Are Analyst Forecast Errors Really Kinky?

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Abstract: The distribution of analyst forecast errors exhibits a well-known "kink"—a disproportionate frequency of small positive earnings surprises relative to small misses—widely attributed to managerial earnings management. We show that approximately 66% of this asymmetry is instead attributable to analyst strategic behavior. Analysts systematically under-revise earnings forecasts while issuing directionally consistent target price and recommendation revisions in the same report, a practice we term bundling. Using out-of-sample industry-year coefficients to remove the predictable forecast bias associated with bundling, we find the ratio of small positive to small negative forecast errors falls from 2.43 to 1.49. Bundling intensity predicts earnings surprises at both the report and firm-quarter levels, and intensifies during periods of macroeconomic uncertainty. Firms with higher analyst bundling rely less on discretionary accruals to meet or beat forecasts, suggesting analyst-induced bias and earnings management are substitutes. These findings imply that studies using meet-or-beat indicators as proxies for earnings management are partially capturing analyst strategic behavior.

Keywords: Analyst forecasts; Earnings surprises; Forecast bundling; Kink asymmetry; Earnings management; Target prices; Stock recommendations

JEL Classification: G14, G24, M41

1. Introduction

One of the most prominent empirical regularities in capital market research is the "kink" in the distribution of earnings surprises—an abnormally high incidence of firms meeting or just beating consensus earnings forecasts and a corresponding scarcity of small misses (Degeorge, Patel, and Zeckhauser 1999). This pattern raises questions about earnings quality and capital market efficiency because a systematic avoidance of negative surprises suggests bias in financial reporting or forecasting. Identifying the sources of the kink matters because earnings surprises influence how investors, academics, and regulators interpret financial performance and analyst credibility. Existing explanations of the kink focus predominantly on earnings management. Firms have strong incentives to avoid negative surprises because even minor shortfalls from consensus forecasts can trigger substantial negative market reactions (Skinner and Sloan 2002; Bartov, Givoly, and Hayn 2002). These incentives lead managers to manipulate accruals, engage in real earnings management, or guide analyst forecasts downward (Matsumoto 2002; Brown and Caylor 2005; Roychowdhury 2006; Burgstahler and Eames 2006).

Despite this evidence, there are reasons to question whether earnings management fully explains the kink. For example, Abarbanell and Lehavy (2003) conjecture that asymmetry and heavy tails in forecast error distributions are largely a function of analyst bias rather than earnings management. Dechow, Richardson, and Tuna (2003) find that discretionary accruals alone cannot fully account for the earnings kink: small profit firms do not have higher discretionary accruals than small loss firms. Other research points to alternative explanations such as sampling biases or measurement of forecast errors (Durtschi and Easton 2005). The prevailing earnings-management explanation implicitly assumes analyst forecasts are unbiased benchmarks, without considering whether analysts contribute systematically to the kink by strategically shaping the forecasts firms strive to beat. We provide evidence that they do: adjusting consensus forecasts for predictable bias from analyst strategic behavior reduces the kink by approximately two-thirds, suggesting the role of earnings management has been substantially overstated.

Our study revisits the kink from the analyst perspective, positing that analyst behavior plays a major, previously underappreciated role in generating the observed pattern. Specifically, analysts bundle earnings forecast revisions with concurrent revisions of recommendations or target prices to communicate private information while maintaining achievable earnings targets. This bundling creates systematic forecast bias. To quantify it, we introduce a measure—*bundling intensity—reflecting the frequency with which an analyst concurrently revises forecasts, recommendations, and target prices in the same direction*—and provide empirical evidence that high bundling intensity produces systematically conservative forecasts.

Figure 1 illustrates the central result. Drawing on analyst forecasts issued between 1999 and 2021, the purple curve of unadjusted errors (*Analyst_SUE*) replicates the well-known pattern first documented by Degeorge, Patel, and Zeckhauser (1999)—a disproportionate clustering of small positive forecast errors relative to small negative errors. The red curve (*Analyst_SUE_Adj*), which removes the predictable portion attributable to bundling, exhibits a visibly smaller spike around zero. The unadjusted ratio of small positive to small negative forecast errors is 2.43; after adjusting for bundling, it declines to 1.49—a 66% reduction. Negative skewness also moves toward zero, declining by approximately 95%. More broadly, the adjusted forecast errors shift toward normality: the Anderson-Darling test statistic improves by 55%, and kurtosis declines by 48%.[1]

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[1] High kurtosis reflects too many observations in the tails of the distribution (i.e., extreme misses or extreme beats). After we account for bundling, some of those extreme observations in the tails migrate toward the center, indicating that analysts' systematic bias partly contributes to the excessive "peakedness." Because the Anderson-Darling statistic

Consistent with systematically conservative forecasts, we find that bundling intensity predicts forecast errors at both the individual analyst-report level and the aggregated firm-quarter level. A one-standard-deviation increase in bundling intensity corresponds to quarterly EPS that is, on average, 3 cents higher than consensus expectations—economically significant against the sample mean of 62 cents per share. Bundling also increases with macroeconomic uncertainty, consistent with analysts relying more heavily on recommendations and target prices to convey private information when volatile conditions raise the reputational cost of bold earnings forecasts.

Finally, we investigate how bundling interacts with managerial earnings management. When analysts issue forecasts that give managers a cushion to meet or beat, managers have less need to resort to accrual manipulation or real activities management. We find that firms with higher bundling intensity rely less on positive discretionary accruals to meet or beat forecasts, supporting the view that part of the excess of small positive surprises traces to analysts' strategic conservatism rather than direct managerial effort.

These findings have three implications. First, researchers who use meet-or-beat indicators as proxies for earnings management partially capture analyst strategic behavior; estimates of the prevalence and consequences of earnings management may therefore be overstated. Second, the widely used analyst-based earnings surprise measure (*Analyst_SUE*) contains a predictable component that our bundling adjustment removes, offering a less biased benchmark for event studies of earnings announcements. Third, the substitution between analyst bundling and accrual manipulation suggests that the kink reflects a joint equilibrium between analyst and managerial

penalizes heavy tails, this improvement in kurtosis explains a substantial part of the reduction in the overall non-normality of the forecast error distribution.

behavior, with implications for how regulatory changes affecting one channel (e.g., restrictions on earnings management) may shift activity to the other.

Our study contributes to two literatures. First, we contribute to research on distributional abnormalities in earnings surprises (Hayn 1995; Burgstahler and Dichev 1997; Degeorge et al. 1999; Dechow, Richardson, and Tuna 2003; Beaver, McNichols, and Nelson 2007). We find that the kink and other distributional anomalies attenuate significantly after adjusting the consensus forecast for predictable bias reflected by bundling intensity, suggesting that the kink largely reflects analyst forecast bias rather than earnings management. Second, we contribute to the analyst forecasting literature by showing that stock price reactions to analyst reports increase with bundling intensity, consistent with bundled signals conveying information about future earnings beyond the earnings forecast itself.

Our study is distinct from Berger, Ham, and Kaplan (2019), who document that analysts selectively omit information from their final earnings forecasts and subsequently disclose it through target price and future-quarter earnings revisions. Our analysis complements theirs along three dimensions. First, we study a different margin of analyst behavior. Berger et al. examine the extensive margin—cases in which the analyst omits an EPS forecast revision entirely and instead conveys earnings-relevant information through other outputs. We study the intensive margin—cases in which the analyst does revise the EPS forecast but understates private information, as revealed by concurrent target price and recommendation signals. The two papers' samples are non-overlapping at the report level. Second, we quantify the aggregate distributional consequence of strategic analyst behavior—a question Berger et al. do not address. Individual analyst-level bias need not distort the consensus distribution: if analysts covering the same firm bundle EPS forecasts but do so in different directions or to different degrees, their biases could cancel when averaged.

Our finding that bundling explains approximately two-thirds of the kink demonstrates that it is sufficiently directional and correlated across analysts to distort the distribution of consensus-based forecast errors. Third, we document that analyst bundling and earnings management are substitutes: firms with higher bundling intensity rely less on positive discretionary accruals to meet or beat analyst forecasts, a finding that follows from neither literature alone.

Our study also complements research on consistent versus inconsistent analyst forecast revisions. Prior work finds that forecast accuracy enhances the informativeness of recommendations (Ertimur et al. 2007), particularly when earnings revisions substantiate recommendation changes (Kecskés et al. 2017). Evidence on the implications of inconsistency is mixed: inconsistent signals may reflect lower credibility or strategic bias (Brown and Huang 2013; Malmendier and Shanthikumar 2014), though recent work suggests they do not necessarily indicate lower forecast quality (Iselin et al. 2021). We contribute to this literature by showing that consistent revisions are informative about analysts' private information in a specific way—they permit investors to undo predictable bias in earnings forecasts, significantly reducing the kink in the earnings surprise distribution.

Section 2 discusses related research and develops our hypotheses. Section 3 describes the construction of bundling intensity, Section 4 describes the sample and data, Sections 5 through 8 report empirical results, and Section 9 concludes.

2. Related Research and Basis for Predictions

A well-documented pattern in financial reporting is the "kink" in analyst forecast errors—an excess of small positive earnings surprises relative to small negative surprises (Hayn 1995; Burgstahler and Dichev 1997; Degeorge, Patel, and Zeckhauser 1999; Dechow, Richardson, and

Tuna 2003). This phenomenon matters because analyst forecast errors are widely used as controls in event studies of market reactions to corporate disclosures (Hayn 1995; Dechow et al. 2003). If these errors are systematically biased, inferences about price effects of other disclosures can be distorted. One explanation focuses on cognitive factors: analysts systematically anchor on prior estimates and under-react to new information (Tversky and Kahneman 1974; Elliott, Philbrick, and Wiedman 1995; Einhorn and Hogarth 1986), contributing to the observed kink.

Other work posits that analysts' incentives to avoid bold predictions and maintain beatable forecasts drive the kink (Hong, Kubik, and Solomon 2000; Richardson, Teoh, and Wysocki 2004; Chan, Karceski, and Lakonishok 2007). Because future career opportunities depend on forecast accuracy (Stickel 1992; Mikhail, Walther, and Willis 1999; Harford et al. 2019), analysts risk reputational harm if they stray too far from actual earnings, deterring full incorporation of private information. Moreover, managers prefer lower analyst targets they can comfortably beat (Lim 2001; Bartov, Givoly, and Hayn 2002), creating incentives to cater to management (Matsumoto 2002). The kink thus likely reflects both behavioral factors (anchoring, limited information processing) and strategic considerations (career risk, management appeasement), with the durability of the pattern suggesting these forces dominate the incentive for accuracy.

Although analysts are averse to making bold EPS revisions, they still have incentives to communicate private information to clients. Research finds that analysts exploit soft signals—specifically stock recommendations and target prices—to convey private views indirectly (Mikhail, Walther, and Willis 1997; Berger, Ham, and Kaplan 2019). These signals differ from quarterly earnings forecasts in two ways. First, recommendations and target prices reflect a broader set of valuation information than earnings forecasts, which focus on short horizons (Richardson et al. 2004). Second, there is no direct way to assess their accuracy based on short-term realizations, unlike earnings forecasts, whose accuracy investors can evaluate at the earnings announcement (Mikhail, Walther, and Willis 1999). This reduced accountability allows recommendations and target prices to serve as channels for conveying soft private information while minimizing reputational risk (Huang et al. 2014).

Based on prior literature (Kecskés, Michaely, and Womack 2017; Berger et al. 2019), we posit that the credibility of soft information is enhanced when analysts bundle earnings forecast revisions with congruent changes in recommendations and target prices. For example, an analyst who modestly raises an earnings estimate might simultaneously upgrade the stock and lift the target price, signaling greater optimism than the earnings revision alone conveys. To the extent investors interpret these bundled signals as indicating the analyst's true expectation exceeds the reported forecast, we predict a larger stock price reaction to earnings forecast revisions accompanied by consistent target price and recommendation revisions. Huang et al. (2014) find that the stock price reaction to simultaneously released forecast, target price, and recommendation revisions is larger when accompanied by interpretive text. Bundling plays a related but distinct role: consistent revisions help investors specifically undo bias in the earnings forecast, whereas in Huang et al. (2014) accompanying text provides unspecified information aiding interpretation.

Bundling allows analysts to keep the earnings forecast conservative while conveying private information through soft disclosures, making part of the subsequent forecast error predictable. When analysts bundle multiple positive signals with a positive earnings revision, the forecast is likely intentionally conservative; over many observations, this creates the kink. If a significant fraction of the kink stems from bundling-induced under-revision, adjusting for the predictable effect of bundling should reduce or eliminate the excess clustering at small positive errors. This discussion suggests two hypotheses underlying our prediction that the kink reflects bias in analyst earnings forecasts:

Hypothesis 1: Earnings forecast revisions accompanied by consistent revisions in target prices and recommendations will be associated with stronger market reactions.

Hypothesis 2: There is a positive relation between bundling intensity and analysts' earnings per share forecast error.

Assuming Hypotheses 1 and 2 are empirically valid, our key prediction follows:

Hypothesis 3: Removing the predictable portion of the forecast error attributable to bundling will reduce the concentration of small positive errors relative to small negative ones, thus mitigating the kink.

3. Bundling Intensity

3.1 Construction of Report Level Bundling Intensity

To test H1 and H2, we construct a report-level measure of bundling intensity, BR_Score_{ijkt}, where subscripts denote firm (i), analyst (j), report (k), and quarter (t). For each analyst report containing a revision to the quarterly EPS forecast (*EPS_rev*), *BR_Score* counts the number of concurrent signals—EPS forecast revision, recommendation revision (*REC_rev*), and target price revision (*TP_rev*)—that share the same sign, and assigns a value between −3 and +3 based on the sign of *EPS_rev*. Specifically, *BR_Score* equals ±1 if the report contains only a stand-alone EPS revision with no concurrent recommendation or target price revision; ±2 if the report also contains a same-sign recommendation or target price revision, but not both; and ±3 if the report contains same-sign revisions to all three outputs. *BR_Score* equals zero otherwise (e.g., when concurrent revisions move in the opposite direction from *EPS_rev*).[2] Each revision is computed as the analyst's current value less the prior value, scaled by the cross-sectional standard deviation of all analysts' corresponding outputs for the firm-quarter. Appendix A provides a detailed description of *BR_Score*.

3.2 Construction of Firm-Quarter Measure of Bundling Intensity

To construct a firm-level measure, BF_Score_{it}, we first sum *BR_Score* across all reports containing earnings forecast revisions for each analyst *j* covering firm *i* in quarter *t*, yielding an analyst-level aggregate of bundling intensity. BF_Score_{it} is then the mean of these analyst-level sums across all analysts covering the firm, producing a consensus measure of bundling intensity. Eq. (1) defines BF_Score_{it}.

$$BF\_Score_{it} = \frac{1}{n}\sum_{n=1}^{j}\left(\sum_{m=1}^{k} BR\_Score_{ijkt} \text{ for each firm } i\text{, analyst } j\text{, year-qtr } t\right) \qquad (1)$$

Appendix B illustrates the construction of *BF_Score* for a hypothetical firm-quarter with three analysts (A, B, and C). Analyst A issues two reports: report 1 has *BR_Score* = 3 ((+) *EPS_rev*, (+) *TP_rev*, and (+) *REC_rev*), and report 2 has *BR_Score* = 2 ((+) *EPS_rev* and (+) *TP_rev*). Summing across reports, $BR\_Score_A = 5$. Following the same procedure, $BR\_Score_B = -3$ and $BR\_Score_C = 1$. *BF_Score* for the firm-quarter is the mean of (5, −3, 1) = 1.

4. Sample and Descriptive Statistics

We obtain analyst earnings forecasts for the current quarter from the IBES detail files for fiscal years ending 1999–2021, beginning in 1999 when IBES coverage first includes target prices. We require each observation to have a nonzero *EPS_rev*, because our research question centers on

[2] Appendix B defines all variables used in this study.

the implicit signals conveyed by target price and recommendation revisions accompanying an earnings forecast revision. Constructing *EPS_rev* requires at least two earnings forecasts per analyst-firm-quarter. We also obtain analyst stock recommendations and target prices from IBES to construct *REC_rev* and *TP_rev*, and in turn *BR_Score* and *BF_Score*. Control variable data are drawn from Compustat and CRSP and are discussed below.[3]

We require each firm-quarter to have earnings forecasts from at least two analysts to ensure a meaningful consensus. To construct *Analyst_SUE*, we obtain reported earnings from IBES and stock prices from CRSP.[4] We winsorize continuous variables at the 1st and 99th percentiles. The sample for Eqs. (2) and (3) comprises 779,917 analyst-report-level observations; the sample for Eq. (4) comprises 82,164 firm-quarter observations.

Table 1, Panel A, presents distributional statistics for the analyst earnings forecast revisions used to construct *BR_Score* and *EPS_rev*. Of all earnings forecast revisions, 41% are positive and 59% are negative. Seventy percent are stand-alone; 21% are accompanied by a same-sign target price or recommendation revision, but not both; 2% are accompanied by both; and 8% are accompanied by revisions of the opposite sign.

Table 1, Panel B, provides a frequency distribution of *BR_Score* along with the mean and standard deviation of *EPS_rev* for each level from −3 to +3. Consistent with Panel A, negative observations outnumber positive observations at each *BR_Score* level (e.g., 351,851 observations at *BR_Score* = −1 versus 238,498 at +1). The mean of *EPS_rev* increases in magnitude across negative *BR_Score* levels (−0.5686, −0.6644, −0.7159) but does not increase across positive levels

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[3] Following prior literature, our regressions control for firm characteristics that capture cross-sectional variation in forecasted earnings and expected returns. These variables are firm size (*SIZE*), book-to-market (*BM*), accruals (*ACC*), long-term growth forecast (*LTG*), and six-month stock-price momentum (*MOM*).
[4] Analyst_SUE is the firm-quarter earnings surprise based on analyst consensus calculated as follows. Analyst_SUE = (Actual quarterly EPS − consensus analyst EPS forecast measured on the day prior to the earnings announcement) / stock price at the prior fiscal quarter-end

(0.4213, 0.4308, 0.4151), suggesting that analysts suppress positive earnings information when bundling. Column 5 presents mean abnormal stock returns on analyst report dates; higher absolute *BR_Score* is associated with larger absolute returns, with differences significant at conventional levels (*t*-statistics reported in the table).[5] These return patterns suggest investors recognize that *BR_Score* reflects information about firm value.

Table 2, Panel A, presents descriptive statistics for the primary variables in our firm-level analyses. Mean *Analyst_SUE* is 0.00013 (standard deviation 0.021), close to zero. Consistent with Table 1, Panel B, mean *BF_Score* is negative (−0.169), and the means of the three aggregate revisions—*EPS_aggrev*, *REC_aggrev*, and *TP_aggrev*—are −0.168, −0.028, and 0.001, respectively. Panel B presents Pearson correlations. The three revisions are positively correlated with *BF_Score* and with each other. *Analyst_SUE* is also positively correlated with *BF_Score* (0.07), consistent with H2.

5. Analyst Report Announcement Returns and Prediction of Forecast Errors

We begin by testing whether report-level bundling intensity conveys incremental information and biases the analyst's forecast. H1 predicts a positive association between *BR_Score* and the market reaction to the analyst report (*CAR_report*). H2 predicts that *BR_Score* is positively associated with the report-level forecast error, indicating that bundling systematically withholds part of the analyst's private information from the EPS revision.[6] We test these two predictions using equations (2) and (3).

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[5] Throughout we use a five percent significance level under a one-sided alternative when we have a signed prediction and under a two-sided alternative otherwise.

[6] For ease of exposition, we use the same notation for coefficients and error terms across Eqs. (2) and (3), and across Eqs. (4), (5) (8), (9), and (10). In all likelihood, they differ.

$$CAR\_report_{i,j,k,t}=\beta_1 BR\_Score_{i,j,k,t}+\beta_2 EPS\_rev_{i,j,k,t}+\beta_3 EPS\_rev_{i,j,k,t}+\beta_4 REC\_rev_{i,j,k,t}$$
$$+\gamma' X_{i,t}+A_j+F_i+Y_t+\varepsilon_{i,j,k,t} \quad (2)$$

$$FE\_report_{i,j,k,t}=\beta_1 BR\_Score_{i,j,k,t}+\beta_2 EPS\_rev_{i,j,k,t}+\beta_3 EPS\_rev_{i,j,k,t}+\beta_4 REC\_rev_{i,j,k,t}$$
$$+\gamma' X_{i,t}+A_j+F_i+Y_t+\varepsilon_{i,j,k,t} \quad (3)$$

CAR_report$_{ijkt}$ is the three-day market-adjusted return around the analyst report date, and *FE_report*$_{ijkt}$ is actual EPS minus the report's forecasted EPS, scaled by the firm's stock price at the end of the prior fiscal quarter.

Based on H1 and H2, we predict that β_1, the coefficient on *BR_Score*, is positive in both equations. Although we have no predictions for the coefficients on *EPS_rev*, *REC_rev*, and *TP_rev*, these variables may have predictive power for *CAR_report* or *FE_report*. Because *BR_Score* is constructed from the three revisions and is correlated with them (Table 2, Panel B), we include them as controls in Eqs. (2) and (3). Both equations also include a vector of controls, **X′**, identified in prior literature as determinants of earnings and expected returns (e.g., Sloan 1996; Fama and French 2006; So 2013): the natural logarithm of market value of equity (*SIZE*), book-to-market ratio (*BM*), accruals (*ACC*), long-term growth forecast (*LTG*), and six-month stock price momentum (*MOM*). We have no prediction for the signs of these coefficients. Eqs. (2) and (3) also include analyst, firm, and year-quarter fixed effects, *A*, *F*, and *Y*, as controls for potentially omitted variables that are constant for a specific analyst, firm, or time-period. We calculate *t*-statistics associated with coefficient estimates in both equations based on standard errors clustered at the firm level.[7]

[7] Inferences remain unchanged when we compute standard errors using two-way clustering by firm and year-quarter.

Table 3, panel A, presents findings from estimating three versions of Eq. (2). The first version includes only *BR_Score*, and firm, analyst, and year fixed effects. The second (third) version adds controls for the magnitudes of the earnings, recommendation, and target price revisions (the full vector of firm controls). As H1 predicts, the *BR_Score* coefficient (multiplied by 1,000 for ease of interpretation) is positive and significant, β_1 = 9.942, (*t*-stat. = 19.492), which indicates a positive association between bundling intensity and the market's reaction to analyst reports that contain earnings forecast revisions.

In Column 2, the coefficient on *BR_Score*, β_1, also is positive and significant (coef. = 2.937, *t*-stat. = 10.304). That β_1 is smaller in Column 2 than in Column 1 reflects the fact that the magnitudes of the revisions are highly correlated with *BR_Score*, as reported in Table 2, panel B. The coefficients on *EPS_rev*, *REC_rev*, and *TP_rev* (also all multiplied by 1,000 in all tables for ease of interpretation) are positive and significant, which is consistent with findings in prior research that the market responds in the same direction of the analyst's revisions of prior forecasts and recommendations (Barber et al. 2001; Brav and Lehavy 2003; Gleason and Lee 2003; Ivković and Jegadeesh 2004). Column 3 reveals similar inferences in that the *BR_Score* coefficient, β_1, is positive and significant even after the addition of a vector of firm controls (coef. = 2.694; *t*-stat. = 8.918). Economically, the findings presented in Column 3 indicate that a one-point increase in *BR_Score* equates to a 27 basis point increase (1 × 2.694 / 1,000) in the firm's market capitalization. Taken together, the findings in Table 3, panel A, support H1, i.e., that the market interprets report-level bundling intensity as informative regarding firm value.

Table 3, panel B, presents regression summary statistics from estimating the same three corresponding versions of Eq. (3) that panel A presents for Eq. (2). In all three columns, the *BR_Score* coefficient, β_1, is significantly positive (coefs. range from 0.108 to 0.933; *t*-stats. range from 2.296 to 11.513). Notably, β_1 is larger in Column 2 when Eq. (3) includes controls for the magnitudes of the three revisions, *EPS_rev*, *REC_rev*, and *TP_rev*. In Column 1 β_1= 0.108, and in Column 2 β_1 = 0.933 (*t*-stats. = 2.296 and 11.513). These larger coefficients are notable because *BR_Score* is highly correlated with the magnitude of each of the three revisions and its coefficient is smaller when the magnitudes of the three revisions are included in Column 3 in Table 3, panel A. Overall, the findings in Table 3, panel B, provide support for H2, that bundling intensity at the report level is predictive of the report's earnings forecast error.

6. Predicting Consensus Earnings Surprise

Finding that report-level bundling intensity predicts forecast errors does not imply that bundling generates predictable bias in the consensus forecast, because aggregation across analysts could attenuate or eliminate the relation. To test whether the result extends to the firm level—where our distributional analyses and H3 operate—we estimate Eq. (4), which regresses *Analyst_SUE* on firm-level bundling intensity.[8]

$$Analyst\_SUE_{it} = \beta_1 BF\_Score_{it} + \beta_2 EPS\_aggrev_{it} + \beta_3 TP\_aggrev_{it} + \beta_4 REC\_aggrev_{it} + \gamma' X_{it} + F_i + Y_t + \varepsilon_{it} \quad (4)$$

Following Livnat and Mendenhall (2006), *Analyst_SUE* is the firm's quarterly EPS minus the consensus forecast as of the day prior to the earnings announcement, scaled by stock price at the end of the prior fiscal quarter. *EPS_aggrev* is the mean across all analysts covering firm *i* of each analyst's earnings forecast revision over the quarter—defined as the analyst's forecast on the day prior to the earnings announcement minus the forecast at the beginning of the quarter, scaled by

[8] We do not estimate a version of equation (2) for consensus forecasts because—unlike individual analyst forecasts—there is no single event date associated them.

the cross-sectional standard deviation of all analysts' earnings forecasts for the firm-quarter. We define the beginning-of-quarter forecast as the analyst's first current-quarter EPS forecast issued after the firm's prior-quarter earnings announcement. *REC_aggrev* and *TP_aggrev* are constructed analogously using recommendation and target price revisions, respectively. Eq. (4) includes the same controls as Eqs. (2) and (3), as well as firm (*F*) and year-quarter (*Y*) fixed effects.

To illustrate the relation between bundling intensity and analyst-based earnings surprise, we first examine the bivariate relation between the two measures. Table 4, panel A, tabulates summary statistics related to ranks of *BF_Score* and the firm-quarter measure of analyst-based earnings surprise, *Analyst_SUE*. Specifically, for each firm-quarter we rank *BF_Score* into deciles and present the mean *Analyst_SUE* for each *BF_Score* decile. Panel A reveals that mean *Analyst_SUE* increases monotonically with higher deciles of *BF_Score*, with the exception of decile rank 4. It also reveals that the difference in mean *Analyst_SUE* between Decile 10 and Decile 1 is significantly positive (0.0049 = 0.0022 – (–0.0027); *t*-stat. = 15.2018). Figure 2 presents a scatterplot of *Analyst_SUE* and percentile ranks of *BF_Score*. Figure 2 visually confirms a strong linear relation between the two variables and reveals that the correlation is 0.70. Untabulated statistics reveal that the correlation is significant (p-value < 0.01). Overall, these statistics reveal a positive association between firm-level bundling intensity and the quarterly earnings surprise based on the analyst consensus forecast.

Turning to the multivariate test of the association between *Analyst_SUE* and *BF_Score*, Table 4, panel B, presents regression summary statistics from estimating Eq. (4). Columns 1 to 3 present the findings from estimating the same three versions of Eq. (4) as in Table 3, panel B, except that the report-level forecast revisions—*EPS_rev*, *REC_rev*, and *TP_rev*—are replaced by firm-level consensus revisions—*EPS_aggrev*, *REC_aggrev*, and *TP_aggrev*. The findings reveal that coefficient on *BF_Score* is significantly positive in all three estimations (coefs. range from 0.514 to 1.000; *t*-stats. range from 4.463 to 12.189). The *BF_Score* coefficient in Column 3, 0.514, indicates that for a firm with a share price equal to the untabulated sample mean of $51.68, a one standard deviation increase in *BF_Score* is associated with an increase in earnings surprise of $0.03.[9]

Taken together, the findings in Table 4—both the univariate and multivariate findings—support the H2 prediction that bundled forecasts can be used to predict consensus analyst earnings surprise.

7. Effects of Adjusting Earnings Forecast Errors for Bias

The findings in Section 6 suggest that adjusting *Analyst_SUE* for the impact of *BF_Score* yields a less biased measure of the earnings surprise. If so, the distribution of adjusted forecast errors should differ from the unadjusted distribution in two ways. First, removing the incentive-driven component should reduce extreme forecast errors, shifting mass from the tails toward the center—a reduction in kurtosis. Second, the excess of small positive forecast errors relative to small negative errors should diminish. More generally, the adjusted distribution should more closely approximate normality.

To adjust each firm's quarterly surprise for the effect of *BF_Score*, we estimate *BF_Score* coefficients by industry-year rather than pooling the full sample. This avoids look-ahead bias and allows the effect of bundling to vary across industries and over time. Specifically, for each of the 276 industry-year subsamples (Fama-French 12 classifications), we estimate Eq. (5) using the

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[9] The earnings surprise increase of $0.03 is calculated as follows. A one standard deviation increase in *BF_Score* is associated with an increase in *Analyst_SUE* of (0.99)(0.514)/1000 = 0.00050886. Multiplying this by the sample mean share price of $51.68 yields a change in earnings surprise of $0.03.

same controls as Eq. (4) but omitting fixed effects, and apply the prior year's industry-year coefficient to compute the predicted bundling impact for the current year.

$$Analyst\_SUE_{it} = \beta_1^{FF12\cdot year} BF\_Score_{it} + \beta_2^{FF12\cdot year} EPS\_aggrev_{it} + \beta_3^{FF12\cdot year} TP\_aggrev_{it} + \beta_4^{FF12\cdot year} REC\_aggrev_{it} + \gamma^{FF12\cdot year'} X_{it}^{'} + \varepsilon_{it} \quad (5)$$

To create *Adj_Analyst_SUE*, we remove the predictable portion of the forecast error attributable to bundling. For each industry-year, we estimate Eq. (5) using prior-year data, compute the predicted impact of *BF_Score* on each firm's forecast error, and subtract this predicted impact from *Analyst_SUE* (Eqs. (6) and (7)).

$$BF\_\widehat{Score}\_Impact_{it} = \hat{\beta}_1^{FF12*lag(year)} BF\_Score_{it} \quad (6)$$

$$Adj\_Analyst\_SUE_{it} = Analyst\_SUE_{it} - BF\_\widehat{Score}\_Impact_{it} \quad (7)$$

Figure 3 presents the 276 industry-year *BF_Score* coefficients from Eq. (5) used to construct *Adj_Analyst_SUE*. The mean coefficient is 0.77 (*t*-stat. = 5.29), similar in magnitude to the pooled estimates in Table 4. Of the 276 coefficients, 94 are negative, either because analysts do not use bundling to convey withheld earnings information in that industry-year, or because their bundled private information is, on average, incorrect. To the extent *BF_Score* measures this information with error, the ability of *BF_Score_Impact* to improve the distributional properties of *Analyst_SUE* is attenuated.

To quantify the distributional impact of the bundling adjustment, we construct histograms of *Analyst_SUE* and *Adj_Analyst_SUE* using 20 equally sized bins and compare them on four metrics: (1) the Anderson-Darling (AD) statistic, measuring departure from normality (AD = 0 for a normal distribution); (2) kurtosis (Kurt), measuring tail heaviness (Kurt = 3 for a normal distribution); (3) the *Kink Asymmetry Ratio*, defined as the number of observations in the bin just right of zero divided by the number just left of zero (Degeorge et al. 1999); and (4) skewness (Skew), measuring overall asymmetry (Skew = 0 for a normal distribution).

Figure 1 overlays the adjusted distribution of *Adj_Analyst_SUE* on the unadjusted distribution, with the four metrics tabulated below. Both distributions differ significantly from normality, but the adjustment yields substantial improvement: the AD statistic improves by 55.9% toward zero,[10] and kurtosis declines by 48% toward the normal benchmark of 3.[11] The reduction in kurtosis—reflecting a migration of extreme observations toward the center—accounts for a substantial part of the AD improvement, consistent with bundling-induced conservatism generating excess tail observations in the unadjusted distribution.

The *Kink Asymmetry Ratio* falls from 2.43 (= 32,806/13,500) in the unadjusted distribution to 1.49 (= 22,350/15,000) in the adjusted distribution—a 66% improvement toward the normal-distribution benchmark of 1.[12] Testing the reduction on a year-over-year basis confirms it is significant (*t*-stat. = –19.58; *p*-value < 1%). Skewness likewise declines by 95%, from –0.0624 to –0.0031.[13] Together, these results indicate that the bundling adjustment produces economically meaningful improvements in the distributional properties of *Analyst_SUE*, consistent with analysts' use of bundling being driven substantially by the incentive to issue beatable forecasts.

As a placebo test, we construct *RND_BF_Score*, a random variable matching the empirical mean and variance of *BF_Score* over the sample period. We multiply *RND_BF_Score* by the estimated coefficients from the 276 industry-year regressions to compute *RND_Adj_Analyst_SUE*. Figure 4 compares the distributions of *Analyst_SUE* and *RND_Adj_Analyst_SUE*. Across all four

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[10] % AD statistic improvement = 55.9% = [(3,728.5 – 0) – (1,643.5 – 0)] / (3,728.5 – 0);
[11] % Kurtosis reduction = 48% = [(7.6418 – 3) – (5.4351 – 3)] / (7.6418 – 3)
[12] % *Kink Asymmetry Ratio* improvement = 66% = [(2.43 – 1) – (1.49 – 1)] / (2.43 – 1)
[13] % Skewness reduction = 95% = (|–0.0624| – |–0.0031|) / |–0.0624|

metrics, the improvements from the actual bundling adjustment are substantially larger than those from the random adjustment—for example, the reduction in kurtosis is 48% using *BF_Score* versus only 3% using *RND_BF_Score*. These findings confirm that the distributional improvements are driven by the specific information in analysts' bundling behavior rather than mechanical properties of the model. As an alternative, we regress *Analyst_SUE* on the full set of controls in Eq. (4) and define *ALL_Adj_Analyst_SUE* as the residual. Figure 5 compares the two distributions. The residual distribution is nearly flat with no visible kink, indicating that the regression removes virtually all predictable variation.

We also examine accrual-based earnings management by constructing *ACC_Adj_Analyst_SUE*, which adjusts *Analyst_SUE* only for the component predicted by discretionary accruals (*Discret_Acc*). Figure 6 plots the two distributions. The accrual-based adjustment moves the distribution toward normality—the kink is smaller and small positive surprises are reduced—but the kink remains pronounced. The discretionary-accrual adjustment reduces the *Kink Asymmetry Ratio* from 2.43 to 1.97 (32% toward the benchmark of 1) and the AD statistic from 3,728.5 to 2,611.6 (30%). By comparison, the *BF_Score* adjustment reduces the *Kink Asymmetry Ratio* to 1.49 (66%) and the AD statistic to 1,643.5 (56%), with a larger reduction in kurtosis (48% versus 28%). Discretionary accruals thus explain part of the kink, but bundling accounts for a substantially larger share of the predictable distortion in analyst forecast errors.

8. Additional tests

8.1. BF_Score, Uncertainty, and Analyst-Based Earnings Surprise

Prior research shows that analysts who issue inaccurate bold forecasts are more likely to face termination (Hong, Kubik, and Solomon 2000), and that analysts averse to bold revisions exhibit higher forecast errors because their forecasts do not fully reflect private information (Clement and Tse 2005). Because analysts' informational advantages relate primarily to processing macro-level information (Piotroski and Roulstone 2004; Wang 2019), their private signals are likely less precise during periods of high macroeconomic uncertainty. Analysts may therefore rely more heavily on bundled revisions to convey private information while avoiding bold earnings forecasts that could jeopardize career prospects. We test this prediction below.

Figure 7 presents a violin plot of monthly mean unsigned bundling intensity, *Mean(Abs(BR_Score))*, by year. Three patterns emerge. First, bundling intensity trends upward over the sample period, with the earliest years exhibiting the lowest levels. Second, the maximum monthly *Mean(Abs(BR_Score))* is 1.64, 33% above the median of 1.23. Third, five of the six highest monthly values occur during the COVID-19 shutdown or the Global Financial Crisis—periods of sharply elevated macroeconomic uncertainty.

Motivated by these patterns, we test two predictions: (1) whether firm-level bundling intensity correlates with macroeconomic uncertainty, and (2) whether the predictive power of *BF_Score* for earnings surprises increases with uncertainty. To test (1), we estimate Eq. (8). Because we make no assumption about the sign of analysts' private information, we use absolute values of *BF_Score* and the three forecast revisions.

$$\begin{aligned} Abs(BF\_Score)_{it} = {} & \beta_1 UNCERT_t + \beta_2 Abs(EPS\_revagg_{it}) + \beta_3 Abs(REC\_revagg_{it}) \\ & + \beta_4 Abs(TP\_revagg_{it}) + \gamma' X'_{it} + F_i + Y_t + \varepsilon_{it} \end{aligned} \tag{8}$$

UNCERT is one of five proxies for macroeconomic uncertainty: (1) *VIX*, the mean of the ten highest daily CBOE volatility index values during quarter *t*; (2) *EM_Volatility*, a newspaper-based measure of equity market volatility from Baker, Bloom, and Davis (2016); (3–4) *Disp_ngdp* and *Disp_rgdp*, the dispersion of nominal and real GDP forecasts from the Federal Reserve Bank's

Survey of Professional Forecasters; and (5) *Disp_indprod*, the dispersion of industrial production forecasts from the same survey. Controls and fixed effects follow Eq. (4).

Table 5 presents results from estimating Eq. (8), with each column corresponding to a different *UNCERT* proxy. All five *UNCERT* coefficients are significantly positive (coefs. range from 0.002 to 0.039; *t*-stats. range from 3.059 to 4.266), indicating that absolute bundling intensity is higher during periods of greater macroeconomic uncertainty. Controls and fixed effects are included but untabulated.

To test whether the predictive power of *BF_Score* for earnings surprises increases with uncertainty, we augment Eq. (8) with an interaction term, *BF_Score* × *UNCERT*, and estimate Eq. (9). A positive coefficient on the interaction would indicate that bundling intensity is more predictive of earnings surprises when macroeconomic uncertainty is higher.

$$\begin{aligned} Analyst\_SUE_{it} = {} & \beta_1 BF\_Score_{it} + \beta_2 UNCERT_t + \beta_3 BF\_Score_{it} \times UNCERT_t + \\ & \beta_4 EPS\_aggrev_{it} + \beta_5 TP\_aggrev_{it} + \beta_6 REC\_aggrev_{it} + \\ & \gamma' X_{it} + F_i + Y_t + \varepsilon_{it} \end{aligned} \quad (9)$$

Table 6 presents results from estimating Eq. (9). The coefficient on *BF_Score* × *UNCERT* is significantly positive across all five proxies (coefs. range from 0.019 to 0.130; *t*-stats. range from 2.233 to 2.823), confirming that bundling intensity is more predictive of earnings surprises when uncertainty is higher. Together, Tables 5 and 6 indicate that analysts convey a larger share of their private information through bundled revisions during periods of elevated macroeconomic uncertainty, consistent with greater boldness aversion when the cost of forecast errors is high.

8.2 Bundling Intensity and the Propensity to Barely Meet-Or-Beat

The findings in Section 6 indicate that the consensus forecast is biased downward for higher levels of *BF_Score*, consistent with analysts suppressing earnings-relevant information from the EPS forecast. Because biased forecasts are easier for firms to meet, we next test whether higher bundling intensity increases the likelihood that firms barely meet or beat the consensus forecast.

Specifically, we test whether firms with positive *BF_Score* are more likely to fall in the first bin just right of zero in the earnings surprise distribution (Degeorge et al. 1999). We define *Meet_Beat* as an indicator equal to one if 0 < *Analyst_SUE* < 0.0015, constructed by partitioning firm-quarters with positive *Analyst_SUE* into ten equal-width bins (width = 0.0015). Of the 82,164 firm-quarters in our sample, 32,867 fall in this bin. We estimate Eq. (10) to test whether higher *BF_Score* increases the probability of meeting or barely beating the consensus forecast:

$$\begin{aligned} Meet\_Beat = {} & \beta_1 BF\_Score_{it} + \beta_2 Discret\_Acc + \\ & \beta_3 EPS\_aggrev_{it} + \beta_4 TP\_aggrev_{it} + \beta_5 REC\_aggrev_{it} + \\ & \gamma' X_{it} + F_i + Y_t + \varepsilon_{it} \end{aligned} \tag{10}$$

Becaue prior literature identifies accrual-based earnings management as a primary driver of the kink, we include discretionary accruals, *Discret_Acc*, measured using the modified Jones model with performance matching on ROA (Kothari et al. 2005), as an additional control. Other controls and fixed effects follow Eq. (4).

Table 7 presents results from estimating Eq. (10). In Column 1, which omits *BF_Score*, the coefficient on *Discret_Acc* is 0.131 (*t*-stat. = 3.070), consistent with prior evidence that managers use accruals to exceed earnings thresholds. Column 2 adds *BF_Score*: its coefficient (×1,000) is 10.018 (*t*-stat. = 4.428), indicating that higher bundling intensity is associated with a greater probability of meeting or beating the consensus forecast. Column 3 adds the interaction *BF_Score* × *Discret_Acc*. The *BF_Score* coefficient remains significantly positive (*t*-stat. = 4.218), and the interaction coefficient is significantly negative (*t*-stat. = –2.663), indicating that firms rely less on discretionary accruals when bundling intensity is higher. Economically, a one-standard-deviation increase in *BF_Score* reduces the *Discret_Acc* coefficient from 0.115 to 0.032—a 72% decrease.

Together, these findings indicate that bundling-induced forecast bias and accrual-based earnings management are substitutes: when analysts provide more beatable forecasts, firms rely less on discretionary accruals to meet or beat them. This pattern is consistent with analysts currying favor with management by channeling positive earnings information through target price and recommendation revisions rather than the earnings forecast itself.

9. Conclusion

A longstanding puzzle in the capital markets literature is the pronounced "kink" in analyst forecast errors—a disproportionate frequency of just-meet-or-just-beat outcomes relative to small misses. Our study shows that removing the predictable bias attributable to bundling target-price and recommendation revisions with earnings forecasts reduces this kink asymmetry by 66%. This finding indicates that the kink traditionally ascribed to managerial earnings management is, in large part, a product of analyst strategic behavior.

We document that analysts systematically bundle their earnings forecasts with concurrent recommendation and target-price revisions of the same sign, thereby withholding part of their private information from the official EPS forecast. This strategy allows analysts to avoid “bold” forecast changes—aligned with their own career and reputational concerns—while still signaling positive or negative news through “softer” channels. Indeed, we find that bundling intensity correlates positively with the market reaction to analyst reports, implying that investors recognize this extra information.

Moreover, bundling intensity—measured at both the analyst-report and firm-quarter levels—predicts the magnitude of analyst-based earnings surprises. We show that analysts bundle more intensively when macroeconomic uncertainty is greater, reflecting heightened aversion to large forecast errors. As a result, firms covered by analysts who bundle more aggressively are more likely to meet or barely beat the consensus forecast, and managers in turn rely less on discretionary accruals to achieve those small earnings beats. Bundling thus lowers the effective performance threshold, reducing the need for overt earnings management.

By demonstrating that de-biasing analyst forecasts for bundling intensity substantially diminishes the kink, our study calls into question the assumption that small positive earnings surprises necessarily reflect managerial manipulation. These results have three implications for empirical research. First, studies using meet-or-beat indicators as proxies for earnings management partially capture analyst strategic behavior, potentially overstating the prevalence and consequences of managerial manipulation. Second, the standard analyst-based earnings surprise measure contains a predictable component that our bundling adjustment removes, offering a less biased benchmark for event studies relying on consensus forecasts. Third, the substitution between bundling-induced bias and discretionary accruals suggests that the kink reflects a joint equilibrium between analyst and managerial behavior, implying that regulatory or market changes affecting one channel may shift activity to the other.

References

Abarbanell, J., & Lehavy, R. (2003). Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts. *Journal of Accounting and Economics*, *36*(1-3), 105-146.

Barber, B. M., Lehavy, R., McNichols, M., & Trueman, B. (2001). Can investors profit from the prophets? Security analyst recommendations and stock returns. *Journal of Finance*, 56(2), 531-563.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4), 1593–1636.

Bartov, E., Givoly, D., & Hayn, C. (2002). The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics, 33*(2), 173–204.

Berger, P. G., Ham, C. G., & Kaplan, Z. R. (2019). Do analysts say anything about earnings without revising their earnings forecasts? *The Accounting Review, 94*(2), 29–52.

Beaver, W. H., McNichols, M. F., & Nelson, K. K. (2007). An alternative interpretation of the discontinuity in earnings distributions. *Review of Accounting Studies*, 12, 525-556.

Brav, A., & Lehavy, R. (2003). An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *Journal of Finance*, 58(5), 1933-1967.

Brown, L. D., & Caylor, M. L. (2005). A temporal analysis of quarterly earnings thresholds: Propensities and valuation consequences. *The Accounting Review*, 80(2), 423–440.

Brown, L. D., & Huang, K. (2013). Recommendation-forecast consistency and earnings forecast quality. *Accounting Horizons*, 27(3), 451-467.

Burgstahler, D., & Dichev, I. (1997). Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics*, 24(1), 99-126.

Burgstahler, D., & Eames, M. (2006). Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. *Journal of Business Finance & Accounting, 33*(5–6), 633–652.

Chan, L. K. C., Karceski, J., & Lakonishok, J. (2007). Analysts' conflicts of interest and biases in earnings forecasts. *Journal of Financial and Quantitative Analysis*, 42(4), 893-913. https://doi.org/10.1017/S0022109000003434

Clement, M. B., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance*, 60(1), 307-341.

Dechow, P. M., Richardson, S. A., & Tuna, I. (2003). Why are earnings kinky? An examination of the earnings management explanation. *Review of Accounting Studies*, 8, 355-384.

Degeorge, F., Patel, J., & Zeckhauser, R. (1999). Earnings management to exceed thresholds. *Journal of Business*, 72(1), 1-33.

Durtschi, C., & Easton, P. (2005). Earnings management? The shapes of the frequency distributions of earnings metrics are not evidence ipso facto. *Journal of Accounting Research*, 43(4), 557–592.

Einhorn, H. J., & Hogarth, R. M. (1986). Judging probable cause. *Psychological Bulletin, 99*(1), 3–19.

Elliott, J. A., Philbrick, D. R., & Wiedman, C. I. (1995). Evidence from archival data on the relation between security analysts' forecast errors and prior forecast revisions. *Contemporary Accounting Research, 11*(2), 919–938.

Ertimur, Y., Sunder, J., & Sunder, S. V. (2007). Measure for measure: The relation between forecast accuracy and recommendation profitability of analysts. *Journal of Accounting Research*, 45(3), 567–606.

Fama, E., & French, K. (2006). Profitability, investment and average returns. *Journal of Financial Economics*, 82(3), 491-518.

Gleason, C., & Lee, C. (2003). Analyst forecast revisions and market price discovery. *The Accounting Review*, 78(1), 193-225.

Harford, J., Jiang, F., Wang, R., & Xie, F. (2019). Analyst career concerns, effort allocation, and firms' information environment. *The Review of Financial Studies*, 32(6), 2179-2224.

Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics*, 20(2), 125-153.

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

Huang, A. H., Zang, A. Y., & Zheng, R. (2014). Evidence on the information content of text in analyst reports. *The Accounting Review*, 89(6), 2151–2180.

Iselin, M., Park, M., & Van Buskirk, A. (2021). Seemingly inconsistent analyst revisions. *Journal of Accounting and Economics*, 71(1).

Ivković, Z., & Jegadeesh, N. (2004). The timing and value of forecast and recommendation revisions. *Journal of Financial Economics*, 73(3), 433-463.

Kecskés, A., Michaely, R., and Womack, K. (2017). Do Earnings Estimates Add Value to Sell-Side Analysts' Investment Recommendations? Management Science 63(6):, 1855-1871.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1), 163-197.

Lim, T. (2001). Rationality and analysts' forecast bias. *Journal of Finance, 56*(1), 369–385.

Livnat, J., & Mendenhall, R. R. (2006). Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research*, 44(1), 177-205.

Malmendier, U., & Shanthikumar, D. (2014). Do security analysts speak in two tongues? *The Review of Financial Studies*, 27(5), 1287-1322.

Matsumoto, D. A. (2002). Management's incentives to avoid negative earnings surprises. *The Accounting Review, 77*(3), 483–514.

Mikhail, M. B., Walther, B. R., & Willis, R. H. (1997). Do security analysts improve their performance with experience? *Journal of Accounting Research*, 35(Supplement), 131–157.

Mikhail, M. B., Walther, B. R., & Willis, R. H. (1999). Does forecast accuracy matter to security analysts? *The Accounting Review*, 74(2), 185-200.

Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review*, *79*(4), 1119-1151.

Richardson, S., Teoh, S. H., & Wysocki, P. D. (2004). The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research*, 21(4), 885-924.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3), 335-370.

Skinner, D. J., & Sloan, R. G. (2002). Earnings surprises, growth expectations, and stock returns, *Review of Accounting Studies, 7*(2–3), 289–312.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3), 289-315.

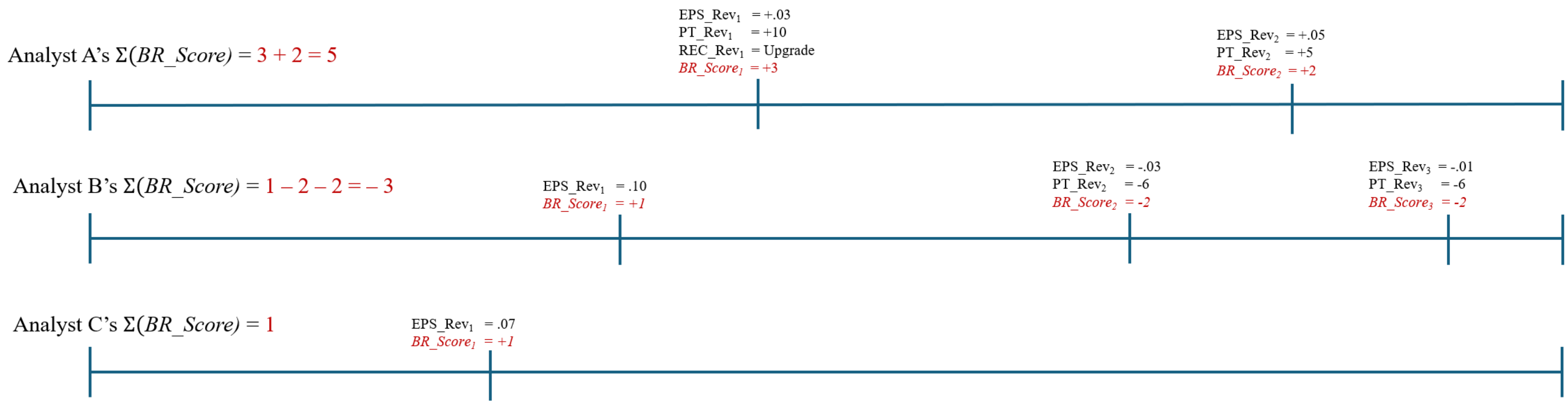
So, E. C. (2013). A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts? *Journal of Financial Economics*, 108, 615-640.

Stickel, S. E. (1992). Reputation and performance among security analysts. *Journal of Finance*, 47(5), 1811-1836.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124–1131.

Wang, S. (2019). Informational environments and the relative information content of analyst recommendations and insider trades. *Accounting, Organizations and Society*, *72*, 61-73.

Appendix A: Sample Calculation of *BF_Score*



Firm's BF_Score = Mean(∑(BR_Score$_A$), ∑(BR_Score$_B$), ∑(BR_Score$_C$)) = Mean(5, -3, 1) = 1

Appendix A illustrates the construction of *BF_Score* for a hypothetical firm-quarter in which three analysts (A, B, C) issue earnings revisions for the firm. The construction of BF_Score is detailed in Section 3.2 and Eq (1). Variables are defined in Appendix B.

Appendix B: Variable Description

Appendix B provides variable definitions for variables used in this study.

Abs_BF_Score	Measure of absolute *BF_Score* at firm level
Acc	Accruals measured as income minus operating cash flow (excluding extraordinary items and discontinued operations)
Analyst_SUE	Actual earnings per share for the quarter minus the consensus analyst earnings forecast, scaled by the end of the previous quarter share price
BF_Score	Firm-level measure of EPS revision bundling intensity calculated as mean of bundling intensity at the analyst level, which is sum of *BR_Score* for each analyst for each firm and year-quarter
BM	Book value of equity divided by market value of equity
BR_Score	Report level measure of EPS revision bundling intensity where Defining $sign(x)$ as a function that returns 1 if $x > 0$, -1 $if \ x < 0$, then BR_Score_{ijkt} equals: 0 if $\text{sign}(EPS\_rev) \neq sign(TP\_rev)$ OR $\text{sign}(EPS\_rev) \neq sign(REC\_rev)$ Then, for all remaining reports: 3 if $\text{sign}(EPS\_rev) = 1\ sign(REC\_rev) = sign(TP\_rev) = 1$ 2 if $\text{sign}(EPS\_rev) = 1$ AND $[sign(REC\_rev) = 1$ OR $sign(TP\_rev) = 1]$ 1 if $\text{sign}(EPS\_rev) = 1$ -1 if $\text{sign}(EPS\_rev) = -1$ -2 if $\text{sign}(EPS\_rev) = -1$ AND $[sign(REC\_rev) = -1$ OR $sign(TP\_rev) = -1]$ -3 if $\text{sign}(EPS\_rev) = sign(REC\_rev) = sign(TP\_rev) = -1$ Note: The above conditions are mutually exclusive and should be checked in sequential order.
CAR_Report	Three-day market-adjusted return centered on the date of the analyst's EPS revision.
Discret_Acc	Discretionary accruals using the Modified Jones model with ROA based on Kothari et al. (2005)
Disp_INDPROD	Quarter-year measure of dispersion in industrial production estimates released by Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters
Disp_NGDP	Quarter-year measure of dispersion in nominal GDP estimates released by Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters
Disp_RGDP	Quarter-year measure of dispersion in real GDP estimates released by Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters

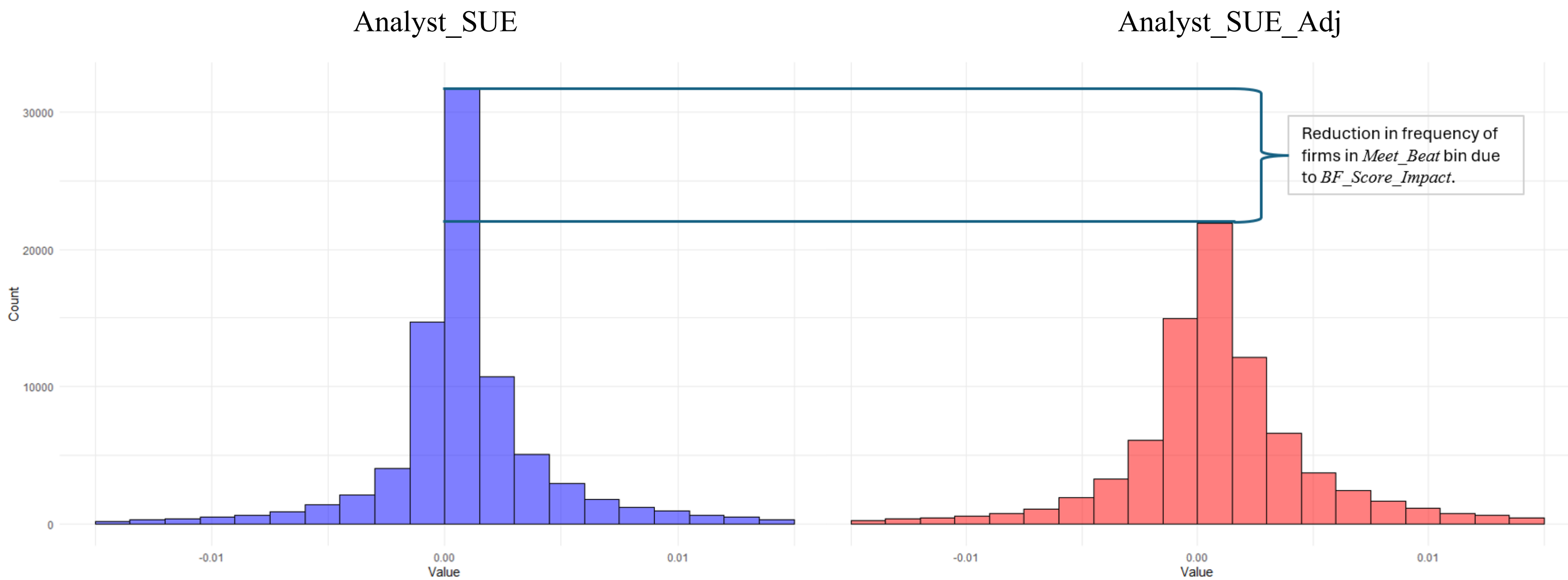
EM_Volatility	Equity market volatility based on Baker, Bloom and Davis (2016)
EPS_aggrev	Mean aggregate earnings forecast revision across all analysts covering firm *i,* where each analyst's earnings forecast revision is calculated as the analyst's earnings forecast on the day prior to the earnings announcement for the current quarter minus the analyst's earnings forecast at the beginning of the quarter, scaled by the standard deviation of all analysts' earnings forecasts in the firm-quarter.
EPS_rev	Analyst's current earnings per share forecast less the corresponding amounts in the analyst's prior report scaled by the standard deviation of individual analyst forecasts for each firm and year-quarter
FE_Report	Actual earnings per share for the quarter minus the analyst earnings forecast, scaled by the end of the previous quarter share price
LTG	Consensus long term growth forecast in IBES
Meet_Beat	1 if *Analyst_SUE* is above or equal to 0 or below 0.0015, 0 if otherwise
Momentum	6 months market adjusted return
REC_aggrev	Mean analyst's recommendation revision over the quarter, where each analyst's current recommendation revision is the analyst's recommendation prior to the earnings announcement minus the recommendation at the beginning of the quarter, scaled by the standard deviation of all analysts' recommendations in the firm-quarter.
REC_rev	Analyst's current recommendation less the recommendation in the analyst's prior report scaled by the standard deviation of individual analyst recommendations for each firm and year-quarter
Size	Log of market value of equity
TP_aggrev	Mean target price revision over the quarter, where each analyst's current target price revision is the analyst's target price prior to the earnings announcement minus the target price at the beginning of the quarter, scaled by the standard deviation of all analysts' target prices in the firm-quarter.
TP_rev	Analyst's target price forecast less the corresponding target price in the analyst's prior report scaled by standard deviation of individual analyst target prices for each firm and year-quarter
VIX	1 for months where the mean of top 10 days daily VIX index is above median, 0 if otherwise

Appendix C: Equation 1

Appendix C provides Eq 1.

$$
BR\_Score_{ijkt} = \begin{cases} 0 \text{ if sign}(EPS\_rev) \neq sign(TP\_rev) \text{ OR sign}(EPS\_rev) \neq sign(REC\_rev) \\ \\ \text{Then, for all remaining reports:} \\ \\ 3 \text{ if sign}(EPS\_rev) = 1 \; sign(REC\_rev) = sign(TP\_rev) = 1 \\ 2 \text{ if sign}(EPS\_rev) = 1 \text{ AND } \left[sign(REC\_rev) = 1 \text{ OR } sign(TP\_rev) = 1 \right] \\ 1 \text{ if sign}(EPS\_rev) = 1 \\ -1 \text{ if sign}(EPS\_rev) = -1 \\ -2 \text{ if sign}(EPS\_rev) = -1 \text{ AND } \left[sign(REC\_rev) = -1 \text{ OR } sign(TP\_rev) = -1 \right] \\ -3 \text{ if sign}(EPS\_rev) = sign(REC\_rev) = sign(TP\_rev) = -1 \end{cases} \quad (1)
$$

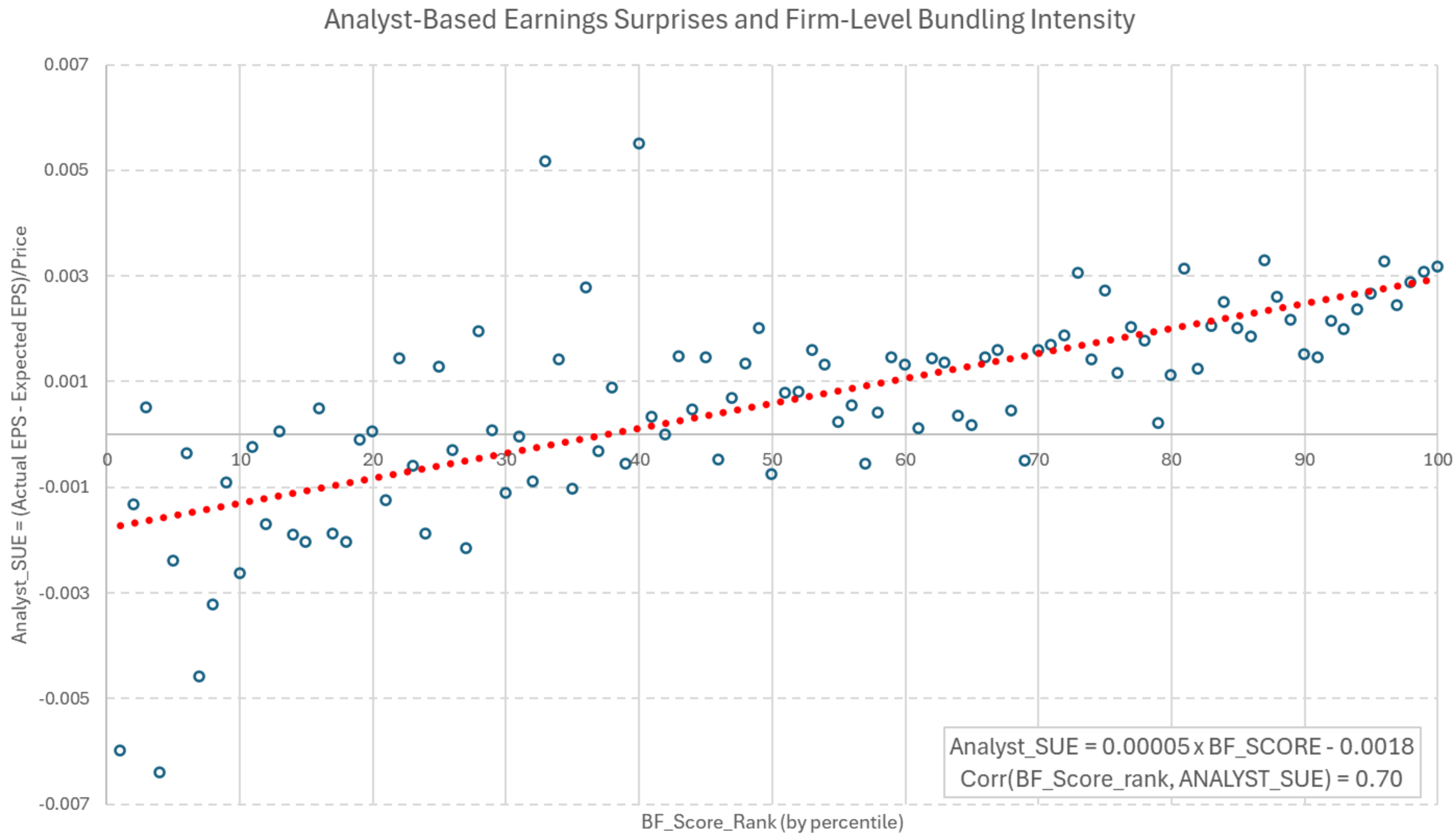
Figure 1. Histogram of Analyst_SUE vs Analyst_SUE_ Adj



	Analyst_SUE (Unadjusted)	Adj_Analyst_SUE (BF_Score_Impact)	Characteristics of Normal Distribution	Improvement towards Normal Distribution
Kink Asymmetry Ratio	2.43	1.49	1.00	66%
Anderson-Darling test	AD 3728.5 p-value < 1%	AD 1643.5 p-value < 1%	0.00	55.9%
Skewness	-0.0624	-0.0031	0.00	95%
Kurtosis	7.6418	5.4351	3.00	48%

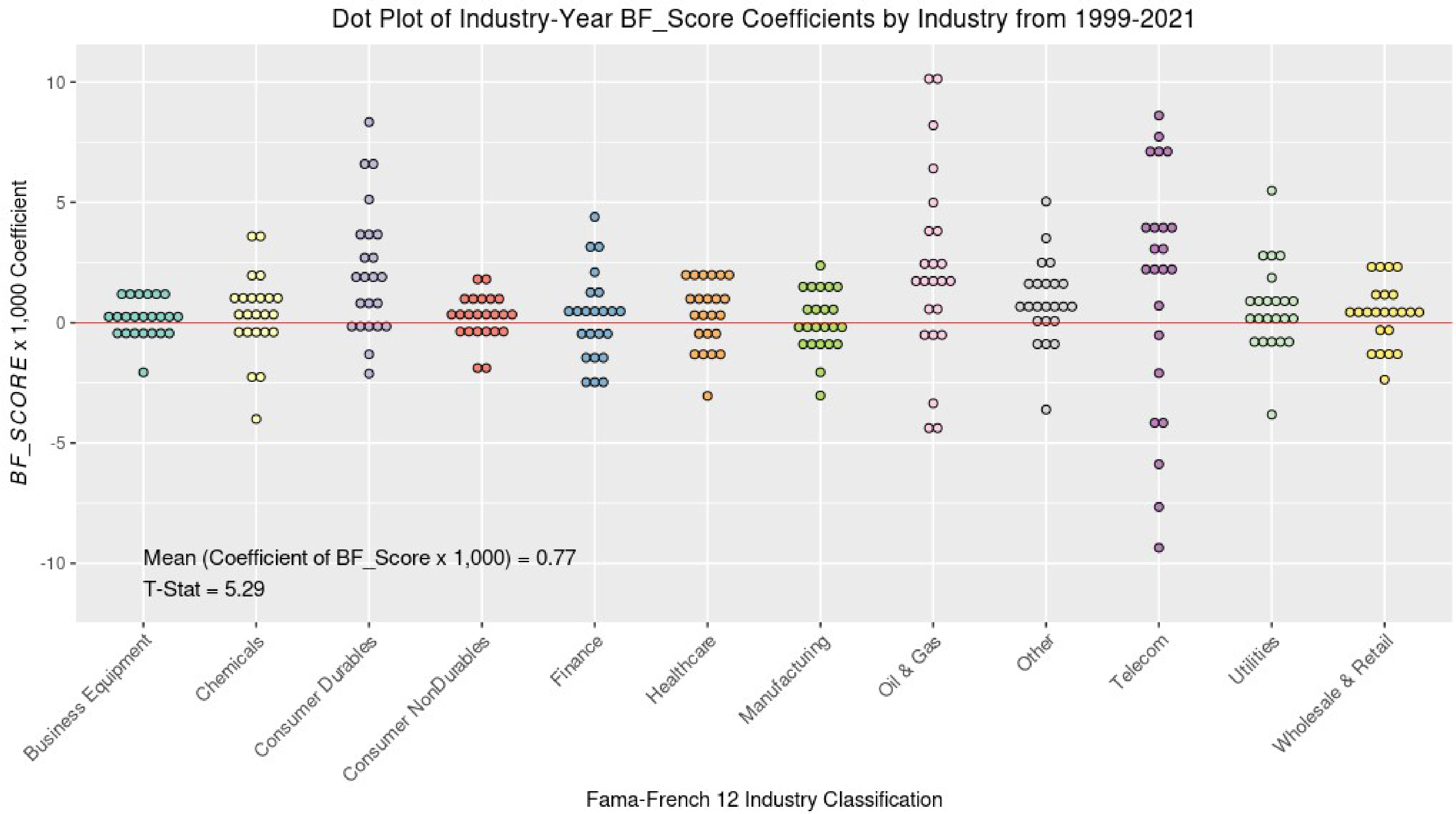
This figure is a histogram of that illustrates the adjustments from the impact of *BF_Score*, which we describe in detail in Section 7. The blue represents the reduction in frequency following the adjustment, while the orange represents the increase in frequency within each bin of *Analyst_SUE*. *KS*, *AD, Skew, Kurt* metrics are reported for both the distributions of *Analyst_SUE* and *Adj_Analyst_SUE*. Improvement towards normal is calculated based on the metrics observed in a normal distribution. All variables are defined in Appendix B.

Figure 2



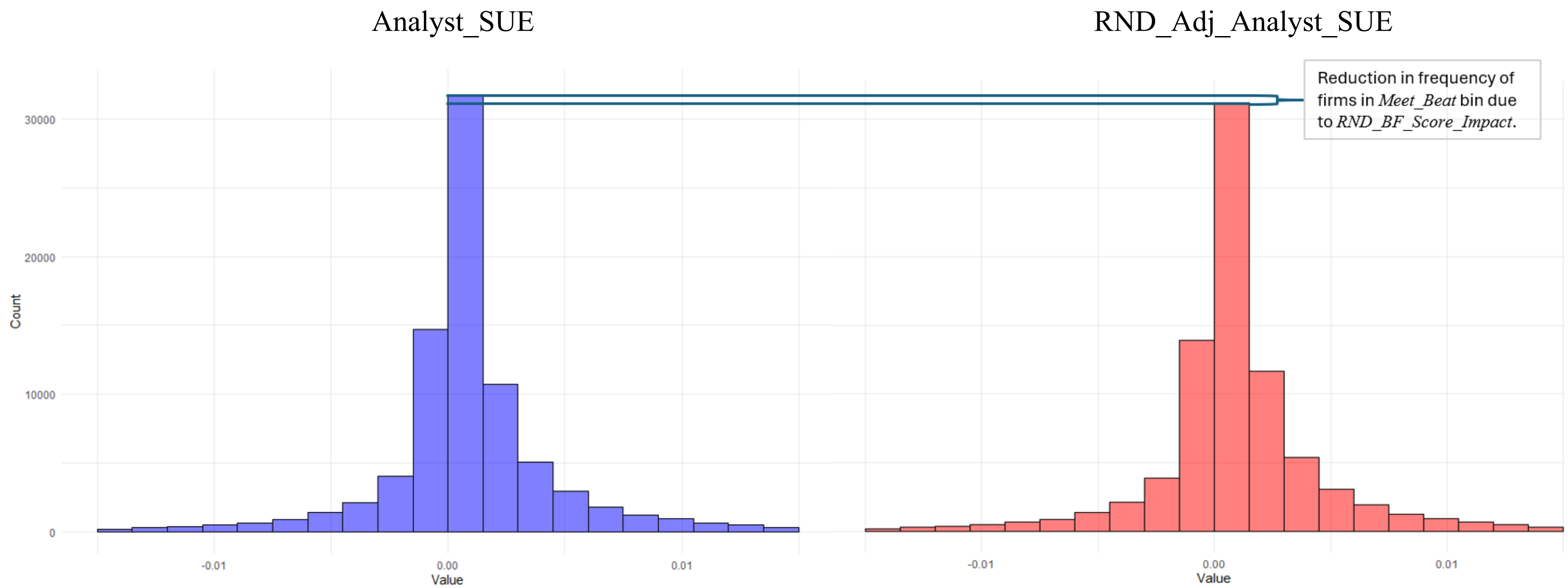
This scatterplot reports the average quarterly *Analyst_SUE* for each percentile rank of *BF_Score* where average *Analyst_SUE* is displayed on the y-axis and the *BF_Score_Rank* (by percentile) is displayed on the x-axis. The red-dotted line represents the best fit line of the data, with the linear regression equation and the correlation between the two variables reported in the lower right-hand corner. All variables are defined in Appendix B.

Figure 3



This figure represents a dot plot which illustrates all 276 industry-year coefficient values for *BF_Score* from Eq (5) which are used in the construction of *Adj_Analyst_SUE.* Industry definitions are based on Fama-French 12 classifications, from Ken French's website. The mean coefficient and t-statistic from all 276 estimations is reprinted in the bottom left-hand corner. All variables are defined in Appendix B.

Figure 4. Histogram of Analyst_SUE vs RND_Adj_Analyst_SUE_Adj

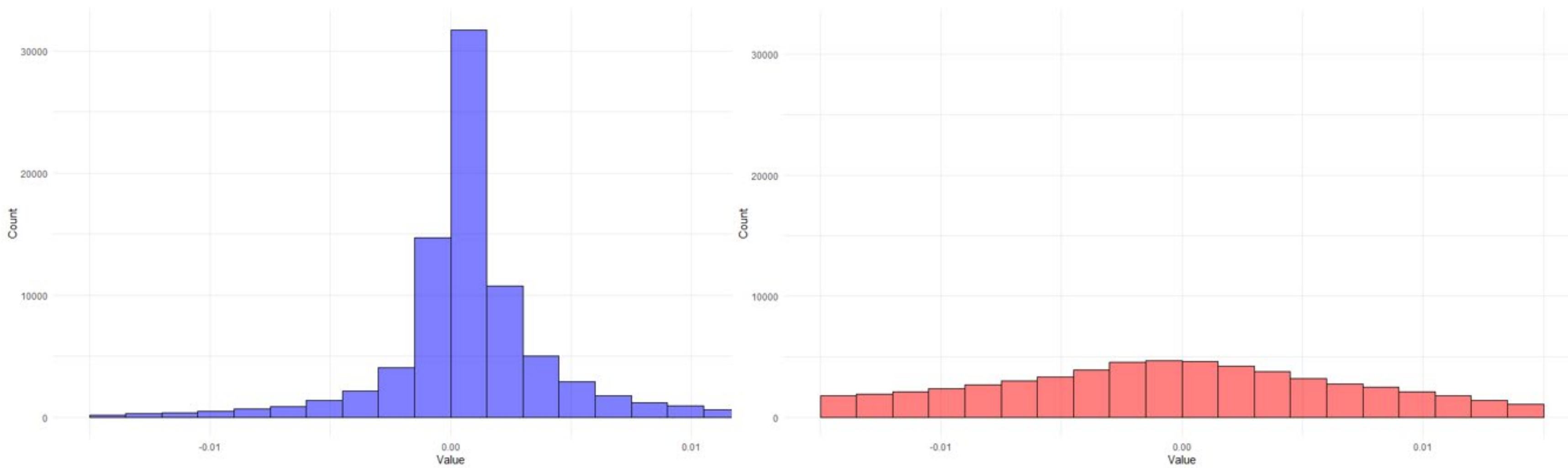


	Analyst_SUE (Unadjusted)	**Adj_Analyst_SUE (BF_Score_Impact)**	**Characteristics of Normal Distribution**	**Improvement towards Normal Distribution**
Kink Asymmetry Ratio	2.43	2.25	1.00	13%
Anderson-Darling test	AD 3728.5 p-value < 1%	AD 3478.2 p-value < 1%	0.00	6.7%
Skewness	-0.0624	-0.0302	0.00	51%
Kurtosis	7.6418	7.4825	3.00	3%

This figure is a histogram of that illustrates the adjustments from randomized values generated from a distribution with the same mean and variance as *BF_Score*, which we describe in detail in Section 7. The blue represents the reduction in frequency following the adjustment, while the orange represents the increase in frequency within each bin of *Analyst_SUE*. *KS*, *AD* and *Skew* metrics are reported for both the distributions of *Analyst_SUE* and *RND_Adj_Analyst_SUE*. Improvement towards normal is calculated based on the metrics observed in a normal distribution. All variables are defined in Appendix B.

Figure 5. Histogram of Analyst_SUE vs ALL_Adj_Analyst_SUE

Analyst_SUE | ALL_Adj_Analyst_SUE

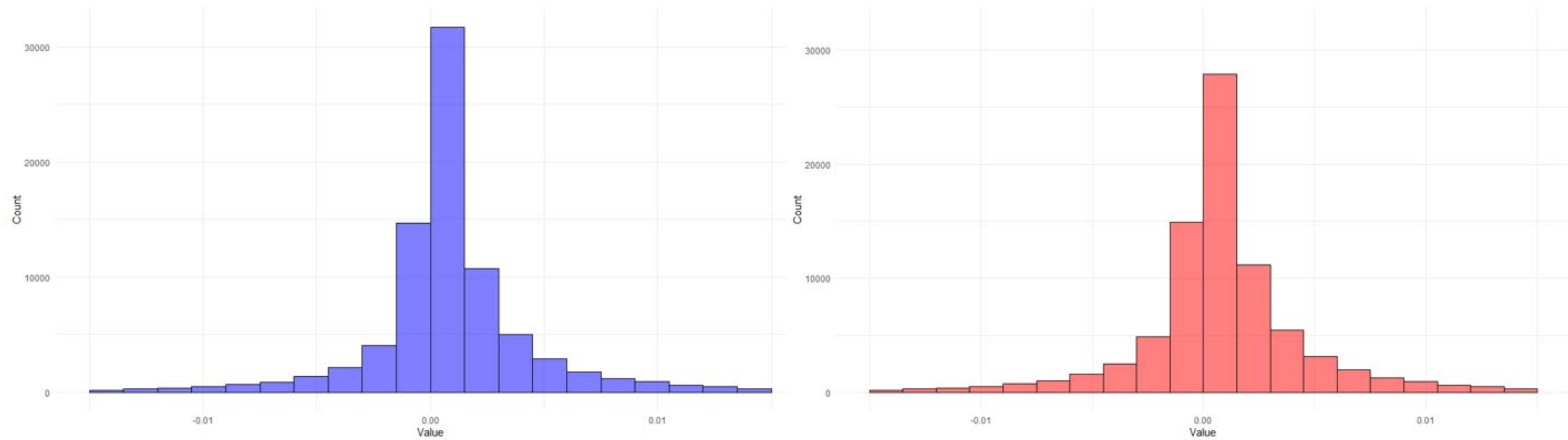


	Analyst_SUE (Unadjusted)	**Adj_Analyst_SUE (BF_Score_Impact)**	**Characteristics of Normal Distribution**	**Improvement towards Normal Distribution**
Kink Asymmetry Ratio	2.43	0.98	1.00	101.4%
Anderson-Darling test	AD 3728.5 p-value < 1%	AD 676.31 p-value < 1%	0.00	81.9%
Skewness	-0.0624	0.1457	0.00	-133.49%
Kurtosis	7.6418	6.8776	3.00	16.5%

This figure is a histogram that illustrates the adjustments from the predicted values generated using the control variables included in our regression. The blue represents the reduction in frequency following the adjustment, while the orange represents the increase in frequency within each bin of *Analyst_SUE*. *KS*, *AD* and *Skew* metrics are reported for both the distributions of *Analyst_SUE* and *ALL_Adj_Analyst_SUE*. Improvement towards normal is calculated based on the metrics observed in a normal distribution. All variables are defined in Appendix B.

Figure 6. Histogram of Analyst_SUE vs ACC_Adj_Analyst_SUE

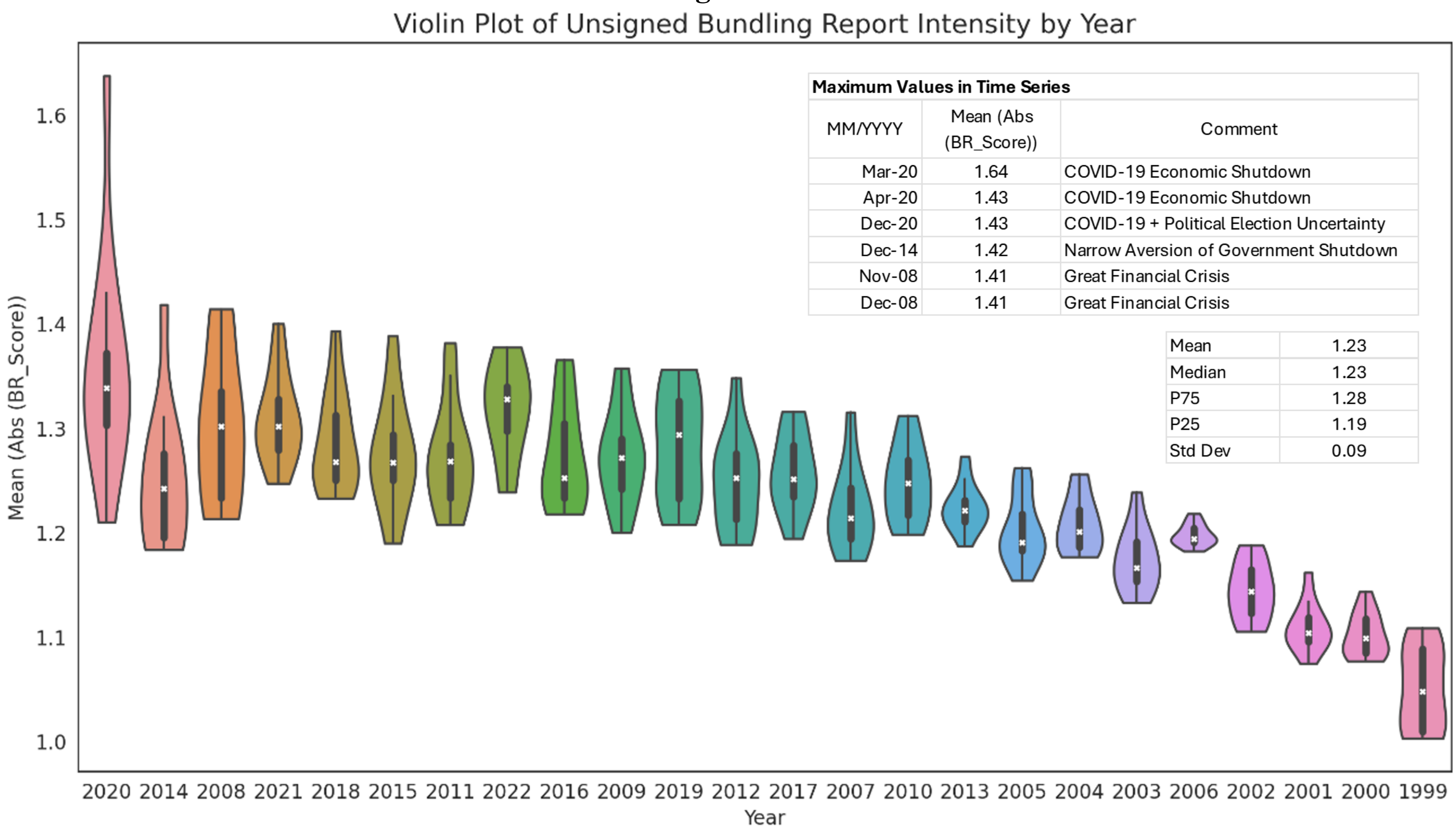
Analyst_SUE — ACC_Adj_Analyst_SUE



	Analyst_SUE (Unadjusted)	**Adj_Analyst_SUE (BF_Score_Impact)**	**Characteristics of Normal Distribution**	**Improvement towards Normal Distribution**
Kink Asymmetry Ratio	2.43	1.97	1.00	32.17%
Anderson-Darling test	AD 3728.5 p-value < 1%	AD 2611.6 p-value < 1%	0.00	29.96%
Skewness	-0.0624	-0.0192	0.00	69.23%
Kurtosis	7.6418	6.3219	3.00	28.44%

This figure is a histogram that illustrates the adjustments from the predicted values of discretionary accruals. The blue represents the reduction in frequency following the adjustment, while the orange represents the increase in frequency within each bin of *Analyst_SUE*. *KS*, *AD* and *Skew* metrics are reported for both the distributions of *Analyst_SUE* and *ACC_Adj_Analyst_SUE*. Improvement towards normal is calculated based on the metrics observed in a normal distribution. All variables are defined in Appendix B.

Figure 7



This figure represents a violin plot of unsigned bundling report intensity (without kernel density estimation) by descending year. Each year's violin plot represents the mean unsigned bundling intensity for each EPS forecast report, *Mean(Abs(BR_Score))* in a given year-month. The width of each violin represents the density of observations. "X" in each year represents the median value. Each box represents the interquartile range (IQR), while whiskers represent outliers that extend beyond 1.5x IQR. The upper right corner tabulates the year-month of the top 6 values in the time series along with univariate summary statistics for unsigned bundling report intensity, *Mean(Abs(BR_Score))*. All variables are defined in Appendix B.

Table 1. Descriptive Statistics – Bundling Intensity

Panel A Bundling at report level

	Total	Stand-Alone	Bundle-2	Bundle-3	Inconsistent
FEPS-All	846,472	590,349	176,354	13,214	66,079
		70%	21%	2%	8%
FEPS-Pos	346,247	238,498	78,473	5,855	23,421
	41%	69%	23%	2%	7%
FEPS-Neg	500,225	351,851	97,881	7,359	43,134
	59%	70%	20%	1%	9%

Panel B Univariate statistics for report-level bundling intensity, *BR_Score*.

(1) *BR_Score*	(2) Frequency	(3) Mean EPS_Rev	(4) SD of EPS_REV	(5) Mean_CAR	(6) *t*-stat of CAR	(7) Comparison
-3	7,359	-0.7159	0.6973	-0.0648***	-89.8243	(-3 vs -2)
-2	97,881	-0.6644	0.6448	-0.0314***	-33.9007	(-2 vs -1)
-1	351,851	-0.5686	0.5989	-0.0099***	-95.3771	(-1 vs zero ret)
1	238,498	0.4213	0.4423	0.0064***	57.099	(1 vs zero ret)
2	78,473	0.4308	0.4379	0.0177***	50.7037	(2 vs 1)
3	5,855	0.4151	0.431	0.0361 ***	26.7502	(3 vs 2)

The sample comprises analyst earnings forecasts for the current quarter's earnings relating to fiscal years ending from 1999 to 2021. Panel A of this table presents distributional statistics for analyst EPS forecast revisions that are used to construct *BR_Score* and *EPS_rev*. Panel A reveals the frequency of positive and negative FEPS revisions, and the relative frequency of stand-alone observations, observations that are bundled with 1 other consistent signal (Bundle-2) and observations that are bundled with 2 other consistent signals (Bundle-3). Revisions that are bundled with signals that are inconsistent as the FEPS revision are labeled as inconsistent. Panel B of this table provides a frequency distribution of *BR_Score* from [-3 to +3] as well as the mean and standard deviation of *EPS_rev* for each level of *BR_Score* from [-3 to 3] in columns 3 and 4. Columns 5 and 6 tabulate the mean 3-day market-adjusted event return around the EPS revision And the corresponding t-statistic based on the comparisons in column 7.

Table 2. Descriptive Statistics and Correlation Matrix

Panel A Descriptive Statistics

Variables	Mean	SD	P25	P50	P75	N
Analyst_SUE	0.00013	0.021	0.000	0.000	0.002	82,164
BF_Score	-0.169	0.990	-1.000	-0.250	0.667	82,164
EPS_aggrev	-0.168	0.590	-0.386	-0.073	0.138	82,164
REC_aggrev	-0.028	0.717	0.000	0.000	0.000	82,164
TP_aggrev	0.001	0.680	-0.276	0.000	0.344	82,164
Size	8.189	1.678	7.003	8.114	9.342	82,164
BM	0.504	0.426	0.232	0.415	0.674	82,164
LTG	14.889	21.103	8.880	12.730	18.100	82,164
Momentum	0.025	0.281	-0.120	0.019	0.160	82,164
Acc	-0.030	0.061	-0.052	-0.020	0.000	82,164
MB	0.394	0.489	0.000	0.000	1.000	82,164
D_Acc	-0.006	0.045	-0.009	0.000	0.000	82,164
VIX	-0.024	0.956	-0.634	-0.247	0.280	82,164
Volatility	21.125	9.231	15.187	18.273	24.220	82,164
Disp_ngdp	1.566	1.323	1.087	1.228	1.583	82,164
Disp_indprod	2.820	3.512	1.605	2.059	2.677	82,164
Disp_rgdp	1.077	1.140	0.682	0.811	1.100	82,164

This table provides descriptive statistics for firm-level variables used in this study. All variables are defined in Appendix B.

Panel B Correlation Matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
(1) Analyst_SUE																
(2) BF_Score	0.07															
(3) EPS_aggrev	0.06	0.69														
(4) REC_aggrev	0.02	0.23	0.14													
(5) TP_aggrev	0.04	0.52	0.32	0.25												
(6) Size	0.07	0.18	0.20	0.06	0.16											
(7) BM	-0.07	-0.18	-0.15	-0.03	-0.16	-0.30										
(8) LTG	0	0.01	-0.01	-0.01	-0.01	-0.06	-0.11									
(9) Momentum	0.07	0.27	0.19	0.07	0.26	0.11	-0.27	0.05								
(10) Acc	0.05	0.01	0.02	0.01	0.03	0.13	-0.01	-0.03	0.04							
(11) Meet_Beat	0.0171	0.095	0.079	0.014	0.076	0.232	-0.223	0.013	0.101	0.078						
(12) D_Acc	0.0092	0	0.013	0.007	0.007	0.011	0.032	-0.032	-0.032	0.190	-0.014					
(13) VIX	-0.031	-0.150	-0.094	-0.020	-0.229	-0.113	0.180	-0.011	-0.023	-0.068	-0.083	-0.028				
(14) Volatility	-0.024	-0.151	-0.091	-0.021	-0.222	-0.084	0.126	0.008	-0.015	-0.036	-0.060	-0.025	0.809			
(15) Disp_ngdp	0.017	0.091	0.060	0.026	0.065	0.060	0.020	-0.047	-0.008	-0.030	-0.060	0.014	0.250	0.205		
(16) Disp_indprod	0.019	0.093	0.054	0.028	0.064	0.037	0.035	-0.058	0.011	-0.059	-0.064	0.007	0.290	0.224	0.926	
(17) Disp_rgdp	0.016	0.080	0.049	0.020	0.049	0.055	0.020	-0.043	-0.005	-0.004	-0.058	0.011	0.287	0.244	0.961	0.929

This table provides Pearson correlation coefficients for firm-level variables used in this study. All variables are defined in Appendix B.

Table 3. Report-Level Bundling Intensity and 3-Day Event Returns

Panel A Bundling Intensity and Cumulative Abnormal Return

Dependent Variable:	***CAR_Report***		
	(1)	(2)	(3)
	Coef.	Coef.	Coef.
	t-Stat.	*t*-Stat.	*t*-Stat.
BR_Score	*9.942****	2.937***	2.694***
	(19.492)	(10.304)	(8.918)
EPS_rev		12.209***	12.135***
		(16.355)	(15.737)
REC_rev		20.490***	18.698***
		(30.541)	(26.404)
TP_rev		13.412***	11.302***
		(13.451)	(12.350)
Size			-0.170
			(-0.977)
BM			-4.445***
			(-4.523)
Acc			0.003
			(1.181)
LTG			-0.025
			(-1.479)
Momentum			0.005***
			(3.852)
Fixed effects			
Firm	Yes	Yes	Yes
Analyst	Yes	Yes	Yes
Year-Quarter	Yes	Yes	Yes
Adjusted R-Squared	12.1%	14.9%	16.7%
No. of Observations	779,917	779,917	603,145

This table presents the results of estimating Eq (2) with the cumulative abnormal return on the EPS report date as the dependent variable (*CAR_report*). Each column reports estimates using OLS regression. Coefficients on *BR_Score*, *EPS_rev*, *REC_rev* and *TP_rev* are multiplied by 1,000 for ease of interpretation. Control variables are defined in Appendix B. Each unit of observation is one analyst EPS report revision. All regressions include firm, analyst and year-quarter fixed effects. t-statistics are in parentheses beneath coefficient estimates. Standard errors are clustered at the firm level. Significance levels are indicated: * = 10%, ** = 5%, *** = 1%.

Panel B Bundling Intensity and forecast error

Dependent Variable:	***FE_Report***		
	(1)	(2)	(3)
	Coef.	Coef.	Coef.
	t-Stat.	*t*-Stat.	*t*-Stat.
BR_Score	*0.108***	0.933***	0.776***
	(2.296)	(11.513)	(9.729)
EPS_rev		-2.483***	-2.377***
		(-13.363)	(-11.775)
REC_rev		-0.122	-0.142
		(-0.621)	(-0.762)
TP_rev		0.334**	-0.062
		(2.248)	(-0.351)
Size			-0.007
			(-0.032)
BM			-3.717***
			(-3.258)
Acc			0.006*
			(1.667)
LTG			-0.007
			(-0.300)
Momentum			0.005***
			(4.540)
Fixed effects			
Firm	Yes	Yes	Yes
Analyst	Yes	Yes	Yes
Year-Quarter	Yes	Yes	Yes
Adjusted R-Squared	12.5%	12.6%	14.3%
No. of Observations	779,917	779,917	603,145

This table presents the results of estimating Eq (3) with the forecast error at the report level (*FE_Report*). Each column reports estimates using OLS regression. Coefficients on *BR_Score*, *EPS_rev*, *REC_rev* and *TP_rev* are multiplied by 1,000 for ease of interpretation. Control variables are defined in Appendix B. Each unit of observation is one analyst EPS report revision. All regressions include firm, analyst and year-quarter fixed effects. t-statistics are in parentheses beneath coefficient estimates. Standard errors are clustered at the firm level. Significance levels are indicated: * = 10%, ** = 5%, *** = 1%.

Table 4. Report-Level Bundling Intensity and Report Forecast Error

Panel A Bundling Intensity Decile Rank and *Analyst_SUE*

BF_Score_Rank10	**Analyst_SUE**	**SD of Analyst_SUE**	**Frequency**
10	0.0022	0.0127	8150
9	0.002	0.0129	3856
8	0.0018	0.0175	10954
7	0.0007	0.0183	8117
6	0.0005	0.0195	9421
5	-0.0001	0.0222	8800
4	0.0004	0.0209	3114
3	-0.0008	0.0223	13089
2	-0.0013	0.0246	8325
1	-0.0027	0.0265	8338
(10 – 1)	**-0.0049**	**t-stat = -15.2018**	

This table provides the mean and standard deviation of *Analyst_SUE* for each decile of rank of *BF_Score* in the sample and provides a univariate test comparing *Analyst_SUE* for decile 10 minus decile 1. All variables are defined in Appendix B.

Panel B: Analyst-based Earnings Surprise and *BF_Score*

Dependent Variable:	***Analyst_SUE***		
	(1)	(2)	(3)
	Coef.	Coef.	Coef.
	t-Stat.	*t*-Stat.	*t*-Stat.
BF_Score	1.000***	0.649***	0.514***
	(12.189)	(5.632)	(4.463)
EPS_aggrev		0.705***	0.562**
		(2.920)	(2.362)
REC_aggrev		0.019	0.052
		(0.183)	(0.501)
TP_aggrev		0.211	-0.063
		(1.591)	(-0.472)
Size			0.452
			(1.312)
BM			-2.984***
			(-3.587)
Acc			0.022***
			(7.637)
LTG			-0.035***
			(-2.881)
Momentum			0.002***
			(3.970)
Fixed effects			
Firm	Yes	Yes	Yes
Year-Quarter	Yes	Yes	Yes
Adjusted R-Squared	13.1%	13.1%	13.7%
No. of Observations	82,164	82,164	82,164

This table presents the results of estimating Eq (4) with the analyst-based earnings surprise (*Analyst_SUE*). Each column reports estimates using OLS regression. *Coefficients on BF_Score, EPS_aggrev, REC_aggrev and TP_aggrev are multiplied by 1,000 for ease of interpretation.* Control variables are defined in Appendix B. The unit of observation is a firm-quarter. All regressions include firm and year-quarter fixed effects. *t*-statistics are in parentheses beneath coefficient estimates. Standard errors are clustered at the firm level. Significance levels are indicated: * = 10%, ** = 5%, *** = 1%.

Table 5. Macroeconomic Uncertainty and Bundling Intensity

Dependent Variable:	***Abs_BF_Score***				
	(1)	(2)	(3)	(4)	(5)
	Coef.	Coef.	Coef.	Coef.	Coef.
	t-Stat.	*t*-Stat.	*t*-Stat.	*t*-Stat.	*t*-Stat.
VIX	*0.039****				
	(4.266)				
EM_Volatility		*0.002****			
		(3.844)			
Disp_ngdp			*0.005****		
			(3.059)		
Disp_indprod				*0.003****	
				(4.108)	
Disp_rgdp					*0.007****
					(3.650)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Firm	Yes	Yes	Yes	Yes	Yes
Quarter-Year	Yes	Yes	No	No	No
Adjusted R-Squared	36.7%	36.7%	35.8%	35.8%	35.8%
No. of Observations	82,164	82,164	82,164	82,164	82,164

This table presents the results of estimating Eq (8) with the absolute firm-level forecast bundling (*Abs_BF_Score)* as the dependent variable. Each column reports estimates using OLS regression. Control variables are *Abs_EPS_aggrev*, *Abs_REC_aggrev*, *Abs_TP_aggrev*, *Size*, *BM*, *Acc*, *LTG*, and *Momentum*. The unit of observation is a firm-quarter. Column (1) and Column (2) include quarter-year fixed effects. t-statistics are in parentheses beneath coefficient estimates. Standard errors are clustered at the firm level. Significance levels are indicated: * = 10%, ** = 5%, *** = 1%. All variables are defined in Appendix B.

Table 6. Macroeconomic Uncertainty, Bundling Intensity and Forecast Error

Dependent Variable:	*Analyst_SUE*				
	(1)	(2)	(3)	(4)	(5)
	Coef.	Coef.	Coef.	Coef.	Coef.
	t-Stat.	*t*-Stat.	*t*-Stat.	*t*-Stat.	*t*-Stat.
*VIX*BF_Score*	*0.019****				
	(2.633)				
EM_Volatility BF_Score*		*0.024***			
		(2.522)			
Disp_ngdp BF_Score*			*0.099****		
			(2.823)		
Disp_indprod BF_Score*				*0.035***	
				(2.233)	
Disp_rgdp BF_Score*					*0.130***
					(2.429)
BF_Score	0.111	0.063	0.401***	0.459***	0.419***
	(0.672)	(0.304)	(4.021)	(5.007)	(4.290)
VIX	-0.000				
	(-1.016)				
EM_Volatility		-0.000			
		(-1.299)			
Disp_ngdp			0.000***		
			(4.687)		
Disp_indprod				0.000***	
				(4.243)	
Disp_rgdp					0.000***
					(3.978)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Firm	Yes	Yes	Yes	Yes	Yes
Quarter-Year	No	No	No	No	No
Adjusted R-Squared	13.4%	13.4%	13.4%	13.4%	13.4%
No. of Observations	82,164	82,164	82,164	82,164	82,164

This table presents the results of estimating Eq (9) with the analyst forecast error (*Analyst_SUE)* as the dependent variable. Each column reports estimates using OLS regression. Coefficients on BF_Score are multiplied by 1,000 for ease of interpretation. Control variables are *EPS_aggrev*, *REC_aggrev*, *TP_aggrev*, *Size*, *BM*, *Acc*, *LTG*, and *Momentum*. The unit of observation is a firm-quarter. All regressions include firm fixed effects. *t*-statistics are in parentheses beneath coefficient estimates. Standard errors are clustered at the firm level. Significance levels are indicated: * = 10%, ** = 5%, *** = 1%. Control variables are defined in Appendix B.

Table 7. Bundling Intensity and Meeting or Beating Analyst Forecasts

Dependent Variable:		***Meet_Beat***	
	(1)	(2)	(3)
	Coef.	Coef.	Coef.
	t-Stat.	*t*-Stat.	*t*-Stat.
*BF_Score *Discret_Acc*			-83.715***
			(-2.663)
BF_Score		10.018***	9.567***
		(4.428)	(4.218)
Discret_Acc	0.131***	0.130***	0.115***
	(3.070)	(3.062)	(2.655)
Controls	Yes	Yes	Yes
Fixed effects			
Firm	Yes	Yes	Yes
Year-Quarter	Yes	Yes	Yes
Adjusted R-Squared	23.3%	23.3%	23.4%
No. of Observations	82,164	82,164	82,164

This table presents the results of estimating Eq (10) with Meet or Beat analyst consensus earnings forecast (*Meet or beat)* as the dependent variable. Coefficients on BF_Score are multiplied by 1,000 for ease of interpretation. Control variables are *EPS_aggrev*, *REC_aggrev*, *TP_aggrev*, *Size*, *BM*, *Acc*, *LTG*, and *Momentum*. The unit of observation is a firm-quarter. All regressions include firm and year-quarter fixed effects. t-statistics are in parentheses beneath coefficient estimates. Standard errors are clustered at the firm level. Significance levels are indicated: * = 10%, ** = 5%, *** = 1%. Control variables are defined in Appendix B.