Contrast Effects and Analyst Forecasts

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Abstract

Contrast effect occurs when decision makers unconsciously interpret a signal by contrasting it with the preceding signal. Using the setting of analyst forecast revisions in response to firms' earnings announcements on consecutive days, we document evidence of contrast effects only if the announcing firms on both days are covered by the same analyst. The effects are driven by less experienced or skilled analysts and by scenarios where the benchmark earnings news on the preceding day likely receives more attention, such as larger earnings surprise or larger announcing firm. While investors are found to contrast earnings news against the preceding day's earnings news from bellwether firms, analysts do not appear to benchmark against these firms if they are not covered. We also find that contrast effects negatively impact the analyst forecast accuracy and that analysts seek to correct initial errors with subsequent revisions, consistent with contrast effect as an unconscious bias rather than an intentional strategy. Additional analyses suggest that our results are not driven by mechanical relations between earnings news on consecutive days such as information transfer and are exacerbated when analysts suffer from limited attention or decision fatigue.

Keywords: financial analysts, earnings forecasts, contrast effects

EFM Classification Codes: 200, 350, 710, 720,

1. Introduction

Extensive evidence from psychology research shows that people tend to interpret information by contrasting it with their recent observations (Pepiton and DiNubile, 1976; Kenrick and Gutierres, 1980). This heuristic is referred to as contrast effects, which can manifest as a magnification (or a diminishment) of perception following a previous exposure to something of lesser (or greater) quality but of the same base characteristics.[1]

While most anecdotal evidence of contrast effects comes from laboratory experiments, recent empirical studies try to examine how contrast effects impact decision making in real-world settings. For example, Hartzmark and Shue (2018) document that investors mistakenly perceive earnings news today as more (less) impressive if yesterday's earnings surprise was bad (good), consistent with the contrast effect theory.[2] Researchers in finance and accounting have long been interested in financial analysts as sophisticated information intermediaries, as evidenced by a vast literature (e.g., Ramnath, Rock, and Shane 2008; Beyer, Cohen, Lys, and Walther 2010; Kothari, So, and Verdi 2016). While most prior studies focus on analysts' reactions to individual earnings announcements, in this paper, we study how a sequence of earnings announcements affects analyst forecast revisions by examining whether contrast effects manifest in analyst forecast revisions in response to earnings announcements on consecutive days, and if so, how they differ from investors in terms of their exhibited contrast effects.

We examine how previous earnings news affects an analyst's perception of subsequent earnings news. This investigation is not trivial, as it is unclear whether analysts are subject to

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[1] See definition from Study.com: https://study.com/academy/lesson/contrast-effect-definition-example

[2] An earlier study by Simonsohn (2006) documents that people just moving to a new city tend to choose longer commutes if they had longer commutes in their previous city.

contrast effects. On the one hand, their skills and experience as sophisticated information intermediaries should make them less susceptible to common behavioral biases. On the other hand, analysts often have to analyze multiple earnings announcements in a short time period, which could increase their susceptibility to contrast effects.

In particular, earnings announcements are increasingly clustered in recent years (Driskill, Kirk, and Tucker, 2020). Depending on an analyst's coverage portfolio, such clustering could require her to analyze multiple earnings news concurrently or within a short window. Driskill et al. (2020) find that over half of their sample firm-quarter-analyst observations contain multiple earnings announcements on the same day. Moreover, earnings announcements are typically scheduled weeks ahead, with the median firm scheduling its earnings announcement 14 days before the actual announcement date deHann et al., 2015). Thus, the actual earnings announcement date is likely exogenous to individual analyst characteristics and is unlikely to be correlated with firm fundamentals (Hirshleifer et al., 2019).

Applied to the setting of earnings announcements, contrast effects theory implies that yesterday's earnings news should inversely bias the perception of today's earnings news. Consistent with this for investors' perceptions, Hartzmark and Shue (2018) find that stock price reaction to today's earnings news is negatively related to yesterday's earnings news from large and influential firms. We focus on analyst forecast revisions as their responses to today's earnings news and examine the influence of yesterday's earnings news. Contrast effect theory predicts that analysts' earnings revisions will be inversely impacted by yesterday's earnings surprise. If yesterday's earnings surprise was positive, it will make today's positive earnings news less impressive but today's negative earnings news more disappointing. Conversely, if yesterday's earnings surprise was negative, it will make today's negative earnings news less disappointing but positive earnings news more impressive. In other words, according to contrast effects, we expect analysts to underreact (overreact) to earnings news if it is preceded by earnings news in the same (opposite) direction on the previous day. Our main results are consistent with this prediction.

We next explore the cross-sectional variations of the contrast effects documented above. We first examine how contrast effect varies with an analyst's experience and ability. On the one hand, more experienced analysts with higher prior forecast accuracy are more capable of multitasking and working under pressure and thus less susceptible to contrast effects. On the other hand, even junior analysts without a record of accurate prior forecasts are professionals well-trained to work under pressure during earnings seasons and hence are expected to guard against the contrast effects (Bradshaw et al., 2017). Consistent with the former argument, we find that less experienced analysts and analysts with less accurate prior forecasts are affected by contrast effects whereas more experienced analysts and those with more accurate prior forecasts are not affected.

We then investigate whether contrast effect varies with the salience of the benchmark earnings signal on day t-1. Given analysts' resource and time constraints, we expect them to allocate more time and effort to earnings news on day t-1 if the earnings news magnitude on day t-1 is larger or if the announcing firm on day t-1 is relative large hence more important. Consistent with these expectations, we find significant contrast effect in the subsample with larger earnings news magnitude on day t-1 and larger announcing firms on day t-1, but no significant evidence of contrast effect in the subsample with smaller earnings news on day t-1 and smaller announcing firms on day t-1.

The above finding leads us to further explore the benchmark earnings news that subject analysts to contrast effects. Hartzmark and Shue (2018) show that investors exhibit contrast effect with respect to market-wide earnings news or earnings announcement from large influential firms on the prior day. Interestingly, when we use the same benchmark following their approach, we find no contrast effects on analysts, suggesting that analysts only exhibit contrast effect with respect to firms in their coverage portfolios. To further evaluate this, we construct a control sample of analysts that cover the same firms announcing earnings on day t but do not cover the benchmark firms announcing earnings on day t-1 as our treatment analysts do. We find no evidence of contrast effect among this control group. This group also does not exhibit contrast effect with regard to large or influential firms announcing earnings on day t-1. Together, these findings highlight a unique feature of contrast effects on analysts, that is, they only exhibit contrast effects with respect to benchmark firms in their coverage portfolio but not to large or influential firms as investors do (Hartzmark and Shue 2018).

Next, we address the consequence of the contrast effect in terms of its impact on analyst forecast accuracy and subsequent revision. This investigation is important because it helps us better understand whether our documented contrast effect is indeed a behavioral bias that leads to sub-optimal decisions or it is an artifact of some intentional strategy adopted by some analysts. To do so, we first regress analyst forecast error on an indicator for analysts subject to contrast effects (i.e., if they cover both announcing firms on day t-1 and day t) along with control variables. We find that, compared with control analysts not covering the benchmark firm announcing earnings on day t-1, treatment analysts issue forecasts with larger average errors, suggesting an adverse impact of contrast effect on analyst forecast accuracy. As forecast accuracy may not necessarily be the focus of analysts, we next investigate whether analysts subsequently revise their forecasts to correct the under-(over-)reaction in their initial revisions caused by contrast effect when two of their covered firms announce earnings news with the same (opposite) sign on consecutive days, in which scenario we would expect the subsequent revision to be in the same (opposite) direction as the initial revision. Consistent with this and after accounting for analysts' self-select decisions to issue a subsequent revision, we find that analysts tend to revise in the direction predicted by the contrast effect. Together, our findings suggest that contrast effect is unlikely an intentional strategy but rather a behavioral bias that leads to suboptimal decisions that analysts later choose to correct upon realization of the error.

Lastly, we conduct several additional analyses to further our understanding of the contrast effect in analyst forecasts. First, we replace analyst revision with a "pseudo revision" with perfect foresight, which revises an analyst's original forecast fully to the actual earnings. As expected, we do not find evidence of contrast effects using this "pseudo revision", suggesting that contrast effect we document is a unique behavioral trait and is not driven by some mechanical relation between earnings news on consecutive days. Second, to examine how attention-related behavioral biases (e.g., limited attention and decision fatigue) affects contrast effects, we partition our sample based on whether an analyst is considered as "busy" (proxied by the number of forecasts issued by the analyst on day t and whether the revision for firm announcing earnings on day t is timely). We find that contrast effect is driven by the subsample of "busy" analysts but not among the "non-busy" analysts. This finding suggests an interactive effect among behavioral biases in the sense that when analysts are constraint in their efforts and attention, they are more susceptible to other forms of behavioral biases such as contrast effect. Finally, to mitigate the concern that some firms might strategically time their earnings announcements, which then may confound our results, we follow prior studies to construct a subsample of non-strategic earnings announcements. In this subsample we continue to find significant evidence of contrast effect, while we do not find such evidence in the subsample of strategic earnings announcements. This finding suggests that our evidence of contrast effect is not driven by some firms strategically timing their earnings announcements.

Our study contributes to several streams of literature. First, we draw on the literature of contrast effects (e.g., Pepiton and DiNubile, 1976; Kenrick and Gutierres, 1980; Hartzmark and Shue, 2018) to examine whether and how contrast effects manifest in the setting of analyst forecasting. While most existing evidence on analysts' psychological biases mainly comes from experiments and surveys (e.g., Maines and Hand, 1996; Sedor, 2002; Kadous et al., 2006), we empirically examine and find that financial analysts, generally recognized as sophisticated capital market participants, are still subject to cognitive biases when analyzing clustered earnings announcements.

Second, our study also contributes to research on how various factors influence analyst forecast properties. Prior studies find investment banking relationship, trading incentives, and underwriting incentives to affect analyst forecast properties (Hong and Kubik, 2003; Cowen et al., 2006). We document that one type of psychological bias, i.e., contrast effects, also affect analyst forecast properties. Our additional analyses suggest that the contrast effects we document cannot be explained by limited attention or decision fatigue on part of the analysts (Driskill et al. 2020, Hirshleifer et al. 2018).

Finally, our findings suggest that even financial analysts, as sophisticated information intermediaries in the capital market, still exhibit contrast effects when reacting to clustered earnings announcements. As earnings announcement are becoming more clustered in recent years, firms may find it worthwhile to avoid clustering their earnings announcements with other companies, as it may result in unintended consequences, such as suboptimal reactions in analysts' earnings forecasts.

2. Related Literature

Extensive evidence from psychology research shows that people make biased decisions based on past experiences. One example is the "gambler's fallacy", which suggests that people believe that if something happens more frequently than normal during some periods, it will happen less frequently in the future (Tversky and Kahneman, 1971, 1974). Chen et al. (2016) study three real-world settings and show that the gambler's fallacy can bias decision-making. Specifically, they find that asylum judges are more likely to deny asylum after granting asylum to previous application, loan officers are more likely to deny a loan application after approving the previous application, and baseball umpires are more likely to call the current pitch a ball after calling the previous pitch a strike.

Hartzmark and Shue (2018) extend this line of research to the financial market. They show that the stock price reaction to an earnings announcement is inversely related to the earnings surprise announced by large firms on the prior day. This phenomenon that people interpret information by contrasting it with the information that precedes it is referred to as contrast effects.

Prior studies document various incentives that systematically bias analyst forecasts. For example, analysts affiliated with firms' underwriters tend to issue more optimistic forecasts than non-affiliated analysts (Lin and McNichols 1998, Hong and Kubik 2003). Analysts employed by brokerages that fund research through underwriting and trading activities issue relatively pessimistic forecasts due to their trading incentives (Cowen et al. 2006). Analysts also tend to issue more optimistic forecasts for the long-term but more pessimistic forecasts for the short-term to assist managers in meeting short- term expectations (Ke and Yu 2006).

Recent studies also examine how psychological biases affect analyst forecasts. Surveying 86 sell-side analysts, consistent with the psychology theory that scenario thinking inflates individuals' beliefs, Sedor (2002) finds that analysts make more optimistic forecasts when managers provide them with information in scenarios, as opposed to lists. Driskill, Kirk, and Tucker (2020) show that analysts tend to issue lower quality forecast, delay or even skip issuing forecasts when more than one firm in their coverage portfolios announce earnings on the same day. Hirshleifer et al. (2019) document that consistent with decision fatigue, forecast accuracy declines over the course of a day as the number of forecasts the analyst has issued increases.

In this study, we examine whether contrast effects manifest in the setting of analyst forecasts. On the one hand, analysts often have to analyze multiple earnings announcements in a limited time period and are likely subject to contrast effects, resulting in biased reaction to earnings announcements. On the other hand, analysts are sophisticated information intermediaries and are trained to efficiently process and unpack complex information; thus they should be less prone to such bias. This implies that it is an empirical question as whether contrast effects manifest in analyst forecasts. The main prediction of the contrast effects is that, when reacting to earnings announcements on consecutive days, analysts misinterpret today's (day t) earnings news in contrast to yesterday's (day t-1) earnings news. In other words, a positive earnings surprise on day t-1 makes earnings news on day t look slightly worse and a negative earnings surprise on day t-1 makes earnings news on day t look slightly better.

3. Data and Descriptive Statistics

Following Driskill, Kirk, and Tucker (2020), our sample starts from 1999, when the date and time for earnings announcements and individual analyst forecasts became widely available, and ends in 2019. We obtain earnings announcement dates from the I/B/E/S actual data file and exclude earnings announcement dates that are more than 90 days after the fiscal quarter end (deHann et al. 2015). We require analyst forecasts of quarter q to be issued after the earnings announcement for quarter q-1 and before the earnings announcement for quarter q+1 (deHaan et al., 2015; Driskill, Kirk, and Tucker, 2020). We drop observations where the analyst identification is missing (i.e., the analyst code is "000000") and firm observations with only one analyst following. In addition, we require analysts to issue forecast in at least three quarters in a fiscal year. We retrieve firm financial data from Compustat and stock market information from CRSP. Our final sample consists of 260,216 firm-quarter-analyst-forecasts, covering 75,982 unique firm-quarters.

A key variable in our study is earnings surprise. We follow prior research and measure it as the difference between reported earnings and the earnings expectation prior to the earnings announcement. Following Hartzmark and Shue (2018), we take each analyst's most recent forecast for a firm and then take the median of this number within a certain time window of each firm's earnings announcement as the earnings expectation for the firm. In the main analysis, we use analyst forecasts made between 2 and 30 days prior to the earnings announcement. In robustness tests, we show that the results are similar when the window starts from 15 or 45 days prior to the earnings announcement.

Similar to Hartzmark and Shue (2018), we scale the difference between the actual earnings and the median analyst forecast by share price of the firm three days prior to the earnings announcement. The estimate of earnings surprise, or unexpected earnings (UE) is:

$$\mathrm{UE}_t = \frac{(Actual\ earnings_t - Median\ analyst\ forecast_{[t-30,t-2]})}{Stock\ price_{t-3}}$$

where day t is the earnings announcement date. Following Hartzmark and Shue (2018), when multiple firms announce earnings on day t-1, we use the earnings surprise of the firm with the largest market capitalization on that day because such a firm presumably receives the most market attention. Given the constraint of time and effort, analysts are likely to direct their attention to the earnings surprise of the largest firm in their coverage portfolios.[3] To mitigate undue influences of outliers, we winsorize the earnings surprise measure at the 1^{st} and 99^{th} percentiles.

The main dependent variable is analyst revision of earnings forecasts. We measure analyst revision for quarter q as the change in the analyst's forecast for quarter q surrounding the earnings announcement of quarter q-1, scaled by the stock price at the end of the previous quarter q-1.

[3] Multiple earnings announcements on day t-1 account for about 50% of the sample.

Table 1 Panel A reports the summary statistics. The mean (median) analyst forecast revision is -0.0023 (-0.0004), indicating that analysts, on average, revise their forecasts downward, consistent with the 'walk-down' phenomenon documented in prior literature (e.g., Matsumoto, 2002; Richardson et al., 2004; Cotter et al., 2006). The median of earnings surprise on day t and day t-1 are both positive (0.0004), implying that firms, on average, beat the earnings expectation.

Figure 1 shows the distribution of quarterly earnings announcement dates of firms in an average analyst's coverage portfolio. For each earnings season, the date that the first firm announces earnings is set to 0. Roughly 32% of earnings announcements are within 5 trading days after day 0 and 70% of earnings announcements are within 10 trading days after day 0. The mean (median) number of firms covered by an analyst is 14 (15); thus it is common that multiple earnings announcements cluster in time.[4]

4. Empirical Results

4.1 Baseline results

We estimate the following model to assess how the earnings new announced by firm *j* on day t-1 impacts analysts' forecast revisions for firm i, which announces earnings on the following day (day t):

$$\begin{aligned} Revision_{i,t} = {} & \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + \beta_4 UE_{i,t} * \left|UE_{i,t}\right| + \beta_5 UE_{j,t} \\ & * \left|UE_{j,t}\right| + \beta_6 Days\_to\_revise + \beta_7 Prior\_forecast\_error \\ & + \beta_8 CAR[-8,-1] + \beta_9 Log\_analyst + \beta_{10} Log\_firm\_exp + \beta_{11} Log\_firm \\ & + \beta_{12} Log\_mktcap + \beta_{13} B/M + \beta_{14} Special\_items + \beta_{15} Loss \\ & + Analyst\ FE + Firm\ FE + Year\_quater\ FE \\ & + \varepsilon_{i,t} \end{aligned} \quad (1)$$

The dependent variable is analyst forecast revision surrounding the earnings

[4] Driskill, Kirk, and Tucker (2020) report that 52.1% of their sample firm-quarter-analysts experience at least one concurrent announcement (i.e., multiple earnings announcements on the same day).

announcement on day t, scaled by stock price at the end of the previous quarter q-1. $UE_{i,t}$ and $UE_{j,t-1}$ are earnings surprises of firm *i* on day t and firm *j* on day t-1, respectively. The key variable of interest is the interaction term of earnings surprise on day t ($UE_{i,t}$) and day t-1 ($UE_{j,t-1}$). The theory of contrast effects predicts that a positive earnings surprise on day t-1 makes any surprise on day t look slightly worse, leading to an underreaction (overreaction) to a positive (negative) earnings surprise on day t; conversely, a negative earnings surprise on day t-1 makes any surprise on day t look better, leading to an overreaction (underreaction) to a positive (negative) earnings surprise on day t. To put it differently, we expect analysts to underreact to the earnings news on day t if the earnings surprise on day t-1 and day t are of the same sign and overreact to the earnings news on day t if the earnings surprise on day t-1 and day t are of the opposite sign. Given that $\beta_3 * UE_{j,t-1}$ captures the over- or under-reaction to earnings news on day t relative to the base line reaction captured by β_1,[5] we predict a negative coefficient on β_3 if the earnings surprise on day t is positive, and a positive coefficient on β_3 if the earnings surprise on day t is negative. To facilitate the interpretation of the coefficient, we multiply the interaction term ($UE_{i,t} * UE_{j,t-1}$) by minus one (-1) if the earnings surprise on day t is negative such that a negative coefficient on β_3 would be consistent with the predications of contrast effects. We include quadratic terms of earnings surprises ($UE_{i,t} * |UE_{i,t}|$ and $UE_{j,t} * |UE_{j,t-1}|$) to account for potential nonlinearity (Gong et. al, 2011). Following prior literature, we also control for other analyst and firm characteristics that could be associated with analyst revisions. Specifically, we control for the number of analyst following (*Log_analyst*), firm experience of the analyst (*Log_firm_exp*), the number

[5] To see this, take the first derivative of equation (1) with respect to earnings news on day t ($UE_{i,t}$), and the resulting response coefficient consists of the base line element (β_1) plus the incremental element ($\beta_3 * UE_{j,t-1}$).

of firms an analyst follows (*Log_firm*), market capitalization of the firm (*Log_mktcap*), book-to-market ratio of the firm (*B/M*), whether the firm has non-zero special items (*Speical_items*) and whether the firm reports a loss (*Loss*) (Gong et al., 2011; Driskill, Kirk, and Tucker, 2020). We further control for the number of days from the analyst's previous forecast to the current revision (*Days_to_revise*). We also include the analyst's forecast error in the previous quarter (*Prior_forecast_error*) to account for potential mean reversion. Lastly, we control for the cumulative abnormal return over the seven days prior to the earnings announcement (*CAR[-8,-1]*).

Table 2 reports the baseline results, where we include (exclude) control variables in Column 2 (Column 1). Both regressions include analyst, firm, and year-quarter fixed effects to account for variations within analysts, firms, and year-quarters. The results are consistent with the predictions of the contrast effect theory. The coefficient on the interaction term (β_3) of earnings surprises on day t ($UE_{i,t}$) and day t-1 ($UE_{j,t-1}$) is significantly negative at 1% level in both columns (t-stats = -2.65 and -2.25), suggesting that more positive (negative) earnings surprise on day t-1 is associated with less (more) positive revision on day t. The coefficient (β_1) on earnings surprise on day t ($UE_{i,t}$) is also significantly positive, indicating that analysts revise up (down) their forecasts in response to a positive (negative) earnings surprise, in the absence of any earnings surprise on day t-1.

Turning to the control variables, consistent with longer-horizon analyst forecasts are on average more optimistic (Bradshaw, 2011), *Days_to_revise* is significantly negative (t-stat = -3.54), indicating more downward revisions from longer-horizon analyst forecasts. Moreover, consistent with analysts revising their forecasts to correct prior errors, *Prior_forecast_error* is significantly negative (t-stat = -15.56), indicating more downward revisions from forecasts with more positive errors and vice versa.[6] Including the control variables improves model adjusted R-squared from 0.210 in Column 1 to 0.247 in Column 2, with the sample size decreasing from 258,812 to 240,247 observations.

4.2 Cross Sectional Analyses of Contrast Effects

4.2.1 Analyst's Forecasting Ability and Experience

In this section, we explore how the contrast effect documented in the previous section varies with analysts' ability and experience. On the one hand, more skillful and experienced analysts should be less susceptible to contrast effects. On the other hand, even junior analysts are professionals well-trained to work under pressure during earnings seasons and hence may also not be affected by contrast effect (Bradshaw et al., 2017). Therefore, it is an empirical question whether contrast effect is attenuated by an analyst's ability and experience.

We use an analyst's forecast accuracy in the previous quarter to proxy for analyst ability. Specifically, forecast accuracy is measured as the absolute forecast error of an analyst's last forecast scaled by the stock price at the end of the previous quarter . We measure an analyst's general forecasting experience as the number of quarters since the analyst's first forecast.[7] Table 3 Panel A presents the results. We partition the sample by the median accuracy of analysts' previous forecasts and report the results of the subsample below (above or equal) the median in Columns (1) and (2) (Columns (3) and (4)). We find significant contrast effect, indicated by a negative coefficient (β_3) of the interaction term of earnings surprise on day t

[6] When the analyst's forecast for the previous quarter proves to be overly optimistic (pessimistic) (i.e., containing positive (negative) forecast error) following the earnings announcement, the analyst is likely to revise the current quarter's forecast downward (upward) accordingly, because there is usually a positive correlation in the forecast error in the same analyst's forecasts for the previous quarter and for the current quarter.

[7] In untabulated tests, we also measure use an analyst's firm-specific forecasting experience and obtain similar results. In the rare case where the analyst temporarily skips forecasting for one or more quarters, we subtract those quarters in counting the total of number of quarters of forecasting experience.

($UE_{i,t}$) and day t-1 ($UE_{j,t-1}$), in Columns (1) and (2) but not in Columns (3) and (4). This finding suggests that contrast effect is mainly driven by less skillful analysts, who are more susceptible to psychological bias. Similarly, when we partition the sample by the median forecasting experience, we find significant contrast effects in the subsample with low experience (Columns (5) and (6)) but not in the subsample with high experience (Columns (7) and (8)). This suggests that contrast effect is mainly driven by less experienced analysts, who are more susceptible to psychological bias.

Taken together, our results suggest that forecasting experience and the ability to forecast more accurately appear to mitigate an analyst's susceptibility to contrast effects.

4.2.2 Analyst Attention to the Preceding Day's (Day t-1) Earnings Announcement(s)

Under contrast effects, analysts process earnings news on day t by contrasting it to news on day t-1. We posit that this effect will be more pronounced if the earnings news on day t-1 is more salient or demands more attention from analysts, in which cases it is more likely that analysts are still subconsciously processing earnings news from day t-1 when they react to the earnings news on day t. Prior research suggests that both the magnitude of earnings surprise and the size of the announcing firm are important determinants of analysts attention (Harford, Jiang, Wang, and Xie 2019; Driskill, Kirk, and Tucker 2020). Hence, we expect to observe stronger contrast effects if the earnings news on day t-1 is relatively large or is announced by a relatively large firm covered by the analyst.

To test this prediction, we partition the sample by (a) the magnitude of earnings surprise on day t-1 and (b) the size of firm announcing earnings on day t-1. We then estimate equation (1) separately for each subsample formed by the sample median. Table 3 Panel B presents the results. In Columns (1) and (2) (Columns (3) and (4)), the magnitude of earnings surprise of firm *j* is below (above or equal to) the sample median. Consistent with our prediction, we find significant contrast effects in Columns (3) and (4) (t-stats = -2.34 and -1.90 respectively) but not in Columns (1) and (2) (t-stats=1.09 and 0.98 respectively). This suggests that analysts are more subject to contrast effect if the magnitude of earnings surprise on day t-1 is larger, thus attracting more attention from analysts. In Columns (5) and (6) (Columns (7) and (8)), the size of the firm announcing earnings on day t-1 is below (above or equal to) the sample median. We measure firm size by market capitalization. Similarly, we find significant contrast effects in Columns (7) and (8) (t-stats = -2.08 and -1.77 respectively), but not in Columns (5) and (6) (t-stats=-1.26 and -1.15 respectively). Together, these findings are consistent with the notion that contrast effects are more pronounced when the benchmark firm (i.e., the firm announcing earnings on day t-1) attracts more attention from analysts.

4.3 Benchmark Firms for Contrast Effects Exhibited by Analysts

4.3.1 Using Large Firms *not* Covered by the Analyst as Benchmark

Our analyses thus far focus on earnings announcements on day t-1 from firms covered by the analyst, it remains unclear whether earnings announcements from large firms (as documented by Hartzmark and Shue 2018) not covered by the analyst can also subject the analyst to contrast effects. On the one hand, analysts likely pay less immediate attention to firms they do not cover, and thus are less influenced by these firms' earnings announcements, attenuating contrast effects. On the other hand, Hartzmark and Shue (2018) document that earnings news from large firms on day t-1 subject investors to contrast effects in responding to earnings news on day t. Moreover, earnings news from large firms or from the aggregate market conveys more information on the macro economy and could be important inputs for analysts' fundamental analysis (Hugon, Kumar, and Lin, 2015). Furthermore, as professional information intermediaries, analysts develop their information advantage mainly from their superior knowledge regarding the overall economy (Hutton, Lee, and Shu, 2012). Thus, it is possible that analysts pay close attention to earnings news from large firms even if they do not cover these firms announcing earnings on day t-1. If so, we may observe contrast effects in analyst forecast revisions with benchmark against large firm's earnings news on day t-1, similar to the findings about investors documented by Hartzmark and Shue (2018).[8]

To examine this question, we repeat our analyses by replacing $UE_{j,t-1}$ with two proxies for news from firms not covered by the analyst ($UE_{mkt,t-1}$): (1) earnings surprise of the largest firm, measured by market capitalization, (2) equal-weighted earnings surprise of all large firms, where large firms are defined as firms with a market capitalization that exceeds the 90th percentile of the NYSE index. Table 4 Panel A reports the results from this analysis. In contrast to our earlier findings, we find no evidence of contrast effects in all columns, as the coefficient of the interaction term ($UE_{i,t}*UE_{mkt,t-1}$) is insignificant at conventional levels. This finding is notable in light of the results from Hartzmark and Shue (2018), who show that investors suffer from contrast effects with regard to market-wide earnings news or news from large firms on day t-1. We find that analysts suffer from a different type of contrast effects in that they are not influenced by market-wide earnings news or news from large firms on day t-1, but instead from announcing firms covered in their coverage portfolios.

4.3.2 Analysts Covering Firm *i* on Day t but *not* Covering Firm *j* on Day t-1

The results in the previous section suggest that the contrast effect of analysts differs

[8] Similar to Hartzmark and Shue (2018), our setting is also subject to the alternative story of "information transfer" in the sense that large firms announcing earnings on day t-1 may inform analysts of earnings news on day t, thus affecting analyst reaction to earnings news on day t. We address this issue in section 5.2.

from that of investors as it is the coverage rather than the size of the benchmark firms announcing earnings on day t-1 that is driving the contrast effect for analysts. To further examine the importance of being covered of the benchmark firm for the contrast effect to apply to analysts, and to mitigate the concern that it is some mechanical relation between earnings news on two consecutive days that is driving the contrast effect, we identify a control group of analysts who cover the same firm *i* (announcing earnings on day t) but *not* the same firm *j* (announcing earnings on day t-1) as our previous treatment group of analysts. This setting is ideal because both groups of analysts observe the same sequence of earnings news, and thus any difference in the results can be reasonably attributed to the fact that the control analyst does not cover the benchmark firm announcing earnings on day t-1. Column (1) of Table 4 Panel B presents the result from this analysis. We do not observe a significant contrast effect as the coefficient on the interaction term $UE_{i,t}*UE_{j,t-1}$ is insignificant in Columns (1) and (2) (t-stats = -0.55 and -0.29). This finding mitigates the concern that our main result is driven by some mechanical relation between the earnings news on consecutive days, but instead suggests that only analysts covering both firms announcing earnings exhibit contrast effects when reacting to sequential earnings news.

Continuing with the control group of analysts, who do not exhibit contrast effects with regard to the earnings news from firm j announcing earnings on day t-1 since they do not cover firm j, we next examine whether they exhibit contrast effects instead with regard to large firms announcing earnings on day t-1 as Hartzman and Shue (2018) show for investors. We perform the same analyses on the control group, and report the results in Columns (3)~(6) of Table 4 Panel B. Similar to Columns (1) and (2), we do not find significant contrast effects as the coefficient on the interaction term $UE_{i,t}*UE_{x,t-1}$ is insignificant across Columns (3)~(6) (t-stats range from -1.34 to -0.05). These findings further suggest that financial analysts differ from equity investors as their contrast effects are not driven by large firms but rather by firms in their coverage portfolios.

4.4 The Effect of Recency on Contrast Effects

Our cross-sectional results highlight one dimension of drivers for analysts' contrast effects in terms of the relative importance (thus analyst attention) and the quantity of benchmark signals on day t-1. In this section, we extend this line of investigation to the timing dimension of the benchmark signals, as prior research finds recency (i.e., the immediacy of a past experience relative to the current one) to be a critical factor for contrast effects. Specifically, it is documented that individuals react more strongly in contrast to more recent observations. For example, Hartzmark and Shue (2018) show that investors exhibit the most pronounced contrast effects in their reactions to earnings surprises that are released on day t-1 but weaker for those released on day t-2, and day t-3.

Although a similar finding to Hartzmark and Shue (2018) may extend to our setting of analyst forecast revisions, a different observation is possible given our earlier finding of no contrast effects from analysts with regard to large firms announcing earnings on day t-1. To explore this empirically, we modify equation (1) by adding another two interaction terms, $UE_{i,t}*UE_{k,t-2}$, where $UE_{k,t-2}$ represents the earnings news from firm *k*, which is the latest to be released prior to day t-1 (i.e., on day t-2 or earlier), and $UE_{i,t}*UE_{l,t-3}$, where $UE_{l,t-3}$ represents the earnings news from firm *l*, which is the latest to be released prior to firm k (i.e., on day t-3 or earlier). The coefficients on these interaction terms capture contrast effects from a less recent benchmark earnings surprise than that on day t-1.

Table 4 Panel C presents the results from this analysis with Column (2) (Column (1)) including (excluding) the control variables. In both columns, we find significant contrast effects with regard to earnings surprise from day t-1 (t-stats = -2.17 and -1.89) but insignificant effects with regard to earnings surprise on day t-2 (t-stats = 0.29 and 0.73) and earnings surprise on day t-3 (t-stats = 1.21 and 1.06). These results are consistent with prior findings regarding the effect of recency on contrast effects that individuals react more strongly in contrast to more recent observations.

4.5 How Contrast Effect Affects Analyst Forecast Accuracy and Subsequent Revisions

4.5.1 Contrast Effect and Analyst Forecast Accuracy

In this section, we explore whether contrast effects impact the quality of analyst forecasts. Prior study shows that analysts issue less accurate forecasts when subjected to psychological biases such as decision fatigue or inattention (e.g., Hirshleifer et al., 2019). Therefore, one would expect analysts impacted by contrast effects also to issue less accurate forecasts.

In this analysis, we compare the treatment group of analysts who cover both firm *i* and firm *j* announcing earnings on consecutive days with a control group of analysts who cover the same firm *i* that announces earnings on day t, but do not cover the same firm *j* that announces earnings on day t-1 (same sample as in Table 4 Panel B). Our earlier results suggest that, on average, analysts from the treatment group are subject to contrast effects, while analysts from the control group are not. We then estimate the following equation:

$$Forcast\_error = \alpha + \beta_1 Treatment + Controls + \ Fixed\ Effects + \ \varepsilon_{i,t} \qquad (2)$$

where *forecast_error* is measured as the absolute value of the difference between analyst earnings forecasts and actual reported earnings, scaled by stock price at the end of the previous fiscal quarter. *Treatment* is a dummy variable, which equals 1 for analysts from the treatment group and equals 0 for analysts from the control group. We include the same set of control variables and fixed effects as in equation (1).

Table 5 Panel A presents the results. The coefficient on *treatment* is significantly positive in both Columns (1) and (2) (t-stats = 6.02 and 4.91), implying that compared with analysts from the control sample who do not cover the benchmark firm announcing earnings on day t-1, analysts who cover the benchmark firm and thus subject to the contrast effects issue less accurate forecasts (i.e., with larger forecast errors). The results highlight how psychological biases (i.e., contrast effects) could adversely impact the accuracy of analyst forecasts.

4.5.2 Contrast Effect and Analyst Subsequent Revisions

Psychological biases, such as contrast effects, often lead to suboptimal decision-making (Chen et al., 2016; Hartzmark and Shue, 2018). If analysts fail to revise forecasts efficiently in response to earnings news (i.e., either over- or under-react) due to the contrast effects (depending on whether the earnings news on two consecutive days are in the opposite or the same direction), then analysts are likely to revise their forecasts again (in the opposite or the same direction as the initial revision) to correct the over- or under-reaction in their initial revisions. To test this conjecture, we examine whether analysts revise forecasts subsequent to their initial revision in the direction predicted by the contrast effects; namely, if earnings news on two consecutive days are in the same (opposite) direction, contrast effects predict that analysts tend to underreact (overreact) to earnings news in their initial revision, to correct which the analysts are expected to revise their forecasts in the same (opposite) direction subsequently. This leads to the prediction that whether earnings news on two consecutive days are in the same direction will positively explain whether an analyst's subsequent revision will be in the same direction as her initial revision. Empirically, this prediction translates into a positive coefficient on an indicator of "same sign earnings news" in a regression of the likelihood that an analyst's subsequent revision will be in the "same direction" as her initial revision.

One empirical challenge of this analysis is that only a fraction of analysts revise their forecasts subsequent to their initial revision and at various times throughout the quarter; thus self selection is a valid concern as we observe the direction of analyst subsequent revision only if the analyst decides to revise again. To mitigate this concern, we adopt a Heckman two-stage model, where in the first stage, we model the probability of an analyst revising her forecast as a function of a set of analyst and firm characteristics to compute the inverse mills ratio. In the second stage, we then estimate a Probit model of the likelihood that the analyst's subsequent revision is in the same direction as her initial revision as a function of an indicator of "same sign earnings news" (*News_same_sign*), the inverse mills ratio, and control variables. Specifically, we estimate the following Probit regression in the first stage:

$$Subsequent\ Revision\ Dummy = \alpha + \beta_i Analyst\ and\ Firm\ Characteristics + \varepsilon_{i,t} \quad (3a)$$

where the dependent variable is an indicator that equals to 1 if an analyst revises her forecasts within a certain time window (7, 14, or 30 days) after her initial forecast and equals to 0 otherwise. We then compute the inverse mills ratio and include it in the second stage Probit regression specified as below:

$$Same\ Direction\ Revision\ Dummy$$
$$= \alpha + \beta_1 News\_same\_sign + \beta_2 Inverse\_Mills\_Ratio + \beta_3 Controls + \varepsilon_{i,t} \quad (3b)$$

where the dependent variable is an indicator variable that equals to 1 if an analyst's subsequent revision is in the same direction as her initial revision following the earnings announcement (i.e., both upward or downward) and equals to 0 otherwise. The main independent variable, *News_same_sign*, is an indicator variable that equals 1 if the earnings news on day t-1 and on day t have the same sign (i.e., both positive or negative), and equals 0 otherwise.

Table 5 Panels B1 and B2 present the results from estimating equations (3a) and (3b) respectively. Panel B1 shows the likelihood of an analyst revising her forecast increases in the absolute error of her prior forecast. In addition, more experienced analysts are less likely to revise forecasts, possibly because more experienced analysts issue more accurate forecasts in the first place and therefore have less need to revise subsequently. In Panel B2, we find a positive coefficient on *News_same_sign* in all specifications over various revision windows (t-stat ranges between 13.81 and 16.30). This result is consistent with analysts who are subject to contrast effects revising in the direction that corrects the over- or under-reaction in their initial forecast revisions caused by the contrast effects. Notably, the coefficient on the inverse mills ratio is significant in all specifications, suggesting the necessity of accounting for the self-selection of analysts' decisions to revise again following the initial revision.

Collectively, the findings in this section are consistent with the notion that contrast effects lead analysts to suboptimal decision-making when reacting to a cluster of earnings announcements. Although the initial revisions by analysts subject to contrast effects are less accurate, these analysts appear to partially correct such errors in their subsequent revisions.

5. Additional Analyses and Alternative Explanations

5.1 Pseudo Revisions with "Perfect Foresight"

While our main results are consistent with analysts subject to contrast effects in the sense that they overreact (underreact) to earnings news on day t if another of their covered firms announces earnings on day t-1 in the opposite (same) direction as the earnings news on day t. Two concerns about this interpretation motivate us to use pseudo revisions with "perfect foresight" as the dependent variable (i.e., assuming that analysts know the actual earnings, then they would revise their forecasts to the actual earnings). The first concern is that our results may be driven by a mechanical relation between earnings news announced on consecutive days rather than the behavioral explanation of contrast effects.[9] If our results are driven by contrast effects, we do not expect to obtain similar results using pseudo revisions as they do not depend on analysts' judgement. The second concern is that our results may reflect some analysts' intentional revision strategies that somehow enable them to revise forecasts closer to actual earnings.[10] If this is the case, we would expect pseudo revisions to exhibit similar contrast effects as we document in analyst revisions.

Table 6 Panel A reports the results. We find that the interaction term of earnings surprise on day t ($UE_{i,t}$) and day t-1 ($UE_{j,t-1}$) is insignificant in both Columns (1) and (2) (t-stats = 1.05 and 0.65), hence no evidence of contrast effects for pseudo revisions. This finding suggests that contrast effect is uniquely a human factor that we observe in analyst revisions but not in

[9] The insignificant result on contrast effect on a control sample of analysts not covering the benchmark firms (reported in Table 4 Panel B) partially mitigates this concern.

[10] Our findings of lower forecast accuracy by analysts subject to contrast effects than their peers not subject to contrast effects and their tendency to revise subsequently to partially correct their initial forecast errors (reported in Table 5) partially mitigate this concern.

pseudo revisions that do not depend on analysts' judgement. This also mitigates the concern that our results are attributable to a mechanical relation in firms' earnings news announced on consecutive days. Moreover, this finding is inconsistent with analysts whose forecasts exhibit contrast effects seeking to forecast close to actual earnings. Instead our evidence corroborates our earlier finding that contrast effects adversely affect the accuracy of analyst forecasts.

5.2 Information Transfer

Information transfer, the phenomenon that earnings news announced on day t-1 conveys information about firms announcing earnings on day t, can be a confounding factor for contrast effects for investors. For example, if investors already react positively to good news from firm j announcing earnings on day t-1, they will have a muted reaction to good news from firm i announcing earnings on day t since part of the good news is already incorporated on day t-1 from firm j's earnings. Hartzmark and Shue conduct a battery of tests to tease out the effect of information transfer and continue to find significant evidence of contrast effects.

A key difference between our setting from that of Hartzman and Shue (2018) suggests that information transfer is an unlikely confounding effect in the setting of analyst revisions. When two firms (j and i) announce earnings on two consecutive days (t-1 and t), while stock prices of both firms likely react to earnings news on day t-1, most analysts do not revise forecasts for firm i until after firm i's earnings announcement on day t.[11] In other words, the information from firm j "transfers" to firm i's stock price but not to firm i's analyst forecasts. To the extent that Hartzmark and Shue continue to find significant evidence of contrast effects in stock prices after accounting for information transfer, we expect our evidence of

[11] In our sample, no analyst revises forecast on day t-1 for firms announcing earnings on day t.

contrast effects on analysts to be robust to the consideration of information transfer.

An alternative form of "information transfer", however, may be present in the setting of analyst forecasts. Specifically, given that analysts tend to cover industry peers or related firms (Kadan et al. 2012), earnings news on day t-1 may provide a specific context for analysts to interpret the earnings news on day t. Under this premise, the moderating effect of earnings news on day t-1 on analysts' reaction to earnings news on day t that we document may not be due to contrast effects, but rather consistent with an alternative explanation that, if the two consecutively announcing firms are industry competitors, then good news from firm j could imply bad news for firm i, dampening analysts' reaction to firm i's earnings news on day t.

Note that this alternative explanation relies on an important assumption, that is, the news from firm j conveys mainly competitive news that bodes in the opposite direction for its peers, rather than industry-wide common news that bodes in the same direction for its competitors. However, our empirical results do not support this assumption. First, our baseline regressions (as well as cross-sectional and additional analyses) reveal a significantly positive coefficient on earnings surprise on day t-1, suggesting that earnings news from firm j largely conveys news in the same direction for firm i, resulting in analysts revising forecasts for firm i in the same direction. Second, we directly examine whether earnings news on day t-1 predicts earnings news on day t in the opposite direction, as predicted by the alternative explanation. To do so, we regress day t's earnings news on day t-1's earnings news and find the coefficient to be positive and significant at the 0.01 level (t-stat=7.67). Hence, contrary to the alternative explanation, the results suggest that earnings news from day t-1 tends to "transfer" positively to analyst revision on day t; therefore "information transfer" cannot explain the contrast effect result, which suggests a negative effect of earnings news from day t-1 on analysts' reaction to earnings news on day t.

5.3 Distinctions and Joint Effects of Psychological Biases

We also consider whether and how other forms of psychological biases documented in prior literature may contribute to our results. For example, Driskill et al. (2020) document that analysts are subject to limited attention, resulting in delayed and lower quality forecast revisions when multiple firms in their coverage portfolios announce earnings on the same day. Hirshleifer et al. (2019) find that the accuracy of analyst forecasts declines over the course of a day as the number of their issued forecasts increases. As our study also examines analysts' reaction to clustered earnings announcements, analysts are likely subject to limited attention and decision fatigue simultaneously. Yet, there are a few distinctions in our study. First, both limited attention and decision fatigue predict that analysts issue forecasts of lower quality when they issue multiple forecasts on the same day. Instead of focusing on forecast accuracy, our study focuses on how analysts' revisions to one firm's earnings news vary with that from another firm.[12] Second, while theories of limited attention and decision fatigue predict a more muted response to earnings news on day t, *unconditional* on earnings news on day t-1, contrast effect predicts analysts' responses to earnings news on day t to be negatively related to the earnings news on day t-1. Our finding of a significant negative coefficient on the interaction term of earnings news on day t and day t-1 supports the contrast effects theory but not theories of limited attention or decision fatigue. Finally, both Driskill et al. (2020) and Hirshleifer et al. (2019) study events that occur on the same day, a setting where limited

[12] For completeness, we use forecast accuracy as the dependent variable and re-estimate equation (1). The coefficient on the interaction term of earnings news on day t and day t-1 is 15.58 (t-stat=1.48) and is insignificant. Also, the coefficient is statistically insignificant on earnings news on day t (t-stat= -0.55).

attention and decision fatigue are likely most acute.[13] In contrast, our setting of earnings surprises on two consecutive days is less likely to be affected by these biases, but rather is found to be more suitable for contrast effects (Hartzmark and Shue, 2018).

Despite the above fundamental differences between contrast effects we document and these other psychological biases, we acknowledge that they are not mutually exclusive and may simultaneously impact analyst revisions. To assess their potential interactive effect and further differentiate their effects, we perform subsample analyses based on analyst busyness and forecast speediness. We expect busier analysts and forecasts made more speedily to be more subject to contrast effects, as the time pressure is likely to subject analysts to more psychological biases. To operationalize the tests, we rerun equation (1) on partitioned sample by the median of (a) the number of forecasts an analyst issues on day t, and (b) the number of days it takes an analyst to revise forecast for firm *i*, which announces earnings on day t. As shown in Columns (1)~(4) in Table 6 Panel B, we find evidence of contrast effects, indicated by a significantly negative coefficient on the interaction term of earnings surprises on day t and day t-1 only among analysts who issue above-median number of forecasts but not among analysts who issue median-or-below number of forecasts. Likewise, Columns (5)~(8) show evidence for contrast effects only among forecasts that are issued more speedily than median forecast but not among less speedy forecasts, consistent with analysts more subject to contrast effects if they rush to issue forecasts.

Together, the above results suggest an interactive effect between psychological biases in the sense that biases of inattention (e.g., limited attention and decision fatigue) can constrain

[13] Driskill et al. (2020) focus on analyst reaction to multiple earnings announcements on the same day. Hirshleifer et al. (2019) focus on multiple issuing of earnings forecasts on the same day.

analysts' efforts and abilities to overcome other forms of behavioral biases, making them more susceptible to more specific behavioral biases such as contrast effects.

5.4 Strategic Timing of Earnings Announcements

Prior research suggests that some firms strategically delay earnings announcements with negative news (deHaan, Shevlin, and Thornock, 2015, Johnson and So, 2018). If firms with negative news strategically schedule their earnings announcements after other firms, then our documented negative coefficient on the interaction term of earnings surprises on day t and day t-1 may be attributed to the strategic timing of earnings announcement rather than psychological biases caused by contrast effects. However, we do not believe the strategic timing of earnings announcement is driving our findings for two reasons. First, the earnings surprises of other firms are difficult to predict and hence it is unclear whether firms are able to strategically follow other firms. Second, as suggested by deHaan et al. (2015), firms typically schedule their earnings announcements 14 days before the actual announcement date. Hence, firms likely have insufficient time to strategically alter their announcement.

To directly test whether strategic timing of earnings announcement drives our result, we examine earnings announcement that are likely to be strategically scheduled and those that are not. Following Hartzmark and Shue (2018), an earnings announcement is categorized as strategic if it deviates from its previous same-quarter date by five or more days.[14] We then partition the sample based on whether the timing of the earnings announcement on day t is categorized as strategic and re-run equation (1) separately. Table 6 Panel C reports the results. As shown in the table, the coefficient on the interaction term of earnings surprise on day t and

[14] In our sample, about 80% of earnings announcements are categorized as non-strategic, which is comparable to the finding in Hartzmark and Shue (2018).

day t-1 is significantly negative in Columns (1) and (2), where earnings announcements are classified as non-strategic. In contrast, in Columns (3) and (4), where earnings announcements are categorized as strategic, the coefficient on the interaction term is not significant at conventional levels. Together, these results suggest that our results are not driven by firms that shifted the date of earnings announcement.

6. Conclusion

We examine whether analysts are subject to contrast effects, a form of unconscious cognitive bias, when reacting to earnings announcements on consecutive days from firms they follow. Our findings suggest that analysts respond to earnings news in contrast to earnings news preceding it, resulting in an underreaction (overreaction) to news that are in the same (opposite) direction, consistent with the predictions of contrast effect theory.

Our cross-sectional analyses show that the contrast effects are driven by scenarios where the analyst is less skilled and relatively inexperienced, thus more susceptible to contrast effect, and where earnings news on day t-1 is large in magnitude or announced by large firms, thus attracting more attention from analysts to earnings news on day t-1. While investors are shown to exhibit contrast effects with regard to the dominant or market-wide earnings news on day t-1, we find that analysts exhibit contrast effects only with regard to firms they cover. Besides, our evidence suggests that our results are not driven by alternative explanations such as information transfer, limited attention, or decision fatigue of analysts.

Our study contributes to the literature of behavioral finance and accounting by documenting that analysts, as sophisticated information gatherers and processors, exhibit the biases from contrast effects with regard to firms they cover rather than to market-wide news in general. Our finding has important implications for researchers who study analyst forecasts, as well as for investors and analysts who use and produce these forecasts. Given the increasing trend of earnings announcement clusters, such bias is likely to play a greater role. Dispersing earnings announcements by firms and avoiding following firms in an earnings announcement cluster by analysts are likely to mitigate such unconscious bias.

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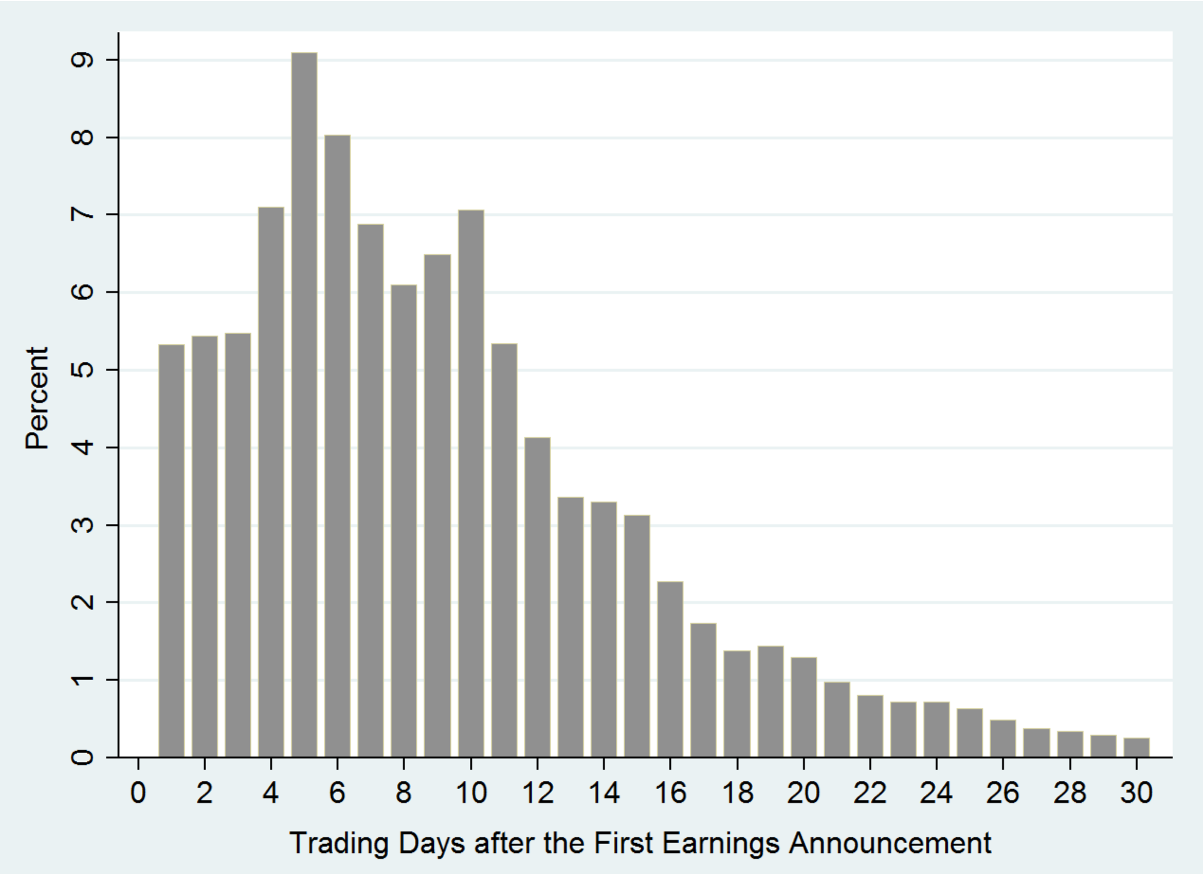
Appendix A. Variable Definitions

Variable	Definition
Dependent variables	
Revision	= analyst forecast revision, measured as the analyst's first forecast after the earnings announcement minus the same analyst's last forecast before the earnings announcement, then scaled by stock price at the end of the previous fiscal quarter q-1.
Earnings surprise variables	
$UE_{i,t}$	= earnings surprise of firm *i* on day t, scaled by stock price at the end of the previous fiscal quarter q-1. Earnings surprise is measured as the reported earnings minus the median analyst forecast in quarter q.
$UE_{j,t-1}$	= earnings surprise of firm *j* on day t-1, scaled by stock price at the end of the previous fiscal quarter q-1. Earnings surprise is measured as the reported earnings minus the median analyst forecast in quarter q.
$UE_{mkt,t-1}$ *(largest firm)*	= earnings surprise of the largest firm (conditional on it being a large firm) on day t-1. Earnings surprise is measured as the reported earnings minus the median analyst forecast in quarter q. Large firm is a firm with market capitalization that exceeds the 90th percentile cutoff of the NYSE index.
$UE_{mkt,t-1}$ *(large firms)*	= equal-weighted earnings surprise of all large firms that announced earnings on day t-1. Earnings surprise is measured as the reported earnings minus the median analyst forecast in quarter q. Large firm is a firm with market capitalization that exceeds the 90th percentile cutoff of the NYSE index.
$UE_{i,t}$* $UE_{j,t-1}$	= the interaction term between earnings surprise of firm *i* on day t and earnings surprise of firm *j* on day t-1 (see detailed descriptions above). We multiply this interaction term by minus one (-1) if and only if the earnings surprise of firm *i* on day t is negative, so that the prediction on its coefficient is clear under contrast effect theory.
Control variables	
Days_to_revise	= (natural logarithm of 1 plus) the days between an analyst's current forecast revision and her previous forecast.
Prior_forecast_error	= analysts' forecast errors in the previous quarter q-1.
CAR[-8,-1]	= abnormal (size-adjusted) returns accumulated 7 days prior to the earnings announcement date
Log_analyst	= (natural logarithm of 1 plus) the number of analysts who cover the firm.
Log_firm_exp	= (natural logarithm of 1 plus) the number of quarters an analyst covers the firm
Log_firm	= (natural logarithm of 1 plus) the number of companies an analyst covers.

Log_mktcap	= (natural logarithm of) the firm's market value of common equity (stock price times the number of common shares outstanding) at the end of the previous quarter q-1.
B/M	= the firm's book-to-market ratio measured at the end of the previous fiscal quarter q-1.
Special_items	= 1 if the firm reports non-zero special items for the previous fiscal quarter q-1 and 0 otherwise.
Loss	= 1 if the firm's previous quarter q-1 net income is negative and 0 otherwise.

Figure 1. Distribution of Consecutive Earnings Announcement Dates of Firms Covered by the Same Analyst



This graph plots the distribution of earnings announcement dates of firms covered by the same analyst with date 0 representing the earliest announcement in a fiscal quarter. The graph includes 202,286 analyst-quarters during the sample period of 1999-2019.

Table 1. Descriptive Statistics

Variable	Observation	Mean	Median.	S.D.	P10	P25	P75	P90
Dependent variable								
Revision	260,166	-0.0023	-0.0004	0.0186	-0.0067	-0.0020	0.0008	0.0032
Earnings surprise variables								
$UE_{i,t}$	260,117	-0.0010	0.0004	0.0234	-0.0059	-0.0010	0.0021	0.0062
$UE_{j,t}$	260,166	-0.0004	0.0004	0.0180	-0.0049	-0.0007	0.0020	0.0056
$UE_{mkt,t-1}$ *(largest firm)*	253,118	0.0009	0.0004	0.0066	-0.0022	-0.0002	0.0014	0.0043
$UE_{mkt,t-1}$ *(large firms)*	253,118	-0.0078	-0.0001	0.0324	-0.0265	-0.0080	0.0028	0.0082
$UE_{k,t-2}$	234,264	-0.0008	0.0005	0.0296	-0.0058	-0.0008	0.0021	0.0065
$UE_{l,t-3}$	216,392	-0.0006	0.0005	0.0296	-0.0050	-0.0006	0.0020	0.0060
Control variables								
Days_to_revise	260,185	3.9172	4.2767	0.9016	2.6391	3.3322	4.5109	4.6540
Prior_forecast_error	259,849	0.0005	-0.0005	0.0269	-0.0070	-0.0024	0.0009	0.0056
CAR[-8,-1]	250,951	-0.0029	-0.0017	0.0757	-0.0749	-0.0334	0.0283	0.0665
Log_analyst	260,185	2.4512	2.4849	0.6106	1.6094	1.9459	2.9444	3.2189
Log_firm_exp	252,061	2.3953	2.3979	0.8441	1.0986	1.7918	3.0445	3.4965
Log_firm	260,034	2.7614	2.7726	0.4219	2.1972	2.4849	3.0445	3.2581
Log_mktcap	259,596	10.3968	9.3007	3.6899	6.2559	7.4685	13.8350	15.8282
B/M	258,869	0.5988	0.4893	0.7890	0.1157	0.2679	0.7869	1.1358
Special_items	260,185	0.9838	1	0.1264	1	1	1	1
Loss	260,185	0.2342	0	0.4235	0	0	0	1

Table 2. Baseline Result of Contrast Effects: Earnings News Announced on Day t-1

Dep. Variable = *Revision*		
	(1)	(2)
$UE_{i,t}$	0.2153***	0.0561***
	(19.65)	(2.60)
$UE_{j,t-1}$	0.0081*	0.0259***
	(1.90)	(3.37)
$UE_{i,t}$* $UE_{j,t-1}$	-2.3854***	-2.1771**
	(-2.65)	(-2.25)
$UE_{i,t}$*|$UE_{i,t}$|		-0.0470
		(-0.25)
$UE_{j,t-1}$*|$UE_{j,t-1}$|		-0.1537**
		(-2.50)
Days_to_revise		-0.0002***
		(-3.54)
Prior_forecast_error		-0.1868***
		(-15.56)
CAR[-8,-1]		0.0094***
		(8.25)
Log_analyst		-0.0009***
		(-3.77)
Log_firm_exp		-0.0003***
		(-4.55)
Log_firm		-0.0003*
		(-1.82)
Log_mktcap		0.0015***
		(5.69)
B/M		-0.0011***
		(-2.96)
Special_items		-0.0004
		(-1.18)
Loss		-0.0003
		(-1.09)
Analyst FE & Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	258,812	240,247
Adj R^2	0.210	0.247

Note: this table presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3. Cross Sectional Analyses of Contrast Effects

Panel A: Analyst's Forecasting Experience for a Given Firm (Firm Experience) or for Any Firm (General Experience)

	Dep. Variable = *Revision*							
	Low Accuracy		High Accuracy		Low Experience		High Experience	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$UE_{i,t}$	0.2127***	0.0569**	0.0982**	0.1167*	0.2024***	0.0318	0.2267***	0.0840***
	(19.38)	(2.53)	(2.17)	(1.73)	(14.52)	(1.17)	(17.45)	(3.07)
$UE_{j,t-1}$	0.0070	0.0324***	0.0006	-0.0071	0.0074	0.0231**	0.0063	0.0149
	(1.11)	(2.77)	(0.13)	(-0.96)	(1.25)	(1.98)	(0.98)	(1.37)
$UE_{i,t}$* $UE_{j,t-1}$	-2.2132**	-2.2881**	3.3313	4.5407	-2.5464*	-2.5091*	-0.9726	-0.0115
	(-2.39)	(-2.26)	(0.78)	(1.01)	(-1.83)	(-1.79)	(-0.46)	(-0.01)
$UE_{i,t}$*|$UE_{i,t}$|		-0.0925		-0.2931		-0.0113		-0.0466
		(-0.48)		(-0.34)		(-0.05)		(-0.20)
$UE_{j,t-1}$*|$UE_{j,t-1}$|		-0.2003**		0.0515		-0.1229		-0.1013
		(-2.24)		(1.05)		(-1.40)		(-1.09)
Days_to_revise		-0.0002***		-0.0001***		-0.0002***		-0.0001**
		(-2.73)		(-2.72)		(-3.18)		(-2.29)
Prior_forecast_error		-0.1851***		-0.3037***		-0.1959***		-0.1679***
		(-15.31)		(-5.64)		(-11.65)		(-10.13)
CAR[-8,-1]		0.0108***		0.0055***		0.0103***		0.0084***
		(6.81)		(7.63)		(6.21)		(6.48)
Log_analyst		-0.0012***		-0.0006***		-0.0009**		-0.0009***
		(-2.71)		(-4.23)		(-2.20)		(-3.38)
Log_firm_exp		-0.0004***		-0.0001***		-0.0003**		-0.0003***
		(-3.16)		(-3.13)		(-2.29)		(-3.93)
Log_firm		-0.0003		-0.0001		-0.0006*		-0.0001
		(-1.09)		(-1.64)		(-1.82)		(-0.66)
Log_mktcap		0.0018***		0.0004**		0.0011**		0.0016***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		(4.43)		(2.31)		(2.47)		(6.00)
B/M		-0.0009**		-0.0015***		-0.0010**		-0.0011**
		(-2.17)		(-3.04)		(-1.98)		(-2.48)
Special_items		-0.0004		0.0000		-0.0009**		-0.0001
		(-0.75)		(0.13)		(-1.97)		(-0.31)
Loss		-0.0000		0.0001		0.0004		-0.0006**
		(-0.15)		(0.64)		(1.11)		(-2.24)
Analyst FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,653	118,904	128,222	119,405	104,547	97,087	153,383	142,251
Adj R^2	0.202	0.240	0.250	0.247	0.208	0.247	0.221	0.255

Note: this panel presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. We partition the sample based on (a) the analyst's forecast accuracy in the previous quarter, measured by the absolute forecast errors of her last forecast for the given firm, and (b) analyst's general experience, measured by the number of quarters since an analyst issued her first forecast of any firm. Columns (1) and (2) (Columns (3) and (4)) report the results where the analyst's forecast accuracy is lower than (higher than or equal to) the sample median. Columns (5) and (6) (Columns (7) and (8)) report the results where the analyst's general experience is lower than (higher than or equal to) the sample median. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3. Cross Sectional Analyses of Contrast Effects (Cont'd)
Panel B: Analyst Attention to the Preceding Day's (Day t-1) Earnings Announcement(s)

	Dep. Variable = *Revision*							
	Small $UE_{j,t-1}$ Magnitude		Large $UE_{j,t-1}$ Magnitude		Small Firm *j* Size		Large Firm *j* Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$UE_{i,t}$	0.2028***	0.0755**	0.2122***	0.0508**	0.2243***	0.0425	0.1921***	0.0481
	(12.18)	(2.22)	(16.88)	(1.98)	(19.10)	(1.64)	(8.87)	(1.24)
$UE_{j,t-1}$	0.0746	0.0201	0.0053	0.0210***	0.0016	0.0133	0.0305***	0.0627***
	(0.74)	(0.18)	(1.21)	(2.68)	(0.33)	(1.46)	(2.94)	(2.96)
$UE_{i,t}$* $UE_{j,t-1}$	2.9975	2.7776	-2.1286**	-1.8613*	-1.5039	-1.2569	-5.1935**	-4.7097*
	(1.09)	(0.98)	(-2.34)	(-1.90)	(-1.26)	(-1.15)	(-2.08)	(-1.77)
$UE_{i,t}$*|$UE_{i,t}$|		-0.0982		-0.0889		0.0002		-0.0050
		(-0.33)		(-0.41)		(0.00)		(-0.01)
$UE_{j,t-1}$*|$UE_{j,t-1}$|		0.1731		-0.1272**		-0.0961		-0.4076
		(0.34)		(-2.01)		(-1.38)		(-1.62)
Days_to_revise		-0.0001***		-0.0002**		-0.0002**		-0.0001
		(-2.87)		(-2.23)		(-2.47)		(-1.29)
Prior_forecast_error		-0.1562***		-0.1979***		-0.2067***		-0.1604***
		(-7.88)		(-13.87)		(-13.20)		(-7.32)
CAR[-8,-1]		0.0091***		0.0099***		0.0090***		0.0105***
		(6.96)		(6.19)		(5.65)		(6.23)
Log_analyst		-0.0011***		-0.0006		-0.0009**		-0.0010***
		(-4.25)		(-1.59)		(-2.47)		(-2.80)
Log_firm_exp		-0.0001**		-0.0003***		-0.0003***		-0.0002***
		(-2.05)		(-3.67)		(-2.66)		(-2.61)
Log_firm		-0.0002		-0.0002		-0.0003		-0.0004*
		(-1.37)		(-0.87)		(-1.19)		(-1.75)
Log_mktcap		0.0014***		0.0015***		0.0011***		0.0018***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		(4.36)		(4.30)		(3.09)		(4.37)
B/M		-0.0014***		-0.0009*		-0.0017***		-0.0004
		(-3.05)		(-1.96)		(-3.00)		(-0.96)
Special_items		-0.0003		-0.0005		-0.0006		-0.0002
		(-0.82)		(-1.00)		(-0.75)		(-0.78)
Loss		-0.0004		-0.0001		-0.0000		-0.0001
		(-1.26)		(-0.28)		(-0.05)		(-0.28)
Analyst FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,182	119,058	128,731	119,259	116,576	108,038	116,939	108,578
Adj R^2	0.238	0.258	0.210	0.254	0.223	0.272	0.184	0.209

Note: this panel presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. We partition the sample based on two proxies for analyst's attention to the preceding day's (day t-1) earnings announcement(s): (a) the magnitude of earnings surprise of firm j, which announces earnings on day t-1, and (b) the size of firm j, which announces earnings on day t-1. In Columns (1) and (2) (Columns (3) and (4)), the magnitude of earnings surprise of firm *j* is lower than (higher than or equal to) the sample median. In Columns (5) and (6) (Columns (7) and (8)), the size of firm *j* is lower than (higher than or equal to) the sample median. Firm size is measured by the market capitalization. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4. Benchmark Firms for Contrast Effects Exhibited by Analysts

Panel A. Using Large Firms (following Hartzmark and Shue (2018)) *not* Covered by the Analyst as Benchmark

	Dep. Variable = *Revision*			
	$UE_{mkt,t-1}$ (the largest firm)		$UE_{mkt,t-1}$ (all large firms)	
	(1)	(2)	(3)	(4)
$UE_{i,t}$	0.2196***	0.0578***	0.2203***	0.0581***
	(20.69)	(2.66)	(20.40)	(2.68)
$UE_{mkt,t-1}$	-0.0153*	-0.0268	-0.0013	0.0040
	(-1.92)	(-1.41)	(-0.84)	(0.93)
$UE_{i,t}$* $UE_{mkt,t-1}$	0.0718	0.1059	-0.1341	-0.2226
	(0.44)	(0.66)	(-0.66)	(-1.08)
$UE_{i,t}$*$\|UE_{i,t}\|$		-0.0350		-0.0280
		(-0.19)		(-0.15)
$UE_{mkt,t-1}$*$\|UE_{mkt,t-1}\|$		0.2867		-0.0323
		(0.43)		(-0.99)
Days_to_revise		-0.0002***		-0.0002***
		(-3.52)		(-3.53)
Prior_forecast_error		-0.1873***		-0.1873***
		(-15.45)		(-15.46)
CAR[-8,-1]		0.0095***		0.0093***
		(7.97)		(7.82)
Log_analyst		-0.0009***		-0.0009***
		(-3.51)		(-3.51)
Log_firm_exp		-0.0002***		-0.0003***
		(-4.37)		(-4.39)
Log_firm		-0.0003*		-0.0003*
		(-1.65)		(-1.68)
Log_mktcap		0.0014***		0.0014***

		(5.20)		(5.26)
B/M		-0.0011***		-0.0011***
		(-3.06)		(-3.06)
Special_items		-0.0004		-0.0004
		(-1.25)		(-1.26)
Loss		-0.0002		-0.0002
		(-0.73)		(-0.76)
Analyst FE & Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	251,798	233,780	251,798	233,780
Adj R^2	0.212	0.250	0.212	0.250

Note: this panel presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{mkt,t-1} + \beta_3 UE_{i,t} * UE_{mkt,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. Following Hartzmark and Shue (2018), we define a "large" firm as a firm with market capitalization that exceeds the 90th percentile cutoff of the NYSE index. We use two measures of market-wide earnings news on day t-1 ($UE_{mkt,t-1}$). Column (1) and (2) report the results when market-wide earnings news is measured as the earnings surprise of the largest firm (conditional on it being a large firm) on day t-1. Column (3) and (4) reports the results when market-wide earnings news is measured as the equal-weighted earnings surprise of all large firms on day t-1. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4. Benchmark Firms for Contrast Effects Exhibited by Analysts (Cont'd)
Panel B. Analysts Covering Firm *i* on Day t but *not* Covering Firm *j* on Day t-1

	Dep. Variable = *Revision*					
$UE_{x,t-1}$	$UE_{j,t-1}$		$UE_{mkt,t-1}$ (the largest firm)		$UE_{mkt,t-1}$ (all large firms)	
	(1)	(2)	(3)	(4)	(5)	(6)
$UE_{i,t}$	0.2047***	0.0570**	0.2034***	0.0595**	0.2065***	0.0547**
	(14.69)	(2.44)	(14.68)	(2.53)	(16.05)	(2.55)
$UE_{x,t-1}$	-0.0017	0.0157*	0.0079	0.0312	0.0023	0.0033
	(-0.42)	(1.66)	(0.60)	(1.16)	(0.64)	(0.43)
$UE_{i,t}$* $UE_{x,t-1}$	-0.1960	-0.0945	-1.3968	-0.0882	-0.7713	-1.0037
	(-0.55)	(-0.29)	(-0.64)	(-0.05)	(-1.02)	(-1.34)
$UE_{i,t}$*|$UE_{i,t}$|		0.1590		0.1343		0.1966
		(0.74)		(0.63)		(1.08)
$UE_{x,t-1}$*|$UE_{x,t-1}$|		-0.1688**		-1.7964		-0.0018
		(-2.10)		(-1.39)		(-0.05)
Days_to_revise		-0.0002***		-0.0002***		-0.0002***
		(-5.36)		(-5.30)		(-5.26)
Prior_forecast_error		-0.1256***		-0.1253***		-0.1259***
		(-16.13)		(-15.89)		(-16.03)
CAR[-8,-1]		0.0116***		0.0116***		0.0115***
		(8.65)		(8.62)		(8.71)
Log_analyst		-0.0020***		-0.0020***		-0.0020***
		(-6.63)		(-6.54)		(-6.81)
Log_firm_exp		-0.0000		-0.0000		-0.0000
		(-0.49)		(-0.53)		(-0.51)
Log_firm		-0.0003**		-0.0003*		-0.0003*
		(-2.03)		(-1.83)		(-1.92)
Log_mktcap		0.0018***		0.0018***		0.0018***

		(7.51)		(7.60)		(7.62)
B/M		-0.0009***		-0.0009***		-0.0009***
		(-2.91)		(-2.87)		(-2.93)
Special_items		0.0002		0.0002		0.0002
		(0.42)		(0.47)		(0.49)
Loss		-0.0013***		-0.0013***		-0.0013***
		(-4.88)		(-4.98)		(-5.21)
Analyst FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197,323	192,323	195,149	190,196	195,149	190,196
Adj R^2	0.196	0.242	0.197	0.244	0.198	0.245

Note: this panel presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{x,t-1} + \beta_3 UE_{i,t} * UE_{x,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. The sample includes analysts covering firm *i* (announces earnings on day t) but not covering firm *j* (announces earnings on day t-1). We use three measures of earnings news on day t-1. In Column (1) it is measured as the earnings surprise of firm *j* (as in Table 2).[15] In Column (2) it is measured as the earnings surprise of the largest firm (as in Table 4). In Column (3) it is measured as the average of all earnings surprises of large firms (as in Table 4). The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

[15]When there are multiple earning announcements on day t-1, we use the average value.

Table 4. Benchmark Firms for Contrast Effects Exhibited by Analysts (Cont'd)
Panel C. Recency of the Benchmark Earnings Announcements

Dep. Variable = *Revision*		
	(1)	(2)
$UE_{i,t}$	0.2149***	0.0474**
	(18.03)	(2.14)
$UE_{j,t-1}$	0.0091	0.0252**
	(1.46)	(2.43)
$UE_{k,t-2}$	-0.0023	0.0011
	(-0.62)	(0.18)
$UE_{l,t-3}$	0.0001	0.0063
	(0.07)	(1.25)
$UE_{i,t}$* $UE_{j,t-1}$*(most recent)*	-2.2961**	-2.1488*
	(-2.17)	(-1.89)
$UE_{i,t}$* $UE_{k,t-2}$*(2nd most recent)*	0.0510	0.1275
	(0.29)	(0.73)
$UE_{i,t}$* $UE_{l,t-3}$*(3rd most recent)*	0.1738	0.1540
	(1.21)	(1.06)
$UE_{i,t}$*|$UE_{i,t}$|		-0.0111
		(-0.06)
$UE_{j,t-1}$*|$UE_{j,t-1}$|		-0.1279*
		(-1.71)
$UE_{k,t-2}$*|$UE_{k,t-2}$|		-0.0311
		(-1.01)
$UE_{l,t-3}$*|$UE_{l,t-3}$|		-0.0391
		(-1.48)
Days_to_revise		-0.0001**
		(-2.47)
Prior_forecast_error		-0.1900***
		(-15.17)
CAR[-8,-1]		0.0092***
		(7.14)
Log_analyst		-0.0010***
		(-3.34)
Log_firm_exp		-0.0003***
		(-4.21)
Log_firm		-0.0002
		(-1.10)
Log_mktcap		0.0014***
		(4.60)
B/M		-0.0012***
		(-2.96)
Special_items		-0.0003
		(-0.96)

Loss		-0.0000
		(-0.15)
Analyst FE & Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	215,077	200,115
Adj R^2	0.211	0.250

Note: this table presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{k,t-2} + \beta_4 UE_{i,t} * UE_{j,t-1} + \beta_5 UE_{i,t} * UE_{k,t-2} + \beta_6 UE_{i,t} * UE_{l,t-3} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. $UE_{k,t-2}$ and $UE_{l,t-3}$ are the earnings surprises of firm *k* and firm *l* in the same analyst's coverage portfolio. Firm *k* is the last firm to announce earnings before firm *j* and firm *l* is the last firm to announce earnings before firm *k*.[16] Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

[16] Firm *k* (*l*) may announce earnings on day t-2 (t-3) or earlier as there may be a gap between two consecutive earnings announcements. We use the subscript '*t-2 (t-3)*' merely to indicate the sequence of announcements.

Table 5: How Contrast Effect Affects Analyst Forecast Accuracy and Subsequent Revisions

Panel A. Contrast Effect and Analyst Forecast Accuracy

	Dep. Variable = *Forecast Error*	
	(1)	(2)
Treatment	0.0019***	0.0016***
	(6.02)	(4.91)
Timeliness		0.0001
		(0.05)
Days_to_revise		-0.0002
		(-1.16)
Prior_forecast_error		0.3106***
		(10.55)
CAR[-8,-1]		-0.0287***
		(-4.98)
Log_analyst		0.0127***
		(9.66)
Log_firm_exp		0.0024***
		(13.07)
Log_firm		0.0017***
		(3.95)
Log_mktcap		-0.0260***
		(-19.50)
B/M		0.0076***
		(4.95)
Special_items		0.0009
		(0.43)
Loss		0.0128***
		(11.12)
Analyst FE & Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	455,022	432,198
Adj R^2	0.454	0.499

Note: this table presents the results from estimating $Forcast\_error = \alpha + \beta_1 Treatment + Controls + Analyst\ FE + Firm\ FE + Year\_quater\ FE + \varepsilon_{i,t}$. The dependent variable is *Forcast_error*, which is measured as the absolute value of the difference between analyst earnings forecasts and actual reported earnings, scaled by stock price at the end of the previous fiscal quarter. Treatment is a dummy variable, which equals 1 when the analyst is subject to contrast effects (i.e., the analyst covers both the firm that announces earnings on day t and the firm that announces earnings on day t-1) and equals 0 when the analyst is not subject to the contrast effects (i.e., the analyst covers the firm that announces earnings on day t but does not cover the firm that announces earnings on day t-1). *Timeliness* is the logarithm of one plus the days between earnings announcement and analyst forecast. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5: How Contrast Effect Affects Analyst Forecast Accuracy and Subsequent Revisions (Cont'd)

Panel B1. Contrast Effect and Analyst Subsequent Revision: Heckman Two-Stage Estimation (First Stage: Decision to Revise)

Dep. Variable = *Subsequent Revision Dummy*			
Subsequent Revision Window	7 Days	14 Days	30 Days
	(1)	(2)	(3)
Log_gen_exp	-0.0065***	-0.0145***	-0.0221***
	(-4.04)	(-11.40)	(-22.94)
Prior_forecast_error	0.0342***	0.0385***	0.0524***
	(6.81)	(9.62)	(16.85)
CAR[-8,-1]	0.0444	0.0644	-0.0784
	(0.52)	(0.98)	(-1.56)
Log_analyst	0.2014***	0.2958***	0.4008***
	(17.65)	(32.47)	(57.73)
Log_firm	0.0780***	0.1236***	0.1558***
	(4.69)	(9.44)	(15.75)
Log_mktcap	-0.0265***	-0.0315***	-0.0377***
	(-12.85)	(-19.33)	(-30.80)
B/M	0.0256***	0.0258***	0.0297***
	(3.92)	(4.73)	(6.83)
Special_items	-0.1995***	-0.2024***	-0.1539***
	(-4.34)	(-5.47)	(-5.19)
Loss	-0.0429***	-0.0343***	-0.0166*
	(-2.70)	(-2.74)	(-1.76)
Observations	258,812	258,812	258,812
Pseudo R^2	0.017	0.030	0.048

Table 5: How Contrast Effect Affects Analyst Forecast Accuracy and Subsequent Revisions (Cont'd)

Panel B2. Contrast Effect and Analyst Subsequent Revision: Heckman Two-Stage Estimation (Second Stage: Revision Direction)

	Dep. Variable = *Same Direction Revision Dummy*					
Subsequent Revision Window	7 Days		14 Days		30 Days	
	(1)	(2)	(3)	(4)	(5)	(6)
News_same_sign	0.0862***	0.0747***	0.0859***	0.0747***	0.0861***	0.0747***
	(16.30)	(13.81)	(16.25)	(13.82)	(16.29)	(13.82)
Inverse_mills_ratio	-0.4748***	-0.9882***	-0.3423***	-0.6267***	-0.2535***	-0.4376***
	(-27.44)	(-14.07)	(-27.30)	(-14.10)	(-25.90)	(-13.94)
Controls	No	Yes	No	Yes	No	Yes
Observations	258,812	258,780	258,812	258,780	258,812	258,780
Pseudo R^2	0.003	0.008	0.003	0.008	0.003	0.008

Note: Panel B presents the results from a Heckman two-stage regression model, in which the first stage (Panel B1) models the likelihood of analysts revising their forecasts subsequent to their initial forecast revision immediately following an earnings announcement, and the second stage (Panel B2) examines whether the analysts' subsequent forecast revisions are in the direction consistent with their correction of the over- or under-reaction in their initial forecast revision in response to earnings announcements induced by contrast effects, while accounting for the analysts' selective decision to revise forecasts. Columns (1), (2), and (3) report the results where subsequent revisions are made within 7, 14, and 30 days after the initial revision, respectively. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel B1 presents the results from estimating the Probit regression:

$$Subsequent\ Revision\ Dummy = \alpha + \beta_i Analyst\ and\ Firm\ Characteristics + \varepsilon_{i,t}.$$

The dependent variable is a binary variable (*Subsequent Revision*) and equals to one if analyst revises her forecasts within a certain time window after her initial forecast and equals to zero otherwise. Other variables are defined as in Appendix.

Panel B2 presents the results from estimating the Probit regression:

$$Same\ Direction\ Revision\ Dummy = \alpha + \beta_1 News\_same\_sign + \beta_2 Inverse\_Mills\_Ratio + \beta_3 Controls + \varepsilon_{i,t}$$

The dependent variable is a binary variable (*Same Direction Revision Dummy*) and equal to one if analyst's the first revision after earnings announcement and her subsequent revision are in the same direction (i.e., both upward or downward), and equal to zero otherwise. The independent variable, *News_same_sign*, is a binary variable and equals to one if earnings news on day t-1 and day t are in the same direction (i.e., both positive or negative) and equal to zero if earnings news on day t-1 and day t are in the opposite direction (i.e., one positive and one negative). *Inverse mills ratio* is calculated from estimating the Probit regression in Panel B1. Other variables are defined as in Appendix A.

Table 6: Additional Analyses and Alternative Explanations
Panel A. Pseudo Revision with "Perfect Foresight"

Dep. Variable = *Pseudo Revision*		
	(1)	(2)
$UE_{i,t}$	0.1879***	0.4821***
	(46.18)	(60.43)
$UE_{j,t-1}$	0.0059***	0.0083**
	(3.07)	(2.22)
$UE_{i,t}* UE_{j,t-1}$	0.2962	0.1544
	(1.05)	(0.65)
$UE_{i,t}*\|UE_{i,t}\|$		-2.8962***
		(-50.71)
$UE_{j,t-1}*\|UE_{j,t-1}\|$		-0.0561**
		(-2.24)
Days_to_revise		-0.0000
		(-1.07)
Prior_forecast_error		-0.0752***
		(-19.27)
CAR[-8,-1]		0.0020***
		(4.17)
Log_analyst		-0.0003**
		(-2.48)
Log_firm_exp		-0.0002***
		(-5.73)
Log_firm		-0.0000
		(-0.49)
Log_mktcap		0.0007***
		(6.91)
B/M		0.0005***
		(4.16)
Special_items		0.0000
		(0.09)
Loss		-0.0041***
		(-26.55)
Analyst FE & Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	244,437	226,868
Adj R^2	0.392	0.509

Note: this table presents the results from estimating Pseudo $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. The dependent variable is *Pseudo Revision*, which is measured as the reported earnings of the quarter minus the last forecast from the analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6: Additional Analyses and Alternative Explanations (Cont'd)
Panel B. The Effect of Busyness on Contrast Effects

	Dep. Variable = *Revision*							
	Low Number of Forecasts Issued		High Number of Forecasts Issued		Low Speediness Forecasts		High Speediness Forecasts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$UE_{i,t}$	0.2425***	0.0613**	0.2014***	0.0467*	0.2092***	0.0543*	0.2217***	0.0447*
	(17.68)	(2.04)	(14.38)	(1.82)	(13.53)	(1.72)	(18.08)	(1.76)
$UE_{j,t-1}$	0.0026	0.0170	0.0117**	0.0274***	0.0017	-0.0005	0.0120**	0.0393***
	(0.35)	(1.30)	(2.29)	(2.91)	(0.27)	(-0.04)	(2.11)	(4.29)
$UE_{i,t}$* $UE_{j,t-1}$	-1.1910	-0.8663	-3.2601***	-3.1935**	-1.6924	-0.7673	-2.6822**	-2.8787**
	(-0.92)	(-0.64)	(-2.84)	(-2.56)	(-1.06)	(-0.45)	(-2.47)	(-2.46)
$UE_{i,t}$*|$UE_{i,t}$|		0.3533		-0.2034		0.1952		-0.2388
		(1.40)		(-0.88)		(0.72)		(-1.16)
$UE_{j,t-1}$*|$UE_{j,t-1}$|		-0.1059		-0.1427*		-0.0034		-0.2224***
		(-0.88)		(-1.93)		(-0.03)		(-2.83)
Days_to_revise		-0.0003***		-0.0001		-0.0001		-0.0001**
		(-3.96)		(-1.32)		(-1.37)		(-2.42)
Prior_forecast_error		-0.1586***		-0.2023***		-0.1567***		-0.2216***
		(-8.30)		(-14.29)		(-9.04)		(-13.99)
CAR[-8,-1]		0.0099***		0.0096***		0.0124***		0.0072***
		(7.09)		(6.39)		(6.74)		(5.46)
Log_analyst		-0.0009***		-0.0010***		-0.0006		-0.0012***
		(-2.83)		(-3.21)		(-1.36)		(-4.54)
Log_firm_exp		-0.0002***		-0.0003***		-0.0004***		-0.0002***
		(-2.65)		(-4.05)		(-3.89)		(-3.14)
Log_firm		-0.0005**		-0.0002		-0.0002		-0.0002
		(-2.07)		(-0.99)		(-0.87)		(-0.90)

Log_mktcap		0.0018***		0.0014***		0.0018***		0.0012***
		(6.03)		(4.13)		(4.31)		(4.43)
B/M		-0.0009*		-0.0012***		-0.0004		-0.0020***
		(-1.81)		(-2.83)		(-0.87)		(-4.71)
Special_items		-0.0004		-0.0002		0.0004		-0.0007*
		(-0.78)		(-0.59)		(0.80)		(-1.87)
Loss		-0.0001		-0.0002		-0.0000		-0.0003
		(-0.36)		(-0.70)		(-0.13)		(-1.03)
Analyst FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97,969	90,748	159,113	147,740	95,640	88,269	161,007	149,788
Adj R^2	0.249	0.278	0.198	0.241	0.198	0.231	0.229	0.273

Note: this table presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. We partition the sample based on (a) the number of forecasts an analyst issues on day t, and (b) forecast speediness for firm i, which announces earnings on day t. Columns (1) and (2) (Columns (3) and (4)) report the results where the number of forecasts an analyst issues on day t is lower than (higher than or equal to) the sample median. Columns (5) and (6) (Columns (7) and (8)) report the results where speediness of the first forecast an analyst issues for firm *i* after its earnings announcement on day t is lower than (higher than or equal to) the sample median. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix A. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6: Additional Analyses and Alternative Explanations (Cont'd)
Panel C. Strategic Timing of Earnings Announcement

	Dep. Variable = *Revision*			
	Non-Strategic EA		Strategic EA	
	(1)	(2)	(3)	(4)
$UE_{i,t}$	0.2135***	0.0608**	0.2093***	-0.1048*
	(17.39)	(2.56)	(8.10)	(-1.65)
$UE_{j,t-1}$	0.0087*	0.0216***	-0.0024	0.0738**
	(1.90)	(2.59)	(-0.13)	(2.28)
$UE_{i,t}$* $UE_{j,t-1}$	-2.8260***	-2.4959**	-2.6471	-2.9070
	(-2.92)	(-2.45)	(-1.01)	(-1.01)
$UE_{i,t}$*|$UE_{i,t}$|		-0.0730		1.1083**
		(-0.35)		(2.06)
$UE_{j,t-1}$*|$UE_{j,t-1}$|		-0.1013		-0.7173**
		(-1.53)		(-2.24)
Days_to_revise		-0.0001**		-0.0007***
		(-2.36)		(-3.01)
Prior_forecast_error		-0.1825***		-0.2174***
		(-13.81)		(-6.50)
CAR[-8,-1]		0.0095***		0.0084**
		(7.26)		(2.29)
Log_analyst		-0.0009***		-0.0008
		(-3.18)		(-0.73)
Log_firm_exp		-0.0002***		-0.0003
		(-3.69)		(-1.12)
Log_firm		-0.0003		-0.0003
		(-1.63)		(-0.50)
Log_mktcap		0.0014***		0.0017**
		(4.64)		(2.07)
B/M		-0.0010***		-0.0010
		(-2.79)		(-1.15)
Special_items		-0.0005		0.0020
		(-1.38)		(0.92)
Loss		-0.0002		0.0006
		(-0.75)		(0.72)
Analyst FE & Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	223,004	207,121	20,679	18,997
Adj R^2	0.216	0.253	0.251	0.307

Note: this table presents the results from estimating $Revision = \alpha + \beta_1 UE_{i,t} + \beta_2 UE_{j,t-1} + \beta_3 UE_{i,t} * UE_{j,t-1} + Controls + Analyst\ FE + Firm\ FE + Year\_quarter\ FE + \varepsilon_{i,t}$. We partition the sample based on whether the timing of the earnings announcement on day t is categorized as strategic. Following Hartzmark and Shue (2018), an earnings announcement is categorized as strategic if it differs from its previous same-quarter date by five or more days. In Columns (1) and (2), we report the results when earnings announcement on day t is categorized as non-strategic. In Columns (3) and (4), we report the results when earnings announcement on day t is categorized as strategic. The dependent variable is *Revision*, which is measured as the first analyst forecast after the earnings announcement minus the last forecast from the same analyst before the earnings announcement, scaled by stock price at the end of the previous fiscal quarter. Other variables are defined as in Appendix. The model includes analyst, firm, and year-quarter fixed effects. T-stats reported in parentheses are calculated using standard errors are robust to heteroscedasticity and clustered by firm-quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.