A Game of Disclosing "Other Events": Insights for Retail Investors*

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We investigate retail investors' vulnerability to strategic corporate disclosure using a novel setting – "Other Events" (OE) disclosure, a less scrutinized voluntary item in 8-K filings. We find evidence that firms distort the sentiment in OE disclosures, resulting in a significant immediate price response that fully reverses in the post-disclosure period. Consistent with distorted disclosure, sentiment in OE disclosure negatively predicts the firm's future operating performance. A ChatGPT-interpreted latent topics analysis reveals that the sentiment distortion is more pronounced in hard-to-verify non-financial OE disclosures. We do not observe these patterns in more regulated non-OE disclosures. Compared with sophisticated investors who use machine-processing tools, retail investors particularly suffer from this sentiment distortion, as evidenced by their information acquisition and trading activities. Finally, these repercussions seem to stem from firms' tendencies to distort OE sentiment when it is beneficial for managers (e.g., insider selling, option grants) and firms (e.g., seasoned equity offerings, stock mergers).

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JEL Classification : G14, D12, M41

Information disclosure plays a vital role in enhancing the efficiency of financial markets, as investors' demand for information typically expedites price discovery. However, existing literature also highlights strategic information disclosure by firm managers, which may distort stock prices and result in losses for investors.[1] Our study investigate whether individual investors, who are typically considered less informed and sophisticated, are more likely to be misled by strategic corporate disclosures and incur losses when compared to institutional investors.[2] While previous studies shed light on retail investors' responses to financial disclosures (e.g., Lee, 1992; Hirshleifer, Myers, Myers, and Teoh, 2008), there has been little evidence regarding the impact of *strategic corporate disclosure* on retail investors.

Our study examines the possible strategic disclosure of "Other Events" (OE) in Form 8-K filings. Firms file Form 8-K to the U.S. Securities and Exchange Commission (SEC) to disclose important and material current events in a timely manner, which includes OE disclosures designated as Item 8.01. Two key aspects of OE disclosures make them a particularly suitable setting for studying the impact of strategic disclosure on individual investors.

First, OE disclosure is ripe for opportunism compared to the other 8-K categories.[3] Although OE disclosure occurs in about one-fourth of 8-Ks, the SEC's guidance on 8-K filings, which spans 24 pages, dedicates a mere 64 words to the OE disclose.[4] The SEC's broad definition of OE information–that which is "*not otherwise called for by this form [8-K], that the registrant deems of importance to security holders*"–offers limited direction, potentially paving the way for firms to manipulate the disclosures, particularly regarding intangible topics. Furthermore, the voluntary nature of OE

[1] For example, previous studies document firms' news manipulation (Ahern and Sosyura, 2014; Edmans, Goncalves-Pinto, Groen-Xu, and Wang, 2018) and management of tone in earnings press releases (Huang, Teoh, and Zhang, 2014).
[2] Previous studies demonstrate that retail investors make poor information-processing and attention-induced trading choices, and have difficulties understanding financial disclosures (e.g., Maines and McDaniel, 2000; Barber and Odean, 2008; Miller, 2010; Ayers, Li, and Yeung, 2011; Rennekamp, 2012; Hwang and Kim, 2017; Lawrence, Ryans, Sun, and Laptev, 2018; Blankespoor, deHaan, Wertz, and Zhu, 2019; Barber, Huang, Odean, and Schwarz, 2022).
[3] While both Item 7.01 and 8.01 are voluntary corporate disclosures, we focus on Item 8.01 because Item 7.01 is Regulation FD disclosure governing communications with institutional investors, analysts, and certain other security holders, offering less opportunity for manipulation compared to Item 8.01.
[4] The SEC's 8-K filing guidance can be found at https://www.sec.gov/files/form8-k.pdf.

disclosures exempts them from regulations such as Section 10(b) or Rule 10b-5 of the Securities Exchange Act of 1934 (Segal and Segal, 2016). As a result, regulators may less scrutinize strategic distortions in OE disclosures than in non-OE disclosures.

Second, investors face the challenge of deciphering up to nine distinct categories of news, or "items", in 8-K filings.[5] Extensive literature documents the difficulties investors experience in their search for and processing complex corporate disclosure (e.g., Loughran and McDonald, 2014; Hwang and Kim, 2017; Blankespoor, deHaan, and Marinovic, 2020; Cohen, Malloy, and Nguyen, 2020). These complexities can make individual investors, as opposed to institutional investors, more susceptible to potential distortions in OE disclosures. Importantly, by classifying nearly all EDGAR internet traffic into retail and institutional, following the approach of Cao, Jiang, Yang, and Zhang (2023), we can assess retail investors' engagement with 8-K filings. This allows us to investigate how OE disclosures differentially affect individual versus institutional investors.

This paper studies three key questions. First, do firm managers distort the sentiment in OE disclosures? Second, does OE sentiment manipulation mislead individual investors, causing them to bear the costs of mispricing? Third, how do managers and their firms profit from this sentiment distortion?[6]

For our empirical analysis, we assemble the universe of 8-Ks filed by U.S. public firms from August 2004 to August 2020, and construct a sample of 489,817 8-Ks with available data for our analyses.[7] We focus on three subsamples: 1) "All OE": A subsample of 114,953 8-Ks that includes

[5] These nine items are: Section 1 – Registrant's Business and Operations, Section 2 – Financial Information, Section 3 – Securities and Trading Markets, Section 4 – Matters Related to Accountants and Financial Statements, Section 5 – Corporate Governance and Management, Section 6 – Asset-Backed Securities, Section 7 – Regulation FD, Section 8 – Other Events, and Section 9 – Financial Statements and Exhibits.

[6] We focus on the sentiment distortion as the existing literature shows sentiment is an important tool of strategic disclosure (e.g., Ahern and Sosyura, 2014; Huang, Teoh, and Zhang, 2014; Edmans, Goncalves-Pinto, Groen-Xu, and Wang, 2018). There could be other manifestations of strategic disclosure, such as delaying a filing or bundling with other pieces of news.

[7] Our sample starts from August 23, 2004, because that is when the SEC finalized the current regime of rules for the disclosure of 8-Ks (SEC 2004).

Item 8.01, which account for 23.5% of the sample 8-Ks; 2) "Standalone OE": A narrower subsample of 79,856 8-Ks that reports only Item 8.01 and thus is a subset of "All OE"; and 3) "Non-OE": A benchmark sample of the 374,864 8-Ks without Item 8.01 disclosures. We measure textual sentiment in each 8-K as the difference between the proportion of positive words and negative words, based on the Loughran and McDonald's (2011) dictionary. This sentiment measure is not only a replicable benchmark in the literature but also indicative of how individual and institutional investors process financial information (Cao, Jiang, Yang, and Zhang, 2023).

To test our first research question regarding potential OE sentiment distortion, we estimate regressions of buy-and-hold abnormal returns (BHAR) in the four-day disclosure window [0, +3] and the three-month post-disclosure window [+4, +63] on OE sentiment using the "All OE" sample. We find that a one standard deviation increase in OE sentiment is associated with a statistically significant increase of 0.19% in event returns, but a subsequent decline of 0.21% in post-disclosure returns.[8] Therefore, long-run returns *fully* erase the initial response. This reversal is even more pronounced when we focus on the "Standalone OE" sample, with a 0.25% increase in event returns followed by a reversal of 0.33%. These results suggest that distortions in OE sentiment mislead investors, resulting in a significant initial price reaction followed by a price correction.

Interestingly, a placebo analysis using the "non-OE" sample shows that a one standard deviation increase in non-OE sentiment is associated with a statistically significant increase of 0.06% in event returns, followed by a continued 0.11% *increase* in post-disclosure returns. This post-disclosure *drift*, contrary to the reversal pattern for OE sentiment, fits the well-documented investor under-reaction to corporate announcements.

While our regression analysis provides an average effect of OE sentiment on stock prices,

[8] For economic comparison, Loughran and McDonald (2011) report a one standard deviation increase in firms' annual report (i.e., 10-K) sentiment is associated with a 0.11% higher event return.

manipulation more likely occurs in cases of extreme sentiment. To better assess the impact of OE sentiment distortion, we plot the difference in BHAR between the high-sentiment (top 10 percent) and low-sentiment (bottom 10 percent) groups of OE disclosures in Figure 1. In both the "All OE" and "Standalone OE" samples, we observe an initial surge in differential BHAR, peaking at approximately 1.5% during the four days following the disclosure. This initial spike is then followed by a gradual reversal over the next three months. In contrast, the differential BHAR for non-OE sentiment shows a gradual upward drift after the initial spike, without a significant reversal.

To corroborate our return analysis, we conduct two additional analyses to investigate the potential OE sentiment manipulation. First, we follow Huang, Teoh, and Zhang (2014) and examine the relationship between OE sentiment and future operating performance. We find that OE sentiment *negatively* predicts future return on assets (ROA) in the two years following disclosure, whereas non-OE sentiment *positively* predicts future ROA. This sharp contrast lends further support to the hypothesis of sentiment distortion in OE disclosures. Second, we examine the likelihood of future SEC comment letters to test the underlying assumption that OE disclosures are subject to less regulatory scrutiny compared to non-OE disclosures. Consistent with our assumption, we find that a significantly lower likelihood of receiving SEC comment letters for OE disclosures relative to non-OE disclosures.[9]

Next, we examine the impact of OE sentiment manipulation on retail investors. To gauge retail investors' engagement with 8-K disclosures, we follow Cao, Jiang, Yang, and Zhang (2023) and analyze download activity on the EDGAR system. Specifically, we classify EDGAR visits as retail when they originate from human downloads, and as institutional when they originate from machine downloads. The rationale is that retail investors typically access disclosures directly and do not employ

[9] In addition to these findings on the extensive margin, along the intensive margin, we also find that proxies for the level of sentiment distortion, i.e., the absolute value of either OE sentiment or event returns, are not associated with the likelihood of future SEC comment letters.

automated tools such as web-crawlers or sophisticated machine algorithms, which better characterizes institutional investors' practices (e.g., Ben-Rephael, Da, Easton, and Israelsen, 2022; Callen, Kaniel, and Segal, 2023). To validate our classification approach, we use Boehmer, Jones, Zhang, and Zhang's (2021) algorithm to identify retail orders and find a significant association between human EDGAR 8-K downloads and retail order imbalances, but no such relationship with machine downloads.[10]

We begin by examining the trading behavior of retail investors following OE disclosure. We find that higher OE sentiment is associated with significantly higher retail order imbalances in the event window, indicating that individual investors tend to trade strongly in accordance with OE sentiment in the event window. Notably, we find that retail investors continue to trade in alignment with the OE sentiment even in the post-disclosure period, potentially delaying price correction.

Next, we examine the relationship between retail readership of OE disclosures and the price responses to OE sentiment. Consistent with our previous findings on retail order imbalances, we find that greater retail readership leads to significantly stronger initial price responses to OE sentiment but weaker reversals in the post-disclosure period. For example, a one standard deviation increase in retail readership is associated with a 1.5 times stronger initial price reaction but a 15% weaker reversal post-disclosure.[11] In contrast, we do not observe these patterns with machine readership of OE information. To validate our findings based on retail readership, we further use institutional ownership as a proxy for retail investor activity and find that lower levels of institutional ownership associate with larger mispricing. Taken together, our analyses suggest that retail investors primarily bear the impact of OE sentiment distortion.

To study our third research question, which addresses the motives behind OE sentiment

[10] This finding is consistent with Chi and Shanthikumar (2018) who find that retail investors use EDGAR filings data in making trading decisions.
[11] In contrast, we find little evidence that higher machine readership leads to stronger initial price responses or slower subsequent price corrections.

distortion, we examine four corporate events that could lead managers or their firms to benefit from temporary stock price fluctuations. We first examine insider sales and CEO option grants, as managers could personally benefit from inflated stock prices before insider sales, and deflated stock prices before option grants (e.g., Yermack, 1997; Lie, 2005; Heron and Lie, 2007). Consistent with managers' incentives for strategic disclosure, we find a significantly positive relation between OE sentiment and the probability of subsequent insider sales. In contrast, there is a significantly negative relation between OE sentiment and the likelihood of subsequent option grants.

We also investigate two corporate events where firms can derive benefits from temporary inflated stock prices, namely, seasoned equity offerings (SEOs) and stock mergers (e.g., Rangan, 1998; Teoh, Welch, and Wong, 1998; Ahern and Sosyura, 2014; He, Liu, Netter, and Shu, 2020). Consistent with the strategic disclosure hypothesis, we find a significantly positive relation between OE sentiment and the probability of a subsequent SEO. Additionally, we find that OE sentiment has a significantly positive relation with the likelihood of subsequent stock mergers, but not with subsequent cash mergers where firms can derive little benefit from manipulated stock prices.

In our final analysis, we aim to identify the latent topics in OE disclosure that are prone to sentiment distortion. We apply a Latent Dirichlet Allocation (LDA) model to classify OE disclosures into specific topics and utilize ChatGPT to interpret the most probable words representing these topics. We find that sentiment distortion, as evidenced by the pattern of return reversal, is prevalent in the vast majority of topics that make up 89% of the OE filings. Moreover, sentiment distortion appears most pronounced in topics related to intangible information, such as disclosures regarding pharmaceutical R&D and legal proceedings and disputes. These findings suggest that when firms have discretion in their disclosures, topics involving intangible content may be susceptible to sentiment manipulation.

Our study contributes to the finance and accounting literature by providing new evidence on the impact of financial disclosure on individual investors. While previous studies examine the differential trading behaviors between retail investors and institutional investors in response to financial disclosures (e.g., Lee, 1992; Hirshleifer, Myers, Myers, and Teoh, 2008; Ayers, Li, and Yeung, 2011, Ben-Rephael, Da, Easton, and Israelsen, 2022; Callen, Kaniel, and Segal, 2023), as well as how frictions such as reporting complexity and costs of information acquisition may impede optimal trading decisions (e.g., Miller, 2010; Hwang and Kim, 2017; Blankespoor, DeHaan, Wertz, and Zhu, 2019), we extends this literature by investigating the influence of *strategic disclosures* on retail investors. Our analyses reveal that retail investors are particularly vulnerable to opportunistic distortion of disclosure sentiment, highlighting the potential for strategic disclosure to exploit the disadvantages faced by individual investors.[12] In contrast, we find that more sophisticated, machine-enabled information acquisition is immune to these risks, highlighting the disparities faced by different market participants (e.g., Fuster, Goldsmith-Pinkham, Ramadorai, and Walter, 2022).

Our paper also contributes to the literature on strategic corporate disclosures. While existing research finds that 8-K filings contain value-relevant information, they are susceptible to misleading tactics such as strategic timing, bundling with other news, or misclassification of item categories (e.g., Niessner, 2015; Segal and Segal, 2016; Bird, Karolyi, and Ma, 2018; Rawson, Twedt, and Watkins, 2023).[13] Our paper documents a novel form of strategic disclosure in 8-K filings, namely, the manipulation of sentiment in "Other News" disclosures.[14] Our further evidence suggests that managers and their firms may benefit from such sentiment manipulation corporate events.

[12] Our findings complement the existing literature that retail investors benefit from increased disclosure quality (e.g., Lawrence, 2013; Lee and Zhong, 2022).

[13] See, for example, Lerman and Livnat (2010), Zhao (2017), McMullin, Miller, and Twedt (2018), He and Plumlee (2020), and Ben-Rephael, Da, Easton, and Israelsen (2022) for evidence on the value-relevant information disclosed 8-Ks. Noh, So, and Weber (2019) find that 8-Ks can substitute for mandatory disclosure in the context of earnings guidance.

[14] In a contemporaneous work, Balachandran, Pathak, Sivaramakrishnan, and Zufarov (2024) also examine potential sentiment distortion in voluntary 8-K disclosures and document a positive relation between market reaction and OE sentiment. Our study significantly differs from theirs in that we provide comprehensive evidence of OE sentiment distortion, including long-run reversals, future earnings, and regulatory scrutiny. We further examine the implications of such distortion for retail investors and explore firms' incentives for such opportunistic behavior in major corporate events.

Finally, our findings carry important policy implications. The stark difference in stock price movements between OE and non-OE disclosures highlights the potential unintended consequences of existing voluntary disclosure practices. These repercussions could challenge the protection of investors and the integrity of fair and efficient markets, which are two essential pillars of the SEC's three-part mission. Additionally, we find that OE sentiment distortion is more pronounced for hard-to-verify non-financial information. Our findings underscore the necessity of regulatory oversight concerning flexible voluntary corporate disclosures.

1. SAMPLE CONSTRUCTION AND SUMMARY STATISTICS

As detailed in Panel A of Table 1, we start our sample construction with the universe of Form 8-Ks (current reports) from the SEC's EDGAR database, which includes 1,345,485 8-Ks from August 23, 2004, when the SEC implemented the present framework for Form 8-K filings, to August 23, 2020. Of these filings, 345,929 (25.7%) contain "Other Events" (OE) disclosure. We then require firms to have accounting data from the Compustat database and stock data from the Center for Research in Security Prices (CRSP) database. This reduces our sample to 546,985 8-Ks. We further require the firms to have data on additional control variables (described in Appendix A), resulting in a final sample of 489,817 Form 8-Ks. Within the final sample, the "All OE" sample contains the 23.5% of 8-Ks that report Item 8.01, while the "non-OE" sample contains all remaining 8-Ks not reporting Item 8.01. Because the "All OE" sample may bundle Item 8.01 with other items, we also analyze a cleaner "Standalone OE" subsample, which comprises the 69.5% of filings in the "All OE" sample that either solely report Item 8.01 or report Item 8.01 with its appendix, Item 9.01.[15]

We use a standard approach to measure each filing's sentiment as perceived by retail and

[15] We classify 8-Ks that report only Items 8.01 and 9.01 into the "Standalone OE" sample because Item 9.01 provides only supplemental information such as financial statements, pro forma financial information, or exhibits to further explain Item 8.01.

institutional investors (Cao, Jiang, Yang, and Zhang, 2023). Specifically, we apply a bag-of-words approach using the Loughran and McDonald (2011) dictionary, which allows us to tally the positive and negative words in each 8-K. We then compute sentiment as the number of positive words minus that of negative words, scaled by the total count of dictionary words. Panel B of Table 1 presents the summary statistics of sentiment across our 8-K samples. The first row indicates that the average sentiment of 8-Ks in the "All OE" sample is slightly negative at -0.07%, while the median sentiment is slightly positive at 0.21%. Since OE disclosure may bundle with other items in the same 8-K, we also calculate the sentiment specifically for the Item 8.01 section within these 8-Ks. The second-row reports that the average sentiment remains similar at -0.07%, while the median becomes neutral. The third row focuses on the "Standalone OE" sample, where both the mean and median sentiment are slightly positive. The last row shows that the average and median sentiment for non-OE disclosure are also slightly positive, at 0.02% and 0.25%, respectively.

Panel C of Table 1 presents the summary statistics of variables used in our analysis. We find that the median market capitalization for firms filing OE news is $850 million, categorizing them as small-cap stocks. The mean market capitalization is substantially higher at $7.49 billion, indicating a skew towards larger firms. The firms have a median market-to-book ratio of 1.78, and a mean of 3.2, comparable to that of the broader Compustat universe. OE-filing firms are typically recent winners as their median and average pre-event alphas are 1.49 and 1.80 basis points per day, respectively. On average, these firms have institutional ownership of 60.16% and are about equally likely to be listed on NASDAQ and non-NASDAQ exchanges. Regarding operating performance, the median ROA for an OE-filing firm is a modest 1.79%, but the average is much lower at -2.23% due to some firms with extremely poor operational performance. Appendix A provides the definitions of these variables.

2. STRATEGIC DISTORTION OF "OTHER EVENTS" SENTIMENT

In this section, we investigate potential distortion of sentiment in OE disclosures within 8-K filings. Our analysis begins by examining the short-term and long-term market responses to assess whether manipulation of OE sentiment occurs. Next, we corroborate the return analysis by examining the relation between OE sentiment and future firm performance. Additionally, we conduct placebo tests using non-OE sentiment. Finally, we explore a crucial assumption regarding the manipulation of OE sentiment: OE disclosures are less scrutinized by regulators compared to non-OE disclosures.

2.1 Price Responses to OE Sentiment

2.1.1 Test Design

We adopt a regression-based event study methodology to investigate the stock market reaction to the sentiment of OE disclosures. For our analysis of the initial event return, the dependent variable is the buy-and-hold abnormal return (BHAR) in the four-day window [0,+3], with day 0 being the filing date of the 8-K report.[16] To compute expected buy-and-hold returns ($\widehat{AR}_{it}$) for each firm i on the filing date t, we use the following equation:

$$\widehat{AR}_{it} = \prod_{d \in [a,b]} (1 + \hat{\alpha}_i + \hat{\beta}_{i,MKT} MKT_d + \hat{\beta}_{i,SMB} SMB_d + \hat{\beta}_{i,HML} HML_d + \hat{\beta}_{i,MOM} MOM_d) - 1, \qquad (1)$$

where d represents the trading days within the event window $[a, b]$ relative to the filing date, and the Carhart (1997) four-factor model parameters are estimated using data from the one-year window ending 30 days prior to the event ([-282, -30]). The BHARs are then calculated as follows:

$$BHAR_{it} = \prod_{d \in [a,b]} [(1 + r_{id}) - (1 + \widehat{AR}_{it})], \qquad (2)$$

where r_{id} is the delisting-adjusted return for the firm i on day d within the event window $[a, b]$.

Following Loughran and McDonald (2011), we employ event study-based regressions as follows:

$$BHAR_{it} = \gamma Sent_{it} + \text{Controls} + \text{FEs} + \varepsilon_{it}, \qquad (3)$$

[16] For a filing date that is a non-trading day such as weekend or holiday, we use the next trading day as the event day.

where $Sent_{it}$ is the sentiment of the 8-K filed by firm i on day t, γ is the coefficient capturing the differential market reaction to sentiment, and ε_{it} is the error term with a mean of zero. Following Loughran and McDonald (2011), we control for the natural logarithm of market capitalization, the natural logarithm of the market to book ratio, the natural logarithm of the share turnover, the pre-announcement alpha, institutional ownership, and an indicator variable for firms listed on Nasdaq.[17] We define these variables in Appendix A. We also include Fama-French 48 industry fixed effects and year-quarter fixed effects to control for industry- or time-specific unobserved heterogeneity, respectively. We report t-statistics using robust standard errors clustered by year-quarter since 8-K filing occurrences tend to cluster by quarter.

2.1.2 Initial Price Reaction to OE Sentiment

In Panel A of Table 2, the left panel presents regressions of event returns (BHAR [0, +3]) on OE sentiment. Using the "All OE" sample, Column (1) shows that the coefficient on OE sentiment (*Sent*) is positive and significant at the 1% level (t-stat 3.77). The coefficient of 20.11 indicates that a one standard deviation increase in OE sentiment corresponds to a 0.19% increase in event return. This effect is economically large, considering the sample average BHAR is 0.20%.[18]

The "All OE" sample includes 8-Ks that bundle OE disclosures with other items, potentially blurring the specific market reactions to OE sentiment. We address this concern in two ways. First, we measure OE sentiment only within Item 8.01 ($Sent^{8.01}$) rather than the entire document. Column (2) of Panel A shows that the coefficient on $Sent^{8.01}$ remains positive and significant at the 1% level (t-stat 5.58), with a one standard deviation increase in $Sent^{8.01}$ corresponding to a 0.18% increase in event

[17] To reduce the effect of outliers, we winsorize the accounting variables at the 0.5 and 99.5 percentiles.
[18] For a comparison, Loughran and McDonald (2011) report that a one standard deviation increase in firms' annual reports sentiment is associated with a 0.11% increase in event return. The 0.19% increase is calculated as the coefficient of 20.11 times the standard deviation of OE sentiment in the "All OE" sample of 0.0093 (the 0.93 in Table 1 divided by 100).

return, which is similar to the baseline result in Column (1).[19] Second, we restrict our analysis to the "Standalone OE" sample that contains 8-Ks with only OE disclosures. Column (3) of Panel A shows that the coefficient of OE sentiment is also positive and significant (t-stat 6.50), and a one standard deviation increase in sentiment corresponds to a 0.25% higher announcement return.[20] Overall, the results in Columns (1) through (3) provide robust evidence of a strong investor response to OE sentiment.

2.1.3 Long-run Price Reaction to OE Sentiment

Several potential explanations exist for the positive relation between event returns and OE sentiment. First, investors may rationally respond to new information presented in OE disclosure ("rational response"), which would lead to insignificant returns in the post-disclosure period. Second, investors may either underreact or overreact to OE disclosure, as suggested by previous studies (e.g., DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009; Cohen, Malloy, and Nguyen, 2020), potentially causing either a drift (underreaction) or reversal (overreaction) in long-run returns. Finally, if managers distort OE sentiment and investors overlook such distortion, the initial price reaction could cause stock mispricing, leading to a reversal in the post-disclosure window as the market corrects the mispricing. Notably, while both overreaction and manipulation explanations predict a long-term reversal, they predict different outcomes for the relationship between combined returns in the event and long-run windows with OE sentiment. Overreaction would predict a positive relationship, while manipulation would suggest a negative or neutral relationship. To distinguish among these competing hypotheses, we proceed to analyze stock returns in the long run.

We re-estimate Equation (3) using the BHAR in the three-month period after the filing (i.e.,

[19] The 0.18% increase is calculated as the coefficient of 51.34 in Column (2) times the standard deviation of $Sent^{8.01}$ (0.35 in Table 1 divided by 100).
[20] The 0.25% increase is calculated as the coefficient of 26.29 in Column (3) times the standard deviation of OE sentiment in the "Standalone OE" sample (0.95 in Table 1 divided by 100).

BHAR [+4, +63]). In Panel A of Table 2, Column (4) shows that for the "All OE" sample, the coefficient on sentiment is negative and significant at the 10% level, indicating a reversal of stock returns after the initial response to OE sentiment. Importantly, the magnitude of the coefficient (-22.7) surpasses that of the event return regression (20.1, Column (1)), suggesting a full reversal of the initial response. Stronger patterns are observed with $Sent^{8.01}$ (-86.7 in Column (5) vs. 51.3 in Column (2)) and the "Standalone OE" sample (-35.2 in Column (6) vs. 26.3 in Column (3)). For example, the result in Column (6) indicates that a one standard deviation increase in OE sentiment is associated with a 0.33% reversal, following a 0.25% increase in event return as indicated by the coefficient in Column (3).[21] Therefore, the results regarding both short-term and long-term returns align with the OE sentiment manipulation.

2.1.4 High-Minus-Low Sentiment Analysis

To visually illustrate our findings, we plot the difference in BHAR between the two subgroups of OE disclosures: high-sentiment and low-sentiment. While the regression analysis reflects average effects, this approach helps us to assess the impact of OE sentiment distortion at the tails of the sentiment distribution, where the sentiment distortion is most likely. Like our regression tests, we compute industry- and past return-adjusted sentiment breakpoints by first classifying 8-Ks into Fama-French 48 industries and then, within each industry, sorting them by their pre-event abnormal return (*PreFFAlpha*). We then classify low- and high-sentiment subgroups using the 10^{th} and 90^{th} percentiles of sentiment, respectively. We plot the difference in BHAR between high and low sentiment subgroups in a period from five trading days before to 63 trading days after the disclosure.

In Figure 1, we observe that for both the "All OE" sample and the "Standalone OE" sample, the differential BHAR spikes up immediately after the disclosure, reaching approximately 1.5% within

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[21] The 0.33% reversal is calculated as the coefficient of -35.15 in Column (6) times the standard deviation of OE sentiment in the "Standalone OE" sample (0.95 in Table 1 divided by 100).

four trading days. After peaking, the differential BHAR flattens, and then fully reverses within three months. The reversal pattern is more pronounced in the "Standalone OE" sample compared with the "All OE" sample. These results corroborate our regression analysis, indicating a full reversal after the initial market reaction.

2.2 OE Sentiment and Future Firm Performance

A crucial feature of the sentiment manipulation hypothesis is that the distorted sentiment misrepresents the actual firm fundamentals. Huang, Teoh, and Zhang (2014) uncover distorted sentiment in earnings press releases by showing a negative association between disclosure sentiment and future operating performance. Following their approach, we re-estimate Equation (3) but replace the dependent variable with the firm's return on assets (ROA) in the subsequent year after OE disclosure.

Columns (1) to (3) in Panel B of Table 2 show that the coefficient on OE sentiment is significantly negative (t-statistics ranging from -2.00 to -2.55). The coefficient in Column (3) indicates that a one standard deviation increase in OE sentiment is associated with a substantial 0.45% decrease in next year's ROA.[22] Columns (4) to (6) further presents the regressions of ROA in year t+2. Remarkably, we find that the coefficient on OE sentiment continues to be significantly negative.[23] These results show that, consistent with sentiment distortion, OE sentiment misrepresents the firm's future performance.

2.3 Placebo Tests with Non-OE Disclosure

Our analysis so far focuses on OE disclosure because it offers managers more flexibility to distort the disclosure sentiment relative to non-OE disclosure in 8-K filings. In this section, we

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[22] The 0.45% decrease is calculated as the coefficient of -0.47 times the standard deviation of OE sentiment in the "Standalone OE" sample (0.95 in Table 1 divided by 100).

[23] We find that the predictability of future ROA with OE sentiment disappears in year t+3.

conduct placebo tests by analyzing non-OE disclosures, under the assumption that investors interpret all sections of 8-K filings in a consistent manner. Specifically, we repeat the baseline regressions of market responses as presented in Panel A of Table 2, but this time using the "non-OE" sample.

Column (1) of Table 3 presents the regression of event returns using the non-OE sample. We find that the coefficient on non-OE sentiment is positive and significant at the 1% level (t-stat 3.35), mirroring the findings for OE sentiment. However, a divergent pattern emerges in the analysis of long-term returns, shown in Column (2). Here, non-OE sentiment has a significantly *positive* coefficient (t-statistic 2.07), suggesting a *drift* in the post-disclosure period rather than the reversal observed with OE sentiment. Economically, a one standard deviation increase in non-OE sentiment corresponds to an 0.06% increase in event return and a 0.11% drift in the subsequent three months.[24]

To corroborate the regression analysis, we also plot the high-minus-low-sentiment BHAR for the "non-OE" sample in Figure 1, which spikes in the event window and slowly drifts upwards, consistent with the regression analysis. Therefore, the price responses to non-OE sentiment are consistent with the well-documented phenomenon of investor underreaction, contrasting sharply with the reversal pattern seen with OE sentiment.

Columns (3) and (4) of Table 3 further show non-OE sentiment *positively* predicts ROA in both the subsequent year (t-statistic 2.62) and two years later (t-statistic 2.28), again contrasting with the negative association previously observed between OE sentiment and firm performance. Therefore, non-OE sentiment, unlike OE sentiment, does contain value-relevant information about a firm's fundamentals, consistent with the broader literature that supports the informative value of increased disclosure. Overall, the placebo tests using non-OE disclosure convey a salient message that OE disclosures are unique among 8-K filings, offering managers distinct opportunities to manipulate

[24] The 0.06% (0.11%) increase is calculated as the coefficient of 8.59 (15.00) times the standard deviation of non-OE sentiment (0.74 in Table 1 divided by 100).

sentiment.

2.4 OE Disclosure and Future Regulatory Scrutiny

Segal and Segal (2016) note that OE disclosure is discretionary because the guidance for filing Item 8.01 does not create an obligation to disclose under Section 10(b) or Rule 10b-5 of the Securities Exchange Act of 1934. Additionally, Segal and Segal (2016) highlight the scarcity of legal cases pertaining to Item 8.01 disclosure.[25] As a result, manipulating OE disclosure may face lower regulatory oversight than non-OE disclosure. We examine this mechanism by analyzing SEC comment letters, which is a vital tool in SEC's oversight process to enforce regulatory compliance (e.g., Dechow, Lawrence, and Ryans, 2016; Kubick, Lynch, Mayberry, and Omer, 2016; Duro, Heese, and Ormazabal, 2019; Liu, Shu, Towery, and Wang, 2022).

We collect data on comment letters related to 8-K filings from Audit Analytics and estimate the following logistic regression:

$$log\frac{p_{it}}{1-p_{it}} = \beta_0 + \beta_1 \times OE + \text{Controls} + \text{FEs}, \tag{4}$$

where p_{it} is the probability of an 8-K filed by firm i on date t receiving a future comment letter from the SEC. OE is our variable of interest, which is an indicator variable that equals 1 if the 8-K filing contains only OE news, and 0 if it contains no OE news. We deliberately exclude 8-K filings that contain both OE and non-OE news to ensure a clean comparison. We include the same control variables and fixed effects as in Equation (3), and report robust standard errors clustered by year-quarter.

Columns (1) and (2) of Table 4 present the regression results. The coefficient of *OE* is negative and significant at the 1% level in both models, indicating that OE disclosures are significantly less likely to receive a comment letter from the SEC compared to non-OE disclosures. This result is also

[25] See their footnote 4 for examples of such cases and law reviews on the subject.

economically significant, as the coefficient in Column (2) indicates the probability of receiving a future comment letter for an OE disclosure is 70.5% lower (i.e., $e^{-1.22} - 1$) than that for a non-OE disclosure. Given this extensive margin evidence on OE sentiment manipulation, we further investigate the intensive margin by estimating Equation (4) within the "Standalone OE" sample and replace the independent variable with the absolute value of either OE sentiment or event returns, two proxies for the level of OE sentiment distortion. Columns (3) and (4) of Table 4 show that the likelihood of receiving SEC comment letters is not significantly higher for either proxy. Overall, the results in Table 4 support the contention that OE disclosures face less regulatory scrutiny than non-OE disclosures along both the extensive and intensive margins.

3. ARE RETAIL INVESTORS MISLED BY OE SENTIMENT MANIPULATION?

Our findings thus far have revealed that distortions in OE sentiment result in stock mispricing. In this section, we investigate which investors are most susceptible to such distortions. Given that previous studies consistently highlight the tendency of individual investors to engage in sub-optimal attention-driven trading and to exhibit behavioral biases (e.g., Barber and Odean, 2008; Barber et al., 2022), we investigate whether retail investors, as opposed to institutional investors, are more susceptible to the manipulation of OE sentiment.

3.1 Measures of Retail EDGAR Readership and Retail Order Imbalances

Previous studies investigating the response of retail investors to corporate disclosure typically categorize retail trades by the size of trades (e.g., Lee, 1992; Bushee, Matsumoto, and Miller, 2003) or using proprietary brokerage data (Lawrence, 2013). We differ from previous studies by using a novel combination of retail investors' actual news consumption based on internet traffic, with recently available data on high frequency retail orders.

To capture the information acquisition behavior of investors, we analyze data on the download activity of financial filings on the SEC's EDGAR database from 2004 to 2017.[26] We measure daily firm-level visits on EDGAR as the number of unique IP addresses that download a firm's filings on a given day. Following Cao, Jiang, Yang, and Zhang (2023), we classify the EDGAR visits as retail when they originate from human downloads, and as institutional when they originate from machine downloads. This classification is based on the plausible assumption that retail investors primarily rely on manually reading disclosures and are not likely to employ automated tools like web-crawlers or sophisticated machine-based algorithms for processing disclosures.

To identify retail order flows, we utilize comprehensive data on trades from the Trade and Quote (TAQ) database. We employ Boehmer et al.'s (2021, BJZZ) algorithm to identify retail orders based on the sub-penny improvements given to marketable retail orders filled by wholesalers and brokers.[27] The BJZZ algorithm offers the advantage of accurately identifying retail orders, and it has the capacity to distinguish between buy and sell orders for cross-sections of thousands of stocks. Following BJZZ, we measure firm-level daily retail order imbalances (ROIB) as total retail buy orders minus sell orders in shares divided by the total retail share volume.

We then check the underlying premise that our classification of retail EDGAR visits accurately reflects retail investors' news consumption and, consequently, their trading. Given the existing literature that retail investors tend to purchase stocks that capture their attention (Barber and Odean, 2008), we would expect a positive relationship between retail EDGAR visits and ROIB. Table 5 presents the firm-level panel regressions of daily ROIB on contemporaneous EDGAR visits. Column (1) shows that the coefficient on total EDGAR visits is positive but insignificant (t-statistic 0.91), which may be driven by the inclusion of non-retail EDGAR visits that obscures the relationship

[26] The SEC acknowledges that due to technical issues with its data processing, there are a small proportion of instances during the sample period when not all SEC IP addresses are available. Despite this issue, previous studies find a strong correlation between EDGAR download activity and investor attention (e.g., Drake, Roulstone, and Thornock, 2014).
[27] These price improvements for marketable retail orders start after the implementation of Regulation National Market System (Reg NMS) in 2005.

between retail EDGAR visits and ROIB. Consequently, we separately investigate machine visits and retail visits. Column (2) shows that retail EGAR visits exhibits a significant and positive relationship with ROIB. In contrast, Columns (3) shows that machine visits do not display a significant association. This contrast lends credibility to our classification of retail EDGAR visits.

3.2 Retail Order Imbalances and OE Sentiment

To investigate the impact of OE sentiment manipulation on retail investors, we first examine how OE sentiment influences retail trading. We calculate initial ROIB for each 8-K filing as the difference between retail buy orders and sell orders in shares in the [0, +3] window, divided by the total share retail volume in this window. We calculate post-disclosure ROIB similarly using the [+4, +63] window.

We use these ROIB measures as dependent variables to re-estimate Equation (3). Columns (1) to (3) of Table 6 present the regressions analyzing initial ROIB and shows that OE sentiment positively and significantly predicts retail order imbalances in the event window. The sentiment coefficient in Column (3) indicates a one standard deviation increase in OE sentiment corresponds to a 0.48 percentage point rise event ROIB, which is approximately 13.6% of the average initial ROIB in our sample.[28] This finding indicates that individual investors tend to trade strongly in the direction of OE sentiment during the event window.

Columns (4) to (6) of Table 6 further present the regressions examining post-disclosure ROIB. Notably, we find that the coefficient on OE sentiment is significantly positive in all three models, indicating that the retail investors consistently trade in alignment with the (distorted) OE sentiment even after the disclosure. For example, Column (6) indicates that a one standard deviation increase in

[28] The 0.48% increase is calculated as the coefficient of 0.49 in Column (3) times the standard deviation of OE sentiment in the "Standalone OE" sample (0.95 in Table 1, divided by 100).

OE sentiment corresponds to a 0.35 percentage point rise post-disclosure ROIB.[29] This finding, together with the observed return reversal in the post-disclosure period, points to a dichotomy among investors: while sophisticated investors arbitrage against and correct the initial mispricing, retail investors tend to continue trading in the direction of the mispricing, potentially delaying the subsequent price correction.[30]

3.3 The Effect of Retail News Consumption to OE Disclosure

We further investigate the impact of OE sentiment manipulation on retail investors by examining retail news consumption as proxied by retail EDGAR readership. For an 8-K filed by firm *i* on day *t*, we calculate retail readership (*Retail_Readership*) in the initial event window [0, +3] using the following measure:

$$Retail\_Readership_{it} = \frac{\sum_{d \epsilon [0,+3]} Retail\_IP_{it}}{\sum_{d \epsilon [0,+3]} IP_{it}}, \qquad (5)$$

where $\sum_{d \epsilon [a,b]} Retail\_IP_{it}$ is the sum of daily number of unique retail IP addresses that download the 8-K filing during the [0, +3] window. To adjust for the general level of investor attention, which may vary over time and across firms, we scale by $\sum_{d \epsilon [0,+3]} IP_{it}$, which is the sum of the daily number of unique IP addresses that download any of the filings by firm *i* in the [0, +3] window. Thus, this retail readership measure quantifies the proportion of retail EDGAR traffic dedicated to the 8-K filing relative to total firm-level EDGAR traffic. We similarly construct a measure for machine readership (*Machine_Readership*) by replacing the numerator in Equation (5) with the number of unique machine IPs (rather than retail IPs).

We re-estimate our baseline regressions (Equation (3)) by including an interaction term of OE

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[29] The 0.35% increase is calculated as the coefficient of 0.36 in Column (3) times the standard deviation of OE sentiment in the "Standalone OE" sample (0.95 in Table 1, divided by 100).

[30] This finding is consistent with Griffin et al. (2011) who demonstrate that individual investors continue to buy even after the price peak during the crash of the tech bubble.

sentiment with either retail or machine readership of 8-K filings. Panel A of Table 7 presents the regressions of the BHAR in the [0, +3] window. In Column (1), which uses the "All OE" sample, the interaction of retail readership is positive and significant at the 1% level, suggesting that higher retail readership leads to a significantly stronger initial price reaction to OE sentiment. This result is also economically significant. Absent retail readership, the price response to a one standard deviation increase in OE sentiment is just marginally significant at 0.07% (t-statistic 1.68).[31] This response is higher by an additional 0.10%, or by 1.5 times, with a one standard deviation increase in retail readership.[32] In Column (2), the coefficient on the interaction of machine readership is negative, although it is not statistically significant. The contrast between retail and machine readership persists in Columns (3) and (4), which examine the "Standalone OE" sample. Therefore, during the event window, higher retail readership leads to a significantly stronger price response to OE sentiment, while machine readership does not exhibit such an impact.

In Panel B of Table 7, we further examine EDGAR readership and returns in the post-disclosure window. We construct the retail and machine readership measures for the post-disclosure window similarly as Equation (5), except that the numerator is now calculated over the [+4, +63] post-disclosure window. We estimate the regressions of long-run BHAR using the "All OE" sample. Column (1) shows that the coefficient on the interaction of retail readership is significant and *positive*, which mitigates the *negative* coefficient on OE sentiment (reversal effect). Absent retail readership, a one standard deviation increase in OE sentiment corresponds a -0.33% reversal. However, this reversal is reduced by 0.05% with a one standard deviation increase in retail readership.[33] On the other

[31] The 0.07% increase absent retail readership is calculated as the $Sent^{8.01}$ coefficient of 19.06 in Column (1) times the standard deviation of $Sent^{8.01}$ (0.35 in Table 1, divided by 100).
[32] The 0.10% marginal effect is calculated as the interaction term coefficient of 386.31 in Column (1) times standard deviation of $Sent^{8.01}$ (0.35 in Table 1, divided by 100) times standard deviation of retail readership (7.35 in Table 1, divided by 100).
[33] The -0.33% reversal absent retail readership is calculated as the $Sent^{8.01}$ coefficient of -93.79 in Column (2) times the standard deviation of $Sent^{8.01}$ (0.35 in Table 1, divided by 100). The 0.05% reduction is calculated as the interaction term

hand, we find no evidence that additional machine readership hampers market efficiency, as Column (2) shows that the interaction of machine readership is insignificant. These results persist when we examine the "Standalone OE" in Columns (3) and (4). Overall, the results in Table 7 align with our previous finding of persistent retail order imbalances in the post-disclosure window (Table 6), confirming that retail investors not only generate stronger mispricing in the event window, but also delay the price correction process in the post-disclosure window.

3.4 Analysis Based on Institutional Ownership

Despite the validation, we acknowledge that our approach of classifying retail EDGAR readership based on human downloads may not perfectly divide retail and sophisticated readership. For example, sophisticated investors may also access 8-K filings through human downloads as well. Consequently, we use institutional ownership as an alternative means to differentiate between retail and sophisticated investors.

We repeat the regression analysis from Table 7 but replace EDGAR readership with a dummy variable for high institutional ownership that equals one if the filing firm's institutional ownership in the quarter of the filing date is above the sample median, and zero otherwise. Columns (1) and (2) of Table 8 present the regressions of event returns, where the interaction of institutional ownership is significantly negative in both models. This indicates that firms with higher institutional ownership, which suggests a lower retail presence, experience significantly weaker price responses in the event window. This result is also economically significant. For example, in Column (2), the interaction term has a coefficient of -17.95, while that for OE sentiment is 35.47. This indicates that for firms with high institutional ownership, the positive association between price response and OE sentiment is reduced by half (17.95/35.47). In Columns (3) and (4), we further examine long-term returns following

coefficient of 12.21 in Column (2) times standard deviation of $Sent^{8.01}$ (0.35 in Table 1, divided by 100) times standard deviation of retail readership (131.45 in Table 1, divided by 100).

OE disclosure, where the coefficient of the interaction term is not significant in either model. Overall, the findings using institutional ownership support our findings using EDGAR readership that retail investors are more susceptible to OE sentiment manipulation.

4. HOW DO FIRMS AND CORPORATE INSIDERS BENEFIT FROM OE SENTIMENT MANIPULATION?

Recognizing the influence of OE sentiment manipulation on retail investors, we now turn to motives that drive firms and their management to engage in such manipulation. Specifically, we investigate occurrences of OE sentiment distortion prior to corporate events that could yield personal or organizational benefits to managers or their firms from short-term price fluctuations. We estimate a logistic regression model (Loughran and McDonald, 2011) as below:

$$log \frac{p_{it}}{1 - p_{it}} = \lambda_0 + \lambda_1 Sent_{it} + \text{Controls} + \text{FEs}, \quad (6)$$

where parameter $p_{it} = P(Y = 1)$ is the probability of a corporate event shortly after the 8-K filed by firm i on date t. Specifically, the outcome indicator variable Y equals 1 if a corporate event occurs in either the [+1, +1] or [+1, +3] window relative to the disclosure of the 8-K, and 0 otherwise. *Sent* is the *OE* sentiment previously defined. The control variables and fixed effects are similarly defined as in Equation (4).

In this regression framework, λ_1 is the coefficient of interest. Under the strategic disclosure hypothesis, we would expect λ_1 to be significantly positive for a corporate event that benefits from temporarily inflated stock prices, while significantly negative for a corporate event that benefits from temperately deflated stock prices. Note a significant λ_1 may arise from two possible situations: 1) OE sentiment manipulation prior to a pre-planned corporate event, such as inflating sentiment prior to a stock merger; or 2) The OE sentiment disclosure leads to managerial actions, such as insider sales following a negative sentiment manipulation that suppresses stock prices. We follow the literature and investigate two events where temporary price movements would benefit managers, as well as two events where temporary price movements are likely to benefit the firms.

4.1 Insider Sales

The first event we investigate is insider sales, as managers may benefit from selling shares at higher prices driven by positive OE sentiment. We collect data on shares sold by insiders from the Thomson Financial Insider Filing database, which compiles the data from Forms 3, 4, and 5 filed to the SEC. We follow Lou (2014) and define insider sales as the selling of shares by executive-level corporate insiders, specifically the chair of the board, chief executive officer, chief financial officer, chief operating officer, general counsel, and the president. We construct a measure of quarterly insider sales as the split-adjusted shares sold by insiders divided by the total shares outstanding at the end of the quarter. We then follow Lou (2014) and construct an indicator variable of notable insider sales that equals 1 if the insider sale is above the 25th percentile of the sample distribution, and 0 otherwise.[34]

Columns (1) and (2) of Table 9 examine the occurrence of insider sales in the day after OE disclosure for the "All OE" sample and the "Standalone OE" sample, respectively. We find that the coefficient of OE sentiment is significantly positive in both regressions. These results are also economically significant. For example, Column (1) indicates that a one standard deviation increase in OE sentiment is associated with a 12.0% higher likelihood of a large insider sale.[35] The OE sentiment coefficient remains significantly positive when we examine insider sales in the [+1, +3] window in Columns (3) and (4). Overall, these findings support the notion that managers might benefit from bundling their insider sales with OE sentiment manipulation.

4.2 Option Grants

[34] The intuition of this indicator variable is to focus on large insider sales as the benefit from small insider sales could be negligible.
[35] The 12.0% higher likelihood is calculated as $\exp(32.44 \times 0.35/100) - 1$, where 32.44 is the coefficient in Column (1), and 0.35 is the standard deviation of OE sentiment for the "All OE" sample (Table 1).

While insider sales are associated with incentives to *increase* stock prices, we examine another event where managers may have incentives to *decrease* stock prices: the issuance of executive option grants. Because employee stock options are typically granted at-the-money, a temporarily deflated stock price can reduce the exercise price of the options, thereby increasing the option value (e.g., Yermack, 1997; Lie, 2005; Heron and Lie, 2007). Therefore, we examine whether there is a negative relation between OE sentiment and the probability of subsequent option grants.

We follow the literature (e.g., Fich, Cai, and Tran, 2011; Shue and Townsend, 2017) and use data from ISS Incentive Lab to construct our sample of unscheduled option grants to the CEO.[36] Specifically, we first identify scheduled option grants as those granted within the [-14, +14] window surrounding the one-year anniversary of a prior option grant, where day 0 marks the anniversary. This approach is motivated by the common practice of scheduled option grants annually on a regular basis. Subsequently, we classify all other option grants as unscheduled.

We estimate Equation (6) with the dependent variable being an indicator for an unscheduled option grant. Columns (1) and (2) of Table 10 present the results for option grants occurring the day after OE disclosure. We find that the coefficient on OE sentiment is *negative* and significant at the 1% level in both models, indicating that lower OE sentiment predicts a higher chance of a CEO option grant. Economically, Column (1) indicates that a one-standard *decrease* in OE sentiment corresponds to a 20.9% higher likelihood of an option grant to the CEO.[37] Columns (3) and (4) conduct the analysis using option grants in the [+1, +3] window, where the OE sentiment coefficient remains negative in both models and significant in one. These results suggest that CEOs appear to benefit from bundling low OE sentiment with their option grants.

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[36] A manager can have up to four roles in a company in the ISS data. We classify managerial option grants as to CEO if one of the four roles of the manager is CEO.

[37] The 20.9% higher likelihood is calculated as $\exp(-54.26\times0.35/100) - 1$, where -54.26 is the coefficient in Column (1), and 0.35 is the standard deviation of OE sentiment for the "All OE" sample (Table 1).

4.3 Seasoned Equity Offerings

Next, we investigate two corporate events where firms could benefit from temporary price fluctuations. For the first event, we examine if OE sentiment is related to subsequent seasoned equity offerings (SEOs), as previous studies find evidence that firms engage in earnings management to boost stock prices before equity issuance (e.g., Rangan, 1998; Teoh, Welch, and Wong, 1998).

Following Cohen and Zarowin (2010), we construct our sample of SEOs using the Thomson Reuters SDC New Issue database. We require the sample of SEOs to be common stocks of U.S. firms that are listed on the NYSE, NASDAQ, or AMEX exchanges, and have an offer price above $5.[38] Table 11 presents the regression results for SEOs based on the issue date. Columns (1) and (2) examine SEOs in the [+1, +1] window, where the OE sentiment coefficient is positive and significant at the 1% level in both models. Column (1) indicates that a one standard deviation increase in OE sentiment corresponds to a 44.0% higher likelihood of a SEO.[39] Columns (3) and (4) consider SEOs in the [+1, +3] window, where the coefficient of OE sentiment remains positive and significant, albeit at the 10% level. Overall, these results are consistent with firms benefiting from OE sentiment manipulation prior to SEOs.

4.4 Mergers and Acquisitions

For the second corporate event where firms would benefit from temporary price movements, we examine stock mergers, where the acquiring firms can benefit from higher stock prices by using fewer shares to purchase the target firms. It is worth noting that the potential gains from manipulated stock prices are pertinent only when the payment is made in stock rather than cash (e.g., He, Liu, Netter, and Shu, 2020). Therefore, we aim to test whether OE sentiment is positively associated with

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[38] We also follow the literature and exclude spin-offs, reverse LBOs, closed-end funds, unit investment trusts, REITS, and limited partnerships, rights, and standby issues, simultaneous or combined offers of several classes of securities such as unit offers of stocks and warrants, and non-domestic and simultaneous domestic-international offers.

[39] The 44.0% higher likelihood is calculated as $\exp(104.09 \times 0.35/100) - 1$, where 104.09 is the coefficient in Column (1), and 0.35 is the standard deviation of OE sentiment for the "All OE" sample (Table 1).

to the likelihood of stock deals, while having no significant relationship with cash deals.

We collect data on mergers and acquisitions from the Thomson Reuters SDC Platinum database.[40] We categorize deals as cash mergers if the payment is exclusively in cash. Conversely, deals that involve stock payment as classified stock mergers. Next, we estimate Equation (6) where the dependent variable is an indicator variable that equals 1 if a merger announcement occurs after OE disclosure, and 0 otherwise.

Panel A of Table 12 presents the results for stock deals. The coefficient on OE sentiment is significantly positive in all four models, suggesting a positive association between OE sentiment and the likelihood of a stock merger. This effect is also economically large. For example, Column (1) indicates that a one standard deviation increase in OE sentiment is associated with an 80.5% higher likelihood of a stock merger.[41] Interestingly, when we examine cash mergers in Panel B of Table 12, we find starkly different results, as the coefficient on OE sentiment is insignificant in all four models. This finding is consistent with the rationale that there is minimal advantage to be gained from inflated stock prices in cash transactions.

In summary, the consistent patterns identified across four corporate events lend support to the notion that OE sentiment manipulation can be beneficial to managers and their firms, though it may concurrently impose costs on individual investors.

5. WHICH OE CONTENT IS SUBJECT TO SENTIMENT DISTORTION?

Finally, we employ an unsupervised Latent Dirichlet Allocation (LDA) approach to identify latent topics that may be especially prone to sentiment distortion. Methodologically, LDA has several

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[40] We follow the literature (e.g., He, Liu, Netter, and Shu, 2020) and require the deals to be completed and have deal values of at least $20 million, where the percentage acquired is greater than or equal to 50%, the acquirer is public, and the target's ownership status is one of public, private, or subsidiary.

[41] The 80.5% higher likelihood is calculated as exp(168.77×0.35/100) – 1, where 168.77 is the coefficient in Column (1), and 0.35 is the standard deviation of OE sentiment for the "All OE" sample (Table 1).

advantages as an increasingly used method in financial and accounting research: it does not require pre-defined topics and can efficiently handle large volumes of text in 8-K filings.

Before implementing the algorithm, we pre-process the textual data for the corpus of text within our "Standalone OE" sample, which excludes non-8.01 sections of the 8-K filings. For each document, we start with the raw text that includes attached exhibits and press releases, and remove any XML or HTML tags, punctuation, numbers and stop words. Then, after lemmatizing, we create a document-term matrix of all unigrams (single words) across the corpus of documents. Finally, we eliminate uninformative words that appear less than 200 times (rare words) or in more than half of our "Standalone OE" sample (common words).

The LDA algorithm requires a user-specified number of topics (*k*). To tune this hyperparameter, we explore a range of pre-specified topic counts, starting at 2 and incrementing by one up to 15. To assess the optimal number of topics, we use coherence scores, which evaluate the semantic similarity among words within topics, and supplement this measure with human judgement. We find that setting the number of topics to five or more achieves high average and maximum coherence scores. In our manual reading of the most probable words in each topic for a given number of topics, the LDA algorithm discerns similar sets of topics for any *k* above 5. Therefore, we proceed with *k* = 8 topics. To facilitate reproducibility, we ask ChatGPT 3.5 to interpret the themes of the eight topics by summarizing the fifty most probable words in each topic.

Utilizing the output of the eight topic LDA model, we decompose the short- and long-run market responses to OE sentiment by topic. Specifically, we estimate the following regression,

$$BHAR_{it} = \gamma_0 Sent_{it} + \sum_{\tau=1}^{8} \gamma_\tau Topic_{\tau,it} \times Sent_{it} + Controls + FEs + \varepsilon_{it}, \quad (7)$$

where $Topic_{\tau,it}$ is an indicator variable that equals 1 if the LDA probability of topic τ exceeds 0.30 for the OE disclosure by firm *i* on date t, and 0 otherwise. The threshold of 0.30 is chosen because it ensures that nearly every document is categorized into at least one topic.[42] In this model, $\hat{\gamma}_0$ captures the market reaction to OE sentiment for documents that are not classified under any specific topic, while $\hat{\gamma}_0 + \hat{\gamma}_\tau$ represents market reaction to OE sentiment for topic τ. As in Equation (3), the dependent variable is the BHAR either in the four-day event window or over a three-month post-disclosure window. Consistent with our LDA implementation, we measure OE sentiment ($Sent_{it}$) within the entire document, which includes any attached exhibits and press releases. Additionally, we include controls and fixed effects consistent with Equation (3). To test for the significance of the total effect for topic τ, we report Wald statistics based on the robust covariance matrix clustered by quarter. These statistics test against the null hypothesis $H_0: \gamma_0 + \gamma_\tau = 0$, determining whether the topic-specific response to OE sentiment is statistically significant.

Table 13 reports our LDA results, where we organize the ChatGPT-derived themes of the eight topics into three self-evident categories. The category "Intangible Disclosures" includes three topics on largely qualitative non-financial information: 1) *Pharmaceutical R&D*; 2) *Legal Proceedings and Disputes*; and 3) *Legal and Contractual Agreements*. The category "Financing Disclosures" includes three financial topics: 1) *Financial Accounting and Reporting*; 2) *Financial Management and Banking*; and 3) *Stocks and Securities Transactions*. The category "Operational Disclosures" includes two topics related to firms' business operations: 1) *Business Development and Marketing*; and 2) *Business and Financial Analysis*. To corroborate these descriptions, Appendix B provides for each topic the top fifty keywords identified by the LDA algorithm.

Table 13 first presents the distribution of filings across the identified topics, noting that a single filing can encompass multiple topics. The most prevalent category is "Financing Disclosures", representing almost 60% of all OE disclosures, followed by "Operational Disclosures" (about 40%)

[42] While a higher cutoff also does so, it also unrealistically limits documents to having mostly one topic. Thus, our choice of 0.30 strikes a balance between multiple topics per document and full topic classification of each document.

and "Intangible Disclosures" (about 29%). Overall, OE disclosures on average contain 1.3 topics, suggesting that the LDA model uncovers complex, multifaceted themes within the OE disclosures.

Next, we proceed to detect the OE topics that are most prone to sentiment manipulation by examining the return reversal pattern across the eight topics. The remaining columns of Table 13 present the regression results from estimating Equation (7), where the topics are arranged by the strength of post-disclosure return reversal in descending order, from the strongest to the weakest. Several interesting patterns emerge. First, all of the eight topics, except for *Business and Financial Analysis*, exhibit a pattern of a positive initial return reaction followed by return reversal, which is consistent with the full sample results. Specifically, for these seven topics, $\gamma_0 + \gamma_\tau$ is positive in the regression of event turn (BHAR [+0, +3]) but negative in the regression of post-disclosure return (BHAR [+4, +63]). These results seem to suggest that sentiment distortion is a common phenomenon, as these seven topics together account for 89% of OE disclosures.

Second, the topic *Business and Financial Analysis* exhibits a significant return drift in the post-disclosure window after the initial price reaction, suggesting that this category could be less prone to sentiment manipulation. Third, among the seven topics with reversals, the two topics of *Pharmaceutical R&D* and *Legal Proceedings and Disputes* experience statistically significant return reversals, as indicated in the last column of Table 13.[43] These two topics often require specialized expertise, training, and experience (e.g., in the biological or legal fields, respectively) that typical retail investors may not possess. In contrast, sophisticated institutional investors are more likely to have the resources to employ professionals with the necessary expertise to correctly evaluate such intangible content. Given that both topics fall under the "Intangible Disclosures" category, this suggests that when firms have disclosure flexibility, the intangible content can be an acute risk to retail investors.

[43] To address the concern that our results might be driven by the pharmaceutical industry, we conduct robustness tests by excluding the pharmaceutical industry, and our results remain similar.

6. CONCLUSION

Our study investigates the impact of strategic disclosure on retail investors in the context of "Other Events" disclosures in 8-K filings, a voluntary disclosure category that firms can use flexibly. Using a comprehensive dataset of 8-Ks from 2004 to 2020, we document robust evidence of sentiment distortion in OE disclosures. There is a strong initial price response in the direction of OE sentiment, which completely reverses in the post-disclosure period. Furthermore, we find that OE sentiment negatively predicts future operating performance. In contrast, non-OE disclosures lead to a continuous price drift (rather than a reversal) and exhibit a positive association with future operating performance.

Furthermore, we find that retail investors are particularly vulnerable to OE sentiment distortions. We observe that retail investors trade strongly in the direction of OE sentiment, both during and after the OE disclosure. Moreover, higher retail EDGAR readership leads to a significantly stronger price response to OE sentiment in the event window and a slower price correction in the post-disclosure period. These results hold when we use institutional ownership as an alternative measure to distinguish between sophisticated and retail investors.

Consistent with managers' incentives for strategic disclosure, we find a significantly positive relation between OE sentiment and subsequent insider sales (where managers can benefit from inflated stock prices), and conversely, a significantly negative relation between OE sentiment and subsequent option grants (where managers can benefit from deflated stock prices). Additionally, we find OE sentiment has a significantly positive relation with subsequent seasoned equity offerings or stock mergers where firms can benefit from inflated stock prices.

Finally, we apply a LDA model to divide OE disclosures into specific topics and utilize ChatGPT to interpret these topics. We find that while sentiment distortion exists in the vast majority of topics, it is most pronounced in topics related to intangible non-financial information. Our study uncovers the distortion of OE sentiment as a novel form of opportunistic disclosure employed by firm managers and highlights the implications of strategic corporate disclosure on individual investors. Our findings underscore the necessity for regulators to exercise increased scrutiny over voluntary corporate disclosures, especially those involving intangible information, to curb strategic disclosures that can mislead investors and disrupt market efficiency.

References

Ayers, Benjamin C., Oliver Zhen Li, and P. Eric Yeung, 2011, Investor trading and the post-earnings-announcement drift, *The Accounting Review* 86, 385–416.

Ahern, Kenneth R., and Denis Sosyura, 2014, Who writes the news? Corporate press releases during merger negotiations, *Journal of Finance* 69, 241-291.

Balachandran, Sudhakar V., Jalaj Pathak, Shiva Sivaramakrishnan and Rustam Zufarov, 2024, Is Tone in Voluntary Disclosure Credible? Working Paper.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785-818.

Barber, Brad M., and Terrance Odean, 2013, The behavior of individual investors, *Handbook of the Economics of Finance* 2, 1533-1570.

Barber, Brad M., Xing Huang, Terrance Odean, and Christopher Schwarz, 2022, Attention-Induced Trading and Returns: Evidence from Robinhood Users, *Journal of Finance* 77, 3141-3190.

Ben-Rephael, Azi, Zhi Da, Peter D. Easton, and Ryan D. Israelsen, 2022, Who pays attention to SEC Form 8-K? *The Accounting Review* 97, 59-88.

Bird, Andrew, Stephen A. Karolyi, and Paul Ma, 2018, Strategic disclosure misclassification, Working Paper, Chapman University.

Blankespoor, Elizabeth, Ed deHaan, and Ivan Marinovic, 2020, Disclosure processing costs, investors' information choice, and equity market outcomes: A review, *Journal of Accounting and Economics* 70, 101344.

Blankespoor, Elizabeth, Ed deHaan, John Wertz, and Christina Zhu, 2019, Why do individual investors disregard accounting information? The roles of information awareness and acquisition costs. *Journal of Accounting Research* 57, 53-84.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang, 2021, Tracking retail investor activity. *Journal of Finance* 76, 2249-2305.

Bushee, Brian J., Dawn A. Matsumoto, and Gregory S. Miller, 2003, Open versus closed conference calls: the determinants and effects of broadening access to disclosure, *Journal of Accounting and Economics* 34, 149-180.

Callen, Jeffrey L., Ron Kaniel, and Dan Segal, 2023, Filing speed, information leakage, and price formation, *Review of Accounting Studies* 28, 1618-1656.

Cao, Sean, Wei Jiang, Baozhong Yang, Alan L. Zhang, 2023, How to talk when a machine is listening: Corporate disclosure in the age of AI, *Review of Financial Studies* 36, 3603-3642.

Chi, Sabrina, and Devin M. Shanthikumar, 2018, Do retail investors use SEC filings? Evidence from EDGAR search, Working paper, University of California, Irvine.

Cohen, Daniel A., and Paul Zarowin, 2010, Accrual-based and real earnings management activities around seasoned equity offerings, *Journal of Accounting and Economics* 50, 2-19.

Cohen, Lauren, Christopher Malloy, and Quoc Nguyen, 2020, Lazy prices, *Journal of Finance* 75, 1371-1415.

Dechow, Patricia M., Alastair Lawrence, and James P. Ryans, 2016, SEC comment letters and insider sales." *The Accounting Review* 91, 401-439.

DellaVigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and Friday earnings announcements, *Journal of Finance* 64, 709-749.

Drake, Michael S., Darren T. Roulstone, and Jacob R. Thornock, 2015, The determinants and consequences of information acquisition via EDGAR, *Contemporary Accounting Research* 32, 1128-1161.

Duro, Miguel, Jonas Heese, and Gaizka Ormazabal, 2019, The effect of enforcement transparency: Evidence from SEC comment-letter reviews, *Review of Accounting Studies* 24, 780-823.

Edmans, Alex, Luis Goncalves-Pinto, Moqi Groen-Xu, and Yanbo Wang, 2018, Strategic news releases in equity vesting months, *Review of Financial Studies* 31, 4099-4141.

Fich, Eliezer M., Jie Cai, and Anh L. Tran, 2011, Stock option grants to target CEOs during private merger negotiations, *Journal of Financial Economics* 101, 413-430.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther, 2022, Predictably unequal? The effects of machine learning on credit markets, *Journal of Finance* 77, 5-47.

Griffin, John M., Jeffrey H. Harris, Tao Shu, and Selim Topaloglu, 2011, Who drove and burst the tech bubble? *Journal of Finance* 66, 1251-1290.

He, Jing, and Marlene A. Plumlee, 2020, Measuring disclosure using 8-K filings, *Review of Accounting Studies* 25, 903-962.

He, Jie, Tingting Liu, Jeffry Netter, and Tao Shu, 2020, Expectation management in mergers and acquisitions, *Management Science* 66, 1205-1226.

Heron, Randall A., and Erik Lie, 2007, Does backdating explain the stock price pattern around executive stock option grants? *Journal of Financial Economics* 83, 271-295.

Hirshleifer, David, Sonya Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance* 64, 2289-2325.

Hirshleifer, David, James N. Myers, Linda A. Myers, and Siew Hong Teoh, 2008, Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades, *The Accounting Review* 83, 1521–1550.

Huang, Xuan, Siew Hong Teoh, and Yinglei Zhang, 2014, Tone management, *The Accounting Review* 89, 1083-1113.

Hwang, Byoung-Hyoun, and Hugh Hoikwang Kim, 2017, It pays to write well, *Journal of Financial Economics* 124, 373-394.

Kubick, Thomas R., Daniel P. Lynch, Michael A. Mayberry, and Thomas C. Omer, 2016, The effects of regulatory scrutiny on tax avoidance: An examination of SEC comment letters, *The Accounting Review* 91, 1751-1780.

Lawrence, Alastair, James Ryans, Estelle Sun, and Nikolay Laptev, 2018, "Earnings announcement promotions: A Yahoo Finance field experiment." *Journal of Accounting and Economics* 66, 399-414.

Lawrence, Alastair, 2013, Individual investors and financial disclosure, *Journal of Accounting and Economics* 56, 130-147.

Lee, Charles MC, 1992, Earnings news and small traders: An intraday analysis, *Journal of Accounting and Economics* 15, 265-302.

Lee, Charles MC, and Qinlin Zhong, 2022, Shall we talk? The role of interactive investor platforms in corporate communication, *Journal of Accounting and Economics* 74, 101524.

Lerman, Alina, and Joshua Livnat, 2010, The new Form 8-K disclosures, *Review of Accounting Studies* 15, 752-778.

Lie, Erik, 2005, On the timing of CEO stock option awards, *Management Science* 51, 802-812.

Liu, Tingting, Tao Shu, Erin Towery, and Jasmine Wang, 2022, The role of external regulators in mergers and acquisitions: Evidence from SEC comment letters, *Review of Accounting Studies*, https://doi.org/10.1007/s11142-022-09723-y

Lou, Dong, 2014, Attracting investor attention through advertising, *Review of Financial Studies* 27, 1797-1829.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *Journal of Finance* 66, 35-65.

Loughran, Tim, and Bill McDonald, 2014, Measuring readability in financial disclosures, *Journal of Finance* 69, 1643-1671.

Maines, Laureen A., and Linda S. McDaniel, 2000, "Effects of comprehensive-income characteristics on nonprofessional investors' judgments: The role of financial-statement presentation format, *The Accounting Review* 75, 179–207.

McMullin, Jeff L., Brian P. Miller, and Brady J. Twedt, 2019, Increased mandated disclosure frequency and price formation: Evidence from the 8-K expansion regulation, *Review of Accounting Studies* 24, 1-33.

Miller, Brian, 2010, The effects of reporting complexity on small and large investor trading, *Accounting Review* 85, 2107–2143.

Noh, Suzie, Eric C. So, and Joseph P. Weber, 2019, Voluntary and mandatory disclosures: Do managers view them as substitutes?, *Journal of Accounting and Economics* 68, 101-243.

Niessner, Marina, 2015, Strategic disclosure timing and insider trading, Working Paper.

Rangan, Srinivasan, 1998, Earnings management and the performance of seasoned equity offerings, *Journal of Financial economics* 50, 101-122.

Rawson, Caleb, Brady J. Twedt, and Jessica C. Watkins, 2023, Managers' strategic use of concurrent disclosure: Evidence from 8-K filings and press releases, *The Accounting Review* 98, 345-371.

Rennekamp, Kristina, 2012, Processing fluency and investors' reactions to disclosure readability, *Journal of Accounting Research* 50, 1319-1354.

Securities and Exchange Commission. Financial reporting release nos. 33-8400; 34-49424: Final rule: Additional Form 8-K disclosure requirements and acceleration of filing date (August 23, 2004).

Segal, Benjamin, and Dan Segal, 2016, Are managers strategic in reporting non-earnings news? Evidence on timing and news bundling, *Review of Accounting Studies* 21, 1203-1244.

Shue, Kelly, and Richard R. Townsend, 2017, How do quasi-random option grants affect CEO risk-taking?, *Journal of Finance* 72, 2551-2588.

Teoh, Siew Hong, Ivo Welch, and Tak J. Wong, 1998, Earnings management and the long-run market performance of initial public offerings, *Journal of Finance* 53, 1935-1974.

Yermack, David, 1997, Good timing: CEO stock option awards and company news announcements, *Journal of Finance* 52, 449-476.

Zhao, Xiaofei, 2017, Does information intensity matter for stock returns? Evidence from Form 8-K filings, *Management Science* 63, 1382-1404.

Figure 1

High-Minus-Low Sentiment Buy-and-Hold-Abnormal Returns around 8-K Disclosure

This figure plots the high-minus-low sentiment buy-and-hold-abnormal returns (BHARs) starting 5 days before to 63 days after disclosures of 8-Ks. We compute industry- and past return-adjusted sentiment breakpoints by first sorting 8-Ks by its Fama and French 48 industry and then, within each industry, by the median pre-event abnormal return (*PreFFAlpha*). We then use the 10th and 90th percentiles of sentiment as the breakpoints to identify low-sentiment and high-sentiment subsamples, respectively. The high-minus-low sentiment event BHAR is the high sentiment group's average BHAR minus the low sentiment group's average BHAR on each event day relative to the filing date. We plot average BHARs for the "All OE", "Standalone OE", and "Non-OE" samples. The sample period is from August 23, 2004, to October 23, 2020.

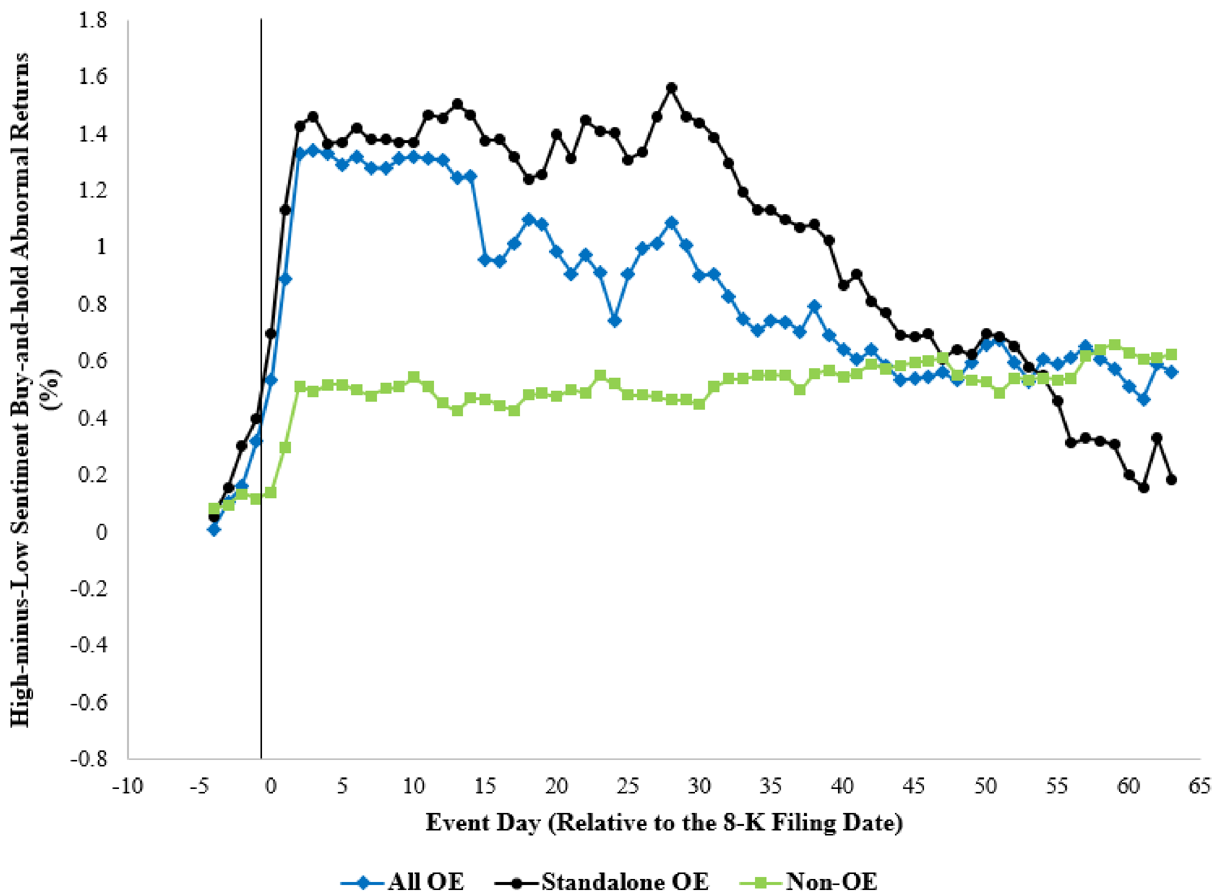

Table 1
Summary Statistics

Panel A reports our sample construction procedure for arriving at the final sample of 8-Ks. The sample period is from August 23, 2004, to October 23, 2020. The three subsamples are the "All OE" sample that contains all 8-Ks with Item 8.01 ("other news"), the "Standalone OE" sample that contains 8-Ks with only Item 8.01, and the "non-OE" sample that contains all 8-Ks without Item 8.01. Panel B reports on the summary statistics for sentiment across samples. We compute sentiment as the number of positive words minus negative words as defined by the Loughran and McDonald (2011) dictionary, scaled by the total dictionary word count. Panel C reports on the summary statistics for all other variables used in our analysis. The definitions of all variables are provided in Appendix A. The unit of observation (N) is the number of 8-Ks.

Panel A: Sample Construction

	8-Ks	All OE	Standalone OE	Non-OE
SEC EDGAR	1,345,485	345,929	244,584	999,556
Require Compustat/CRSP Event Study	546,985	129,142	89,193	417,843
Require Controls (Final Sample)	489,817	114,953	79,856	374,864

Panel B: Summary Statistics of Disclosure Sentiment

	N	Mean	St. Dev.	Median	Min	Max
All OE (Entire Document, %)	114,953	-0.07	0.93	0.21	-13.01	7.79
All OE (Item 8.01 only, %)	114,953	-0.07	0.35	0.00	-7.29	2.71
Standalone OE (%)	79,856	0.02	0.95	0.31	-13.01	7.79
Non-OE (%)	374,864	0.02	0.74	0.25	-8.82	6.82

Panel C: Summary Statistics of Other Variables

	N	Mean	St. Dev.	Median	Min	Max
Market Capitalization ($Bil)	114,953	7.49	0.85	27.01	0.00	895.78
Market to Book	114,953	3.20	1.78	5.30	0.16	52.86
Share Turnover	114,953	2.19	1.64	2.02	0.07	13.95
Pre-FF Alpha (Basis points per day)	114,953	1.80	1.49	19.96	-152.61	365.34
Institutional Ownership (%)	114,953	60.16	66.51	29.87	0.00	100.00
Nasdaq Indicator	114,953	0.52	1.00	0.50	0.00	1.00
ROA (%)	109,924	-2.23	1.79	24.00	-183.38	60.82
ROIB [0, +3] (%)	84,612	-3.52	-1.91	30.72	-100.00	100.00
ROIB [+4, +63] (%)	82,187	-2.98	-1.60	13.21	-100.00	100.00
Retail Readership [0, +3] (%)	100,354	7.70	7.35	5.56	0.00	94.89
Machine Readership [0, +3] (%)	100,354	11.70	12.10	7.95	0.00	96.42
Retail Readership [+4, +63] (%)	99,513	16.47	131.45	5.98	0.00	21,600.00
Machine Readership [+4, +63] (%)	99,513	6.35	26.75	3.64	0.00	2,883.34

Table 2
Market Responses and Firm Performance after OE Disclosure

Panel A presents the regressions of market responses to OE sentiment. The dependent variable is the buy-and-hold abnormal return (BHAR) in the [0, +3] window in Columns (1) to (3), and BHAR in the [+4, +63] window in Columns (4) to (6), where day 0 is the filing date of 8-K. Columns (1), (2), (4), and (5) use the "All OE" sample, which includes all 8-Ks that include OE disclosure. The variable of interest in Columns (1) and (4) is the sentiment of the entire 8-K filing (*Sent)*, and the variable of interest in Columns (2) and (5) is the sentiment of the Item 8.01 section ($Sent^{8.01}$). Columns (3) and (6) use the "Standalone OE" sample, which includes 8-Ks that include only OE disclosure, and the variable of interest is the sentiment of the entire document for 8-Ks. Panel B presents the regressions of firms' subsequent performance on OE sentiment, where the dependent variable is the firm's return on assets in the one or two years after disclosure. All regressions include firm-level controls including market capitalization, market-to-book ratio, share turnover, past performance, institutional ownership, and a dummy for NASDAQ firms, which are defined in Appendix A. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Initial and Long-run Market Reactions to OE Sentiment

	Dep. Variable: BHAR [0, +3]			**Dep. Variable: BHAR [+4, +63]**		
	All OE		**Standalone OE**	**All OE**		**Standalone OE**
	(1)	(2)	(3)	(4)	(5)	(6)
Sent	**20.11*****		**26.29*****	**−22.70***		**−35.15*****
	(3.77)		**(6.50)**	**(−1.99)**		**(−3.23)**
***Sent*$^{8.01}$**		**51.34*****			**−86.70*****	
		(5.58)			**(−3.19)**	
log(*Size*)	−0.19***	−0.19***	−0.16***	−0.13	−0.12	−0.08
	(−4.90)	(−4.92)	(−3.97)	(−0.67)	(−0.66)	(−0.47)
log(*MB*)	−0.11*	−0.12*	−0.13**	−1.07***	−1.07***	−1.30***
	(−1.92)	(−1.92)	(−2.36)	(−4.94)	(−4.95)	(−4.98)
log(*ShareTO*)	−0.34***	−0.35***	−0.24***	−1.54***	−1.53***	−1.46***
	(−5.77)	(−5.94)	(−4.43)	(−4.14)	(−4.10)	(−3.86)
PreFFAlpha	−2.47***	−2.45***	−2.60***	−46.08***	−46.09***	−46.01***
	(−8.84)	(−8.85)	(−7.26)	(−20.55)	(−20.51)	(−21.75)
InstOwn	0.01***	0.01***	0.01***	0.06***	0.06***	0.05***
	(8.66)	(8.69)	(4.85)	(7.13)	(7.12)	(6.06)
Nasdaq	−0.10	−0.09	−0.18*	−0.28	−0.29	−0.35
	(−1.32)	(−1.23)	(−1.86)	(−0.71)	(−0.72)	(−0.76)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,953	114,953	79,856	111,479	111,479	77,545
Adjusted R^2	0.01	0.01	0.01	0.11	0.11	0.13

Panel B: OE Sentiment and Subsequent Firm Performance

	Dep. Variable: ROA in t+1			Dep. Variable: ROA in t+2		
	All OE		Standalone OE	All OE		Standalone OE
	(1)	(2)	(3)	(4)	(5)	(6)
Sent	**−0.35****		**−0.47****	**−0.39****		**−0.43****
	(−2.00)		**(−2.55)**	**(−2.04)**		**(−2.06)**
Sent$^{8.01}$		**−0.83****			**−0.99****	
		(−2.09)			**(−2.18)**	
log(*Size*)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(7.84)	(7.85)	(6.51)	(9.46)	(9.46)	(8.50)
log(*MB*)	−0.02***	−0.02***	−0.02***	−0.04***	−0.04***	−0.04***
	(−5.78)	(−5.79)	(−5.95)	(−3.13)	(−3.13)	(−2.81)
log(*ShareTO*)	−0.04***	−0.04***	−0.04***	−0.05***	−0.05***	−0.05***
	(−7.69)	(−7.72)	(−6.80)	(−6.47)	(−6.49)	(−5.59)
PreFFAlpha	−0.002	−0.002	−0.02	0.04	0.04	0.04
	(−0.08)	(−0.09)	(−0.83)	(1.67)	(1.66)	(1.16)
InstOwn	0.001***	0.001***	0.001***	0.002***	0.002***	0.001***
	(8.27)	(8.28)	(6.92)	(7.78)	(7.79)	(6.13)
Nasdaq	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(3.99)	(3.97)	(3.82)	(4.19)	(4.17)	(3.85)
ROA_t	0.52***	0.52***	0.66***	0.44***	0.44***	0.53***
	(6.02)	(6.02)	(6.86)	(6.79)	(6.79)	(9.63)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,666	96,662	67,613	88,898	88,894	62,496
Adjusted R^2	0.22	0.22	0.23	0.18	0.18	0.19

Table 3
Placebo Tests Using Non-OE Sentiment

This table reports the results of placebo tests using the non-OE sentiment. The sample is that "non-OE" subsample that includes all 8-Ks without OE disclosure. Columns (1) and (2) are like Panel A of Table 2, where the dependent variable is the buy-and-hold abnormal return (BHAR) in the [0, +3] and [+4, +63] trading day window, respectively. The variable of interest is the sentiment (*Sent*) of the 8-K. Columns (3) and (4) are like Panel B of Table 2, where the dependent variable is the firm's return on assets (ROA) in the one or two years after the disclosure, respectively. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Variable			
	BHAR [0, +3]	**BHAR [+4, +63]**	**ROA in t+1**	**ROA in t+2**
	(1)	(2)	(3)	(4)
Sent	**8.59*****	**15.00****	**0.23****	**0.23****
	(3.35)	**(2.07)**	**(2.62)**	**(2.28)**
log(*Size*)	−0.05**	−0.29	0.02***	0.02***
	(−2.39)	(−1.52)	(11.74)	(12.57)
log(*MB*)	−0.13***	−0.74***	−0.01***	−0.01***
	(−4.93)	(−3.52)	(−2.83)	(−2.93)
log(*ShareTO*)	−0.25***	−1.02***	−0.03***	−0.04***
	(−7.20)	(−3.30)	(−12.15)	(−11.79)
PreFFAlpha	−2.46***	−46.41***	0.03***	0.02
	(−14.20)	(−18.20)	(3.50)	(1.12)
InstOwn	0.01***	0.04***	0.001***	0.001***
	(8.37)	(5.72)	(15.59)	(13.01)
Nasdaq	−0.11***	−0.71**	0.001	0.01***
	(−2.77)	(−2.39)	(0.54)	(2.90)
ROA_t			0.45***	0.45***
			(8.54)	(7.44)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	374,864	370,523	320,400	291,731
Adjusted R^2	0.01	0.12	0.22	0.17

Table 4
Regulatory Scrutiny of OE Disclosure

This table presents results for the regulatory scrutiny of OE disclosure. Columns (1) and (2) present a logistic regression where the dependent variable is the log-odds of a future comment letter filed by the U.S. Securities and Exchange Commission addressing an 8-K. The sample includes 8-Ks with only OE disclosure (Item 8.01, "Standalone OE" sample) and 8-Ks without OE disclosure ("non-OE" sample). The dependent variable of interest *(OE)* is an indicator equal to 1 for the "Standalone OE" subsample, and zero for the "non-OE" subsample. Columns (3) and (4) present the logistic regression using the "Standalone OE" sample, where the dependent variables of interest, the absolute value of *Sent* or *BHAR [0, +3]*), proxies for the level of sentiment distortion. All regressions include firm-level controls including market capitalization, market-to-book ratio, share turnover, past performance, institutional ownership, and a dummy for NASDAQ firms, which are defined in Appendix A. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Variable: Future Comment Letters			
	All 8-Ks		**Standalone OE**	
	(1)	(2)	(3)	(4)
OE	**−1.32*****	**−1.22*****		
	(−13.49)	**(−12.91)**		
abs(Sent)			**−16.41**	
			(−1.21)	
abs(BHAR [0, +3])				**0.004**
				(0.64)
log(*Size*)		0.02	0.05	0.06
		(1.12)	(0.88)	(0.99)
log(*MB*)		−0.03	−0.21	−0.22
		(−0.95)	(−1.54)	(−1.62)
log(*ShareTO*)		0.21***	0.27**	0.28***
		(7.40)	(2.45)	(2.54)
PreFFAlpha		0.07	−0.02	0.001
		(0.54)	(−0.06)	(0.003)
InstOwn		0.0001	0.002	0.002
		(0.07)	(0.59)	(0.54)
Nasdaq		0.33***	0.16	0.19
		(6.69)	(0.81)	(0.95)
Year-Quarter FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Observations	510,084	455,432	80,049	79,856

Table 5
EDGAR Visits and Retail Order Imbalances

This table examines the relationship between EDGAR downloads and retail investors' trading. Column (1) presents the firm-day panel regression of retail order imbalances (ROIB) on contemporaneous daily EDGAR visits to all financial filings. Columns (2) and (3) are similar to Column (1) except the dependent variables are *Retail_Visits* and *Machine_Visits*, respectively. *Retail_Visits* and *Machine_Visits* are EDGAR visits that originated from human downloads and machine downloads, respectively. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Variable: $ROIB_t$		
	(1)	(2)	(3)
$Visits_t$	**0.002**		
	(0.91)		
$Retail\_Visits_t$		**0.030*****	
		(2.59)	
$Retail\_Visits_t$			**0.002**
			(0.68)
Firm FE	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes
Observations	6,639,595	6,639,595	6,639,595
Adjusted R^2	0.01	0.01	0.01

Table 6
Retail Order Imbalances and OE Sentiment

This table examines the relationship between OE sentiment and retail investors' trading in the event-window and the post-disclosure window. The regression design is like our baseline regression in Panel A of Table 2, except the dependent variable is the event ROIB in the [0, +3] window (Columns (1) to (3)) or post-disclosure ROIB in the [+4, +63]) window (Columns (4) to (6)), where day 0 is the filing date of a given 8K. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Variable: ROIB [0, +3]			**Dep. Variable: ROIB [+4, +63]**		
	All OE		**Standalone OE**	**All OE**		**Standalone OE**
	(1)	(2)	(3)	(4)	(5)	(6)
Sent	**0.59*****		**0.49*****	**0.35*****		**0.36*****
	(3.77)		**(6.50)**	**(4.75)**		**(4.31)**
Sent$^{8.01}$		**0.60***			**0.54*****	
		(1.90)			**(2.88)**	
log(*Size*)	−0.0001	−0.0001	0.0002	0.001	0.001	0.001
	(−0.11)	(−0.10)	(0.14)	(0.97)	(0.97)	(1.45)
log(*MB*)	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(4.20)	(4.29)	(4.29)	(5.77)	(5.81)	(5.23)
log(*ShareTO*)	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(3.16)	(2.93)	(2.27)	(7.65)	(7.38)	(6.64)
PreFFAlpha	−0.002	−0.001	−0.002	0.004	0.004	0.003
	(−0.39)	(−0.27)	(−0.35)	(1.09)	(1.19)	(0.81)
InstOwn	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(−2.72)	(−2.68)	(−2.92)	(−4.75)	(−4.69)	(−3.84)
Nasdaq	−0.003	−0.003	0.003	−0.01***	−0.01***	−0.01**
	(−0.61)	(−0.57)	-0.49	(−2.93)	(−2.90)	(−2.12)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,932	84,932	57,598	85,221	85,221	57,939
Adjusted R^2	0.005	0.005	0.01	0.02	0.02	0.02

Table 7

EDGAR Readership of 8-K Filings and Price Responses to OE Sentiment

Panel A reports on the relationship between EDGAR readership of 8-K filings and price responses to OE sentiment in the event window. The dependent variable is the buy-and-hold abnormal return in the [0, +3] window, where day 0 is the filing date of 8-K. Columns (1) and (2) use all 8-Ks with OE disclosure (item 8.01), and Columns (3) and (4) use 8-Ks with only OE disclosure (only item 8.01). The variable of interest is the interaction of OE sentiment in the Item 8.01 section with retail EDGAR readership of 8-K filings or machine EDGAR readership of 8-K filings ($Sent^{8.01}$ × *Retail_Readership* or $Sent^{8.01}$ × *Machine_Readership*). Panel B is like Panel A except that the dependent variable is buy-and-hold abnormal return in the [+4, +63] window. All regressions include firm characteristics as in the baseline regressions (Table 2), and their coefficients are omitted for brevity. We also include year-quarter fixed effects and industry fixed effects in all regressions. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EDGAR Readership and Initial Price Response to OE Sentiment

	Dep. Variable: BHAR [0, +3]			
	All OE Sample		Standalone OE Sample	
	(1)	(2)	(3)	(4)
$Sent^{8.01}$ × Retail_Readership	**386.31*****		**200.48*****	
	(3.03)		**(4.54)**	
$Sent^{8.01}$ × Machine_Readership		**−23.56**		**−24.65**
		(−0.69)		**(−1.05)**
$Sent^{8.01}$	19.06*	56.37***	10.05**	30.67***
	(1.68)	(5.37)	(2.17)	(7.14)
Retail_Readership	0.65		−1.21	
	(0.84)		(−1.67)	
Machine_Readership		−1.72***		−1.07***
		(−4.30)		(−3.11)
Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	100,350	100,350	73,089	73,089
Adjusted R^2	0.01	0.01	0.01	0.01

Panel B: EDGAR Readership and Long-Run Price Response to OE Sentiment

	Dep. Variable: BHAR [+4, +63]			
	All OE Sample		Standalone OE Sample	
	(1)	(2)	(3)	(4)
$Sent^{8.01}$ × Retail_Readership	**12.21*****		**5.35***	
	(4.01)		**(1.69)**	
$Sent^{8.01}$ × Machine_Readership		**3.25**		**−23.85**
		(0.04)		**(−0.48)**
$Sent^{8.01}$	−93.79***	−91.22***	−38.40***	−36.02***
	(−3.13)	(−3.10)	(−3.45)	(−3.39)
Retail_Readership	0.08*		0.02	
	(1.94)		(0.23)	
Machine_Readership		0.25		0.28
		(1.48)		(0.97)
Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	96,334	96,334	70,197	70,197
Adjusted R^2	0.11	0.01	0.01	0.01

Table 8
Institutional Ownership and Price Responses to OE Sentiment

This table reports the relationship between institutional ownership and price responses to OE sentiment in the event window and post-disclosure period. The regression design is like that of Table 7 except that we replace EDGAR readership with a dummy of high institutional ownership, which equals one if the filing firm's institutional ownership in the quarter of the 8-K filing date is above the sample median, and zero otherwise. We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Var.: BHAR [0, +3]		**Dep. Var.: BHAR [+4, +63]**	
	All OE	**Standalone OE**	**All OE**	**Standalone OE**
	(1)	(2)	(3)	(4)
Sent$^{8.01}$ × High_InstOwn	**−45.31*** **	**−17.95** **	**−22.63**	**−4.93**
	(−2.75)	**(−2.27)**	**(−0.34)**	**(−0.19)**
Sent$^{8.01}$	73.76***	35.47***	−81.65*	−31.52*
	(4.73)	(4.77)	(−1.76)	(−1.72)
High_InstOwn	0.44***	0.33***	2.21***	1.87***
	(5.32)	(4.27)	(5.75)	(4.71)
log(*Size*)	−0.17***	−0.15***	−0.04	−0.01
	(−4.55)	(−3.69)	(−0.20)	(−0.04)
log(*MB*)	−0.12**	−0.13**	−1.04***	−1.25***
	(−2.03)	(−2.48)	(−4.78)	(−4.79)
log(*ShareTO*)	−0.27***	−0.19***	−1.27***	−1.18***
	(−4.40)	(−3.59)	(−3.44)	(−3.10)
PreFFAlpha	−2.47***	−2.60***	−46.39***	−46.28***
	(−8.69)	(−7.20)	(−20.54)	(−21.81)
Nasdaq	−0.09	−0.17*	−0.28	−0.41
	(−1.25)	(−1.87)	(−0.70)	(−0.90)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	114,556	79,576	111,076	77,265
Adjusted R^2	0.01	0.01	0.11	0.13

Table 9

OE Sentiment and Subsequent Insider Sales

This table presents the logistic regressions that examine the likelihood of insider sales following OE disclosure. The dependent variable is the log-odds of an insider sales event in the [+1, +1] or [+1, +3] trading day window relative to the filing date of the 8-K. Following Lou (2014), we focus on insider sales by top-level insiders consisting of the chair of the board, the chief executive officer, the chief financial officer, the chief operating officer, the general counsel, and the president. We also follow Lou (2014) and define an insider sales event as large insider sales with the dollar amount above the 25th percentile of the sample distribution. The main variable of interest is the OE sentiment within the Item 8.01 section ($Sent^{8.01}$). Columns (1) and (3) use the "All OE" sample which includes all 8-Ks with OE disclosure (Section 8.01), and Columns (2) and (4) use the "Standalone OE" sample which includes 8-Ks with only OE disclosure (only Section 8.01). We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Var.: Insider Sales [+1, +1]		Dep. Var.: Insider Sales [+1, +3]	
	All OE	**Standalone OE**	**All OE**	**Standalone OE**
	(1)	(2)	(3)	(4)
$Sent^{8.01}$	**32.44*****	**28.04****	**32.68*****	**27.46****
	(3.09)	**(2.46)**	**(4.84)**	**(3.55)**
log(*Size*)	−0.004	−0.01	0.04**	0.02
	(−0.19)	(−0.44)	(2.40)	(0.83)
log(*MB*)	0.28***	0.27***	0.26***	0.25***
	(10.80)	(7.65)	(10.08)	(8.32)
log(*ShareTO*)	−0.03	−0.02	−0.05	−0.05
	(−0.56)	(−0.33)	(−1.08)	(−1.02)
PreFFAlpha	1.19***	1.26***	1.31***	1.38***
	(7.58)	(6.44)	(9.63)	(9.24)
InstOwn	0.02***	0.02***	0.02***	0.02***
	(9.31)	(7.82)	(12.63)	(10.61)
Nasdaq	−0.04	0.04	0.12**	0.17**
	(−0.40)	(0.39)	(2.07)	(2.28)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	115,352	80,045	115,352	80,045

Table 10
OE Sentiment and Subsequent CEO Option Grants

This table presents the logistic regressions that examine the likelihood of option grants to the CEO following OE disclosure. The dependent variable is the log-odds of an unscheduled option grant event in the [+1, +1] or [+1, +3] trading day window relative to the filing date of the 8-K. We follow Shue and Townsend (2017) and construct the sample of option grants, and further follow Fich, Cai and Tran (2011) and classify unscheduled option grants. The main variable of interest is the OE sentiment within the Item 8.01 section ($Sent^{8.01}$). Columns (1) and (3) use the "All OE" sample which includes all 8-Ks with OE disclosure (Section 8.01), and Columns (2) and (4) use the "Standalone OE" sample which includes 8-Ks with only OE disclosure (only Section 8.01). We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Var.: Option Grant [+1, +1]		Dep. Var.: Option Grant [+1, +3]	
	All OE	**Standalone OE**	**All OE**	**Standalone OE**
	(1)	(2)	(3)	(4)
$\boldsymbol{Sent^{8.01}}$	**−54.26*****	**−50.82*****	**−23.07**	**−22.30**
	(−3.29)	**(−2.65)**	**(−1.52)**	**(−1.23)**
log(*Size*)	0.37***	0.36***	0.43***	0.43***
	(4.87)	(3.38)	(8.42)	(5.87)
log(*MB*)	0.24	0.31	0.08	0.13
	(1.35)	(1.43)	(0.76)	(1.00)
log(*ShareTO*)	0.37	0.64	0.40**	0.56***
	(0.96)	(1.50)	(2.50)	(3.02)
PreFFAlpha	−0.64	−0.48	−0.13	−0.37
	(−0.59)	(−0.31)	(−0.19)	(−0.36)
InstOwn	0.01	0.01	0.01*	0.005
	(0.69)	(0.56)	(1.81)	(0.86)
Nasdaq	0.02	0.30	0.08	0.20
	(0.04)	(0.63)	(0.28)	(0.56)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	115,352	80,045	115,352	80,045

Table 11
OE Sentiment and Subsequent Seasoned Equity Offerings

This table presents the logistic regressions that examine the likelihood of seasoned equity offerings (SEOs) following OE disclosure. The dependent variable is the log-odds of a seasoned equity offering in the [+1, +1] or [+1, +3] trading day window relative to the filing date of the 8-K. The main variable of interest is the OE sentiment within the Item 8.01 section ($Sent^{8.01}$). Columns (1) and (3) use the "All OE" sample which includes all 8-Ks with OE disclosure (Section 8.01), and Columns (2) and (4) use the "Standalone OE" sample which includes 8-Ks with only OE disclosure (only Section 8.01). We report, in parentheses, *t*-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep. Var.: SEO [+1, +1]		**Dep. Var.: SEO [+1, +3]**	
	All OE	**Standalone OE**	**All OE**	**Standalone OE**
	(1)	(2)	(3)	(4)
$Sent^{8.01}$	**104.09*****	**105.13*****	**68.07***	**74.70***
	(3.48)	**(3.26)**	**(1.78)**	**(1.78)**
log(*Size*)	0.05	0.04	0.01	0.01
	(0.81)	(0.58)	(0.10)	(0.22)
log(*MB*)	0.28***	0.18	0.19*	0.07
	(2.61)	(1.25)	(1.65)	(0.39)
log(*ShareTO*)	0.43***	0.25	0.39***	0.28
	(3.47)	(1.27)	(2.70)	(1.28)
PreFFAlpha	0.35	0.50	0.82***	0.89***
	(1.08)	(1.31)	(3.68)	(3.06)
InstOwn	−0.01	−0.002	−0.004	−0.001
	(−1.62)	(−0.22)	(−1.14)	(−0.19)
Nasdaq	0.37	0.42	0.47**	0.42*
	(1.54)	(1.32)	(2.53)	(1.78)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	115,352	80,045	115,352	80,045

Table 12
OE Sentiment and Subsequent Mergers and Acquisitions

This table presents the logistic regressions that examine the likelihood of mergers and acquisitions (M&A) following OE disclosure. The dependent variable is the log-odds of a stock merger (Panel A) or a cash merger (Panel B) in the [+1, +1] or [+1, +3] trading day window relative to the filing date of the 8-K. Cash mergers are deals paid for with all cash. Stock mergers are deals with stock payment. The main variable of interest is the OE sentiment within the Item 8.01 section ($Sent^{8.01}$). Columns (1) and (3) use the "All OE" sample which includes all 8-Ks with OE disclosure (Section 8.01), and Columns (2) and (4) use the "Standalone OE" sample which includes 8-Ks with only OE disclosure (only Section 8.01). We report, in parentheses, t-statistics based on robust standard errors clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OE Sentiment and the Likelihood of Stock Mergers

	Dep. Var.: Stock Merger [+1, +1]		**Dep. Var.: Stock Merger [+1, +3]**	
	All OE	**Standalone OE**	**All OE**	**Standalone OE**
	(1)	(2)	(3)	(4)
$Sent^{8.01}$	**168.77***	**234.13***	**165.92***	**141.06***
	(2.84)	**(3.86)**	**(3.85)**	**(2.98)**
log(*Size*)	0.08	0.11	0.25**	0.39***
	(1.26)	(1.13)	(2.02)	(2.66)
log(*MB*)	0.75***	0.54**	0.74***	0.60***
	(4.36)	(2.24)	(5.48)	(2.92)
log(*ShareTO*)	−0.17	−0.20	−0.26	−0.21
	(−0.93)	(−0.89)	(−1.10)	(−0.59)
PreFFAlpha	1.33*	3.01	−0.76	0.69
	(1.86)	(1.62)	(−0.53)	(0.33)
InstOwn	−0.02	−0.0001	−0.005	−0.003
	(−1.24)	(−0.003)	(−0.41)	(−0.24)
Nasdaq	0.04	16.24***	0.11	0.30
	(0.04)	(22.72)	(0.20)	(0.41)
Year × Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	115,352	80,045	115,352	80,045

Panel B: OE Sentiment and the Likelihood of Cash Mergers

	Dep. Var.: Cash Merger [+1, +1]		Dep. Var.: Cash Merger [+1, +3]	
	All OE	Standalone OE	All OE	Standalone OE
	(1)	(2)	(3)	(4)
$Sent^{8.01}$	**−40.88**	**−42.13**	**42.69**	**38.37**
	(−1.06)	**(−1.31)**	**(0.85)**	**(0.78)**
log(*Size*)	0.37	0.43**	0.66***	0.67***
	(1.62)	(1.98)	(4.14)	(3.67)
log(*MB*)	−0.57*	−0.94***	−0.21	−0.49
	(−1.68)	(−3.75)	(−0.62)	(−1.20)
log(*ShareTO*)	0.46	0.13	0.15	−0.01
	(0.75)	(0.20)	(0.33)	(−0.01)
PreFFAlpha	1.39	0.13	1.70	1.57
	(0.95)	(0.06)	(1.49)	(0.92)
InstOwn	0.001	−0.01	0.02	0.02
	(0.02)	(−0.31)	(1.29)	(1.18)
Nasdaq	0.37	−0.05	0.66	0.73
	(0.44)	(−0.03)	(1.15)	(0.97)
Year × Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	115,352	80,045	115,352	80,045

Table 13
LDA Topic Decomposition of the Market Reaction to OE Sentiment

This table reports on the results of using Latent Dirichlet Allocation (LDA) modeling to decompose the market reaction associated with OE sentiment in the "Standalone OE" sample. After implementing the LDA algorithm with eight topics, we label each topic with an interpreted theme based on ChatGPT's reading of the top fifty most probable words in each topic. Then, we decompose the market reaction by estimating,

$$BHAR_{it} = \gamma_0 Sent_{it} + \sum_{\tau=1}^{8} \gamma_\tau Topic_{\tau,it} \times Sent_{it} + Controls + FEs + \varepsilon_{it},$$

where $Topic_{\tau,it}$ is an indicator equal to 1 if the LDA probability of topic τ is greater than 0.30 for the i^{th} Item 8.01 8-K filed on date t and zero otherwise. $\hat{\gamma}_0$ estimates the market reaction associated with OE sentiment among documents classified into none of the topics, while $\hat{\gamma}_0 + \hat{\gamma}_\tau$ estimates the total market reaction associated with topic τ. The dependent variable is either buy-and-hold abnormal returns ($BHAR_{it}$) in the four-day announcement window [0, +3] or that in the three-month post-disclosure window [+4, +63]. We measure OE sentiment ($Sent_{it}$) within the entire filing, including attached exhibits and press releases. We also include controls and fixed effects (FEs) following Equation (3) of the main text. To test the null hypothesis that $H_0: \gamma_0 + \gamma_\tau = 0$, we report Wald ($W$) statistics in the parentheses computed from the robust variance covariance matrix clustered by the quarter of the filing date. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

			BHAR [0, +3]		BHAR [+4, +63]	
τ	ChatGPT Theme	% Filings	$\hat{\gamma}_0 + \hat{\gamma}_\tau$	W	$\hat{\gamma}_0 + \hat{\gamma}_\tau$	W
		Intangible Disclosures				
1	**Pharmaceutical R&D**	**10.64**	**86.96*****	**(7.46)**	**-126.78***	**(2.77)**
2	**Legal Proceedings and Disputes**	**10.76**	**13.98*****	**(7.34)**	**-79.74*****	**(10.53)**
3	Legal and Contractual Agreements	7.25	10.07	(0.67)	-36.54	(0.85)
		Financing Disclosures				
4	Financial Accounting and Reporting	6.37	17.26*	(2.74)	-32.62	(0.97)
5	Financial Management and Banking	32.21	20.49**	(4.81)	-22.30	(0.73)
6	Stock and Securities Transactions	21.30	0.09	(0.00)	-22.03	(0.35)
		Operational Disclosures				
7	Business Development and Marketing	19.25	1.20	(0.01)	-8.54	(0.06)
8	Business and Financial Analysis	20.52	33.47***	(20.75)	63.61*	(3.60)

Appendix A

Variable Definitions

Variable	Definition
Sent	Overall sentiment is measured by the number of positive words minus negative words scaled by the total number of words from the entire 8-K document. Positive, negative, and other neutral words are defined based on the Loughran and McDonald (2011) dictionary.
$Sent^{8.01}$	8.01 sentiment is measured by the number of positive words minus negative words scaled by the total number of words from the Item 8.01 section of an 8-K document. Positive, negative, and other neutral words are defined based on the Loughran and McDonald (2011) dictionary.
BHAR	Event (post-disclosure) returns are measured in the [0, +3] ([+4, +63]) trading day window relative to the 8-K event date by the buy-and-hold abnormal return (BHAR) defined in Equations (1) and (2), relative to the Carhart (1997) four factor model.
ROIB	Event (post-disclosure) retail buying and selling is measured in the [0, +3] ([+4, +63]) trading day window relative to the 8-K event date by the retail order imbalances (ROIB) identified by the Boehmer et al. (2021) algorithm. Retail order imbalances are defined as retail buy orders minus sell orders scaled by the total retail trading volume. Within the event window, we sum up (in shares) the retail imbalances and trading volumes before computing the ratio of the two. Data is from the TAQ database.
Retail_Readership	Event (post-disclosure) visits by retail investors are measured in the [0, +3] ([+4, +63]) trading day window relative to the 8-K event date by the number of visits by human IP addresses to an 8-K relative to total visits to the firm in the [0, +3] event window, as in Equation (5). Human IPs are classified excluding machine IPs following Cao et al. (2023). We use data from the SEC's EDGAR traffic logs.
Machine_Readership	Event (post-disclosure) visits by sophisticated investors are measured in the [0, +3] ([+4, +63]) trading day window relative to the 8-K event date by the number of visits by machine IP addresses to an 8-K relative to total visits to the firm in the [0, +3] event window, as in Equation (5). Machine IPs are classified following Cao et al. (2023). We use data from the SEC's EDGAR traffic logs.
Size	Size is the market capitalization defined as the price times the shares outstanding as of the day before the 8-K filing date from the CRSP database.
MB	Market-to-Book is the market capitalization divided by the book equity in the most recent fiscal year before the 8-K filing date. Book equity, from COMPUSTAT, is computed in the following order of priority as seq-preferStk+txditc, ceq+upstk-preferStk+txditc, and at-lt-preferStk+txditc.
ShareTO	Share turnover is the total CRSP share trading volume in the [-252, -6] trading day window relative to the 8-K filing date divided by the shares outstanding on the filing date. We require more than 60 available volume observations in this event window.
PreFFAlpha	The pre-event alpha in percentages per day is the intercept from a time-series regression of excess returns on market excess returns, the SMB size factor, the HML value factor, and the momentum factor as in Carhart (1997). The regression is estimated in the [-252, -61] day window relative to the 8-K filing date and we require more than 60 available volume observations in this event window. We use data from CRSP and the Ken French data library.
InstOwn	Institutional ownership is the percentage of shares owned by 13F filing institutional investors as of the quarter before the 8-K filing date from Thomson Reuters.
Nasdaq	The NASDAQ indicator is a variable equal to 1 if the CRSP exchange code is 2 and 0 otherwise.

Variable	Definition
ROA	The return on assets is the firm's income before extraordinary items scaled by the prior fiscal year's total assets from COMPUSTAT.

Appendix B

Top 50 Keywords per Latent OE Topic as Identified by the LDA Algorithm

	Intangible Discloses			Financing Disclosures			Operational Disclosures	
Topic	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
ChatGPT Theme	**Pharmaceutical R&D**	**Legal Proceedings and Disputes**	**Legal and Contractual Agreements**	**Financial Accounting and Reporting**	**Financial Management and Banking**	**Stock and Securities Transactions**	**Business Development and Marketing**	**Business and Financial Analysis**
1	develop	approv	author	adjust	bank	offer	product	cost
2	product	determin	repres	measur	director	amend	continu	product
3	pharmaceut	propos	amend	invest	sharehold	price	custom	increas
4	commerci	request	account	present	investor	stock	lead	project
5	patient	receiv	limit	consist	servic	purchas	servic	factor
6	approv	action	effect	calcul	uncertainti	common	offer	rate
7	drug	court	refer	determin	factor	us	begin	uncertainti
8	us	alleg	supplement	us	approv	amount	technologi	servic
9	clinic	claim	mean	account	board	sale	posit	condit
10	trial	vote	enforc	expens	declar	term	develop	develop
11	studi	seek	purchas	alloc	condit	note	investor	custom
12	treatment	meet	respect	estim	common	senior	serv	estim
13	receiv	order	reason	allow	close	instruct	manufactur	anticip
14	complet	enter	determin	receiv	anticip	outstand	brand	effect
15	prepar	continu	present	tax	plan	see	increas	base
16	uncertainti	respect	prepar	effect	stock	plan	solut	could
17	activ	agre	offer	borrow	could	sell	integr	updat
18	indic	reason	constitut	indic	dividend	million	improv	price
19	diseas	grant	control	consolid	updat	made	expand	plan
20	effect	amend	certif	compar	per	receiv	attach	avail
21	updat	against	permit	reflect	annual	transact	us	limit
22	medic	matter	design	continu	invest	aggreg	creat	million
23	potenti	parti	occur	assess	interest	tender	work	impact
24	plan	agreement	person	exclud	hold	per	opportun	continu
25	evalu	director	default	fund	privat	trade	said	econom
26	design	defend	perform	increas	attach	certain	pleas	believ
27	therapeut	termin	compli	evalu	cash	extend	deliv	discuss
28	continu	consid	accept	contribut	avail	director	graphic	energi
29	manufactur	case	affect	rate	record	law	innov	approxim
30	limit	review	agre	repres	subsidiari	due	help	us
31	initi	person	deliv	matur	complet	secretari	global	affect
32	treat	recommend	transfer	purchas	believ	begin	grow	competit
33	factor	make	govern	leas	quarterli	effect	support	litig
34	pleas	respons	assign	amort	litig	counsel	present	natur
35	therapi	violat	advis	collect	base	expir	look	manufactur
36	candid	law	termin	util	mean	refer	enhanc	annual
37	could	regard	consent	decreas	limit	prior	design	perform
38	investor	direct	assum	earn	reform	repurchas	sale	certain
39	program	submit	approv	activ	transact	corp	team	complet
40	regulatori	assert	distribut	comput	within	interest	see	regul
41	lead	final	record	reduc	obtain	option	visit	electr
42	research	district	request	recogn	begin	previous	network	abil
43	phase	effect	origin	loss	regard	accord	leader	involv
44	improv	disclos	confirm	charg	express	close	plan	facil
45	focus	notic	receiv	capit	stockhold	condit	growth	begin
46	believ	negoti	initi	deriv	herein	elect	system	revenu
47	need	govern	law	valu	commerci	regist	on	privat
48	fda	limit	indemnifi	develop	certain	upon	avail	reform
49	present	set	particip	perform	asset	respect	call	ga
50	involv	particip	make	exercis	continu	holder	invest	util