear to gravitate toward the consensus (herding) or go against the consensus (boldness) and analysts that appear to be leaders or followers (Cooper, Day, and Lewis 2001; Clement and Tse 2005; Jegadeesh and Kim 2010; Palmon, Sarath, and Xin 2020).

Finally, we develop a method of identifying analyst forecast types using CLR. Prior studies use individual analyst fixed effects or observable analyst-specific characteristics that do not vary over time. Existing research uses latent class mixture models to explore variations in audit pricing (Larcker and Richardson 2004) and accruals (Allen et al. 2013). This research primarily focuses on persistent differences at the firm level. In contrast, we believe CLR could be used in other settings to assign individuals and financial data into distinct groups.

II. PRIOR LITERATURE AND EMPIRICAL QUESTIONS

The literature examining sell-side analyst earnings forecasts is vast and continues to grow. Much of this literature focuses on identifying factors associated with the quality of individual analyst forecast attributes as typically measured by its accuracy or bias. These determinants can largely be categorized into three groups, including analyst characteristics (e.g., experience and specialization), resource availability (e.g., brokerage size), and incentives (e.g., investment banking spillover). Representative papers that examine these groups of determinants include O'Brien and Bhushan (1990); Clement (1999); Jacob, Lys, and Neale (1999); Irvine (2004); and Corwin, Larocque, and Stegemoller (2017).

The existing sell-side analyst literature, however, has given less attention to *how* analysts construct their forecasts. Specifically, it has not yet delved deeply into identifying the information analysts use to construct their forecasts of earnings. The absence of research in this area likely does not reflect a lack of interest in the topic or indicate its unimportance. Rather, the lack of research on this topic is likely due to the unavailability of data, as it is difficult for researchers to observe the forecasting process of analysts. Brown et al. (2015) provide insights into how analysts construct their forecasts by asking analysts how useful different types of information sources are for determining their earnings forecasts. The survey results reveal that analysts' industry knowledge, private communication, earnings calls, management guidance, and accounting reports are most useful, although the analyst respondents were not asked to identify *specific* pieces of information used to forecast.

Although much of this literature focuses on individual analyst forecasts, a relatively smaller substream of research focuses on the consensus earnings forecast (for reviews of this literature, see Schipper 1991; Ramnath, Rock, and Shane 2008; Bradshaw 2011).[6] Since Brown, Richardson, and Schwager (1987) concluded that the consensus analyst forecast is superior (i.e., more accurate in general) to the time-series forecast, the consensus forecast has been used as a proxy by practitioners and researchers for market expectations of earnings performance. Some even argue that the consensus forecast is among the most widely used financial metrics in capital markets (Graham, Harvey, and Rajgopal 2005; Chang, Hsiao, Ljungqvist, and Tseng 2022; Merkley et al. 2020). Given the importance of the consensus analyst forecast to markets, this stream of research seeks to identify the significant determinants of consensus forecast accuracy. Most relevant to our study, Lys and Soo (1995) argue that the number of analysts covering a stock serves as an indicator of competition among analysts and that increased competition motivates analysts to enhance the precision of their forecasts by increasing spending and effort on research. Consistent with their prediction, they find that the accuracy of analyst earnings forecasts increases with the number of analysts covering the stock.

Although there is considerable focus on consensus forecast accuracy in the literature, a related literature considers the extent to which forecasts in the consensus disagree. Theory argues that consensus disagreement is a product of uncertainty and information asymmetry (Barry and Jennings 1992; Abarbanell, Lanen, and Verrecchia 1995; Barron, Kim, Lim, and Stevens 1998), and research commonly uses forecast dispersion as a proxy for these constructs (Ajinkya, Atiase, and Gift 1991). Several studies suggest a significant association between greater consensus forecast dispersion and capital market outcomes (see, e.g., Ajinkya and Gift 1985; L'her and Suret 1996; Barron, Stanford, and Yu 2009).

[6] Some prior research suggests that analyst forecast accuracy is not of primary importance to analysts because they are not incentivized to forecast accurately. Groysberg, Healy, and Maber (2011) fail to provide any evidence from one investment bank that analyst forecast accuracy is significantly related to the analyst's compensation. Brown et al. (2015) provide survey evidence that analysts rank the accuracy of their forecasts as the least important factor (of nine potential factors) of their compensation. These findings notwithstanding, the consensus analyst forecast continues to be one of the most cited financial metrics of a company. Further, our empirical tests also examine other market effects in addition to consensus forecast accuracy.

Consensus forecast dispersion arises due to differences in forecasts, and prior research attributes some of this dispersion to the unique perspectives of analysts contributing to the consensus. Merkley et al. (2020) find that cultural diversity among analysts is positively related to the accuracy of the consensus. Their tests indicate that the consensus improvement stems, in part, from diversity in forecast errors, which improves forecast quality by reducing forecast error covariance. Similarly, Da and Huang (2020) find that the consensus forecast crowdsourced from social media analysts on Estimize.com is more accurate when the forecasts are more independent, exhibiting less "herding" behavior. The authors conclude that the observed "wisdom of crowds" is most effectively harnessed through the presence of more independent voices.

It is somewhat surprising that the literature has largely shifted away from exploring other determinants of consensus forecast accuracy and dispersion in favor of delving deeper into the factors associated with *individual* analysts' forecast quality. Focusing on individual forecasts is natural due to the richness of the variation available for researchers to examine. However, the consensus earnings forecast remains a very important metric in capital markets. It is typically more accurate than the individual forecasts that underlie it (Clement 1999; Zarnowitz and Braun 1993) and is commonly reported by data aggregators (e.g., Yahoo Finance) for free to investors. Thus, it is a particularly important metric for smaller retail investors.

The intersection of the literatures discussed above motivates our primary research objectives, which are two-fold. First, we classify individual analyst forecast revisions into types based on how each forecast appears to weigh different signals of public information. Second, we examine the market implications for a firm having different types of forecasts in its coverage.

III. METHOD FOR CLASSIFYING FORECASTS

Sample Information and Revision Regression

We begin with a sample of quarterly earnings forecast revisions in I/B/E/S issued by analysts within five days following earnings announcements (days 0 to +5, inclusive). We focus on the days immediately following EAs because most analysts revise their forecasts in the days that immediately follow firms' EA (Clement, Hales, and Xue 2011). We examine one-quarter-ahead earnings forecast revisions to hold the forecast horizon relatively constant. In other words, following the EA for a given firm, nearly all analysts will revise forecasts for the next quarter, and the forecast horizon is roughly similar at approximately one-quarter. This mitigates the concern that differences in information available to analysts at the time of their forecasts influence the forecast type. We identify 370,771 forecasts issued by 3,399 unique analysts at EAs for 2,666 unique firms between 2010 and 2017.

The classification of revisions into unique types requires us to model observable information that analysts potentially use when revising their forecasts. Considering the complexity and nuance of the forecasting process, along with the potentially wide range of different approaches analysts might use, we adopt a comprehensive approach to identify the set of public signals that analysts could potentially consider. As discussed in more detail below, we consider over 140 potential public signals and then allow the data to guide us in identifying the set of signals we ultimately use to categorize forecast revisions. This broad approach increases the likelihood that we capture a variety of different forecasting approaches potentially used by analysts. We acknowledge, however, that consideration of a large set of variables means that some of the factors we examine may not have a direct theoretical link to forecast revisions. Although this is a shortcoming of our approach, we emphasize that, by not limiting the set of variables under consideration, we increase the likelihood that modeled variation captures a significant portion of information potentially used by analysts.[7]

Similar in spirit to Stickel (1990) and Drake, Rees, and Swanson (2011), we categorize the public signals into groups based on the nature of the signal. The *Fundamentals* category includes variables related to financial statement variables. The *Momentum* category includes variables capturing the trajectory of firm performance. The *Valuation Multiples* category includes variables commonly used by analysts and investors to assess relative valuations. The *Herding* category includes indicators of possible herding behavior, which is the tendency of an analyst to incorporate information provided by other analysts and intermediaries. We include factors from each of these categories in the following model:

$$Revision_{i,j,t} = a_0 + \beta Fundamentals_{i,t} + \gamma Momentum_{i,t} + \delta Valuation\ Multiples_{i,t} + \zeta Herding_{i,t} + e_{i,j,t} \quad (1)$$

[7] We acknowledge the possibility that the association between a particular public signal and forecast revisions could be driven by firm characteristics that drive both the signal and the revision. We stress that our primary focus is on identifying differences in how revisions relate to the factors we study, not whether the factors we include are causal determinants of a revision.

Subscripts *i*, *j*, and *t* refer to the firm, analyst, and quarter, respectively. Each category includes many signals, so we use a combination of diagnostics and judgment to identify a subset of significant predictors that capture constructs that span the variation we aim to model. To do this, we start with the large set of public signals examined in Green, Hand, and Zhang (2017); Drake et al. (2011); and Stickel (1990) and add other variables that we identify (e.g., *BusPress*). For variables based on the level of a particular measure, we also consider the seasonal first difference of that measure. We standardize all dependent and independent variables to have a mean of 0 and a standard deviation of 1. In all, we consider 148 variables. We eliminate variables with missing values for more than 10 percent of observations or that are correlated at 90 percent or higher with other variables. This screen results in 115 remaining variables. We then estimate Equation (1) 1,000 times, randomly including between 20 and 40 of the 115 remaining independent variables. We use ridge regressions, which regularize the weights of regression parameters, and use recursive feature elimination with cross-validation (RFECV) to progressively prune each set of regressors down to the most significant variables.[8] We use the 1,000 estimation results to measure the percentage of time each regressor is significant, conditioned on being included in the model. Each candidate independent variable is included in 190 regressions, on average.

Based on these diagnostics, we select three variables as representative variables for each of the four categories of information. Our selection process does not simply prioritize the three most significant variables; instead, we seek a balance between statistical significance and the diversity of signals. For the *Fundamentals* category, we include the change in sales ($\Delta Sales$), change in operating cash flows (ΔOCF), and change in capital expenditures ($\Delta CapEx$). These factors are significant in 93 percent, 97 percent, and 90 percent of regressions, respectively.[9] For the *Momentum* category, we include investor responses to recent earnings surprises (*EAReturns_Prior4*), buy and hold returns since the analyst's last forecast (*ReturnSinceLast*), and the number of recent earnings increases (*IncomeInc*). All three factors are significant in 100 percent of the regressions. For the *Valuation Multiples* category, we include the book-to-market ratio (*BM*), the cash-flow-to-price ratio (*CFP*), and the sales-to-price ratio (*SP*), which are significant in 98 percent, 59 percent, and 98 percent, respectively.[10] Finally, for the *Herding* category, we include the change in consensus ($\Delta Consensus$) and the change in long-term growth forecasts (ΔLTG) since the analyst's prior forecast. We also include average sentiment of business press articles published during the quarter about the firm from RavenPack (*BusPress*) given evidence in Bradshaw, Lock, Wang, and Zhou (2021) that analysts incorporate information from the financial press into their reports. These variables are significant in 100 percent, 90 percent, and 97 percent of estimations, respectively.

Clusterwise Linear Regression

The next step is to classify revisions into various types. We do this using CLR, which identifies discrete groups that maximize the fit of Equation (1). Latent class mixture models, such as CLR, have received considerable attention in statistics (Späth 1979; DeSarbo and Cron 1988; Wedel and DeSarbo 1995) and have been used in the social sciences (e.g., Ramaswamy, DeSarbo, Reibstein, and Robinson 1993; Brusco, Cradit, Steinley, and Fox 2008). However, in accounting research, the use of these models is rare, being used in Larcker and Richardson (2004) and Allen et al. (2013). Larcker (2003; 101) recognizes the usefulness of latent class models, stating these models seem "especially well-suited to empirical accounting research where there are almost certainly distinct clusters within a large sample of observations."

We develop a CLR implementation using Python, as canned packages are not widely available. We provide a detailed description of our procedure for implementing CLR in the Online Appendix. Like many unsupervised machine learning methods, CLR requires the researcher to specify the number of clusters (k). We evaluate model fit for between 2 and 20 clusters and employ a holdout sample to avoid overfitting. To assess fit, we use two metrics: the R^2 value of estimation and the average "confidence" of cluster assignment (or the average weights for assigned clusters) relative to unconditional assignments.[11] We plot these metrics in Figure 1. We note that, in a pooled regression, Equation (1) has an R^2 of approximately 40 percent. This number nearly doubles around $k = 5$, suggesting substantial variation across

[8] We use scikit-learn, a popular machine learning package available in Python, for both ridge regression and RFECV and use five folds for cross-validation.

[9] We do not include changes in earnings performance in *Fundamentals* for three reasons. First, the factors we identify are relevant for predicting future performance for nearly all firms, whereas earnings is less relevant for growth firms or in periods with losses. Second, we include the trajectory of earnings-based performance in *Momentum*. Finally, as discussed in Section V, we suspect that all analysts rely on earnings-related information, which would impede our ability to identify distinct clusters.

[10] We use *SP* instead of the price-to-earnings ratio to avoid issues with zero-earnings or loss firms. Additionally, we use the levels instead of changes for each of these measures because levels were more commonly significant. Finally, *CFP* is noticeably less significant than other factors we included. We chose to include it because other options for valuation multiples were either very similar to other factors included already (e.g., ratios of sales or change in sales to value), not applicable to all firms (e.g., R&D to value, dividend ratio), or relatively sticky (market cap plus debt to price). We also wanted to capture a "flow-to-price" measure that considered outflows.

[11] We define confidence as the mean cluster fit minus $1/k$. For instance, if, for $k = 4$, the average cluster fit was 75 percent, then confidence equals 50 percent (75 percent − 25 percent).

FIGURE 1
Regression Diagnostics

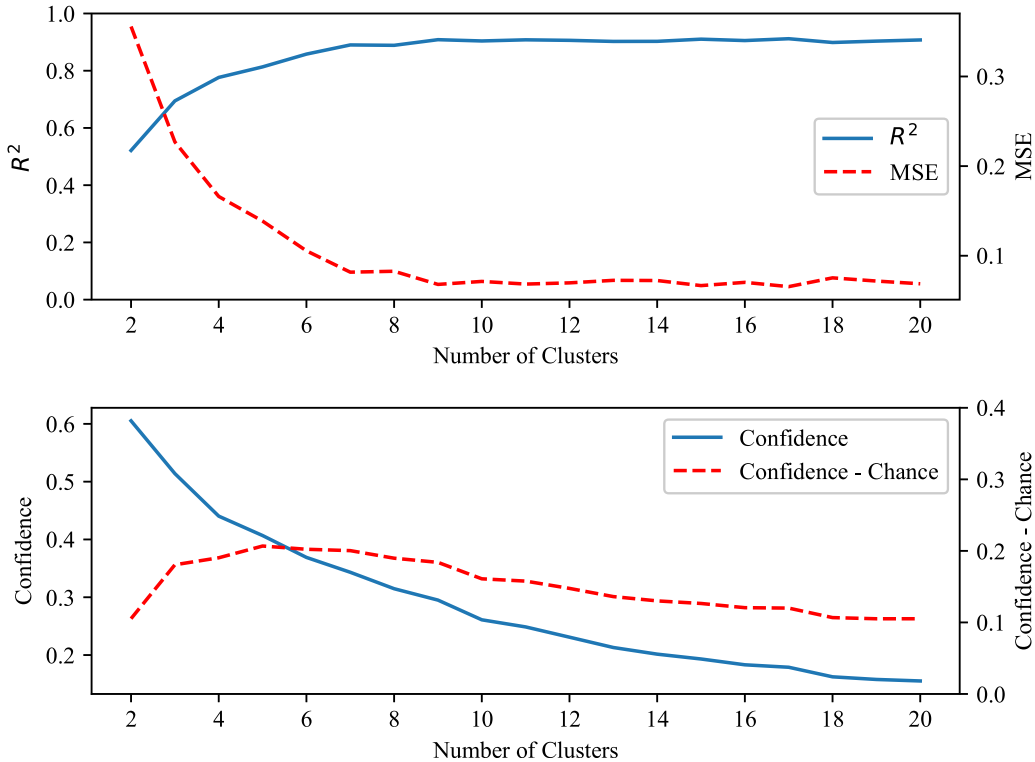

Figure 1 presents results from evaluating the number of appropriate analyst forecast clusters. We evaluate model fit for between 2 and 20 clusters and employ a holdout sample to avoid overfitting. We consider two metrics to evaluate fit: (1) the R^2 value of estimation and (2) the average "confidence" of cluster assignment (or the average weights for assigned clusters) relative to unconditional assignments.
(The full-color version is available online.)

forecast types. Confidence appears to peak between four and six clusters and then declines at higher values. Based on these diagnostics, we identify six clusters.[12]

We note that the CLR procedure does not impose balanced clusters. We find that one cluster contains less than 1 percent of all revisions that, on average, are nearly six times stock price. Therefore, we exclude this cluster from our tests as an outlier and focus on the five other forecast classifications, each of which contains at least 10 percent of the revisions.

Categorizing Forecast Types Based on Use of Publicly Available Information

To facilitate discussion, we assign labels to each forecast classification based on how the revisions weigh publicly available information. We rely on Figure 2 to determine the labels, which plots the Equation (1) coefficients by forecast type. The *x*-axis corresponds to each of the five forecast type assignments. The order of the *x*-axis is not important, but we assign labels so that 1 corresponds to the smallest cluster and 5 to the largest. All dependent and independent variables in these regressions are standardized to have a mean 0 and a standard deviation of 1, which facilitates comparison. Note that the *y*-axis varies with the scale of the coefficients, so we include in the figure a red horizontal line at a standardized coefficient magnitude of 0. We acknowledge that the labels we assign to each forecast type are subjective and depend on both the variables we select for the model and our interpretation of the results in Figure 2.

The first forecast type (far left in each subfigure) appears to place more weight on *Fundamentals* (top row) and *Momentum* (second row) signals. Accordingly, we label this first type "*Quant Forecasts*," as the forecasts leverage

[12] When choosing *k*, our intent is to balance model fit with generating reasonable variability in the number of forecast types. Our main inferences are robust to using values of 4 or 5 for *k*.

FIGURE 2
Use of Public Information by Analyst Forecast Classification

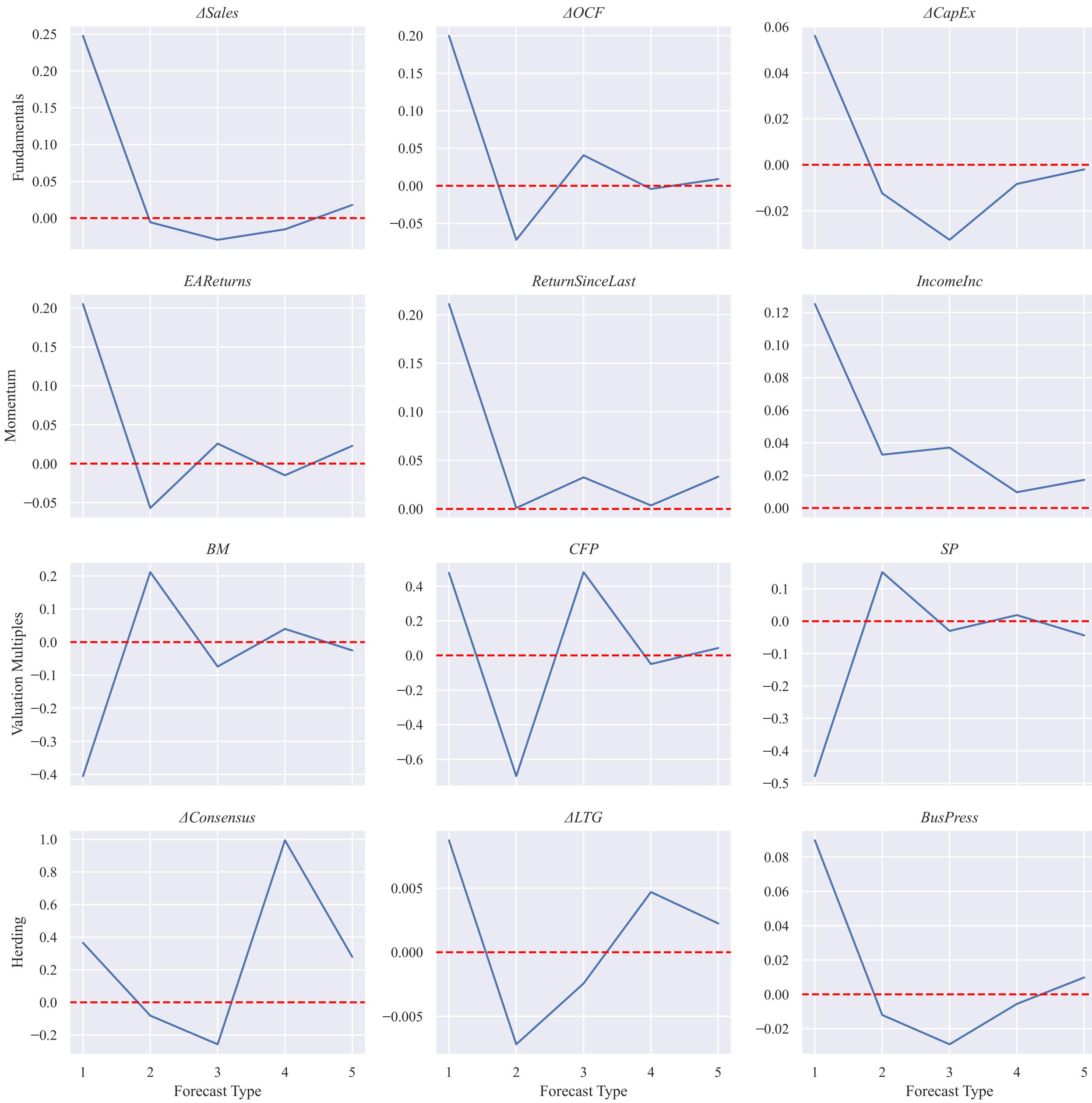

Figure 2 presents plots of the 12 coefficients included in Equation (1). The x-axis corresponds to forecast classification assignments and is increasing with classification accuracy. Forecast Type 1, Quant; Type 2, Sundry; Type 3, Contrarian; Type 4, Herder; Type 5, Independent. To facilitate magnitude and trend comparisons, all variables in these regressions are standardized to have a mean of 0 and a standard deviation of 1. The y-axis varies with the scale of the coefficients, so we include a red horizontal line at a standardized coefficient magnitude of 0.
(The full-color version is available online.)

quantitative information. The second forecast type reveals very few discernable patterns in how the forecasts reflect public information. For example, within the *Valuation* signals, these forecasts appear to positively weigh book to market but negatively weigh cash flow to price. In the *Fundamentals*, all three factors appear to be weakly, negatively weighted, and in *Herding*, two variables exhibit negative coefficients and one positive. Given this lack of clear pattern, we label type 2 as "*Sundry Forecasts*."

The most noticeable pattern for the third forecast type is that all three variables under *Herding* have negative coefficients. Accordingly, we label this type "*Contrarian Forecasts*." The fourth forecast type appears to follow changes in the analyst consensus forecast since the last forecast was provided. This group has the highest R^2 (96 percent; untabulated), and the majority of this explanatory power is driven by Δ*Consensus*, which has a coefficient nearly equal to 1 and a t-statistic of over 300. Thus, we label type 4 "*Herder Forecasts*." Finally, the fifth forecast type shows minimal evidence of the use of any of the 12 variables we consider, indicating that the forecasts are somewhat independent of the information we model. This could reflect that type 5 likely uses unmodeled and potentially private information. This inference is further supported by the fact that the R^2 for type 5 is approximately 71 percent (untabulated), which is the lowest across the five clusters. Given type 5 forecasts' reliance on information that is independent of variables included in our model, we label type 5 as "*Independent Forecasts*."

IV. SAMPLE, EMPIRICAL DESIGN, AND RESULTS

Descriptive Statistics

In Table 1, we present descriptive statistics for variables discussed previously, as well as those defined later. We Winsorize all continuous variables at the 1st and 99th percentile by year to reduce the influence of outliers. In Table 1, we provide descriptive statistics for the variables used to classify forecasts into types in Panel A, and we present statistics for variables used to examine the capital market consequences of forecast types in Panel B. We find that *Revision* and Δ*Consensus* both have slightly negative means, consistent with analyst forecast "walk-down" (Richardson, Teoh, and Wysocki 2004). We observe small average declines (increases) in operating cash flows (capital expenditures). Both returns measures (*EAReturns_Prior4* and *ReturnSinceLast*) have means close to 0. Median media sentiment (*BusPress*) is close to neutral tone (Ravenpack codes sentiment on a 0–100 scale, where 50 is neutral), although the mean is slightly negative. Finally, valuation multiples (*BM*, *CFP*, and *SP*) are in line with prior research. For example, we find a mean book-to-market ratio of 0.437, which is comparable to that reported by Drake et al. (2011).

TABLE 1

Descriptive Statistics

Panel A: Variables Used to Construct Analyst Forecast Types

Variable	n	Mean	Lower Quartile	Median	Upper Quartile	Std. Dev.
Dependent Variable						
Revision	368,060	−0.154	−0.182	−0.039	0.053	0.834
Independent Variables						
Fundamentals						
Δ*Sales*	368,060	1.018	0.990	1.013	1.040	0.062
Δ*OCF*	368,060	−0.010	−0.380	0.024	0.392	1.613
Δ*CapEx*	368,060	0.022	−0.040	0.009	0.081	0.392
Momentum						
EAReturns_Prior4	368,060	0.006	−0.074	0.007	0.087	0.147
ReturnSinceLast	368,060	0.000	−0.055	0.000	0.053	0.116
IncomeInc	368,060	0.891	0.000	1.000	1.000	1.113
Valuation Multiples						
BM	368,060	0.437	0.208	0.361	0.586	0.341
CFP	368,060	0.100	0.053	0.083	0.131	0.104
SP	368,060	1.041	0.324	0.624	1.199	1.277
Herding						
Δ*Consensus*	368,060	−0.063	−0.048	0.000	0.007	0.329
Δ*LTG*	368,060	0.052	−0.200	0.000	0.400	4.908
BusPress	368,060	39.343	43.764	49.621	52.841	21.902

(continued on next page)

TABLE 1 (continued)

Panel B: Variables Used to Evaluate Outcomes of Analyst Forecast Types

Variable	n	Mean	Lower Quartile	Median	Upper Quartile	Std. Dev.
Dependent Variables						
Accuracy	43,645	−0.543	−0.453	−0.182	−0.076	1.166
Dispersion	43,645	0.270	0.055	0.115	0.263	0.449
ΔVolatility	43,645	0.124	−0.227	−0.002	0.325	0.551
AbSpread	43,645	3.069	−0.195	0.934	3.419	9.445
EAReturns	43,645	0.001	−0.038	0.000	0.040	0.074
|EAReturns|	43,645	0.054	0.017	0.039	0.075	0.050
IPE	43,645	2.077	1.887	3.787	4.577	4.440
Jump	43,645	0.721	0.259	0.712	1.145	2.780
Forecast Type Classifications						
Quant Coverage	43,645	0.808	0.000	0.000	1.000	1.783
Sundry Coverage	43,645	1.172	0.000	0.000	2.000	2.013
Contrarian Coverage	43,645	1.392	0.000	1.000	2.000	2.169
Herder Coverage	43,645	2.186	0.000	1.000	3.000	2.682
Independent Coverage	43,645	2.504	1.000	2.000	3.000	2.723
Forecast Type Diversity Proxies						
Consensus Coverage	43,645	2.797	2.000	3.000	3.000	0.996
Consensus Balance	43,645	−1.542	−1.865	−1.440	−1.185	0.536
Other Variables						
Analyst Coverage	43,645	7.967	4.000	7.000	10.000	5.093
Size	43,645	7.819	6.594	7.699	8.885	1.693
BM	43,645	0.356	0.203	0.331	0.489	0.227
ROA	43,645	0.007	0.001	0.011	0.022	0.034
StdROA	43,645	0.017	0.004	0.009	0.019	0.023
Ret	43,645	0.015	−0.001	0.015	0.031	0.030
StdRet	43,645	0.024	0.016	0.022	0.030	0.011
Beta	43,645	1.261	0.888	1.199	1.558	0.515
EPS Variance	43,645	0.365	0.081	0.170	0.382	0.575
EPS Change	43,645	1.760	0.167	0.468	1.380	3.640
Loss	43,645	0.142	0.000	0.000	0.000	0.349
Horizon	43,645	0.251	0.241	0.249	0.266	0.033
EarnSurp	43,645	−0.006	−0.004	0.000	0.002	0.033

Table 1 presents descriptive statistics. Panel A presents descriptive statistics for variables used in generating analyst forecast cluster classification type assignments. The data are at the analyst forecast level. Panel B presents descriptive statistics for variables used in evaluating outcomes of analyst forecast types. The data are at the firm-quarter level. In Panel B, we present underlying values of *Coverage* variables, but we use log-transformed versions in most regressions. All continuous variables are Winsorized by year at the 1st and 99th percentile.

Unique Forecast Types and Consensus Analyst Forecast Accuracy

Our first analysis focuses on whether the various forecast types exhibit differences in forecast accuracy. This test serves, in part, as validation that our CLR procedure identifies important differences in forecast quality, which we believe is a necessary condition to motivate our study of the capital market outcomes later in the paper. Note that all remaining tests are out of sample with respect to cluster assignment (i.e., cluster assignment is made in quarter q, and we examine the earnings announcement in quarter q+1). We compute forecast accuracy as the difference between the forecast of earnings and actual earnings. In Table 2, Panel A, we present mean accuracy by forecast type. Forecast types are sorted by size, but we find that the types also monotonically sort by accuracy. In the table, we also provide t-statistics comparing the accuracy of each forecast type with the previous type. As reported, all differences are statistically significant, providing preliminary evidence that the forecast types we identify through CLR identify important and meaningful differences in revision accuracy.

TABLE 2

Analyst Forecast Types and Forecast Accuracy

Panel A: Univariate Evidence

	Average *Accuracy* (1)	Tests of Difference: Comparison (2)	Tests of Difference: p-value (3)
Type 1: Quant	−0.618		
Type 2: Sundry	−0.489	Quant versus Sundry	0.000***
Type 3: Contrarians	−0.454	Sundry versus Contrarian	0.000***
Type 4: Herders	−0.403	Contrarian versus Herder	0.000***
Type 5: Independent	−0.327	Herder versus Independent	0.000***

Panel B: Regression Evidence

Dependent Variable: *Accuracy*

	Logged Coverage Variables		Raw Coverage Variables	
	(1)	(2)	(3)	(4)
Quant Coverage	**0.008**	**0.018***	**0.001*****	**0.013*****
	(0.790)	**(1.822)**	**(2.757)**	**(4.025)**
Sundry Coverage	**0.032*****	**0.030*****	**0.015*****	**0.014*****
	(3.979)	**(3.923)**	**(5.607)**	**(5.650)**
Contrarian Coverage	**0.028*****	**0.030*****	**0.013*****	**0.014*****
	(3.896)	**(4.312)**	**(5.608)**	**(6.389)**
Herder Coverage	**0.049*****	**0.035*****	**0.018*****	**0.014*****
	(5.672)	**(4.438)**	**(6.969)**	**(6.327)**
Independent Coverage	**0.090*****	**0.082*****	**0.024*****	**0.022*****
	(8.798)	**(8.865)**	**(8.888)**	**(9.254)**
Size		0.072**		0.068**
		(2.509)		(2.366)
BM		−0.158***		−0.155***
		(−6.430)		(−6.317)
ROA		2.012***		2.016***
		(3.740)		(3.748)
StdROA		−3.188***		−3.211***
		(−5.554)		(−5.597)
Ret		4.098***		4.155***
		(14.341)		(14.526)
StdRet		−24.948***		−25.034***
		(−10.388)		(−10.391)
Test of Difference				
Quant versus Independent	0.082	0.064	0.023	0.009
p-value	0.000***	0.000***	0.000***	0.000***
Observations	43,645	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm	Firm
Adjusted R^2	0.581	0.610	0.581	0.610

***, **, * Denote two-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ levels for regression coefficients, respectively.
Table 2 presents tests of how analyst forecast types differ in their forecast accuracy. In Panel A, we present univariate statistics for mean forecast accuracy (*Accuracy*) for each forecast type. Columns (2) and (3) report tests of differences between forecast types. In Panel B, we present regression evidence of differences in accuracy by forecast type. The dependent variable is the consensus analyst forecast accuracy (*Accuracy*). Columns (1) and (2) ((3) and (4)) present results using the natural log of 1 plus following (raw values of following) for each forecast type. Odd (even) columns present results without (with) control variables.
All variables are defined in Appendix A.

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In Table 2, Panel B, we present evidence based on regression analysis to evaluate the accuracy of the consensus forecast rather than the accuracy of individual forecasts, as in Panel A. Research generally assumes that a larger analyst following corresponds to a more accurate consensus forecast (Lys and Soo 1995; Merkley et al. 2020). Given the evidence in Panel A that forecast types identify important differences in accuracy, we expect that separating analyst following by forecast type will similarly reveal different impacts on consensus forecast accuracy. We test this prediction using the following model:

$$\begin{aligned} Accuracy_{i,t} = \alpha &+ \beta_1 Quant\ Coverage_{i,t} + \beta_2 Sundry\ Coverage_{i,t} + \beta_3 Contrarian\ Coverage_{i,t} \\ &+ \beta_4 Herder\ Coverage_{i,t} + \beta_5 Independent\ Coverage_{i,t} + \Sigma Controls_{i,t} + \Sigma FirmFE + e_{i,t} \end{aligned} \tag{2}$$

We estimate Equation (2) at the firm-quarter level. The dependent variable, *Accuracy*, captures the consensus forecast accuracy. The *Coverage* variables refer to each of the five types of forecasts.

We measure each of the forecast type coverage variables in two different ways. To be consistent with the approach generally used in research, we first measure each variable as the natural log of 1 plus the number of forecasts for firm *i*'s one-quarter-ahead earnings identified as belonging to a given forecast type. However, because this is not a true decomposition (we use natural logs),[13] we also use simple counts by style, which effectively decomposes total analyst following by forecast types. We present specifications with and without a vector of firm controls (*Controls*), which are based on prior research (Merkley et al. 2020). We control for size (*Size*), book-to-market ratio (*BM*), return on assets (*ROA*), volatility of performance (*StdROA*), returns (*Ret*), and volatility of returns (*StdRet*). We include firm and time (year-quarter) fixed effects and calculate t-statistics based on standard errors clustered by firm.

We present the Equation (2) results in Table 2, Panel B. In column (1) ((2)), we provide results without (with) controls and using logged variables, and column (3) ((4)) presents count-based estimates without (with) controls. The results indicate that important differences exist in how following by forecast type contributes to consensus accuracy, and these differences are consistent with the univariate results in Table 2, Panel A. Column (1) suggests that all but the least accurate type (i.e., *Quant* revisions) contribute to consensus accuracy. In column (2), we introduce controls and find that all estimates in all five types correspond to increased forecast accuracy. However, we observe that the magnitude of these effects varies greatly. Notably, the coefficient on *Independent Coverage* is more than four times as large as that on *Quant Coverage* (difference significant at p-value < 0.01). The count-based measures in columns (3) and (4) produce similar inferences, although the differences in magnitudes are not as significant. Nevertheless, column (4) suggests that adding a revision by an "independent forecaster" to the consensus (*Independent Coverage*) corresponds to an increase in accuracy that is 75 percent greater than that of a "quant forecaster" (*Quant Coverage*). In sum, the evidence presented in Table 2 suggests that the CLR procedure identifies important differences in forecast types, which translate to different levels of consensus accuracy.[14]

Forecast Types and Characteristics of the Analyst Consensus

Next, we turn to tests examining how variation in coverage from different forecast revision types relates to characteristics of the analyst consensus estimate, including its dispersion and accuracy. To do this, we develop two measures designed to capture the diversity of opinion reflected in the different forecast types, which we refer to as "*Consensus Diversity*." The first measure, *Consensus Coverage*, is the number of unique forecast types making up the consensus for a firm-quarter. Because we have five forecast types, this variable ranges from 1 to 5. We present statistics based on raw values for *Consensus Coverage* in Table 1, but for our remaining analyses, we use log-transformed values to be consistent with how we measure analyst following.[15] To calculate the second measure, *Consensus Balance*, we start by counting the number of analysts contributing forecast revisions from each of the five types. We compute the standard deviation of these counts to capture the variability.[16] We then normalize this measure using the procedure outlined in the detailed

[13] Specifically, $ln(a + b + c)$ does not equal $ln(a) + ln(b) + ln(c)$.

[14] In untabulated analyses, we examine the extent to which the size of each forecast type cluster is potentially impacting the results for logged-based measures of coverage presented in Table 2, Panel B. Relatively more common forecast types have larger standard deviations, which could produce a pattern of coefficients similar to what we observe for logged coverage variables. To evaluate whether this has any impact on our inferences, we run a simulation that randomly shuffles cluster assignments while ensuring that analyst coverage for the firm does not change and that the number of forecasts in each type does not change. We then estimate the model using the random cluster assignments; we repeat this shuffling procedure another 99 times. We find that the coefficients increase monotonically with cluster size increases (as in Table 2, Panel B) in only 5 of the 100 iterations, suggesting that differences in forecast type sizes are unlikely to drive our results.

[15] As in Table 2, Panel B, inferences are generally similar if we instead use count-based measures of both *Analyst Coverage* and *Consensus Coverage*.

[16] To illustrate, consider two firms, each followed by eight analysts contributing forecasts to the consensus. For Firm A, the consensus includes two revisions classified as *Independent*, two as *Herder*, two as *Quant*, two as *Contrarian*, and zero from *Sundry*. For Firm B, the consensus includes five revisions from *Independent*, three revisions from *Quant*, and zero revisions from *Herder*, *Contrarian*, and *Sundry*. The standard deviation for Firm A is derived from the set $\{2, 2, 2, 2, 0\}$, which is 0.89. The standard deviation for Firm B is derived from the set $\{5, 3, 0, 0, 0\}$, which is 2.30. Thus, Firm A's consensus is "more balanced."

variable definition in Appendix A. Finally, we invert this ratio by multiplying it by -1 so that higher values indicate a more balanced distribution of forecast types. We test whether these two measures of consensus diversity are incremental to a traditional measure of general analyst coverage of the firm.

Regarding consensus forecast dispersion, prior work suggests greater analyst following is associated with lower dispersion (e.g., Ajinkya et al. 1991). Alternatively, our previous finding indicating that different forecast types exhibit different associations with accuracy, together with findings from extant research, suggests that less herding and more private information in revisions yield a more disperse consensus (Barron et al. 1998). If incorporating a forecast type not previously included in the consensus contributes a relatively less accurate forecast, then we expect to observe higher levels of analyst forecast dispersion when the consensus is more diverse.

With respect to consensus forecast accuracy, recall that, in Table 2, we find significant differences in how forecasts from various types relate to forecast accuracy. Thus, it is possible that greater diversity in the consensus conveys a greater diversity of views and perspectives of the firm, consistent with Merkley et al. (2020) and Da and Huang (2020). If differences in how information is used reflect independence across analysts, then forecast accuracy may improve. However, it is possible that adding more forecast types to the consensus simply increases consensus forecast accuracy based on whether any new forecast type that is introduced is generally more accurate than the existing forecast types already included in the consensus and *vice versa*.

We estimate the following model to address these questions:

$$\begin{aligned} Dispersion_{i,t} \text{ or } Accuracy_{i,t} = {} & \alpha + \beta_1 Analyst\ Coverage_{i,t} + \beta_2 Consensus\ Diversity_{i,t} \\ & + \Sigma Controls_{i,t} + \Sigma FirmFE + e_i \end{aligned} \tag{3}$$

We estimate Equation (3) at the firm-quarter level. *Consensus Diversity* is either *Consensus Coverage* or *Consensus Balance*. We compare the coefficients on these proxies with the coefficient on *Analyst Coverage*, which is the natural log of 1 plus the number of estimates. In essence, Model (3) evaluates whether *Consensus Coverage* or *Consensus Diversity* is incremental to or even more important than the traditional measure of analyst following.[17]

We present the Equation (3) results using *Dispersion* as the dependent variable in Table 3, Panel A. Consistent with prior research, we find a significantly negative coefficient on *Analyst Coverage*, indicating that higher levels of analyst coverage are associated with lower forecast dispersion. In columns (2) and (3), we find significantly positive coefficients on *Consensus Coverage* and *Consensus Balance*, respectively. These results suggest that having greater diversity in the consensus increases the dispersion of the consensus forecast.

We present the Equation (3) results using *Accuracy* as the dependent variable in Table 3, Panel B. Consistent with multiple viewpoints enhancing accuracy, the results indicate that *Consensus Coverage* is incremental to general analyst coverage in explaining consensus forecast quality. For the median firm in our sample (following $= 7$, *Consensus Coverage* $= 3$), adding a forecast from a new type corresponds to an increase in accuracy of 0.044, approximately 10 percent of the mean value of *Accuracy*. This effect is 2.2 times larger than the effect of adding another analyst from an already included forecasting type.[18] Similarly, higher levels of *Consensus Coverage* also correspond to more accurate consensus forecasts.

Overall, the results are consistent with various forecast types offering unique perspectives rather than simply herding together to a single forecast number. These results also suggest that we are capturing unique forecast types rather than simply higher levels of analyst coverage.

Forecast Types and Capital Markets Effects at Earnings Announcements

We next examine whether consensus diversity relates to three sets of capital market effects at the earnings announcement related to trading characteristics, market reactions, and the speed of price formation.

[17] As a robustness test, we also estimate the model including five analyst controls, including average brokerage size, number of all-stars covering the firm, average years of experience, average number of firms followed, and average number of industries followed. We note that the coefficients on these five variables are almost always insignificant and that the explanatory power of the models does not change very much with the inclusion of these variables (untabulated). We further note that, with one minor exception, all of our primary results remain unchanged in terms of sign or significance and that the coefficients' magnitudes are very similar. The only exception is that, when the dependent variable is *IPE* (Table 6), we no longer find a marginally significant coefficient on *Consensus Balance*.

[18] Moving from seven to eight analysts corresponds to an increase in *Analyst Coverage* of ln(9/8) or 0.12. Multiplying this value by the coefficient on *Analyst Coverage* (0.17) equals 0.020. Moving from three to four types corresponds to an increase in *Consensus Coverage* of ln(5/4) or 0.22. Multiplying this by the coefficient on *Consensus Coverage* (0.11) equals 0.024. Summing 0.020 and 0.024 equals 0.044, which is 2.2 times higher than 0.020.

TABLE 3

Analyst Forecast Diversity and the Characteristics of the Analyst Consensus

Panel A: Consensus Forecast Dispersion

Dependent Variable: *Dispersion*

	(1)	(2)	(3)
Analyst Coverage	−0.102***	−0.147***	−0.077***
	(−9.819)	(−14.664)	(−8.481)
Consensus Coverage		**0.136*****	
		(14.443)	
Consensus Balance			**0.064*****
			(16.928)
Size	−0.001	−0.002	0.001
	(−0.125)	(−0.154)	(0.080)
BM	0.045***	0.044***	0.042***
	(5.135)	(5.092)	(4.926)
ROA	−0.415***	−0.432***	−0.456***
	(−3.336)	(−3.527)	(−3.844)
StdROA	0.026	0.044	0.085
	(0.128)	(0.216)	(0.438)
Ret	−1.591***	−1.593***	−1.622***
	(−15.618)	(−15.681)	(−16.781)
StdRet	7.642***	7.587***	7.507***
	(11.167)	(11.113)	(11.294)
Beta	0.024**	0.024**	0.019*
	(2.099)	(2.101)	(1.722)
EPS Variance	−0.006	−0.006	−0.005
	(−1.123)	(−1.129)	(−0.913)
EPS Change	0.019***	0.019***	0.020***
	(13.650)	(13.806)	(14.488)
Loss	0.111***	0.111***	0.111***
	(9.200)	(9.284)	(9.249)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.612	0.616	0.617

Panel B: Consensus Forecast Accuracy

Dependent Variable: *Accuracy*

	(1)	(2)	(3)
Analyst Coverage	0.212***	0.173***	0.158***
	(8.378)	(7.610)	(7.645)
Consensus Coverage		**0.114*****	
		(5.627)	
Consensus Balance			**0.032*****
			(4.101)
Size	0.033	0.033	0.035
	(1.455)	(1.445)	(1.645)
BM	−0.088***	−0.088***	−0.088***
	(−4.543)	(−4.551)	(−4.818)

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TABLE 3 (continued)

Dependent Variable: *Accuracy*

	(1)	(2)	(3)
ROA	1.102**	1.079**	0.788
	(2.190)	(2.145)	(1.570)
StdROA	−1.117**	−1.104**	−1.012*
	(−2.013)	(−1.992)	(−1.952)
Ret	2.618***	2.598***	2.323***
	(9.846)	(9.785)	(9.000)
StdRet	−14.558***	−14.512***	−13.723***
	(−8.742)	(−8.742)	(−8.769)
EPS Change	−0.027***	−0.027***	−0.026***
	(−6.511)	(−6.477)	(−6.122)
Horizon	−1.585***	−1.570***	−1.461***
	(−9.816)	(−9.745)	(−9.309)
Dispersion	−0.663***	−0.674***	−0.730***
	(−15.784)	(−15.969)	(−16.133)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.642	0.642	0.644

***, **, * Denote two-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ levels for regression coefficients, respectively.
Table 3 presents coefficients (t-statistics) for tests of how forecast types influence the characteristics of the analyst consensus. In Panel A, the dependent variable is the consensus analyst forecast dispersion (*Dispersion*). In Panel B, the dependent variable is the consensus analyst forecast accuracy (*Accuracy*). For both panels, *Analyst Coverage* is the natural logarithm of 1 plus the number of analysts covering the firm. We use two proxies for forecast type diversity: in column (2), our proxy for forecast type diversity is *Consensus Coverage*, which is the natural logarithm of 1 plus the number of unique forecast types covering the firm. In column (3), our proxy for forecast type diversity is *Consensus Balance*, which is the balance of forecast types covering the firm.
All variables are defined in Appendix A.

Earnings Announcement Trading Characteristics

EAs trigger significant information flows that allow sophisticated investors to gain an information advantage (Lee et al. 1993; Kim and Verrecchia 1994). Amiram et al. (2016) provide evidence that analyst forecasts reduce information asymmetry upon issuance, which they interpret to mean that the forecasts are more useful to less informed investors. However, extant research provides minimal evidence that analyst coverage reduces EA information asymmetry (e.g., Yohn 1998; Gomez, Heflin, Moon, and Warren 2024).[19] One potential reason for this lack of evidence is that not all forecasts are equal, as suggested by our earlier tests. We explore this possibility by examining whether consensus forecast diversity is associated with lower bid-ask spreads (a proxy for information asymmetry) and lower return volatility (reflective of investor uncertainty and disagreement about EA news) around earnings announcements.

To test these predictions, we estimate Equation (3) using EA bid-ask spreads or return volatility as alternative dependent variables. We measure *AbSpread* following Bushee, Core, Guay, and Hamm (2010) as the average bid-ask spread on the day of and following the EA, subtracted by the average bid-ask spread during the quarter (ending five days before the EA to avoid capturing the pre-EA run-up in information asymmetry). Following intuition in Billings, Jennings, and Lev (2015), we measure Δ*Volatility* as the difference in standard deviation of returns during the 20 days after the EA and the standard deviation of returns during the 20 days before the EA, scaled by standard deviation of returns during the 20 days before the EA.

We report results using *AbSpread* and Δ*Volatility* as dependent variables in Table 4, Panels A and B, respectively. We use the same table structure as in Table 3. In Panel A, column (1), we observe an insignificant association between *Analyst Coverage* and *AbSpread*. In columns (2) and (3), we include *Consensus Coverage* and *Consensus Diversity*,

[19] Although research suggests average information asymmetry is lower for firms with greater analyst coverage, whether analyst coverage mitigates the spike in information asymmetry at earnings announcements is less clear. For instance, Yohn (1998) reports a positive, although insignificant (t-statistic = 1.50) relation between analyst following and the EA spike in information asymmetry.

TABLE 4

Analyst Forecast Diversity and the Earnings Announcement Trading Characteristics

Panel A: Subsequent Earnings Announcement Bid-Ask Spread

Dependent Variable: *AbSpread*

	(1)	(2)	(3)
Analyst Coverage	−0.120	−0.181	−0.156
	(−0.601)	(−0.840)	(−0.778)
Consensus Coverage		**−0.675*****	
		(−3.263)	
Consensus Balance			**−0.214****
			(−2.156)
Size	−2.031***	−1.409***	−1.346***
	(−6.793)	(−4.101)	(−4.191)
BM	0.312**	0.017	0.064
	(2.010)	(0.109)	(0.409)
ROA	−11.350***	−12.596***	−10.322***
	(−3.064)	(−4.132)	(−3.457)
StdROA	8.468*	10.209**	9.306**
	(1.885)	(2.242)	(2.063)
Ret	−38.198***	−47.992***	−46.210***
	(−13.545)	(−15.792)	(−15.475)
StdRet	−3.486	21.197	21.536
	(−0.342)	(1.458)	(1.475)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.193	0.193	0.196

Panel B: Subsequent Earnings Announcement Volatility

Dependent Variable: Δ*Volatility*

	(1)	(2)	(3)
Analyst Coverage	−0.010	−0.001	−0.016*
	(−1.147)	(−0.142)	(−1.662)
Consensus Coverage		**−0.026****	
		(−2.349)	
Consensus Balance			**−0.015*****
			(−3.014)
Size	−0.016	−0.016	−0.017
	(−1.456)	(−1.451)	(−1.500)
BM	0.004	0.004	0.004
	(0.616)	(0.629)	(0.684)
ROA	−0.503***	−0.500***	−0.535***
	(−3.941)	(−3.913)	(−4.141)
StdROA	−0.250	−0.254	−0.277
	(−1.258)	(−1.276)	(−1.391)

(continued on next page)

respectively. In contrast to *Analyst Coverage*, both consensus diversity measures have a significantly negative coefficient, suggesting more forecast type diversity decreases the spike in EA information asymmetry.

In Table 4, Panel B, we repeat these analyses using Δ*Volatility* as the dependent variable. Note that we remove *StdRet* as a control here since it is used to construct the dependent variable. Column (1) indicates that a higher level of

TABLE 4 (continued)

Dependent Variable: Δ*Volatility*

	(1)	(2)	(3)
Ret	0.443***	0.444***	0.434***
	(4.316)	(4.325)	(4.164)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.240	0.241	0.242

***, **, * Denote two-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ levels for regression coefficients, respectively.
Table 4 presents coefficients (t-statistics) for tests of how forecast types influence aspects of earnings announcement trading.
All variables are defined in Appendix A.

analyst coverage does not correspond to lower levels of price volatility. The models in columns (2) and (3) again introduce *Consensus Coverage* and *Consensus Diversity*, respectively, and indicate negative associations with Δ*Volatility*. Overall, the evidence in Table 4 suggests that the presence of greater diversity of forecast types in the consensus is associated with a better trading environment during earnings announcements.

Earnings Announcement Returns

We next examine the relation between consensus diversity and the direction and magnitude of the market reaction to earnings news. If a more diverse consensus results in a higher quality earnings expectation, this could increase investors' ability to interpret deviations from expectations, thereby increasing the market reaction to earnings surprises. We address this question using Equation (3) with three modifications. First, we change the dependent variable to signed abnormal returns around the EA (*EAReturns*). Second, we include the firm's earnings surprise (*EarnSurp*) and interact this variable with both our variables of interest and controls (deHaan, Moon, Shipman, Swanquist, and Whited 2023). The coefficient on *EarnSurp* is generally referred to as the ERC. Third, we exclude firm fixed effects because they do not isolate within-firm variation in ERCs. Our coefficients of interest are on *EarnSurp* × *Consensus Coverage* (column (2)) and *EarnSurp* × *Consensus Balance* (column (3)).

We present the estimation results in Table 5, Panel A. In column (1), we report results with only analyst coverage and find the ERC is significantly positive in all three models. We further find an insignificant coefficient on *EarnSurp* × *Analyst Coverage*, suggesting greater analyst following does not impact ERCs. In column (2), we add *Consensus Coverage* and find a significantly positive coefficient on its interaction with *EarnSurp* (t-statistic = 2.413). In column (3), we include the interaction term *EarnSurp* × *Consensus Balance* and again observe a significantly positive coefficient (t-statistic = 2.435). These results suggest that ERCs are stronger (more positive) when there is greater consensus diversity.

Next, we consider whether the magnitude of the absolute reaction to EAs varies with *Consensus Diversity*. We do this by replacing the dependent variable in Equation (3) with the absolute value of earnings announcement returns, |*EAReturns*|. We present these results in Table 5, Panel B. In column (1), we report the results excluding our variables of interest and find a marginally positive association between |*EAReturns*| and *Analyst Coverage*.[20] In columns (2) and (3), we report results using our two consensus diversity measures. As reported, neither exhibits a significant association with the magnitude of returns at the earnings announcement. Overall, the results from Table 5 suggest that having greater consensus diversity sharpens investors' responses to earnings news on a per-dollar basis but does not relate to the overall magnitude of information released.[21]

[20] This positive association may appear counterintuitive at first blush, given the theory arguing that announcement returns are negatively associated with the amount of information available before the announcement. However, Christensen, Smith, and Stuerke (2004) find that the relation between announcement returns and analyst following is positive once you control for preannouncement returns, as we do with the inclusion of *Ret* in the model. Subsequent research generally supports this empirical result (e.g., Francis, Schipper, and Vincent 2002; Drake, Jennings, Roulstone, and Thornock 2017; Xu 2023).

[21] We use firm fixed effects throughout our analyses (except for the ERC test) to maintain a similar research design. Nearly all inferences are identical absent firm fixed effects, although the coefficients on the consensus diversity measures become significant in the expected direction in the |*EAReturns*| regressions.

TABLE 5

Analyst Forecast Diversity and Earnings Announcement Returns

Panel A: ERC at the Subsequent EA

Dependent Variable: *EAReturns*

	(1)	(2)	(3)
EarnSurp	0.409***	0.338***	0.504***
	(3.745)	(2.905)	(4.348)
Analyst Coverage	−0.762***	−0.695***	−0.669***
	(−5.222)	(−4.536)	(−4.470)
Consensus Coverage		−0.187	
		(−1.076)	
Consensus Balance			−0.028
			(−0.373)
EarnSurp × Analyst Coverage	−0.028	−0.107***	−0.009
	(−1.166)	(−2.765)	(−0.296)
EarnSurp × Consensus Coverage		**0.150****	
		(2.413)	
EarnSurp × Consensus Balance			**0.071****
			(2.435)
Size	−1.191***	−1.193***	−1.218***
	(−7.944)	(−7.938)	(−8.013)
BM	1.009***	1.009***	1.040***
	(9.584)	(9.581)	(9.781)
ROA	33.822***	33.800***	33.801***
	(14.650)	(14.630)	(14.620)
StdROA	5.642*	5.717*	6.232**
	(1.883)	(1.908)	(2.058)
Ret	−19.378***	−19.467***	−19.462***
	(−10.313)	(−10.366)	(−10.377)
StdRet	10.540	11.120	10.620
	(1.527)	(1.623)	(1.533)
Observations	43,645	43,645	43,645
Fixed Effects	None	None	None
Clustering	EA date	EA date	EA date
Fully Interacted Model	Yes	Yes	Yes
Adjusted R^2	0.035	0.035	0.034

Panel B: Abnormal Subsequent EA Returns

Dependent Variable: |*EAReturns*|

	(1)	(2)	(3)
Analyst Coverage	0.178*	0.138	0.172*
	(1.940)	(1.434)	(1.828)
Consensus Coverage		**0.121**	
		(1.135)	
Consensus Balance			**−0.000**
			(−0.006)
Size	−0.047	−0.048	−0.036
	(−0.392)	(−0.395)	(−0.300)
BM	−0.025	−0.025	−0.043
	(−0.364)	(−0.369)	(−0.622)

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TABLE 5 (continued)

Dependent Variable: |*EAReturns*|

	(1)	(2)	(3)
ROA	0.665	0.648	0.647
	(0.456)	(0.444)	(0.447)
StdROA	7.802***	7.822***	7.815***
	(4.004)	(4.013)	(4.032)
Ret	−9.849***	−9.852***	−10.099***
	(−7.980)	(−7.981)	(−8.129)
StdRet	37.866***	37.827***	39.507***
	(6.267)	(6.258)	(6.472)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.220	0.220	0.220

***, **, * Denote two-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ levels for regression coefficients, respectively.
Table 5 presents coefficients (t-statistics) for tests of how forecast types influence subsequent earnings announcement returns. In Panel A, the dependent variable is signed buy and hold abnormal returns over day 0 and +1 relative to the earnings announcement for which the analyst forecasted (*EAReturns*). The regression is a fully interacted model, but we do not present the results of interactions with controls for brevity. In Panel B, the dependent variable is the absolute value of abnormal returns over the same period (|*EAReturns*|). For both panels, *Analyst Coverage* is the natural logarithm of 1 plus the number of analysts covering the firm. We use two proxies for forecast type diversity: in column (2), our proxy for forecast type diversity is *Consensus Coverage*, which is the natural logarithm of 1 plus the number of unique forecast types covering the firm. In column (3), our proxy for forecast type diversity is *Consensus Balance*, which is the balance of forecast types covering the firm.
All variables are defined in Appendix A.

Earnings Announcement Price Formation

Finally, we examine whether consensus diversity relates to price efficiency. To this point, our evidence suggests consensus diversity contributes to a superior consensus, richer earnings announcement information environment, and sharper responses to earnings news. We consider two measures of price efficiency. First, we construct intraperiod price efficiency (*IPE*) (Blankespoor, deHaan, and Zhu 2018; Blankespoor, deHaan, and Marinovic 2020). *IPE* evaluates the area under the curve of a cumulative price response from day *t*, an event day, to day *t+k* while adjusting for potential over-reactions. We measure *IPE* from day 0 to day 5. Second, we consider the "jump ratio" (*Jump*), as in Campbell, Drake, Thornock, and Twedt (2023). *Jump* captures the proportion of the day 0 to day 5 return that occurs in days 0 and 1 relative to the EA. The primary difference between *IPE* and *Jump* is that the latter focuses on the initial price adjustment whereas *IPE* considers both the initial price change as well as subsequent correction. Higher values of both measures indicate a more efficient price response.

We report the price efficiency results in Table 6, Panels A and B using *IPE* and *Jump* as dependent variables, respectively. In column (1), we report results absent either measure of consensus diversity, and we find no evidence of a significant association between analyst following and price efficiency. In column (2) ((3)), we report results after adding *Consensus Coverage* (*Consensus Balance*) to the model. In column (2), we find a positive and statistically significant coefficient on *Consensus Coverage* ($t = 2.281$), and in column (3), we find a positive and marginally significant coefficient on *Consensus Diversity* ($t = 1.716$).[22] In Table 6, Panel B, we report the results using *Jump* as the dependent variable. In column (1), we find a positive coefficient on analyst following ($t = 1.664$). In column (2), we find that the coefficient on *Consensus Coverage* is statistically insignificant ($t = 1.284$), but the coefficient on *Consensus Balance* in column (3) is positive and marginally significant ($t = 1.732$). Thus, overall, the evidence in Table 6 provides some evidence that consensus diversity is associated with greater price efficiency.

V. ADDITIONAL ANALYSIS AND ROBUSTNESS TESTS

In this section, we first explore whether analysts tend to adopt a particular forecasting type or deploy various types across the firms they cover. We then discuss the robustness of our primary results to considering other information inputs to determine forecast type assignments.

[22] If we used an unlogged measure of *Consensus Coverage,* statistical significance declines below conventional levels ($t = 1.571$).

TABLE 6

Analyst Forecast Diversity and Price Formation following Earnings Announcements

Panel A: Subsequent Earnings Announcement Intraperiod Efficiency

Dependent Variable: *IPE*

	(1)	(2)	(3)
Analyst Coverage	0.008	0.004	0.010
	(1.301)	(0.623)	(1.459)
Consensus Coverage		**0.045****	
		(2.281)	
Consensus Balance			**0.056***
			(1.716)
Size	0.123*	0.119*	0.120*
	(1.731)	(1.679)	(1.675)
BM	−0.018	−0.017	−0.028
	(−0.444)	(−0.428)	(−0.688)
ROA	1.981***	1.955***	2.111***
	(2.696)	(2.661)	(2.810)
StdROA	0.867	0.894	0.875
	(0.753)	(0.776)	(0.750)
Ret	0.601	0.621	0.501
	(0.927)	(0.958)	(0.760)
StdRet	−6.474*	−6.511*	−6.404*
	(−1.914)	(−1.924)	(−1.867)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.018	0.018	0.018

Panel B: Subsequent Earnings Announcement Jump Ratio

Dependent Variable: *Jump*

	(1)	(2)	(3)
Analyst Coverage	0.124*	0.081	0.155*
	(1.664)	(0.987)	(1.863)
Consensus Coverage		**0.127**	
		(1.284)	
Consensus Balance			**0.079***
			(1.732)
Size	0.144*	0.144*	0.151*
	(1.702)	(1.699)	(1.762)
BM	−0.010	−0.010	−0.011
	(−0.181)	(−0.188)	(−0.205)
ROA	2.453**	2.435**	2.740***
	(2.469)	(2.449)	(2.670)
StdROA	−1.207	−1.186	−1.360
	(−0.809)	(−0.795)	(−0.897)
Ret	0.701	0.698	0.765
	(0.779)	(0.776)	(0.834)
StdRet	4.432	4.391	3.753
	(1.007)	(0.997)	(0.841)

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TABLE 6 (continued)

Dependent Variable: *Jump*

	(1)	(2)	(3)
Observations	43,645	43,645	43,645
Fixed Effects	Firm and year-quarter	Firm and year-quarter	Firm and year-quarter
Clustering	Firm	Firm	Firm
Adjusted R^2	0.058	0.058	0.059

***, **, * Denote two-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ levels for regression coefficients, respectively.
Table 6 presents coefficients (t-statistics) for tests of how forecast types influence price formation following an earnings announcement. In Panel A, the dependent variable is intraperiod efficiency (*IPE*). In Panel B, the dependent variable is jump ratio (*Jump*). For both panels, *Analyst Coverage* is the natural logarithm of 1 plus the number of analysts covering the firm. We use two proxies for forecast type diversity: in column (2), our proxy for forecast type diversity is *Consensus Coverage*, which is the natural logarithm of 1 plus the number of unique forecast types covering the firm. In column (3), our proxy for forecast type diversity is *Consensus Balance*, which is the balance of forecast types covering the firm.
All variables are defined in Appendix A.

Individual Analysts and Forecast Type

Our classification of forecasts into types raises the possibility that each individual analyst adopts the use of a particular forecast type over time. In other words, it is possible that each analyst has a persistent "style" of forecasting. Prior research suggests that analyst attributes can drive the quality of their forecasts (Merkley et al. 2020; Cao, Hao, and Yang 2024). However, it is also possible that analysts use different types of forecasts across their portfolio of firms. The CLR procedure we use to classify analysts allows for this possibility, as it does not force an analyst to have one forecast type across coverage or time. We believe this is an important empirical design feature because, in practice, the same analyst has the freedom to change their forecast revision approach across firms and over time.

We begin by considering whether analysts tend to use the same or different forecast types for the firms they cover. In Table 7, we cross-tabulate the number of firms followed by an analyst (rows) with the number of forecast types used (columns). We collapse these data at the analyst-calendar quarter level, yielding 56,803 unique analyst-firm-quarter observations. In each cell, we present two values. The first value represents the proportion of the sample in that cell. The second value in parentheses is the percentage of that row falling in that column. To illustrate, 4.274 percent of the analysts in our sample follow three firms and use two different forecast types. For analysts following three firms, 52.520 percent employ two forecast types. Although subjective, we view the evidence in Table 7 as inconsistent with analysts adopting a particular forecasting style. For instance, for analysts covering two firms (9.394 percent of the sample), 76.289 percent use two forecast types. For analysts covering more than three firms, only 2.820 percent employ a single forecast type for all firms. In sum, the use of a particular forecast type does not appear to reflect a persistent analyst attribute.

Although this evidence suggests that substantial variation exists *within* an analyst's coverage, analysts may still use the same style for the same firm over time. To explore this possibility, we examine the proportion of quarter-over-quarter changes by forecast type usage in Table 8. We tabulate these by forecast type because the number of observations in each type is not balanced and only include observations for which the analyst makes a forecast in the prior and current quarter. We also include the proportion of the sample in each type and the unconditional likelihood of changing (i.e., 1 minus the sample proportion). For all five forecast types, we find that change rates are less than unconditional rates, suggesting some persistence in the use of a given forecast type. However, we note that the differences are not generally large, as we observe that between 65 and 83 percent of analysts change forecast type for a given firm-quarter over quarter, which is only slightly lower than unconditional rates. Overall, this evidence suggests that the use of a particular forecast type is unlikely to be a manifestation of specific analyst attributes (i.e., experience or specialization), as analysts employ different forecast types across their portfolio of firms and exhibit little persistence with respect to forecasting type for a given firm.[23,24]

[23] Although the results in Tables 7 and 8 may be somewhat surprising, we also find that individual analyst accuracy for a given analyst is not very persistent. This inference is supported by two tests (both untabulated). In the first test, we rank analysts covering a firm by accuracy and regress this rank on analyst-firm fixed effects. We find that the analyst-firm fixed effects explain only 5.6 percent of the variation in this ranked accuracy variable. In the second test, we compare a regression of forecast accuracy on firm fixed effects with one using crossed firm-analyst fixed effects. The increase in R^2 from crossing the analyst and firm fixed effects is marginal (it increases the R^2 by only 1.4 percent). This lack of persistence in analyst forecast accuracy could be explained by the lack of incentives to be accurate, as described by Groysberg et al. (2011) and Brown et al. (2015).

[24] The lack of persistence in forecast types also introduces the question of what cross-sectional and time-varying factors explain forecast type assignment. We perform and discuss the results of this exploratory determinants analysis in the Online Appendix, OA2.

TABLE 7

The Number of Unique Forecast Types, Conditional on the Number of Firms Followed by an Analyst

		Number of Forecast Types					
		1 (%)	**2 (%)**	**3 (%)**	**4 (%)**	**5 (%)**	**% of Sample**
# of firms followed	1	13.728 (100.000)					13.714
	2	2.194 (23.711)	7.058 (76.289)				9.394
	3	0.548 (6.727)	4.274 (52.520)	3.317 (40.753)			8.116
	4	0.153 (1.915)	2.327 (29.093)	4.274 (53.433)	1.245 (15.559)		7.991
	5	0.040 (0.515)	1.343 (17.096)	3.956 (50.347)	2.340 (29.778)	0.178 (2.263)	7.836
	6	0.018 (0.227)	0.722 (9.320)	3.297 (42.578)	3.171 (40.941)	0.537 (6.933)	7.748
	7	0.009 (0.118)	0.421 (5.638)	2.595 (34.772)	3.433 (46.001)	1.005 (13.470)	7.744
	8	0.000 (0.048)	0.246 (3.386)	2.083 (28.609)	3.489 (47.932)	1.458 (20.024)	7.263
	9		0.113 (1.760)	1.297 (20.270)	3.287 (51.348)	1.704 (26.623)	6.398
	10+		0.107 (0.445)	2.411 (9.870)	10.547 (43.695)	11.123 (46.080)	24.096

Table 7 cross-tabulates the number of firms followed by an analyst (rows) with the number of unique forecast types employed (columns). We collapse these data at the analyst-calendar quarter level (there are 56,803 unique analyst-firm-quarters in our sample). In each cell, we present two values. The first value represents the proportion of the sample in that cell. The second value in parentheses is the percentage of that row falling in that column.

TABLE 8

Change in Use of Forecast Type Use over Time

		Type 1: Quants	Type 2: Sundry	Type 3: Contrarians	Type 4: Herders	Type 5: Independent
		(1)	**(2)**	**(3)**	**(4)**	**(5)**
a	Percent that change forecast type use from prior quarter	83.420	80.200	78.240	69.200	65.110
b	Percentage of observations in each classification	10.021	14.531	17.251	27.117	31.080
c	Unconditional expectation (1 − b) (%)	89.979	85.469	82.749	72.883	68.920
d	Percent that change as a proportion of unconditional expectation (a / c)	92.711	93.835	94.551	94.947	94.471

Table 8 tabulates the proportion of quarter-over-quarter changes by forecast type use. We tabulate these by forecast type because the number of observations in each classification is not balanced. We also include the proportion of the sample classified as each forecast type and the unconditional likelihood of changing (i.e., 1 minus the sample proportion). For all five classification types, change rates are less than unconditional rates (i.e., row c < row d).

Alternative Information Inputs Used to Determine Forecast Types

In this final section, we evaluate the robustness of our primary results to considering other earnings announcement news signals when determining analyst revision cluster assignments. Notably, our final set of 12 variables used to classify forecast revisions does not include some common earnings announcement "news" variables, such as the revenue surprise or earnings surprise. We exclude these variables because we believe it is highly likely that all forecast types rely heavily on these variables to construct the next period's forecast. Thus, the inclusion of these variables would make it more difficult to identify unique types of forecast revisions.

To evaluate the validity of our arguments and sensitivity of our results, we conduct additional tests (untabulated) where we identify new clusters after including a new category of variables, *News*, consisting of the earnings surprise and the revenue surprise in Equation (2). Based on diagnostics, we identify eight clusters, including one very small outlier cluster that we remove. Diagnostics similar to those plotted in Figure 2 indicate that the quality of assignment is lower than in our primary model. Further, and consistent with our argument above, the earnings surprise variable is either the most or second most important factor in six of the remaining seven clusters (revenue surprise is generally less important).

Thus, the inclusion of the surprise variables results in a larger set of clusters that are more alike, making it difficult for us to identify distinct forecast types.

We then use these seven new clusters to reperform the market consequences tests. We find that most of our inferences remain unchanged, with two minor exceptions. First, there are no significant coefficients when the dependent variable is EA volatility (as in Table 4, Panel B). Second, in Table 6, Panel B, using these seven clusters produces a significant (insignificant) coefficient on *Consensus Coverage* (*Consensus Balance*), whereas the coefficient is insignificant (significant) on *Consensus Coverage* (*Consensus Balance*) in the primary tests.

VI. CONCLUSION

We employ a novel machine learning technique to classify analysts' forecast revisions into five types based on how the revision weighs publicly available signals. Our tests reveal that greater diversity of forecast types is associated with increased consensus diversity and improved consensus accuracy. Consensus diversity also improves the information environment of firms, as reflected in reduced EA information asymmetry and volatility, higher earnings response coefficients, and faster price formation. Our study sheds light on how analysts revise their forecasts and documents capital market benefits associated with different analyst forecasting approaches.

Our study is subject to several limitations. Our forecast classifications are based on a specific set of public signals that we group into four categories. It is possible that a different set of signals, a different set of categories, or both would lead to a different set of inferences. We attempt to mitigate this risk by considering a wide variety of metrics that likely correlate with the types of information analysts rely on for forecast revisions, but we cannot rule out that some other type of information largely orthogonal to the variables we rely on may alter inferences. It is also possible that an omitted, correlated variable explains both consensus diversity and our variables of interest. Importantly, this variable would need to be time varying and affect a variety of market outcomes in a pattern that mimics our results. Nonetheless, in the absence of exogenous variation, we cannot fully rule out concerns of this type. These limitations notwithstanding, we believe our study sheds important new light on how analysts develop their earnings forecasts and documents significant capital market benefits associated with different analyst forecasting approaches.

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APPENDIX A

Variable Definitions

Variable	Definition
Variables Used to Construct Analyst Forecast Types	
Revision	Sell-side analyst forecast revisions of one-quarter-ahead forecasts, measured as the one-quarter-ahead EPS forecast of the individual analyst (FPI = 6) minus the most recent previous EPS forecast of that same analyst (I/B/E/S variable = value), scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), and multiplied by 100 for presentation purposes.
Δ*Sales*	Following Drake et al. (2011), seasonal sales growth, calculated as quarterly sales in quarter *q* scaled by quarterly sales in the same quarter in the prior year (Compustat variable = revtq).
Δ*OCF*	Seasonal change in operating cash flow per share, calculated as operating cash flow per share in quarter *q* minus operating cash flow per share in the same quarter in the prior year, scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), and multiplied by 100 for presentation purposes. Operating cash flow per share is calculated as operating cash flow from Compustat (Compustat variable = oancfq) after removing extraordinary items (Compustat variable = xidocq), scaled by shares outstanding (Compustat variable = cshoq) after applying Compustat's shares adjustment factor (Compustat variable = ajexq).
Δ*CapEx*	Seasonal change in capital expenditures per share, calculated as capital expenditures per share in quarter *q* minus capital expenditures per share in the same quarter in the prior year, scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), and multiplied by 100 for presentation purposes. Capital expenditures per share is calculated as capital expenditures from Compustat (Compustat variable = capxq), scaled by shares outstanding (Compustat variable = cshoq) after applying Compustat's shares adjustment factor (Compustat variable = ajexq).
EAReturns_Prior4	The average of the firm's past four earnings announcement abnormal returns, where abnormal returns are measured as buy and hold abnormal returns (using portfolio returns calculated from Daniel, Grinblatt, Titman, and Wermers (1997) and, if missing, the value-weighted return from CRSP) over day 0 and +1 relative to the earnings announcement.
ReturnSinceLast	Following Stickel (1990), the buy and hold abnormal return from the day after the analyst's prior forecast to the three days before the analyst's current forecast. Abnormal returns are measured as buy and hold abnormal returns (using portfolio returns calculated from Daniel et al. (1997) and, if missing, the value-weighted return from CRSP).
IncomeInc	Following Barth, Elliott, and Finn (1999), the number of consecutive quarters in which the firm had an earnings increase over the same quarter last year (Compustat variable = ibq).
BM	The firm's book-to-market ratio at the beginning of the period, calculated as total shareholders' equity (Compustat variable = seqq), scaled by the product of stock price (Compustat variable = prccq) and shares outstanding (Compustat variable = cshoq).
CFP	Following Desai, Rajgopal, and Venkatachalam (2004), cash flow to price, measured as operating cash flows (Compustat variable = oancfq) after removing extraordinary items (Compustat variable = xidocq), scaled by beginning-of-the-period market capitalization (Compustat variables = prccq $*$ cshoq).
SP	Following Green et al. (2017), sales (Compustat variable = revt) scaled by beginning-of-the-period market capitalization (Compustat variables = prccq $*$ cshoq).
Δ*Consensus*	Following Stickel (1990), the change in the analyst forecast consensus from after the previous analyst forecast to right before the current analyst forecast (I/B/E/S variable = medest), scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), and multiplied by 100 for presentation purposes.
Δ*LTG*	The change in the median long-term growth forecast from after the previous analyst forecast to right before the current analyst forecast (I/B/E/S variable = value for FPI = 0 forecasts).
BusPress	Average RavenPack event sentiment score (RavenPack variable = ess) of business press articles written during the quarter prior to the earnings announcement. We only use articles with relevance scores of 100.
Variables Used to Evaluate Outcomes of Analyst Forecast Types	
Accuracy	Average consensus sell-side analyst forecast accuracy of all analysts for a firm-quarter, measured as the absolute value of the EPS forecast of each individual analyst (I/B/E/S variable = value) minus the actual EPS number (I/B/E/S variable = actual), scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), multiplied by -1 so that the variable is increasing in accuracy and by 100 for presentation purposes.

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APPENDIX A (continued)

Variable	Definition
Dispersion	Consensus analyst forecast dispersion, defined as the standard deviation of all analyst forecasts (I/B/E/S variable = value) scaled by price (Compustat variable = prccq) in the consensus.
ΔVolatility	Percent change in stock return volatility from before to after the earnings announcement, calculated as the standard deviation of returns during the 20 days after the earnings announcement (CRSP variable = ret), minus standard deviation of returns during the 20 days before the earnings announcement (CRSP variable = ret), scaled by standard deviation of returns during the 20 days before the earnings announcement (CRSP variable = ret).
AbSpread	Average abnormal bid-ask spread on the day of and day following the earnings announcement for which the analyst provided a forecast. Abnormal spread is measured as the average percentage effective bid-ask spread (Trade and Quote (TAQ) variable = espreadpct_avgi), on the day of and following the earnings announcement, subtracted by the average percentage effective bid-ask spread during the quarter (using days −80 to −5 relative to the earnings announcement), and multiplied by 10,000 for scaling purposes.
EAReturns	Buy and hold abnormal returns (using portfolio returns calculated from Daniel et al. (1997) and, if missing, the value-weighted return from CRSP) over day 0 and +1 relative to the earnings announcement for which the analyst forecasted and multiplied by 100 for presentation purposes.
|EAReturns|	The absolute value of *EAReturns*.
IPE	Following Blankespoor et al. (2020), intraperiod price efficiency, calculated as the average of $[1 - (\|AR_5 - AR_t\|)/\|AR_5\|]$ measured over days [0,5] relative to the earnings announcement, where AR_t is the buy and hold market-adjusted return over $(0,t)$.
Jump	Following Campbell et al. (2023), the firm's abnormal return on days (0,1) relative to the earnings announcement divided by the firm's abnormal return on days (0,5) relative to the earnings announcement.
Quant Coverage	The natural logarithm of 1 plus the number of analysts following the firm that issue a forecast with "Quant" forecast classification.
Sundry Coverage	The natural logarithm of 1 plus the number of analysts following the firm that issue a forecast with "Sundry" forecast classification.
Contrarian Coverage	The natural logarithm of 1 plus the number of analysts following the firm that issue a forecast with "Contrarian" forecast classification.
Herder Coverage	The natural logarithm of 1 plus the number of analysts following the firm that issue a forecast with "Herder" forecast classification.
Independent Coverage	The natural logarithm of 1 plus the number of analysts following the firm that issue a forecast with "Independent" forecast classification.
Consensus Coverage	The natural logarithm of 1 plus the number of unique forecast types covering the firm during the quarter.
Consensus Balance	The degree to which forecast revision types are equally distributed among the five different types in the consensus forecast. To construct the measure, we count the number of analysts contributing forecast revisions from each of the five types. We then compute the standard deviation of these counts to capture the variability. To normalize this measure, we proceed as follows. We randomly select k forecast revisions, where k is the number of forecasts in the firm's consensus, from firms with the same number of analysts (k), drawn the same quarter. For these selections, we compute the standard deviation of the count the number of analysts contributing forecast revisions from each of the five types in this "pseudo" consensus forecast. Note that we assign a value of 0 for any forecast type not included in the pseudo consensus forecast. We repeat this procedure another 99 times and then average the standard deviations derived from these 100 pseudo consensus forecasts to use as the scalar for normalization. Finally, we invert this ratio by multiplying it by −1, so that higher values indicate a more balanced distribution of forecast types.
Analyst Coverage	The natural logarithm of 1 plus the number of analysts following the firm during the quarter, using the I/B/E/S detail file.
Size	The natural logarithm of the firm's total assets at the beginning of the period (Compustat variable = atq).
ROA	The firm's return on assets at the beginning of the period, measured as income before extraordinary items (Compustat variable = ibq) scaled by total assets (Compustat variable = atq).
StdROA	The standard deviation of the firm's *ROA* over the last five years.
Ret	The firm's average monthly return over the last 12 months (CRSP variable = ret).

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APPENDIX A (continued)

Variable	Definition
StdRet	The standard deviation of daily stock returns (CRSP variable = ret) over the last 12 months.
Beta	Following Green et al. (2017), the firm's stock beta using three years of weekly returns.
EPS Variance	The standard deviation of earnings per share (Compustat variable = epsfxq) over the prior four earnings announcements.
EPS Change	Following Duru and Reeb (2002), the seasonal change in the absolute value of earnings per share, calculated as the absolute value of earnings per share in quarter q less earnings per share in the same quarter in the prior year, scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), and multiplied by 100 for presentation purposes. Earnings per share is calculated as EPS from Compustat (Compustat variable = epsfxq) after applying Compustat's shares adjustment factor (Compustat variable = ajexq).
Loss	An indicator variable equal to 1 if the firm had a negative value of earnings (Compustat variable = epsfxq) for the quarter and 0 otherwise.
Horizon	Average analyst forecast horizon for forecasts issued for the firm-quarter, where horizon is defined as the number of days difference between the date of the forecast (I/B/E/S variable = anndats) and the earnings announcement for which the forecast was made (anndats_act), scaled by 365.
EarnSurp	Earnings surprise of the earnings announcement for which the analyst is forecasting, calculated as the actual EPS number (I/B/E/S variable = actual) minus the average of each analysts' most recent EPS forecast before the earnings announcement (I/B/E/S variable = value), scaled by beginning-of-the-quarter stock price (Compustat variable = prccq), and multiplied by 100 for presentation purposes.