When the Watchdog Speaks: Which SEC Press Releases Really Move Stock Prices?*

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Work in progress

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Abstract

We examine which types of U.S. Securities and Exchange Commission (SEC) press releases affect financial markets. Using a two-decade panel of classified announcements, we find that enforcement-related disclosures, which often describe alleged securities law violations, generate significant negative market reactions. These announcements are followed by persistent stock price declines of approximately 80 basis points within one-week, heightened volatility, increased default risk, and intensified investor attention. The effect is disproportionately larger for speculative firms. In contrast, market responses non-enforcement releases are muted. Pooled dynamic and matching analyses provide evidence highlighting SEC enforcement press releases as a crucial information channel affecting market perceptions beyond corporate disclosures.

Keywords: Securities and Exchange Commission; SEC; Press releases

JEL classifications: G1, G10, G14, G18

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1. Introduction

The U.S. Securities and Exchange Commission (SEC) regularly publishes press releases. These releases cover a range of topics, including rule proposals, leadership changes, accounting standards, whistleblower awards, investor education, and enforcement actions. While press releases serve as the agency's primary channel for disseminating timely and authoritative information, it remains unclear whether all types of announcements influence financial markets in equal measure.

This study examines a central question: Which SEC press releases move the stock market? We provide strong evidence that enforcement-related announcements consistently influence the stock market. These releases often detail alleged violations of securities laws, thus conveying negative narratives. They are associated with statistically and economically significant stock price declines, heightened information uncertainty, increased default risk, and greater investor attention. In contrast, non-enforcement related press releases, even when relevant to policy or regulation, generate a muted market response.

We begin the analysis with a simple but striking empirical observation: nearly one-third of SEC press releases begin with headlines such as "SEC Charges" or "SEC Sues", suggesting a substantial focus on enforcement actions. This notable concentration of similarly themed disclosures raises a natural question: what kind of market impact do these widely issued enforcement-themed press releases actually have? To analyze this question, we develop a hybrid classification framework to systematically categorize the press releases. The process begins with a keyword-based filter that identifies enforcement-related headlines. We then augment this procedure with a large language model (LLM) classification that evaluates the content of each release. This two-step hybrid method captures both conventional enforcement disclosures, and cases that deviate from standardized language patterns but still reflect regulatory action.

We then examine the timing of SEC enforcement-related press releases. These announcements are significantly less likely to be issued on Friday, which suggests that SEC may avoid releasing high-stake news during periods of low investor attention (DellaVigna and Pollet, 2009). Interestingly, this stands in contrast to the common practice among some corporations and government agencies, which often release unfavourable information late on Fridays - a tactic known as the "Friday news dump" aimed at minimizing media and public scrutiny.[1] The SEC's apparent avoidance of this strategy may reflect an institutional preference for transparency and a desire to maximize dissemination and investor awareness, particularly when enforcement actions involve potential consequences to investors or the broader financial system.

We also find that SEC enforcement announcements spike sharply in September, the final month of the agency's fiscal year, noting this anomaly is not apparent for other categories of press releases. This pattern echoes the findings by Donelson et al. (2024), who document a similar September surge in enforcement filings, accompanied by more lenient sanctions. While Donelson et al. analyze internal case filings by the SEC's Division of Enforcement involving both firms and individuals, our study focuses on public press releases, which are real-time disclosures that directly influence investor perception and market behaviour. Therefore, our findings highlight how the SEC uses communication strategically, offering an insight into enforcement practices that internal data alone cannot capture.

[1] See NPR's Sifting Through the "Friday News Dump", which discusses how entities often release sensitive news on Fridays to avoid attention: https://www.npr.org/2005/06/30/4725120/sifting-through-the-friday-news-dump

Turning to the central question of market impact: We find that SEC enforcement-related press releases are significantly associated with negative abnormal returns of approximately 80 basis points, on average, within the first week following the announcement. These releases are followed by a discernible increase in implied volatility, which suggests elevated information uncertainty; a marked decrease in Merton's distance-to-default metric, which indicates higher default risk, and a notable rise in investor attention. The results remain robust after controlling for firm-level characteristics such as size, risk, liquidity, momentum, profitability, and leverage. In contrast, non-enforcement releases are associated with modest positive return drift, and no discernible increase in investor response. An interesting finding is that SEC insider trading announcements, unlike other enforcement actions, are generally followed by positive abnormal returns. This pattern suggests that the market interprets insider trading enforcement as evidence of effective monitoring and governance, particularly when the wrongdoing is isolated to specific individuals rather than the firm.

To better understand how enforcement announcements affect stock prices over time, we implement a pooled dynamic event study that tracks abnormal returns across multiple days surrounding each press release. While non-enforcement disclosures yield muted impact on prices, enforcement announcements are associated with a delayed and persistent decline in returns. The impact becomes statistically significant around day $t = 3$ post-announcements. This gradual price adjustment suggests that the market does not immediately incorporate enforcement-related information; instead, it responds progressively as the implications of regulatory action become clearer.

To strengthen identification, we exploit a matching sample approach, comparing enforcement announcements to a broad set of non-enforcement SEC press releases.

These non-enforcement disclosures, which include rule proposals, personnel appointments and whistleblower awards, serve as a natural control group because they are unlikely to trigger strong price reactions. In contrast, enforcement disclosures, which imply legal and reputation risk, serve as the treatment group. We match firms named in enforcement press releases to similar firms mentioned in non-enforcement press releases using K-nearest-neighbor matching based on size, industry and year. The results show that enforcement targets experience a statistically significant 108 basis point decline in cumulative stock returns over a one-week window relative to matched peers. This finding provides causal evidence that markets penalize firms upon learning of regulatory enforcement actions. To further validate our identification strategy, we conduct a placebo test to examine whether the stock returns are driven by firm-specific noise or latent time trends. The results confirm that the negative market reaction is specific to the timing of SEC enforcement announcements, supporting our interpretation of a causal relationship.

We then show that SEC enforcement activity disproportionately targets speculative firms, characterized by high volatility, extreme positive return potential, illiquidity, and low book-to-market ratios. In particular, firms with these lottery-like characteristics, typically associated with mispricing and sentiment-driven trading (Baker and Wurgler, 2006; Stambaugh et al., 2012), are more likely to be named in enforcement press releases. This evidence connects the SEC's enforcement behaviour to ongoing debates in asset pricing and corporate governance, which suggests that regulatory scrutiny is not evenly applied across the market. Rather, it is concentrated on firms whose risk-return profiles make them more appealing to speculative investors and more susceptible to potential misconduct.

This study makes three primary contributions. First, we provide evidence on the heterogeneous investor reactions to regulatory disclosures. Although the SEC regularly issues a diverse set of press releases, we show that enforcement-related announcements consistently generate meaningful market reactions. Other announcements, even those with apparent policy significance, are largely met with market indifference. This asymmetry highlights a key insight: investors respond primarily to information that carries clear and immediate economic consequences. For regulators seeking to influence investor behaviour through public communication, our findings highlight the importance not only of the news content, but of the perceived stakes embedded in the message.

Second, the findings from our study underscore an often-overlooked information channel: contemporaneous SEC press releases. Prior enforcement research has focused largely on retrospective datasets such as Accounting and Auditing Enforcement Releases (AAERs), litigation records or administrative proceedings. These studies document a variety of short- and long-term impacts, including financial penalties (Karpoff et al., 2008a), reputational damages (Karpoff et al., 2008b), auditor and director turnover (Fich and Shivdasani, 2007), changes in accounting practices (Feroz et al., 1991) and spillover effects on foreign firms (Silvers, 2016). Other research uses SEC enforcement data to predict financial misreporting (Dechow et al., 1995; 1996; 2011) or analyze institutional and political dynamics behind enforcement actions (Kedia and Rajgopal, 2011; Correia, 2014). We shift the focus to public press releases, which often precede formal legal proceedings. In doing so, our study provides new insights into the SEC's influence through its first point of contact with the public.

Third, we show that SEC enforcement press releases operate as a distinct and authoritative information channel, one that is far more influential than either corporate press releases, or traditional media coverage. Prior research shows how firms use corporate press release to influence investor behaviour: strategically timing disclosures (Ahern and Sosyura, 2014; DeHaan et al., 2015), simulating investor attention (Tsileponis et al., 2020) and signaling intent (Neuhierl et al., 2013). Financial press also plays a crucial role in diffusing information and reducing asymmetry, particularly around corporate earnings announcements (Bushee et al., 2010; Drake et al., 2014; Peress, 2014), though often with a sensationalized slant (Coyne et al., 2020). In contrast, SEC enforcement announcements are direct communication from a credible, independent regulator. They require no narrative framing and carry institutional weight. As such, SEC enforcement press releases function as a valuable form of public disclosure, distinct from corporate press releases and media-framed news.

The remainder of the paper proceeds as follows. Section 2 describes the sample selection process, including the collection of SEC press releases, the classification of enforcement and non-enforcement disclosures, the matching of firms, and the integration of additional datasets used in the empirical analysis. Section 3 presents descriptive statistics on the press release sample, enforcement activity, and firm characteristics. Section 4 reports the empirical results, and Section 5 concludes.

2. Sample Selection

2.1 SEC press releases

We use a Python script to retrieve SEC press releases directly from the agency's official repository (https://www.sec.gov/newsroom/press-releases). For each release, we extract the publication date, headline, and full text. Our sample includes 5,886 press releases issued between 1999 and 2022.

A notable feature of the dataset is that nearly one-third of all SEC press releases begin with headlines containing phrases such as "SEC Charges", "SEC Sues", "SEC Sanctions", "SEC Files Charges", "SEC Brings Civil Charges", and "SEC Announces Fraud Charges". This consistent headline pattern reflects a substantial focus on enforcement actions within the SEC's communication strategy. To systematically identify these enforcement-related announcements, we implement a two-step hybrid classification framework combining keyword filtering and large language model (LLM) analysis.

In the first step, we use a keyword-based filter to capture headlines referencing enforcement activities defined by the above phrases such as "SEC Charges" and "SEC Sues". These announcements, which concern legal proceedings, settlements, or penalties imposed by the SEC, generate more investor attention than routine regulatory updates, personnel changes, or administrative notices. This filtering procedure yields 1,617 SEC enforcement press releases.

In the second step, we employ a Large Language Model (LLM) in the form of ChatGPT to classify the remaining press releases and capture enforcement content not flagged by headline keywords. We choose ChatGPT for three reasons: (i) it delivers consistent and objective evaluations, reducing subjective biases commonly observed in manual classification; (ii) it processes and interprets natural language text at scale;

and (iii) it is widely adopted in recent accounting and finance research, including studies by Chen et al. (2022), Hansen and Kazinnik (2023), Smales (2023), Bilinski (2024), Jha et al. (2024), and Kim et al. (2024).

For each press release, we provide ChatGPT (GPT-4o model[2]) with the headline and the first 10 sentences of the full text, as these sections capture the core message and primary context of the announcement. We exclude the remaining text to minimize noise from procedural or peripheral details that could affect model performance. We prompt ChatGPT with the following instruction:

You are an SEC regulatory analyst with expertise in disclosure policy. Your task is to classify each of the following press release excerpts (headline + first 10 sentences) into one of the categories below:

1. *Enforcement and regulatory actions*
2. *Rulemaking and policy proposals*
3. *Leadership and personnel announcements*
4. *Investor protection and transparency initiatives*
5. *Whistleblower awards*
6. *Reports and strategic plans*
7. *Public oversight and board approvals*
8. *Small business and capital formation support*
9. *Others - only use this if the content clearly doesn't fit any of the above categories*

We develop this prompt after manually inspecting a representative sample of press releases across different years and refining it through iterative interactions with ChatGPT. To enhance classification accuracy, we include definitions and example headlines for each category. For instance, a press release is classified as "Rulemaking and policy proposal" if it announces a new rule, rule amendments, or public

[2] GPT-4o (released in May 2024) is a multimodal version of OpenAI's GPT-4 that provides faster inference and improved understanding of complex text patterns. Its use ensures replicability while taking advantage of recent advancements in large language models.

consultations, supported by phrases such as "SEC adopts …." and "amendments to …". We require the model to provide a brief explanation for each assigned label.[3] We manually verify the model's responses and explanations for a randomly selected subset of the data.

Category 1 ("Enforcement and regulatory actions") relates closely to the enforcement announcements identified earlier through headline keywords. This procedure captures 345 press releases whose headlines do not begin with phrases such as "SEC Charges" or "SEC Sues", but whose content is substantively similar. For example, a 2020 release titled "General Electric agrees to pay $200 million penalty for disclosure violations" falls under this category. We merge both groups, those identified through keyword filtering (1,617 releases) and those classified by ChatGPT under Category 1 (345 releases), and label them collectively as SEC enforcement announcements. Together, these account for 1,962 releases, representing one-third (1962/5886 = 33%) of the full sample.

Then, we further classify the 1,962 SEC enforcement press releases into thematic categories to examine varying market responses across enforcement types. Using the same ChatGPT procedure described above (headlines plus first 10 sentences in the text), we categorize each enforcement announcement into one of five themes: (i) fraud (including securities fraud, accounting fraud, Ponzi schemes or misrepresentation of investment products), (ii) insider trading, (iii) market manipulation (including pump and dump schemes, spoofing and coordinated manipulation of trading activity), (iv) registration/disclosure violations (including failing to properly register securities, hiding material information, and omitting required disclosures in filings), and (v) others. We obtain 1,060 fraud cases (54.0%), 235 insider trading cases (12.0%), 164

[3] Full details of the prompt and evaluation procedure are available from the authors upon request.

market manipulation cases (8.4%), 322 registration or disclosure violation cases (16.4%), and 181 other cases (9.2%). This classification is crucial for our analysis, as insider trading violations differ from other enforcement actions in their information content and market reactions. Appendix A.1 provides several SEC enforcement press release examples, while Section 3 discusses how these distinctions guide our empirical analysis.

2.2 Companies

We use a structured entity-matching procedure to identify whether a press release pertains to a specific company. We use the spaCy natural language processing library (http://spacy.io) to perform Named Entity Recognition (NER), extracting all entities labeled as organizations. These extracted entities represent potential company names referenced in the press release.

We match the entities against a reference set of firm names from the CRSP/Compustat Merged (CCM) database. The reference set includes only common stocks (shrcd = {10, 11}) listed on NYSE, AMEX or NASDAQ (exchcd = {1, 2, 3}). We vectorize both sets of names using Term Frequency-Inverse Document Frequency (TF-IDF) and calculate cosine similarity scores for each entity-reference pair. We retain only matches with a similarity score of 85% or higher. We then manually review all retained matches to ensure identification accuracy. This procedure yields 915 SEC press releases referencing 396 publicly listed firms. Of these, 415 unique press releases (415/915 = 45%) are enforcement-related, involving 280 unique firms.

2.3 Other datasets

Our empirical analysis uses a range of firm-level variables drawn from accounting and market data (including market capitalisation and stock prices), primarily sourced from the Compustat and CRSP databases. We employ two distinct proxies to capture institutional investor attention. First, we use abnormal trading volume as a broad indicator of market interest. Second, we construct a measure of abnormal institution attention (AIA), following the methodology of Ben-Rephael et al. (2017, 2021), and Chan and Smales (2025). We retrieve AIA data from Bloomberg terminals. We proxy for information uncertainty using option implied volatility (IV), with options data retrieved from OptionMetrics. We follow Brogaard et al. (2017) and use Merton distance-to-default (DtD) to measure corporate default risk. Conceptually, DtD captures the distance between a firm's asset value and its liability, with higher values indicating lower default risk. Appendix A details the data filters and estimation procedure of each variable.

3. Descriptive Statistics

Figure 1 plots the annual distribution and proportion of SEC press releases across the nine topic categories discussed earlier. The red bars, representing *SEC enforcement announcements*, show a marked increase beginning in 2009, and remain dominant throughout the early to mid-2010s. This pattern is consistent with the aftermath of the 2008 financial crisis, which exposed widespread misconduct and risk management failure, and the subsequent regulatory tightening, most notably the Dodd-Frank Act of 2010.[4] During this period, enforcement actions account for the largest share of SEC press releases, approaching 50% of the total in some years.

< Insert Figure 1 here >

Figure 1 also shows that *Rulemaking and policy proposals* (blue bars), and *Investor protection and transparency initiatives* (green bar), which maintain a consistent presence in the first half of the sample period, decline in relative percentage in the second half. The later years of the sample period, particularly post-2016, exhibit increased topic variety. Categories such as *Whistleblower awards*, and *Small business and capital formation support*, which were absent or minimal in earlier periods, have become more prominent. This expansion suggests a broadening of the SEC's communication agenda beyond traditional enforcement and regulatory actions in recent years.

< Insert Table 1 here >

[4] In June 2009, President Obama introduced what he described as a "sweeping overhaul of the U.S. financial regulatory system, a transformation on a scale not seen since the reforms that followed the Great Depression", culminating in the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010. For details, see https://obamawhitehouse.archives.gov/the-press-office/remarks-president-regulatory-reform

Panel A of Table 1 presents the distribution of companies identified in Section 2.2 and mentioned in SEC press releases across Fama-French 12 industries. The first column reports the number and percentage of companies mentioned in enforcement press releases, while the second column provides corresponding statistics for companies in non-enforcement news. Money and BusEq sectors constitute nearly 50% of all enforcement news. The third column shows that these distributions broadly reflect the industry composition of the Compustat universe. Further analysis shows that Goldman Sachs named most frequently in SEC enforcement press releases (38 times), followed by Morgan Stanley (25 times) and Citigroup (13 times).

Panel B of Table 1 reports summary statistics by SEC announcement type. Firms associated with *SEC enforcement announcements* are significantly smaller (the average logarithm of market cap 15.741 vs. 16.191; Diff. = −0.450, *t*-statistics = −2.977) and have higher systematic risk (Beta = 1.158 vs. 1.082; Diff. = 0.076, *t*-statistics = 1.777). They are more value-oriented (BM 0.689 vs. 0.603; Diff. = 0.085, *t*-statistics = 1.890) and less profitable (ROE −0.009 vs. 0.082; Diff. = −0.091, *t*-statistics = −2.248). Leverage is lower among enforcement firms (6.224 vs. 7.325; Diff. = −1.101, *t*-statistics = −2.279). By contrast, differences in idiosyncratic volatility (0.020 vs. 0.018; Diff. = 0.001, *t*-statistics = 1.233), Amihud illiquidity (0.264 vs. 0.058; Diff. = 0.207, *t*-statistics = 1.517), and momentum (0.102 vs. 0.087; Diff. = 0.015, *t*-statistics = 0.488) are small and statistically indistinguishable from zero. Overall, enforcement firms appear smaller, riskier, and weaker on fundamentals, while recent returns, trading frictions, and leverage are comparable.[5]

Next, we examine whether the timing of SEC enforcement announcements exhibits systematic variation across calendar year and trading week. Prior literature documents

[5] Significance based on Welch *t*-tests.

a notable increase in regulatory activity during September, coinciding with the SEC's fiscal year-end (Donelson et al., 2024) and in December for FINRA (Ling et al., 2025). Related work on earnings announcement (e.g., DellaVigna and Pollet, 2009) highlights lower investor attention to disclosures released on Fridays. Building on these findings, we test for two effects in the timing of SEC enforcement announcements: (i) a fiscal year-end effect, and (ii) a weekday effect.

< Insert Figure 2 here >

Figure 2 presents graphical evidence consistent with both timing effects. Panel A shows that SEC enforcement activity increases markedly in September, supporting the fiscal year-end effect. Panel B shows a pronounced decline in enforcement announcement on Fridays, which suggests that the SEC may strategically avoid end-of-week disclosures when investor attention is lower. This weekday pattern contrasts with the behaviour of some corporations and government agencies that often release negative news late in the week to reduce public and media scrutiny. Instead, the SEC appears to time enforcement communications to avoid low-attention periods. This strategic release pattern likely reflects the agency's objective to maximize investor awareness and ensure that material information is broadly disseminated, particularly when enforcement actions involve consumer protection or market integrity concerns.

To formally examine these patterns, we estimate a negative binomial regression:

$$Enforcement_t = \alpha + \beta Seasonality_t + \gamma X_t + \epsilon_t, \quad (1)$$

where Enforcement_t denotes the count of *SEC enforcement announcements* at time *t*, and Seasaonality_t is a dummy variable equal to 1 in September (for the monthly model) or on Fridays (for the daily model), and 0 otherwise. $\mathbf{X}_t$ is a vector of time-varying macroeconomic control variables including the market risk premium, the implied volatility index, and the U.S. economic policy uncertainty index.

< Insert Table 2 here >

Table 2 reports the regression results. Column (1) shows a significantly positive coefficient on the September dummy (0.678, *p*-value = 0.002), indicating heightened enforcement activity during this month. Column (2) reports a significant negative coefficient on the Friday dummy (-0.533, *p*-value < 0.001), suggesting fewer releases occur at end of the trading week. These findings suggest that SEC enforcement actions are not randomly timed; instead, their timing reflects possible internal agency deadlines, and strategic sensitivity to market attention cycles.

4. Empirical Analyses

4.1 Main empirical findings

We begin the empirical analysis by examining the stock market's response to SEC press releases, with a particular focus on the distinction between enforcement and non-enforcement announcements. Our goal is to assess how different types of regulatory disclosures influence investor behaviour. Using a buy-and-hold abnormal return (BHAR) framework, we track post-announcement stock performance and compare the effects across enforcement subcategories

Figure 3 shows a striking pattern in stock returns for firms named in SEC press releases following the announcements. The red and green lines plot cumulative average BHAR for non-insider and insider trading enforcement news, respectively, while the black line shows average BHAR for non-enforcement news. To mitigate confounding effects from overlapping disclosures, we exclude nearly 2% of press releases issued within +/- 1 trading day of another SEC announcement involving the same firm.

< Insert Figure 3 here >

Stock prices fall sharply following non-insider trading enforcement announcements (red line). Following these announcements, average cumulative BHAR declines by nearly 0.8% in the first week, and a further 0.2% in the second. This decline is economically meaningful, as benchmark return following non-enforcement news (black line) remains close to zero. To assess economic magnitude, we follow Karpoff et al. (2008b) and calculate firm-level dollar losses as the product of market-adjusted abnormal returns and market capitalization on day -1, aggregated over the [-1, +5] event window.

By contrast, insider trading enforcement announcements (green line) are followed by pronounced positive abnormal returns, reaching nearly +1% after two weeks. Appendix Figure B.1 shows a similar pattern in the individual case of Oppenheimer Holdings Inc., where the SEC's insider trading press release preceded a sharp and sustained price increase.

Two mechanisms may explain our finding. First, enforcement against insider trading signals effective compliance and monitoring systems. When internal controls detect and report misconduct, prompting SEC investigation and subsequent enforcement, investors interpret the disclosure as evidence of functioning governance. Fernandes and Ferreira (2008) show that insider trading enforcement improves stock price informativeness, indicating that investors value greater corporate transparency. Together, these favorable perceptions are associated with a rise in share price.

Second, the positive stock price reactions observed following insider trading enforcement announcements can be partly attributed to the nature of the enforcement itself. Unlike most non-insider trading cases, which typically involve firm-level misconduct such as accounting fraud or disclosure violations, insider trading cases predominantly target individual defendants rather than the corporation as a whole.

When enforcement news becomes public, it boosts investor confidence, leading to upward stock price adjustments.

To test this separation hypothesis, we examine whether insider trading cases in our sample target the matched listed firm or individuals. Using ChatGPT classification and manual review (see Appendix A.2), we identify key defendant(s) for each case. Among 120 insider trading announcements mapped to companies in our sample, only one explicitly named the matched firm as defendant. In other cases, enforcement targets individuals without implicating the firm directly.

< Insert Figure 4 here >

Figure 4 provides illustrative examples that highlight the distinction between enforcement cases targeting corporate entities and those targeting individual defendants. Panel A presents an example of a corporate defendant, where the SEC charged Ares Management LLC with compliance failures under the Investment Advisers Act of 1940. In this case, the firm itself is explicitly named as the respondent and subject to a cease-and-desist order, underscoring direct organizational accountability for inadequate internal controls. By contrast, Panel B displays a case involving an individual defendant, where the SEC charged Michael Steinberg, a portfolio manager at Sigma Capital Management, with insider trading. The enforcement action focuses on personal misconduct by an employee rather than firm-level wrongdoing. The juxtaposition of these cases illustrates the central distinction identified in our sample: insider trading announcements typically concern individuals, whereas non-insider trading enforcement actions more frequently involve corporate entities as the primary respondents.

< Insert Table 3 here >

To further examine the employment status of individual defendants, we employ a large-language-model (GPT-4o) classification procedure to identify whether these individuals had already left their companies at the time of enforcement (see Appendix A.3 for methodological details). The analysis reveals that in 91 out of 119 cases (76%), defendants were explicitly or implicitly described as former officers or employees, indicating that most insider trading actions involve individuals who had already departed their firms when the SEC announced charges. This pattern suggests that insider trading enforcement typically targets personal misconduct occurring within a prior employment context rather than penalizing firms directly. Consistent with this interpretation, Karpoff et al. (2008b) document that 93.4% of managers identified as culpable for financial misrepresentation lose their jobs during or immediately after the violation period, with most being explicitly fired, which suggests that regulatory actions frequently coincide with managerial turnover and personal accountability. Table 3 provides illustrative examples of such cases, where defendants, including the former CEOs, counsel, and managers of major corporations, were no longer affiliated with their employers at the time of enforcement.

We now formally analyze the relationship between SEC enforcement announcements and stock returns by estimating the following panel regression:

$$\mathrm{BHAR}_{i,[-1,+5]} = \alpha + D_i + I_i + X_{i,t}'\gamma + \mu_j + \lambda_y + \epsilon_{i,t}, \quad (2)$$

where $\mathrm{BHAR}_{i,[-1,+5]}$ is the cumulative market-adjusted BHAR for firm i over the [-1, +5] event window, and All BHAR values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. D_i is a dummy variable equal to 1 if the press release pertains to an enforcement action (exclude insider trading cases), and 0 otherwise. I_i is the dummy variable equal to 1 if the press release related to the insider trading cases, and 0 otherwise. The control vector $\mathbf{X}_i$ includes firm-level covariates commonly used in return prediction: *MCAP_log* to proxy for size effect (Banz, 1981); *Beta* for systematic risk (Sharpe, 1964); *IVOL* for idiosyncratic risk (Ang et al., 2006); *Amihud* for liquidity (Amihud, 2002); *MOM* for price momentum (Jegadeesh and Titman, 1993); *Leverage* for financial risk (Frank and Goyal, 2009), and *RoE* for profitability (Chen et al., 2010). We include industry and year fixed effects in Equation (3) to account for unobserved heterogeneity across sectors and time.[6]

< Insert Table 4 here >

Table 4 presents the panel regression results assessing the market impact of SEC enforcement announcements on abnormal stock returns, as measured by cumulative BHARs over the [-1, +5] trading-day window. Standard errors (in parentheses) are clustered at the industry level. Column (1) reports the baseline specification without control variables, while Column (2) adds the full set of firm-level covariates. In both columns, the coefficient on the SEC Enforcement dummy is negative and statistically significant at the 5% level, with estimates of -0.794 (*t*-statistic = -2.157) and -0.801 (*t*-statistic = -1.978), respectively. This suggests that enforcement-related announcements are associated with approximately 80 basis points of negative abnormal returns in the following week.

By contrast, the Insider Trading dummy is positive and highly significant across all specifications, indicating that insider trading cases are associated with positive market reactions. The coefficient estimates range from 1.096 to 1.160, all significant at the 1% level. Column (3) adds controls for concurrent earnings announcements and FOMC meetings, while Column (4) introduces a continuous measure of earnings surprises (SUE). The magnitude and significance of the enforcement and insider trading effects

[6] We use industry rather than firm fixed effects because enforcement-related SEC press releases are concentrated in a few industries, particularly *Money* and *BusEq*. Industry effects control for sector-specific differences while preserving the cross-firm variation needed for identification.

remain largely consistent, supporting the robustness of the results. These findings suggest that SEC enforcement actions negatively affect stock performance, particularly when they do not involve insider trading.

To further investigate why insider-trading announcements elicit positive stock-price reactions, we examine the information-environment channel. If insider-trading cases predominantly involve individuals rather than firms, the disclosure of such enforcement actions may alleviate information asymmetry and improve secondary-market liquidity. In contrast, non-insider announcements, typically linked to accounting or disclosure violations, may increase perceived firm-level risk and widen trading frictions.

< Insert Figure 5 & Table 5 here >

Figure 5 plots the daily average abnormal bid-ask spread for firms mentioned in SEC insider trading announcements from event day t = 0 to t = +20. The red line represents insider-trading news, while the blue line denotes non-insider news. Abnormal spreads are computed as the firm's daily bid-ask spread minus its expected pre-event spread, where the expected spread is estimated as the average spread over a 60-day window preceding the event, excluding the most recent 10 days (i.e., using a 60-day estimation window with a 10-day gap). For convenience of interpretation, all bid-ask spreads are multiplied by 1000. Dashed lines indicate each group's mean post-event abnormal spread. The figure shows that bid-ask spreads narrow substantially following insider-trading announcements and remain below zero throughout the 20-day period, whereas spreads widen slightly after non-insider announcements, indicating reduced liquidity.

Table 5 quantifies these changes in abnormal bid-ask spreads over different post-event windows ([0, +1], [0, +5], [0, +10], [0, +20]) for insider- and non-insider-trading cases. The *t*-statistics, based on cross-sectional standard errors, show that the spreads decline significantly after insider-trading announcements (−0.066 to −0.065 basis points; all significant at the 1% level). In contrast, non-insider cases exhibit small and insignificant positive abnormal spreads. The differences between the two groups are uniformly negative and statistically significant (*t*-statistics = −2.334 to −6.054), implying that insider-trading announcement is associated with superior post-event liquidity. These findings are consistent with Bris (2005), who documents that insider trading law enforcement enhances liquidity, a feature often associated with favorable market reactions. Based on this evidence, we exclude insider trading press releases from the enforcement category in our subsequent analysis, focusing instead on announcements that expose firms directly to regulatory security.

We next examine whether the market reactions reflect the arrival of new information, or the repetition of previously disseminated content. The efficient market hypothesis of Fama (1970) posits that asset prices adjust instantly and unbiasedly to new information. Yet, recent evidence shows that markets sometimes react to stale information. Tetlock (2011) finds that investors respond most strongly to new information, but they also react to stale news. Similarly, Huberman and Regev (2001) and Gilbert et al. (2010) document that stale information can influence market behaviour.

To this end, we compare SEC enforcement press releases to prior coverage in *The Wall Street Journal* (WSJ). We focus on the WSJ because of its large circulation, and frequent use in research on media and financial markets (Fang and Peress, 2009; Chan and Smales, 2025). We obtain WSJ print editions from Factiva and identify relevant articles using full-text keyword searches for “Securities and Exchange Commission” or “SEC”. Following Lang and Stice-Lawrence (2015), and Cohen et al. (2020), we measure similarity between press releases and media coverage using three established methods: (i) cosine similarity, (ii) Jaccard similarity, and (iii) semantic similarity based on an LLM.

First, we compute cosine similarity between each SEC enforcement press release and WSJ articles published in the four calendar weeks preceding the release. Cosine similarity is defined as the dot product of the document term vectors, scaled by the product of their lengths. This adjustment removes the influence of document length and captures directional similarity in word usage. Second, we compute Jaccard similarity using same term frequency vectors. Unlike cosine similarity, which accounts for frequency, Jaccard similarity measures the proportion of shared terms, making it an ideal approach for identifying documents that overlap in vocabulary.

Third, we compute semantic similarity using the all-MiniLM-L6-v2 model from the Microsoft-Hugging Face Sentence-BERT library. This pre-trained transformer generates dense vector embeddings that capture contextual and semantic links between words and phrases. We calculate similarity between these embedding to identify documents that may differ in surface wording but convey similar underlying content.

Appendix Figure B.2 presents the distribution of similarity scores. Across all measures, SEC enforcement press releases are largely dissimilar from preceding WSJ articles, suggesting that the press releases provide new rather than recycled information. For example, fewer than a handful of articles exhibit a semantic similarity score above 75%, suggesting that the overlap between SEC press releases and prior media coverage is minimal.

We also analyze the linguistic tone of SEC press releases. We quantify sentiment using the Loughran and McDonald (2011) financial dictionary. Following Goldman et al. (2024), and Chan and Smales (2025), we define net sentiment as the difference between the number of positive and negative words, scaled by their sum. Positive-tone words (e.g., “leadership”, “enable”, “strength”, and “success”), and negative-tone words (e.g., “challenge”, “concerns”, “complain”, and “liquidate”) are obtained from McDonald’s website at https://sraf.nd.edu/loughranmcdonald-master-dictionary.

< Insert Figure 6 here >

Figure 6 plots the average annual net sentiment by press release type. Enforcement-related disclosures (red line) exhibit persistently negative tone across the sample period, whereas non-enforcement releases (blue line) are largely neutral. The time-series average sentiment -0.730 for enforcement announcements, and -0.048 non-enforcement ones, yielding an average difference of -0.682. A two-sample *t*-test assuming unequal variances gives a *t*-statistics of -31.408 (p-value $\leq$ 0.01). These results highlight that SEC enforcement announcements are systematically negative in tone, whereas non-enforcement press releases convey a more neutral narrative.

If enforcement-related disclosures convey negative information, they should also be associated with heightened information uncertainty and increased perceived default risk. Prior research supports this hypothesis. For example, Patell and Wolfson (1979, 1981), Rogers et al. (2009) and Hann et al. (2019) document significant shift in information uncertainty, proxied by option implied volatility, in response to key corporate disclosures such as earnings announcements. Similarly, Tsai et al. (2016) find that corporate disclosures with negative tone are positively associated with heightened default risk. We examine whether SEC enforcement announcements elicit comparable effects.

< Insert Figure 7 here >

Panel A of Figure 7 plots average implied volatility (IV). Following enforcement announcements (red line), IV rises by approximately 7% within a week, indicating a notable increase in information uncertainty. By contrast, non-enforcement announcements (blue line) are followed by about 4% decline in IV, consistent with the resolution of uncertainty. Panel B plots the average daily Merton distance-to-default (DtD) over the [-1, +10] window. We follow Bharath and Shumway (2008), and Brogaard et al. (2017) in using DtD as a proxy for corporate default risk. Conceptually, DtD captures the distance between a firm's asset value and its liability, with higher values indicating lower default risk. Empirical evidence (Bharath and Shumway, 2008; Jensen and Lando, 2015) shows that DtD is a robust predictor of default risk. We find that DtD declines sharply following enforcement-related announcements (red line), consistent with heightened default risk. In contrast, DtD exhibits a moderate increase following non-enforcement releases (blue line), indicating a slight improvement in perceived credit quality.

4.2 Channel of transmission

We examine the channel through which SEC enforcement announcements affect stock prices. Drawing from studies on limited investor attention (Hirshleifer and Teoh, 2003; Barber and Odean, 2008; DellaVigna and Pollet, 2009), we posit that investors prioritize salient and attention-grabbing disclosures. Enforcement-related press releases, by virtue of their severity and reputational risk, are likely to attract heightened investor scrutiny, and thus, generate stronger market reactions than other announcements. This hypothesis is consistent with prior empirical studies documenting that markets respond more strongly to negative news than to positive news (Kothari et al., 2009a, 2009b; Mian and Sankaraguruswamy, 2012; Williams, 2015). Tetlock (2007) shows that negative media sentiment relates more closely with market activity than positive sentiment, while Madsen and Niesser (2019) find that investors disproportionately focus on negative content. Building on these insights, we examine whether SEC enforcement announcements elicit greater investor attention than non-enforcement disclosures.

Building on these insights, we examine whether SEC enforcement announcements, characterized by more negative sentiment and larger stock price declines than non-enforcement disclosures, generate greater investor attention. We proxy investor attention using two commonly used measures: abnormal trading volume (AVOL), and abnormal institutional attention (AIA) scores.

Following Cready and Hurtt (2002), and Beaver et al. (2020), we calculate AVOL by comparing trading volume during the announcement window [-10, +10] to the average daily volume in the pre-event period [-70, -11]. Following Ben-Rephael et al. (2017, 2021), and Chan and Smales (2025), we proxy institutional investor attention using AIA, which reflects Bloomberg terminal usage patterns.[7] AIA provides a daily modified attention score based on user engagement with stock-specific news. The number of times terminal users search for or read news related to stock *i* is tracked and the interactions are scored on a scale from 1 to 10, where a score of 10 reflects active searching and/or reading, and a score of 1 indicates passive reading only. These scores are aggregated into hourly intervals. For each hour, Bloomberg computes a relative attention score by comparing the stock's average hourly engagement over the prior eight hours to all hourly engagement levels observed in the previous 30 days. A score of 0 is assigned if this rolling average is below the 80th percentile, 1 if it falls

[7] Institutional investors are expected to respond more to SEC news than retail investors. Providing support to this conjecture, untabulated analysis using Google Search Volume Index as a proxy for retail investor attention (Da et al., 2011) shows no significant increase in retail searches on SEC announcement days.

between the 80th and 90th percentiles, 2 if it is between the 90th and 94th percentiles, 3 if it is between the 94th and 96th percentiles, and 4 if it is above the 96th percentile. The maximum hourly score for each trading day becomes the stock's daily attention score. Following standard practice, we then transform the daily attention score into a binary variable, which is equal to 1 if the score is 3 or 4, and 0 otherwise. The daily AIA score is calculated by comparing the modified daily score during the announcement window [-10, +10] to average daily score over the pre-event period [-70, -11].

We begin by providing evidence on investor attention at the event date for different types of enforcement actions. Appendix Figure B.3 compares AVOL and AIA on the event day for SEC enforcement and non-enforcement announcements. The patterns indicate that SEC enforcement events generate a sharp spike in both measures of investor attention, far exceeding the relatively muted reaction observed for non-SEC enforcement events.

To analyze the dynamic behaviour of investor attention around SEC press releases, we use a specification modified from Chan and Marsh (2022), and regress investor attention on event day dummies:

$$IA_{i,t} = \delta_t + \gamma_i + \beta_{-10} D_{i,t+10} + \cdots + \beta_0 D_{i,t} + \cdots + \beta_{10} D_{i,t-10} + \epsilon_{i,t}, \quad (3)$$

where $IA_{i,t}$ refers to one of the investor attention measures, AVOL or AIA, of stock *i* on day *t*, and $D_{i,t}$ are dummy variables defined over a twenty-one-day event window around press releases, with $D_{i,t} = 1$ if day *t* is a press release for firm *i*, and 0 otherwise. The γ_i and δ_t variables represent industry and year fixed effects, respectively, to control for differences in the investor attention across industry and to capture changes in the IA measure over time. The coefficients on the event day indicator variables, β_j, are estimated for event days j = -10 to +10, in Equation (3) allows us to identify changes in investor attention during times of press releases.

< Insert Table 6 & Figure 8 here >

Table 6 reports the regression estimates, while Figure 8 plots the corresponding pattern of the estimated coefficients. The results in Table 6 indicate a significant spike in investor attention on the event day. For AVOL, we observe an estimated increase of 2.202 (*t*-statistic = 1.719), which suggests that trading activity surges when the SEC releases firm-specific news. A similar and slightly more pronounced pattern emerges for AIA, with a coefficient of 3.320 (*t*-statistic = 1.842), reflecting a substantial increase in online searches and digital engagement by investors. In the pre-event window, coefficients for both AVOL and AIA remain relatively small and statistically insignificant, implying limited anticipatory attention prior to press release issuance. Post-event coefficients gradually decline, with AVOL and AIA estimates reverting toward zero in the days following the release. These results suggest that investor attention intensifies significantly in direct response to SEC press releases but does not exhibit strong anticipatory or persistent post-event effects. The temporary spike aligns with the hypothesis that such disclosures act as salient attention-grabbing events, especially in the context of retail investor behaviour.

As an illustrative example of how investor attention responds to different types of SEC disclosures, Figure 8 plots AVOL and AIA for firms experiencing enforcement (Panel A) and non-enforcement (Panel B) press releases. There are clear differences between the two panels. In Panel A, AVOL rises sharply on the event day, peaking at over 2.2 that is more than a fivefold increase relative to surrounding days, indicating a substantial surge in trading activity following enforcement disclosures. This spike is short-lived but clearly delineated, with activity returning toward baseline within a few days.

In contrast, Panel B shows that AVOL remains largely flat around non-enforcement disclosures, with only modest fluctuations and no notable increase on or after the event day. This pattern suggests that enforcement announcements are significantly more attention-grabbing for investors, triggering immediate and intense trading responses. The results for AIA follow a similar pattern, with a pronounced jump exceeding 3 on the event day for enforcement cases, while no comparable response is observed around non-enforcement disclosures.

To further investigate whether investor attention moderates the market response to SEC enforcement announcements, we augment the baseline return specification in Equation (2) with an interaction term between enforcement news and attention measures:

$$\text{BHAR}_{i,[-1,+5]} = \alpha + \beta_1 Enforcement_{i,t} + \beta_2 Attention_{i,t} + \beta_3 (Enforcement_{i,t} \times Attention_{i,t}) + X'_{i,t}\gamma + \mu_j + \lambda_y + \epsilon_{i,t}, \quad (4)$$

where $Enforcement_{i,t}$ is a dummy equal to one for SEC enforcement announcements, $Attention_{i,t}$ represents either AVOL or AIA, and $\mathbf{X}_i$ denotes the vector of firm-level controls described earlier. The coefficient β_3 captures whether the price impact of enforcement disclosures is amplified or attenuated when investor attention is high.

< Insert Table 7 here >

Table 7 presents the results of the panel regressions. Column (1) uses AVOL and Column (2) uses AIA as proxies for investor attention. Across both specifications, the coefficient on *SEC Enforcement* is negative and statistically significant at the 5% level, confirming that enforcement announcements lead to negative abnormal returns. Attention is negatively and strongly significant in the AVOL specification, indicating that high trading volume around these events is generally associated with lower returns. In contrast, attention is statistically insignificant in the AIA model.

The interaction term between enforcement and attention is positive but insignificant in the AVOL model, suggesting no meaningful moderating effect when attention is proxied by broad trading volume. However, in the AIA specification, the interaction term is negative and statistically significant at the 5% level, which indicates that institutional investors are more likely to interpret enforcement announcements in a consistent and informed manner, enabling them to respond rapidly to the information. This concentrated and coordinated reaction appears to amplify the immediate price impact and contributes to a stronger aggregate market response. In contrast, AVOL, which reflects the attention of the broader investor base including retail participants, captures more heterogeneous reactions that may dilute the speed and precision of the price adjustment.

Overall, the asymmetric response we observe, manifested in negative abnormal stock returns, strongly negative disclosure sentiment, elevated implied volatility, reduced distance to default, and heightened investor attention following SEC enforcement press releases, suggests that such announcements are perceived as signals of legal exposure, financial penalties, or reputational damage. These disclosures appear to intensify investor concerns about uncertainty and default risk, which leads to negative stock market reactions. This interpretation is consistent with theories of market discipline and prior empirical work (e.g., Karpoff et al., 2008a). In contrast, non-enforcement disclosures are associated with modestly positive abnormal returns, declining implied volatility, rising distant-to-default, and muted investor attention. These findings indicate that non-enforcement press releases, such as policy updates, investor protection efforts, or strategic initiatives, elicit a more favorable informational environment, reduce perceived default risk, and elicit positive market responses, potentially signaling enhanced transparency and stronger corporate governance.

4.3 Pooled dynamic event study

The preceding section shows that SEC enforcement actions negatively impact stock prices at discrete points in time, but it does not capture the temporal dynamics of market reactions. To address this limitation, we employ a pooled dynamic event study framework that enables us to examine stock abnormal returns over multi-day event windows centered on the timing of SEC actions. To this end, we estimate the following dynamic specification:

$$BHAR_{i,t} = \alpha + \sum_{k=0}^{5} \beta_k Day_k + \sum_{k=0}^{5} \theta_k (Day_k \times Enforcement_i) + X'_{i,t}\gamma + \mu_j + \lambda_y + \epsilon_{i,t}, \quad (5)$$

where BHAR$_{i,t}$ denotes the buy-and-hold (market adjusted) abnormal return for firm *i* on event day *t*, and Day_k is a dummy variable equal to 1 if the observation corresponds to event time k ∈ [0, 5], with event day -1 omitted as the baseline. The coefficient β_k captures average return behaviour for non-enforcement press releases (control group), while the interaction term $Day_k \times Enforcement_i$ identify differential abnormal returns associated with enforcement announcements.

< Insert Table 8 here >

Table 8 reports the estimated coefficients. For the control group (non-enforcement press releases), all β_k estimates are statistically indistinguishable from zero across the post-event window, suggesting that routine SEC disclosures do not produce meaningful impact on stock prices. In contrast, the interaction terms show a significantly, and time-varying negative return pattern following enforcement announcements. In particular, the enforcement-related differential impact becomes significant beginning on Day 3. This finding suggests a delayed market reaction, with enforcement information gradually incorporated into stock prices, and the most pronounced effect occurring several days post-enforcement announcements.[8]

4.4 Matched sample analysis

To strengthen causal inference on how SEC enforcement announcements affect stock prices, we contrast market reactions to enforcement announcements with those following non-enforcement SEC press releases that serve as a control group. The non-enforcement disclosures, such as rule proposals, personnel appointments and whistleblower awards, serve as a control group. Compared to the enforcement releases, they are less likely to be firm-specific, are infrequently repeated for the same firm, and generally carry lower informational intensity. Prior literature shows that investors respond more strongly to firm-specific, negative information (Tetlock, 2007; Kothari et al., 2009b), consistent with our empirical setting where enforcement disclosures imply legal risk and reputational damage, whereas non-enforcement releases are unlikely to trigger sharp price reactions.

Specifically, the treatment group includes 324 SEC enforcement cases, while the control group includes 1,316 non-enforcement cases that are closely matched on observable characteristics. Following the K-nearest neighbors algorithm (K-NN*) matching method employed by Easton et al. (2024), we perform matching based on the logarithm of market capitalization, restricting matches to firms within the same Fama-French 12 industry classification and within a +/- 1-year window around the enforcement year.

[8] See Appendix Figure B.4.

< Insert Table 9 here >

Table 9 reports the results based on Equation (2) using the matched sample. The key explanatory variable, *Treated*, is a dummy variable equal to 1 for enforcement firms, and 0 for matched control firms. Across both specifications, the coefficient on *Treated* is negative and statistically significant at the 1% level, indicating that enforcement firms experience significantly lower abnormal returns relative to their matched peers. Specifically, in Column (2) (with controls), the coefficient of -0.950 suggests that firms targeted by SEC enforcement suffer an average decline of approximately 95 basis points in cumulative abnormal returns compared with non-enforcement firms over the event window. This finding suggests that investors swiftly incorporate incorporating regulatory enforcement actions into stock prices, penalizing the targeted firms.

4.5 Placebo test

To further examine whether the abnormal return patterns documented above are uniquely attributable to enforcement timing or potentially driven by firm-specific variation or latent time trends, we conduct a placebo even timing test using within-firm variation. Specifically, we assign each treated firm a random pseudo-event date within a +/- 1-year window of its actual enforcement date, excluding +/- 20 trading days buffer to avoid overlap. These placebo dates are not associated with any known enforcement activity. We then re-analyze regression Equation (2) using a pooled sample of actual and placebo events, with the key explanatory variable, *Actual*, equal to 1 for real enforcement events and 0 for placebo dates.

< Insert Table 10 here >

Table 10 shows, in both specifications, the coefficient on *Actual* is negative and statistically significant, confirming that real enforcement events trigger larger price reactions. Specifically, Column (2) shows a coefficient of -0.693 (t-statistic = −2.699), indicating that actual enforcement disclosures lead to cumulative abnormal returns that are approximately 69 basis points lower than those observed around placebo dates. This finding reinforces that the documented market reaction is specific to the timing of SEC enforcement disclosures and not an artifact of firm-specific noise or broader temporal shocks.

4.6 Speculative stocks

To examine how market reactions to SEC enforcement events vary with firms' speculative characteristics, we stratify the sample based on a range of firm-level characteristics associated with speculative trading activity. Specifically, we split each variable at its median and compare the abnormal returns (BHAR) over a [-1, +10] event window across high and low groups for each speculative factor. The variables include firm size (*MCAP_log)*, maximum daily return (*MAX*), idiosyncratic volatility (*IVOL*), idiosyncratic skewness (*ISKEW*), Amihud illiquidity (*Amihud*), ands book-to-market ratio (*BM*), which captures different aspects of speculative appeal, such as lottery-like payoff potential, trading frictions, and investor sentiment.

< Insert Figure 9 here >

The results are visually summarized in Figure 9. Firms with higher speculative characteristics, such as small size, high *MAX*, high *IVOL*, high *ISKEW*, high *Amihud*, and low *BM*, show significantly more negative BHARs following SEC enforcement announcements. Specifically, small-cap firms experience steeper post-event drops than their large-cap counterparts, consistent with the finding that smaller firms are more vulnerable to speculative trading. The high *MAX* portfolio experiences a steeper decline beginning shortly after the event day, whereas the low *MAX* portfolio shows no comparable drop. Similarly, high *IVOL* and high *ISKEW* firms suffer greater cumulative losses post-enforcement, which highlights the role of investor sentiment and information uncertainty. Illiquid stocks (high Amihud) also show larger negative BHARs, consistent with the notion that such stocks are more sensitive to negative information shocks. Interestingly, firms with low BM ratios (those considered more growth-oriented or overvalued) suffer more pronounced declines than their high BM peers. These patterns suggest that market participants respond more strongly to enforcement actions when the targeted firms exhibit speculative characteristics.

The strong abnormal return patterns among speculative firms raise a natural question: are such firms also more likely to attract regulatory scrutiny? To address this, we construct a composite measure of speculative characteristics, the lottery-like index (LLI), and examine its relationship with the likelihood of being mentioned in SEC enforcement press releases. We hypothesize that such firms tend to exhibit characteristics commonly associated with speculative behaviour. Speculative firms, those that are difficult to value, sensitive to investor sentiment, or subject to heightened information asymmetry, are more likely to attract regulatory scrutiny due to their operational volatility and aggressive financial strategies. This hypothesis is consistent with prior studies such as Baker and Wurgler (2006), and Stambaugh et al. (2012), who show that speculative stocks are more prone to mispricing and investor overreaction, making them natural candidates for increased regulatory attention. Because SEC enforcement press releases are rare and discrete, and our count data shows substantial overdispersion, we estimate a logistic regression model to assess the likelihood of a firm being mentioned in an enforcement action:

$$\Pr(SEC_i = 1) = logit^{-1}(\alpha + \delta LLI_i + X_i'\gamma + \mu_j + \lambda_t), \quad (6)$$

where SEC_i is a binary indicator equal to 1 if firm i is mentioned in an SEC enforcement press release during the sample period (1999–2022), and 0 otherwise. We follow prior literature and include a standardized lottery-like index (LLI_i) to proxy for speculative firm characteristics. The term X_i' represents a vector of firm-level control variables, including *MCAP*_log, *Leverage*, *RoE*, *MOM*, and *Prc_log*.

Given the limited number of enforcement cases in certain years and the highly skewed distribution of enforcement activity across time, we do not include year fixed effects. Instead, we control for macroeconomic conditions using broader macro-period fixed effects. We divide the sample into three economically meaningful periods: pre-crisis (pre-2008), financial crisis and immediate aftermath (2008–2012), and post-crisis regulatory stabilization (2013–2022). This grouping ensures a sufficient number of observations within each period.[9] Therefore, we estimate Equation (6) including fixed effects for macro-period and industry classifications, with standard errors clustered at both macro-period and industry levels.

We carefully filter the CRSP universe to ensure a consistent and meaningful comparison group. We restrict the sample to firms listed as common stocks on NYSE, AMEX or Nasdaq, and we require that each firm have at least five years (20 quarters) of non-missing quarterly fundamental data over the sample period. After applying these criteria, our estimation sample consists of only 220 firms are identified in SEC enforcement press releases compared to more than 12,534 firms that are not subject to enforcement. To address the substantial imbalance in our sample, we employ a propensity score matching (PSM) approach to construct a more comparable control

[9] We classify the sample into three macro-periods based on significant regulatory and economic milestones: pre-crisis (1998–2007), financial crisis and aftermath (2008–2012), and post-crisis stabilization (2013–2022). This grouping yields 148, 214, and 312 firm-year observations in each period, respectively, ensuring adequate within-period variation for estimation while capturing time-specific regulatory environments.

group. The PSM procedure is implemented separately for each year to account for time-varying firm characteristics and economic conditions.

Specifically, we estimate the likelihood of being mentioned in an SEC enforcement announcement using a logistic regression model based on a set of observable firm-level covariates. These covariates include *MCAP*_log, *Leverage*, *RoE*, *MOM*, and *Prc_log*. Each variable captures important dimensions of firm size, valuation, financial condition, investor sentiment, and profitability, all of which may influence both the probability of regulatory scrutiny and the firm's speculative characteristics.

The selection of these control variables is particularly important given the construction of our key independent variable, LLI, which is constructed from five firm-level variables, *MCAP*, *MAX*, *IVOL*, *ISKEW*, *Amihud*, and *BM*, that are widely recognized in the literature as proxies for lottery-like or speculative stock characteristics. These measures respectively capture firm size, extreme positive return potential, idiosyncratic volatility, downside tail asymmetry, trading frictions, and valuation, which features often associated with investors' preference for lottery-type payoffs. To maintain the conceptual coherence of LLI as a composite measure of speculative appeal, we exclude these individual components from the set of control variables in our regression analyses.[10]

For every "enforcement firm" in a given year, we identify the nearest match among the "non-enforcement firms" based on their estimated propensity scores. This one-to-one matching procedure ensures that enforcement and control firms are comparable on observed characteristics. By restricting matching within the same year, we mitigate potential biases from macroeconomic shocks or shifts in enforcement priorities over

[10] Although firm size (*MCAP*) is one of the variables used to construct the LLI, we include it separately as a control in the logit model to capture its standalone predictive power. Since the LLI is calculated as the average of ranked values across all components, it is not linearly dependent on any single raw input. As a result, including both LLI and *MCAP* does not introduce multicollinearity into the model.

time. The resulting matched sample provides a more balanced setting to examine whether LLI are systematically associated with the probability of appearing in SEC enforcement disclosures. Finally, our estimation sample includes 316 observations for each group, resulting in a total of 632 firm-year observations used in the logit regression.

< Insert Table 11 here >

Table 11 presents the results from logistic regression models. Panel A reports the estimates from the matched sample described above. The coefficient on LLI is positive and statistically significant at the 5% level (0.292, *p*-value = 0.033), indicating that firms with stronger lottery-like characteristics are significantly more likely to be targeted in SEC enforcement press releases. This finding supports that speculative stock features are positively associated with regulatory attention, consistent with the view that such firms may engage in behaviour that triggers greater scrutiny.

To assess the robustness of this finding, Panel B of Table 11 reports results from a simulation-based validation procedure. In this approach, we conduct 1,000 repeated logit regressions using resampled control groups of firms not mentioned in SEC enforcement actions. For each simulation, control firms are selected to match the distribution of treated firms (those mentioned in SEC actions) by year, ensuring a comparable structure across time. Each simulation includes macro-period and industry fixed effects and clusters standard errors accordingly.

The simulation-based estimates confirm and strengthen the findings from the matched sample. Across 1,000 iterations, the average coefficient on the standardized LLI is 0.093 and statistically significant at the 1% level, with a *t*-statistic of 24.336. The 99% confidence interval for this coefficient ranges from 0.083 to 0.103, indicating robust and consistent evidence that lottery-like characteristics are positively associated with the likelihood of SEC enforcement announcements.

5. Conclusion

The Securities and Exchange Commission (SEC) communicates critical regulatory and policy information to market participants. This study investigates how equity markets react to these communications, which places particular emphasis on enforcement-related disclosures. Using a comprehensive sample of SEC press releases from 1999 to 2022, we document a pronounced asymmetry in market reactions. Enforcement announcements are associated with economically and statistically significant negative abnormal returns, whereas non-enforcement disclosures are followed by muted and largely neutral price reactions. The estimated market penalty for enforcement announcements is approximately 80 basis points over the [-1, +5] window.

We then analyze the mechanisms underlying this asymmetric effect: sentiment disclosure, changes in information uncertainty, shifts in perceived default risk, and investor attention. Enforcement announcements have a more negative linguistic tone, contain elevated information uncertainty as proxied by implied volatility, and are associated with higher corporate default risk as measured by Merton's distance-to-default. These disclosures also garner more attention, particularly from institutional investors, than non-enforcement announcements. The joint effect regression findings suggest that high institutional attention amplifies the negative price impact of enforcement events, consistent with rapid and more coordinated interpretation of pessimistic information among sophisticated market participants.

The dynamic event study shows that the price impact of enforcement disclosures is not fully realized on the announcement day but unfolds over several trading days, suggesting gradual information incorporation and potential limits to arbitrage. The effects are most pronounced among speculative firms characterized by small capitalization, extreme return potential, high idiosyncratic volatility and skewness, low liquidity, and low book-to-market ratios. This pattern reflects the firms' heightened sensitivity to negative information shocks. Moreover, speculative characteristics, summarized in a lottery-like index, are significantly associated with the likelihood of being named in SEC enforcement actions. This finding suggests that regulatory scrutiny tends to focus on firms that are harder to value, exhibit greater information asymmetry, and display attributes consistent with speculative trading activity.

These insights have important implications for policymakers. The finding that enforcement press releases trigger significant negative market reactions suggests that regulatory communications are not merely procedural; instead, they carry material economic weight. This finding also underscores the importance of disclosure transparency, timing, and clarity in enforcement messaging. By understanding how investors interpret and respond to enforcement disclosures, regulators can design more effective communication strategies that balance deterrence with informational clarity.

Our findings also contribute to the literature on securities regulation, market discipline, and investor behaviour, by showing that SEC enforcement disclosures operate as salient, high-intensity information shocks that affect market perceptions of legal, financial, and governance risk. The evidence also highlights the real economic consequences of regulatory oversight, reflected in the empirical relationship between enforcement activity and firm characteristics linked to speculative trading. Future research could explore how enforcement outcomes, such as penalties or settlements, further modulate market responses and whether heightened transparency in enforcement communication can mitigate some of the uncertainty and value loss documented in this study.

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Table 1: Distribution of Companies

Panel A presents the distribution of companies mentioned in SEC press releases across Fama-French 12 industries. The first column reports the number and percentage of companies mentioned in SEC enforcement press releases, while the second column shows companies in non-enforcement press releases. The third column shows each industry proportion in the Compustat universe. Panel B reports descriptive statistics, comparing firm characteristics of companies mentioned in SEC enforcement announcements with those linked to non-enforcement announcements. All variables are winsorized at the 1st and 99th percentiles. The sample period is January 1999 to December 2022.

Panel A: Distribution of companies sorted by Fama-French 12 industries

Industry	SEC enf. PRs	SEC non-enf. PRs	Compustat universe
Finance (Money)	69 [24.6%]	58 [28.3%]	[23.5%]
Business Equipment (BusEq)	71 [25.4%]	39 [19.0%]	[19.0%]
Health (Hlth)	27 [9.6%]	18 [8.8%]	[13.8%]
Other	24 [8.6%]	28 [13.7%]	[13.7%]
Shops	18 [6.4%]	12 [5.9%]	[7.3%]
Manufacturing (Manuf)	17 [6.1%]	11 [5.4%]	[6.7%]
Energy	9 [3.2%]	5 [2.4%]	[3.8%]
Consumer Nondurables (NoDur)	12 [4.3%]	17 [8.3%]	[3.7%]
Telephone & Television Transmission (Telcm)	7 [2.5%]	2 [1.0%]	[3.3%]
Consumer Durables (Durbl)	13 [4.6%]	5 [2.4%]	[2.0%]
Utilities (Utils)	3 [1.1%]	6 [2.9%]	[1.7%]
Chemicals & Allied Products (Chems)	10 [3.6%]	4 [2.0%]	[1.6%]
Total	280 [100%]	205 [100%]	[100%]

Panel B: Descriptive statistics

	MCAP_log	*Beta*	*IVOL*	*Amihud*	*MOM*	*BM*	*RoE*	*Leverage*
SEC Enforcement announcements								
N	445	437	445	436	434	435	439	439
Mean	15.741	1.158	0.020	0.264	0.102	0.689	-0.009	6.224
Median	16.324	1.066	0.014	0.000	0.077	0.504	0.095	2.568
Min	9.163	-0.428	0.005	0.000	-0.927	-1.135	-6.785	-25.484
Max	19.090	4.061	0.160	40.284	4.256	8.794	3.286	30.011
SD	2.340	0.639	0.017	2.806	0.488	0.799	0.684	7.173
SEC Non-enforcement announcements								
N	421	403	421	403	403	402	408	408
Mean	16.191	1.082	0.018	0.058	0.087	0.603	0.082	7.325
Median	16.858	1.085	0.013	0.000	0.065	0.510	0.109	4.992
Min	8.171	-0.237	0.005	0.000	-0.939	-1.114	-5.920	-11.181
Max	19.112	3.448	0.128	6.325	3.619	2.272	3.067	33.785
SD	2.109	0.600	0.016	0.441	0.402	0.480	0.483	6.883
Diff.	-0.450	0.076	0.001	0.207	0.015	0.085	-0.091	-1.101
t-stat	-2.977	1.777	1.233	1.517	0.488	1.890	-2.248	-2.279

Table 2: Seasonality in SEC Enforcement Actions

This table presents the results of negative binomial regressions analyzing the seasonal patterns in the number of SEC enforcement actions, following Eq. (1). Column (1) investigates the September effect, using monthly data over the sample period, while Column (2) explores the weekly effect using daily data over the sample period. The dependent variable in both specifications is the count of enforcement actions (cases). The key explanatory variable, SeasonDummy, equals one if the observation falls in September (Column 1) or during a weekly period such as Friday (Column 2). Both regressions control for macroeconomic and financial market conditions, including the market premium (*MKTRF*), the CBOE Volatility Index (*VIX*), and the Economic Policy Uncertainty (*EPU*) index. The sample period is Jan-1999 to Dec-2022. *p*-values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) September Effect	(2) Weekly Effect
Intercept	1.546***	-1.126***
	(0.000)	(0.000)
SeasonDummy	0.678***	-0.533***
	(0.002)	(0.000)
MKTRF	0.385	-0.004
	(0.786)	(0.849)
VIX	-0.019**	-0.016***
	(0.036)	(0.000)
EPU	0.003***	0.002***
	(0.003)	(0.000)
No. of Obs.	300	6,291
Adj.R^2	0.072	0.011

Table 3: Examples of Individual Defendants Who Had Left Their Companies in Insider Trading Cases

This table shows examples of insider trading cases in which the individual defendants had already left their companies at the time of the SEC enforcement action.

Date	Headline	Contents
June 12, 2002	SEC Charges Former ImClone CEO Samuel Waksal With Illegal Insider Trading	Washington, D.C., June 12, 2002 — The Securities and Exchange Commission today filed charges against Samuel Waksal, the former CEO of ImClone Systems Inc., for illegal insider trading. In its complaint, the Commission charges that Waksal received disappointing news late last December that the U.S. Food and Drug Administration would soon issue a decision rejecting for review ImClone's pending application to market its cancer treatment drug, Erbitux. The SEC further charges that Waksal told this negative information to certain family members who sold ImClone stock before the news became public and that Waksal himself tried to sell shares of ImClone before the news became public.
Sept. 21, 2011	SEC Charges Former Goldman Sachs Employee and His Father with Insider Trading	Washington, D.C., Sept. 21, 2011 — The Securities and Exchange Commission today charged a former Goldman, Sachs & Co. employee and his father with insider trading on confidential information about Goldman's trading strategies and intentions that he learned while working on the firm's exchange-traded funds (ETF) desk.
April 9, 2019	SEC Charges Former SeaWorld Associate General Counsel With Insider Trading	Washington D.C., April 9, 2019 — The Securities and Exchange Commission today charged a former senior lawyer at SeaWorld Entertainment Inc. with insider trading based on nonpublic information that the company's revenue would be better than anticipated for the second quarter of 2018.
Sept. 17, 2021	SEC Charges Former Pharmaceutical Global IT Manager in $8 Million Insider Trading Scheme	Washington D.C., Sept. 17, 2021 — The Securities and Exchange Commission today announced insider trading charges against Dayakar R. Mallu, of Orlando, Florida, who generated gains and avoided losses totaling over $8 million by trading in the securities of his former employer, Mylan N.V., ahead of four public announcements between Oct. 3, 2017, and July 29, 2019.

Table 4: Event Study for SEC Enforcement Announcements

This table presents the results of panel regressions based on Eq. (2) to examine the impact of SEC enforcement announcements on firms' abnormal returns over the [-1, +5] trading-day event window. The dependent variable is the cumulative BHARs during this window. All BHAR values are winsorized at the 1st and 99th percentiles. Column (1) presents results without control variables, while Column (2) includes firm-level controls, including the natural logarithm of the firm market capitalization (*MCAP_log*), market beta (*Beta*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*Amihud*), momentum (*MOM*), book-to-market ratio (*BM*), return on equity (*RoE*), and financial leverage (*Leverage*). In Column (3), two additional dummy variables are introduced: *Earnings Anct* and *FOMC Anct*. The *Earnings Anct* dummy equals 1 if an earnings-related news announcement occurs within the same [-10, +1] business-day window of the SEC enforcement announcement date, and 0 otherwise. Similarly, the *FOMC Anct* variable equals 1 if a Federal Open Market Committee (FOMC) meeting date falls within the [-10, +1] business-day window, and 0 otherwise. Column (4), a continuous variable is introduced: *Earnings Surprises*, which is defined as standardized unexpected earnings (SUE) if an earnings announcement falls within the [-10, +1] business-day window of the SEC enforcement date, and 0 otherwise. Both specifications include fixed effects for industry and year. The sample period is Jan-1999 to Dec-2022. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels, respectively.

	(1) Without controls	(2) With controls	(3) Earnings Anct. & FOMC Anct.	(4) Earnings surprises
Intercept	-0.046 (-0.259)	0.585 (0.226)	0.850 (0.326)	0.530 (0.198)
SEC Enforcement	-0.794** (-2.157)	-0.801** (-1.978)	-0.785* (-1.947)	-0.813** (-2.067)
Insider Trading	1.160*** (2.630)	1.130*** (2.769)	1.096*** (2.930)	1.117*** (2.767)
Earnings Anct.			0.389 (0.736)	
FOMC Anct.			-0.256 (-0.662)	
Earnings Surprises				3.696 (0.858)
Controls	No	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Obs.	836	806	806	806
Adj.R^2	0.010	0.027	0.028	0.027

Table 5 : Changes in Bid-Ask Spreads Around SEC Insider Trading Announcements

This table reports mean abnormal bid-ask spreads (×1000) for firms mentioned in SEC insider trading announcements over various post-event windows. Abnormal spreads are defined as the difference between the firm's daily bid-ask spread and its expected pre-event spread estimated from days [−70, −10]. Columns [0, +1], [0, +5], [0, +10], and [0, +20] show the average abnormal spreads for insider-trading and non-insider trading events and the difference between the two groups. The student *t*-statistics, shown in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels, respectively. The sample period is Jan-1999 to Dec-2022.

	(1)	(2)	(3)	(4)
	[0, +1]	[0, +5]	[0, +10]	[0, +20]
Insider Trading	-0.720**	-0.661***	-0.571***	-0.653***
	(-2.244)	(-3.440)	(-4.082)	(-6.220)
Non-Insider Trading	0.641	0.265	0.154	0.093
	(1.317)	(1.458)	(1.400)	(1.442)
Diff	-1.361**	-0.926***	-0.725***	-0.746***
	(-2.334)	(-3.500)	(-4.073)	(-6.054)

Table 6 : Investor Attention Around SEC Press Releases

This table reports the estimated coefficients and corresponding *t*-statistics from regressions of investor attention measures on event-day dummy variables surrounding SEC press releases. The dependent variables are abnormal trading volume (AVOL) and abnormal information acquisition (AIA), both standardized and defined at the firm-day level. The regression follows the specification in Equation (3), where event-day dummies β_j indicate trading days from 10 days before to 10 days after a press release (event day 0). Industry and year fixed effects are included to account for cross-sectional variation and time trends in investor attention. The sample period is Jan-1999 to Dec-2022.

	AVOL		AIA	
	Coefficient	*t*-statistics	Coefficient	*t*-statistics
β_{-10}	0.278	(0.606)	-1.020	(-1.337)
β_{-9}	0.323	(0.706)	-1.168	(-1.497)
β_{-8}	0.183	(0.406)	-1.073	(-1.324)
β_{-7}	0.264	(0.587)	-0.774	(-1.075)
β_{-6}	0.250	(0.565)	-0.785	(-0.937)
β_{-5}	0.222	(0.485)	-0.739	(-0.906)
β_{-4}	0.269	(0.582)	-0.373	(-0.465)
β_{-3}	0.231	(0.509)	-0.663	(-0.809)
β_{-2}	0.193	(0.420)	-0.571	(-0.754)
β_{-1}	0.370	(0.741)	-0.098	(-0.112)
β_{0}	2.202*	(1.719)	3.320*	(1.842)
β_{1}	0.717	(1.240)	-0.449	(-0.507)
β_{2}	0.389	(0.827)	-0.890	(-1.129)
β_{3}	0.405	(0.885)	-0.396	(-0.474)
β_{4}	0.356	(0.792)	-0.143	(-0.142)
β_{5}	0.351	(0.760)	-0.840	(-1.084)
β_{6}	0.313	(0.664)	-0.396	(-0.533)
β_{7}	0.336	(0.713)	-0.846	(-1.110)
β_{8}	0.220	(0.476)	-0.460	(-0.616)
β_{9}	0.263	(0.580)	0.020	(0.020)
β_{10}	0.245	(0.534)	-0.443	(-0.577)

Table 7: Joint Effect of SEC Enforcement and Investor Attention

This table presents the results of panel regressions based on Eq. (4) to examine the joint impact of investor attention and SEC enforcement announcements on firms' abnormal returns over the [-1, +5] trading-day event window. The dependent variable is the cumulative BHARs during this window. All BHAR values are winsorized at the 1st and 99th percentiles. Key independent variables include "SEC Enforcement", "Attention", their interaction ("Enforcement × Attention"), and a set of controls. In Column (1), "Attention" is proxied by abnormal trading volume (AVOL), while Column (2) uses Bloomberg AIA metrics. Due to data availability, the analysis covers from 1998 to 2022 for abnormal trading volume, and 2010 to 2022 for Bloomberg AIA metrics. Control variables include the natural logarithm of the firm market capitalization (*MCAP_log*), market beta (*Beta*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*Amihud*), momentum (*MOM*), book-to-market ratio (*BM*), return on equity (*RoE*), and financial leverage (*Leverage*). Both specifications include fixed effects for industry and year. The sample period is Jan-1999 to Dec-2022. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels, respectively.

	(1) AVOL	(2) AIA
Intercept	2.354	3.286
	(1.331)	(1.057)
SEC Enforcement	-1.108**	-1.016**
	(-2.252)	(-2.055)
Attention	-0.778***	-0.120
	(-6.222)	(-1.298)
Enforcement × Attention	0.348	-0.520**
	(0.589)	(-2.451)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
No. of Obs.	804	306
Adj.R^2	0.044	0.073

Table 8: Pooled Dynamic Event Study for SEC Enforcement Announcements

This table reports the results from a pooled dynamic event study regression comparing abnormal returns around SEC enforcement events (treated group) versus non-enforcement firm news events (control group), following Eq. (5). The dependent variable is daily BHAR normalized at the event level. Day_k (k = 0 to 5) denote a set of event-day dummies to capture the average abnormal return path for the control group, and interactions between these dummies and an enforcement indicator ($Day_k \times Enforcement$) capture the differential return behaviour for enforcement cases relative to non-enforcement press releases. Controls include the natural logarithm of the firm market capitalization (*MCAP_log*), market beta (*Beta*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*Amihud*), momentum (*MOM*), book-to-market ratio (*BM*), return on equity (*RoE*), and financial leverage (*Leverage*). Industry-by-year fixed effects are included. Standard errors are clustered at the industry level. The sample period is Jan-1999 to Dec-2022. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels, respectively.

	Coefficient	*t*-statistics	95% CI Low	95% CI High
Intercept	-1.846**	(-2.265)	-3.443	-0.249
Day_0	-0.074	(-0.951)	-0.226	0.078
Day_1	0.063	(0.443)	-0.217	0.344
Day_2	0.071	(0.373)	-0.304	0.446
Day_3	0.220	(1.037)	-0.196	0.636
Day_4	0.171	(1.106)	-0.132	0.473
Day_5	0.208	(1.320)	-0.101	0.516
$Day_0 \times Enforcement$	-0.224	(-0.791)	-0.777	0.330
$Day_1 \times Enforcement$	-0.246	(-0.944)	-0.758	0.265
$Day_2 \times Enforcement$	-0.454	(-1.458)	-1.065	0.157
$Day_3 \times Enforcement$	-0.861*	(-1.800)	-1.798	0.076
$Day_4 \times Enforcement$	-0.972**	(-2.393)	-1.767	-0.176
$Day_5 \times Enforcement$	-1.092***	(-3.500)	-1.704	-0.480
Controls		Yes		
Industry FE		Yes		
Year FE		Yes		
No. of Obs.		5,508		
Adj.R^2		0.230		

Table 9: Matched Sample Analysis for SEC Enforcement Announcements

This table presents the results based on Eq. (2) to explore the effect of SEC enforcement actions on firms' cumulative BHARs over the event window [−1, +5]. All BHAR values are winsorized at the 1st and 99th percentiles. The treatment group consists of firms subject to SEC enforcement, while the control group is constructed via propensity score matching (PSM) using firms with similar market capitalization and operating within a ±1-year window of the enforcement event, but not subject to enforcement. The key explanatory variable, Treated, is an indicator equal to 1 for enforcement firms and 0 otherwise. Firm-level controls include the natural logarithm of the firm market capitalization (*MCAP_log*), market beta (*Beta*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*Amihud*), momentum (*MOM*), book-to-market ratio (*BM*), return on equity (*RoE*), and financial leverage (*Leverage*). Industry and year fixed effects are included to account for unobserved heterogeneity across sectors and time. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses. The sample period is Jan-1999 to Dec-2022. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Without control variables	(2) With control variables
Intercept	0.060	0.172
	(1.063)	(0.105)
Treated	-0.843***	-0.950***
	(-2.975)	(-2.869)
Controls	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
No. of Obs.	1,640	1,092
Adj.R^2	0.004	0.018

Table 10: Placebo Test for SEC Enforcement Announcements

This table presents results of Eq. (2) from a within-firm placebo test. For each treated firm (subject to an actual SEC enforcement action), we construct a placebo event by randomly selecting a non-overlapping date within ±1 year of the actual event, excluding a ±20-day window around the true enforcement date. The dependent variable is cumulative BHARs over the [−1, +5] event window. All BHAR values are winsorized at the 1st and 99th percentiles. The indicator variable, Actual, equals 1 for the actual enforcement event and 0 for the randomly assigned placebo event within the same firm. Firm-level controls include the natural logarithm of the firm market capitalization (*MCAP_log*), market beta (*Beta*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*Amihud*), momentum (*MOM*), book-to-market ratio (*BM*), return on equity (*RoE*), and financial leverage (*Leverage*). Industry and year fixed effects are included to account for unobserved heterogeneity across sectors and time. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses. The sample period is Jan-1999 to Dec-2022. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Without control variables	(2) With control variables
Intercept	-0.343**	1.051
	(-2.556)	(0.299)
Actual	-0.527**	-0.693***
	(-2.290)	(-2.699)
Controls	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
No. of Obs.	555	533
Adj.R^2	0.002	0.060

Table 11: SEC Speculative Characteristics

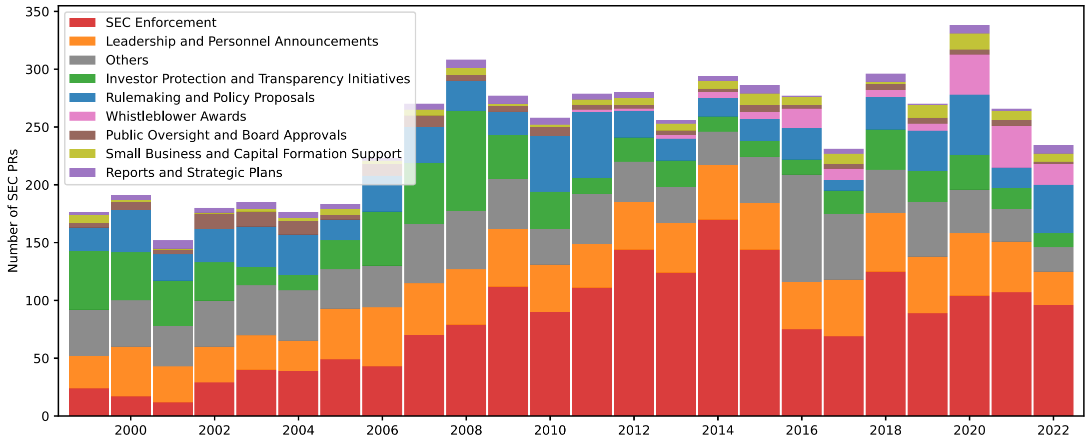
This table presents the results of Eq. (6) for testing SEC speculative characteristics. Panel A presents the results of a logistic regression estimating the probability of being an SEC-flagged firm as a function of firm-level speculative proxies. The number of observations is 632, and the adjusted R^2 is 0.049. The sample includes firms selected through propensity score matching (PSM), where each SEC enforcement firm is matched with a non-enforcement firm based on firm size, leverage, return on equity, momentum, and price level, within the same year. The dependent variable is *SEC Enforcement action*, which equals 1 if a firm is mentioned in an SEC enforcement action and 0 for control groups estimated from PSM. The key independent variable is the standardized Lottery-Like Index (LLI), which captures speculative firm characteristics. Control variables include the natural logarithm of market capitalization (*MCAP_log*), financial leverage (*Leverage*), return on equity (*RoE*), momentum (*MOM*), and the natural logarithm of stock price (*Prc_log*). All regressions include macro-period and industry fixed effects, and standard errors are clustered by both the macro-period and industry levels. Panel B reports simulation-based benchmarks from 1,000 repeated logistic regressions using random samples of non-enforcement firms, where each iteration draws a sample of the same size as the SEC enforcement group. For each variable, we report the mean coefficient, *t*-statistics, standard deviation, N. and 99% confidence intervals across the 1,000 simulations. The sample period is Jan-1999 to Dec-2022. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Intercept	(2) LLI	(3) *MCAP_log*	(4) *Leverage*	(5) *RoE*	(6) *MOM*	(7) *Prc_log*
Panel A: Logit model (PSM)							
Coefficient	-1.567	0.292**	0.130	-0.041***	0.037	-0.192	-0.096
P-value	(0.156)	(0.033)	(0.131)	(0.002)	(0.433)	(0.142)	(0.362)
Panel B: Robustness check—simulation method							
Mean	-8.010***	0.093***	0.709***	-0.001***	0.093***	-0.281***	-0.535***
t_statistics	(-335.597)	(24.336)	(355.631)	(-3.229)	(35.742)	(-75.530)	(-185.480)
std.dev	0.755	0.121	0.063	0.014	0.082	0.118	0.091
N.	1000	1000	1000	1000	1000	1000	1000
99% CI Low	-8.071	0.083	0.704	-0.003	0.086	-0.291	-0.542
99% CI High	-7.948	0.103	0.714	0.000	0.099	-0.272	-0.527

Figure 1: Annual Distribution and Proportion of SEC Press Releases

The figure illustrates the annual composition of SEC press releases across the nine topic categories defined in Section 2. Panel A shows the total number of press releases per year for each category. Panel B presents the corresponding proportions. The sample period is Jan-1999 to Dec-2022.

Panel A: Annual coverage per topic



Panel B: Annual percentages

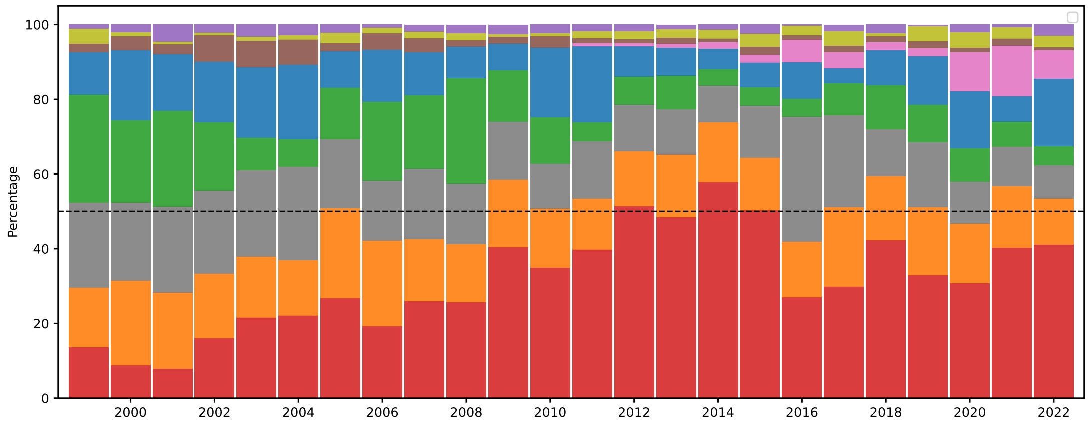
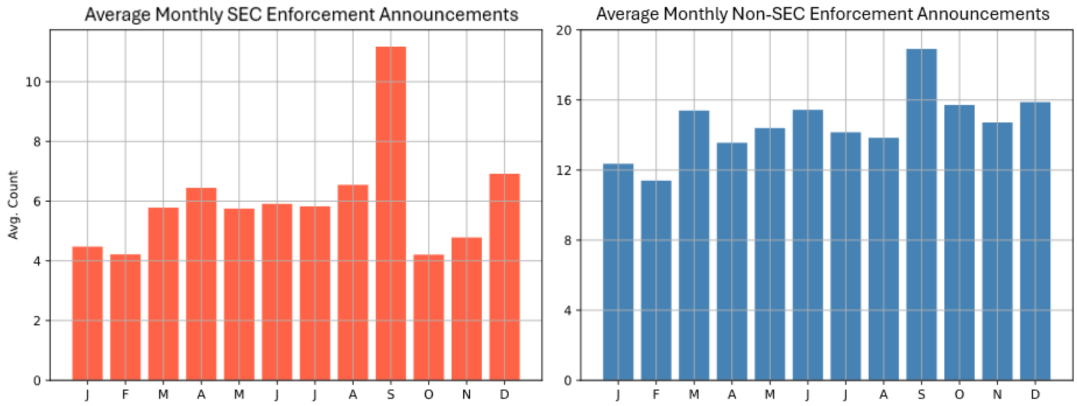


Figure 2: Seasonality in SEC Enforcement Announcements

The figure depicts seasonal patterns in SEC enforcement press releases. Panel A reports the average monthly number of enforcement announcements. Panel B shows the average daily distribution of enforcement announcements. The sample period is Jan-1999 to Dec-2022.

Panel A: Average monthly coverage



Panel B: Average daily coverage

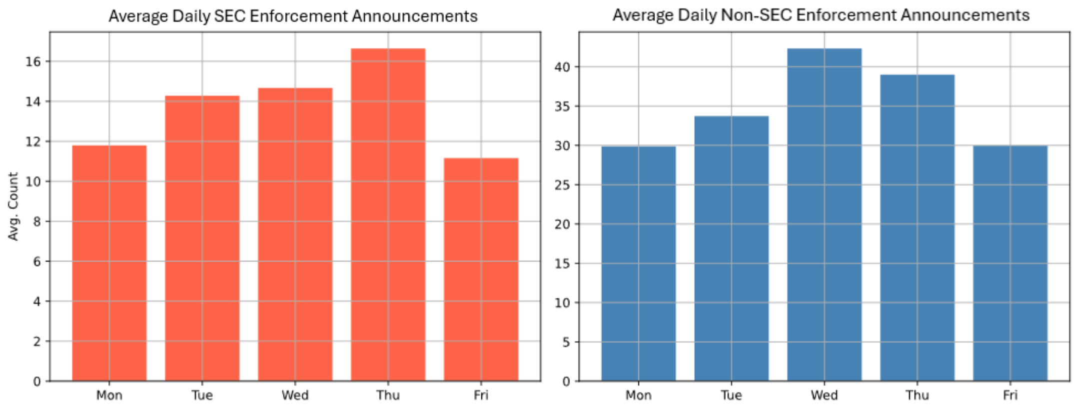


Figure 3: Buy-and-Hold Abnormal Returns

The figure shows average cumulative BHARs over a [-1, +20] event window for firms mentioned in SEC press releases. The red and green lines show stock price average responses to non-insider and insider trading enforcement news, respectively, while the black line shows stock price average responses to non-enforcement news. Firms named in SEC press releases are identified and matched to CRSP/Computstat using the textual analysis procedure detailed in Section 2.2. This yields 324 unique firms in the non-insider trading enforcement sample, 107 in the insider trading enforcement sample, and 405 in the non-enforcement group. The sample period is January 1999 to December 2022.

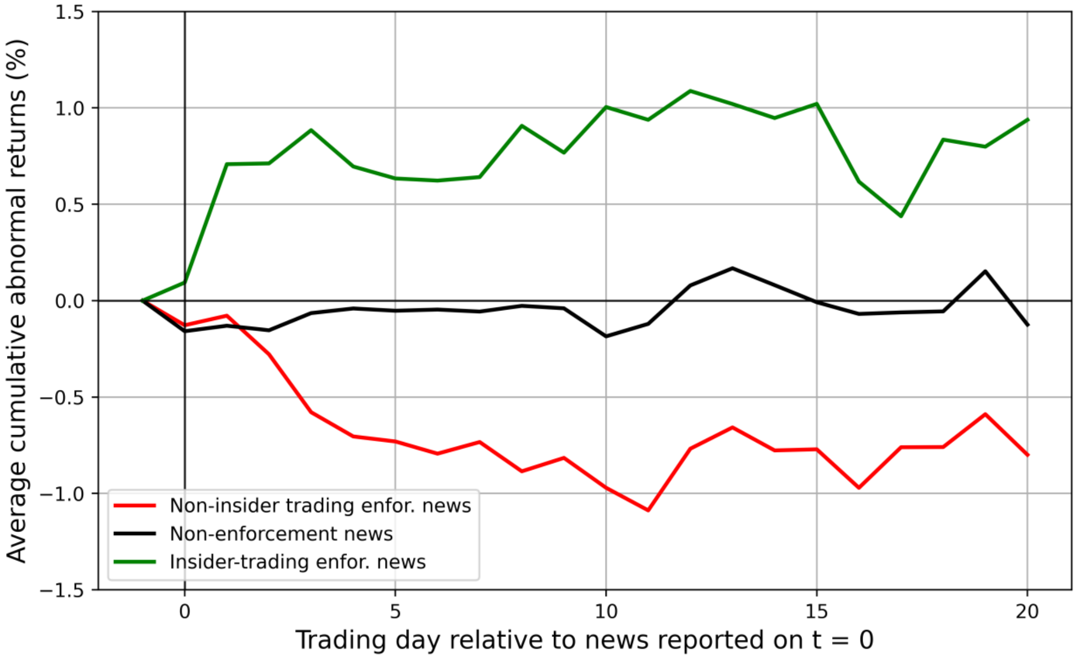


Figure 4: Examples of Corporate Defendants and Individual Defendants

This figure shows illustrative examples of SEC enforcement press releases involving different types of defendants. Panel A presents a case where the company itself is charged as the corporate defendant, while Panel B shows cases where the insider trading action targets individual defendants.

Panel A: Corporate Defendant

PRESS RELEASE

Private Equity Firm Ares Management LLC Charged With Compliance Failures

FOR IMMEDIATE RELEASE | 2020-123

Washington D.C., May 26, 2020 —The Securities and Exchange Commission today announced that Ares Management LLC, a Los Angeles-based private equity firm and registered investment adviser, has agreed to pay one million dollars to settle charges that it failed to implement and enforce policies and procedures reasonably designed to prevent the misuse of material nonpublic information.

UNITED STATES OF AMERICA
Before the
SECURITIES AND EXCHANGE COMMISSION

INVESTMENT ADVISERS ACT OF 1940
Release No. 5510 / May 26, 2020

ADMINISTRATIVE PROCEEDING
File No. 3-19812

In the Matter of **ARES MANAGEMENT LLC** **Respondent.**	**ORDER INSTITUTING ADMINISTRATIVE AND CEASE-AND-DESIST PROCEEDINGS, PURSUANT TO SECTIONS 203(e) AND 203(k) OF THE INVESTMENT ADVISERS ACT OF 1940, MAKING FINDINGS, AND IMPOSING REMEDIAL SANCTIONS AND A CEASE-AND-DESIST ORDER**

I.

The Securities and Exchange Commission ("Commission") deems it appropriate and in the public interest that public administrative and cease-and-desist proceedings be, and hereby are, instituted pursuant to Sections 203(e) and 203(k) of the Investment Advisers Act of 1940 ("Advisers Act") against Ares Management LLC ("Ares" or "Respondent").

Panel B: Individual Defendant

PRESS RELEASE

SEC Charges Sigma Capital Portfolio Manager with Insider Trading

FOR IMMEDIATE RELEASE | 2013-49

Washington, D.C., March 29, 2013 — The Securities and Exchange Commission today charged Michael Steinberg, a portfolio manager at New York-based hedge fund advisory firm Sigma Capital Management, with trading on inside information ahead of quarterly earnings announcements by Dell and Nvidia Corporation.

13 CIV 2082

Sanjay Wadhwa
Attorney for Plaintiff
SECURITIES AND EXCHANGE COMMISSION
New York Regional Office
3 World Financial Center, Suite 400
New York, NY 10281-1022
(212) 336-0181

RECEIVED
MAR 29 2013
U.S.D.C. S.D. N.Y.
CASHIERS

UNITED STATES DISTRICT COURT
SOUTHERN DISTRICT OF NEW YORK

SECURITIES AND EXCHANGE COMMISSION, **Plaintiff,** **-against-** **MICHAEL S. STEINBERG,** **Defendant.**	**COMPLAINT** **ECF CASE**

Plaintiff Securities and Exchange Commission ("Commission"), for its Complaint against defendant Michael S. Steinberg ("Steinberg"), alleges as follows:

Figure 5: Average Abnormal Bid-Ask Spread

This figure shows the daily average abnormal bid–ask spread (×1000) from event day t = 0 to t = +20 for firms mentioned in SEC insider-trading press releases. Abnormal spreads are calculated as the daily bid–ask spread minus the pre-event expected spread estimated over days [−70, −10]. The red line represents insider-trading enforcement announcements, and the blue line represents non-insider enforcement announcements. Dashed lines indicate each group's overall mean abnormal spread during the post-event period. The sample period is Jan-1999 to Dec-2022.

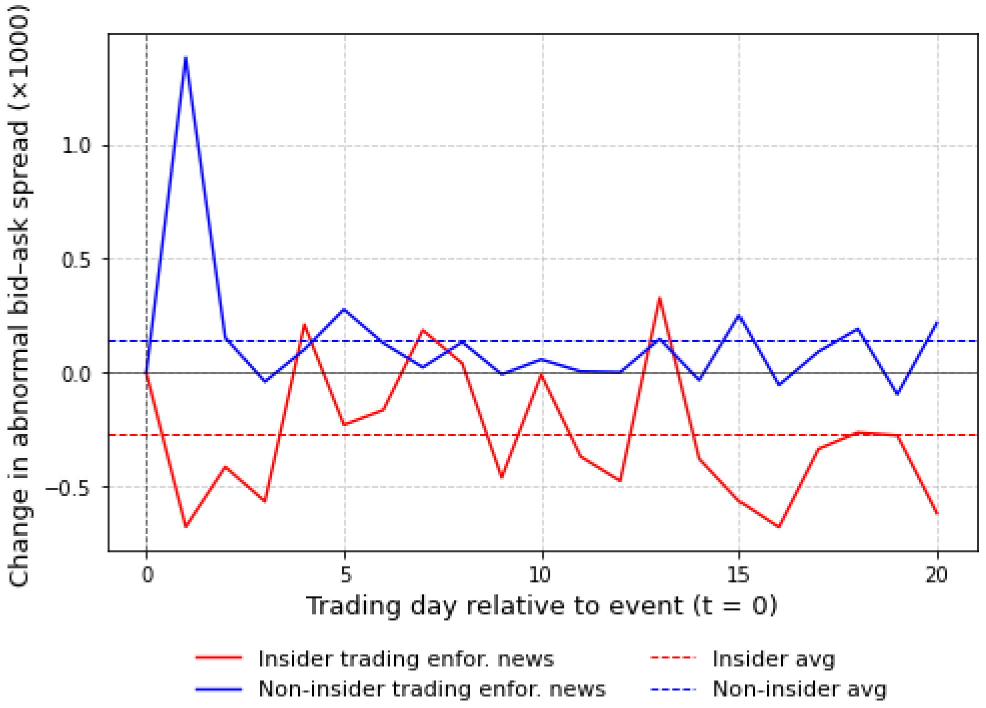


Figure 6: Average Annual Net Sentiment of SEC Press Releases

The figure shows the average annual net sentiment of *SEC enforcement announcements* (red line), press releases covering *non-enforcement topics* (blue line), and all SEC press releases those (dashed line). The sample period is Jan-1999 to Dec-2022.

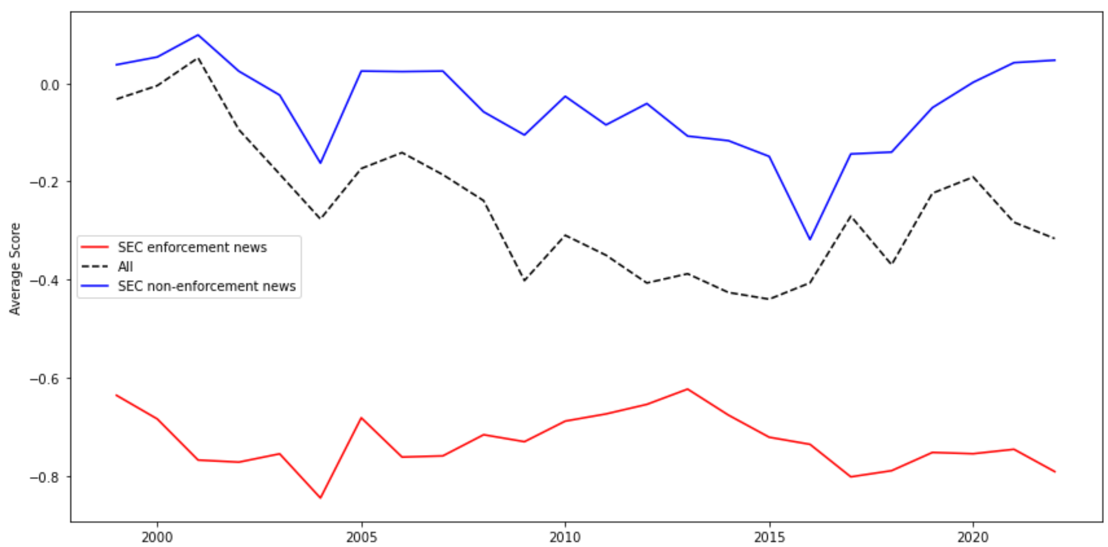
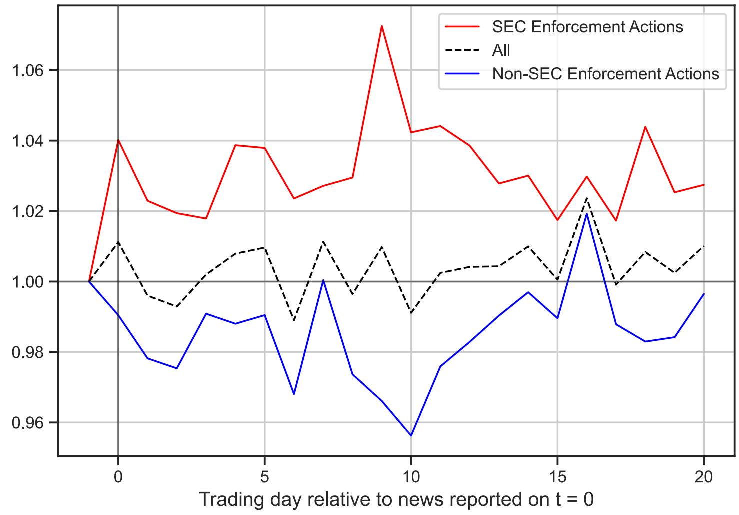


Figure 7: Option Implied Volatility and Distance-to-Default Around SEC Press Releases

The figure shows the pattern of option implied volatility over the [-1, +20] event window. Panel A shows the average change in implied volatility of stocks mentioned in *SEC enforcement announcements* (red line), press releases covering *non-enforcement topics* (blue line), and all SEC press releases those (dashed line). Panel B plots the average daily Merton distance-to-default (DtD) over the [-1, +10] window. The sample period is Jan-1999 to Dec-2022.

Panel A Implied volatility



Panel B DtD

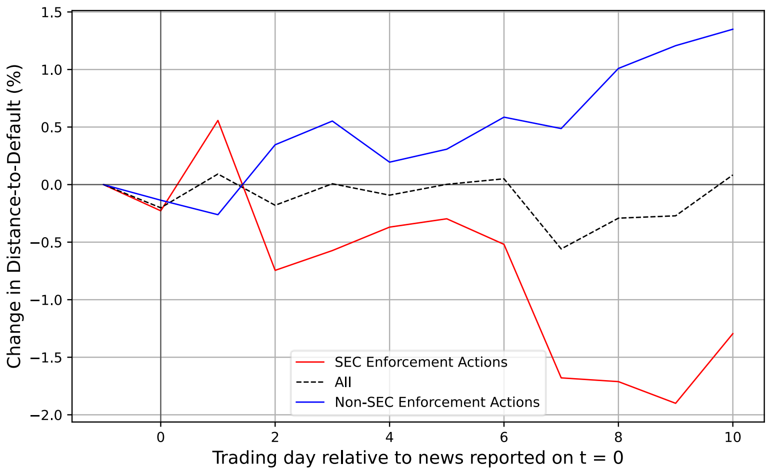


Figure 8: Investor Attention Around SEC Press Releases

The figure presents the estimated coefficients from Equation (3), which regresses investor attention on event-day indicator variables over a [−10,+10] trading-day window around SEC press releases. Panel A shows results for firms mentioned in enforcement announcements, while Panel B shows results for firms mentioned in non-enforcement announcements. The top row reports abnormal trading volume (AVOL), and the bottom row reports abnormal internet attention (AIA). The sample period is Jan-1999 to Dec-2022.

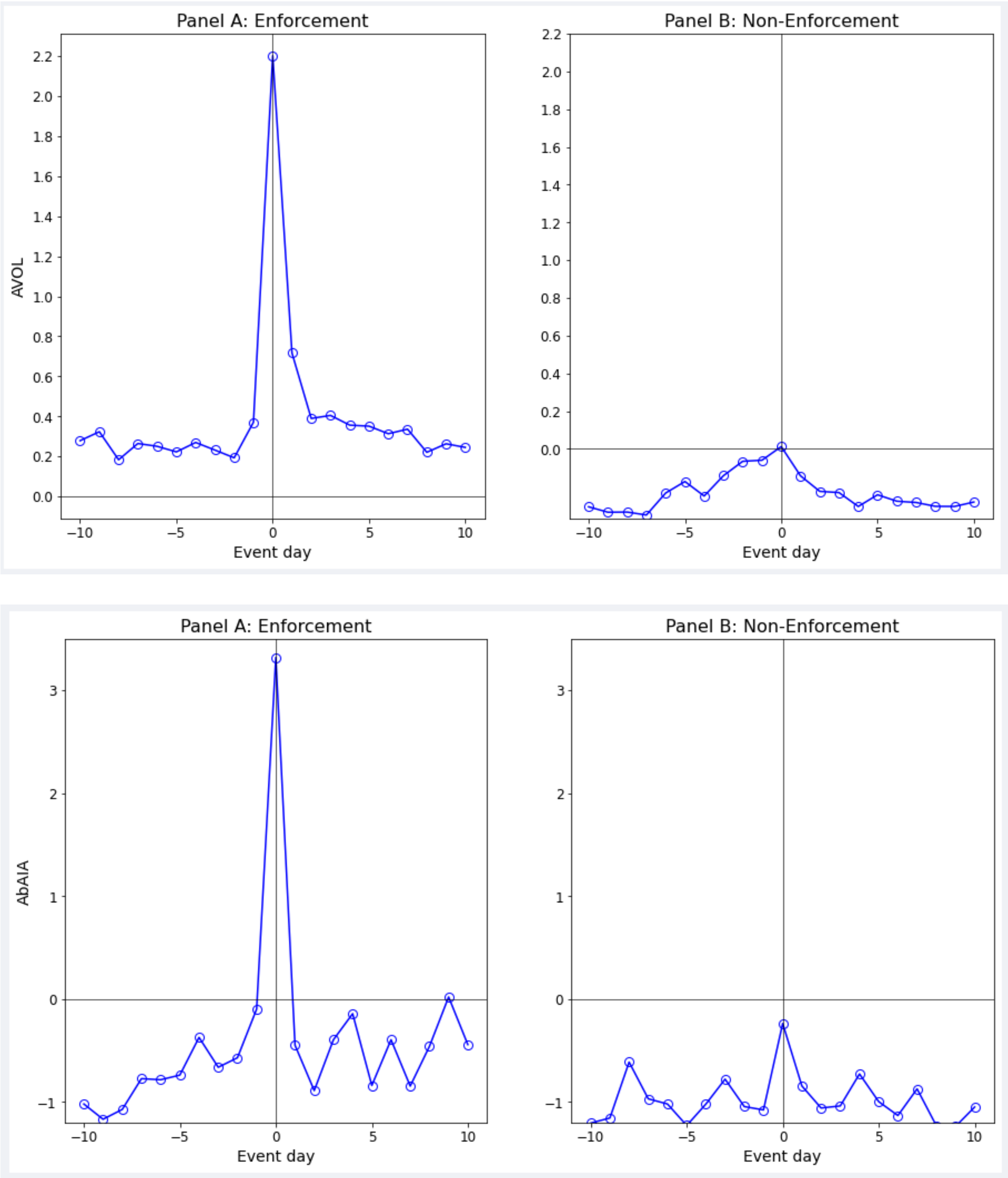
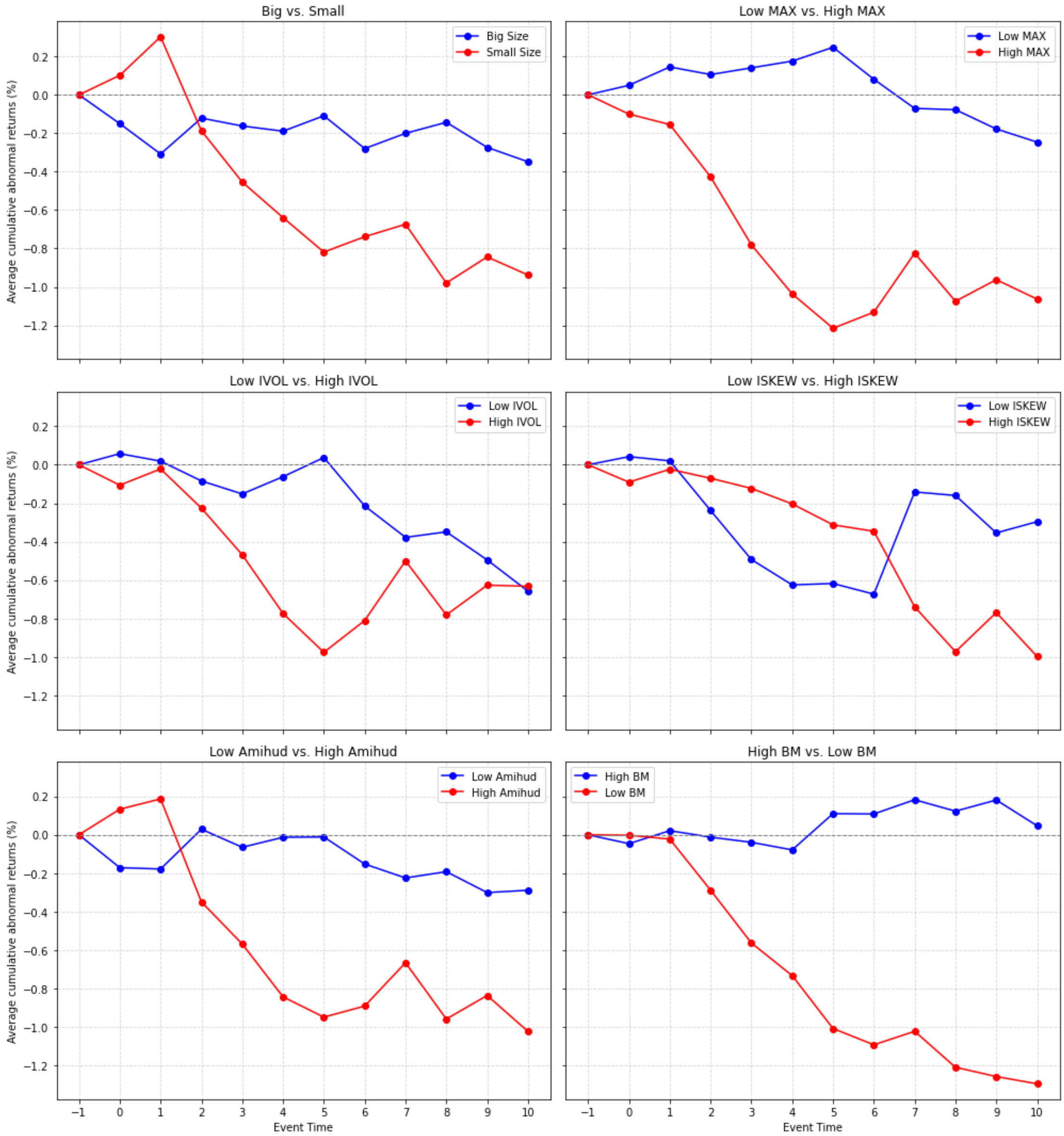


Figure 9: BHARs Around SEC Enforcement Events by Speculative Characteristics

This figure plots cumulative abnormal returns (BHAR) from day –1 to +10 relative to SEC enforcement announcements, split by median values of six firm-level speculative characteristics: firm size (*MCAP_log*), maximum daily return (*MAX*), idiosyncratic volatility (*IVOL*), idiosyncratic skewness (*ISKEW*), Amihud illiquidity (*Amihud*), and book-to-market ratio (*BM*). For each characteristic, firms are divided into "High" and "Low" portfolios based on the median value in the sample. The y-axis represents cumulative BHAR over the event window, while the x-axis denotes the number of days relative to the enforcement disclosure date (day 0).



Appendix A. Additional Descriptions and Data Construction

A.1 Four examples of SEC enforcement press releases.

Example 1: SEC enforcement press release example related to fraud.

Home > News & Statements > Press Releases

About the SEC
Filings (EDGAR)
Regulatory Actions
Staff Interps
Investor Info
News & Statements
News Digest
Press Releases
What's New
Upcoming Events
Speeches
Testimony
Special Studies
Complaint Data
Open Meetings
Other Webcasts
Litigation
Information for...
Divisions

SEC Charges Merrill Lynch, Four Merrill Lynch Executives with Aiding and Abetting Enron Accounting Fraud

FOR IMMEDIATE RELEASE
2003-32

Merrill Lynch Simultaneously Settles Charges for Permanent Anti-Fraud Injunction and Payment of $80 Million in Disgorgement, Penalties and Interest

Washington, D.C., March 17, 2003 -- The Securities and Exchange Commission today charged Merrill Lynch & Co. Inc. and four of its former senior executives with aiding and abetting Enron Corp.'s securities fraud. The Commission's complaint, filed in U.S. District Court in Houston, alleges that Merrill Lynch and its former executives aided and abetted Enron Corp.'s earnings manipulation by engaging in two fraudulent year-end transactions in 1999. The transactions had the purpose and effect of overstating Enron's reported financial results. Specifically, Enron used these transactions to add approximately $60 million to its fourth quarter of 1999 income (improving net income from $199 million to $259 million or 33 percent) and to increase its full year 1999 earnings per share from $1.09 to $1.17.

Simultaneous with the filing of this action, the Commission has agreed to accept Merrill Lynch's offer to settle this matter. Merrill Lynch, without admitting or denying the allegations in the complaint, has agreed to pay $80 million dollars in disgorgement, penalties and interest and has agreed to the entry of a permanent anti-fraud injunction prohibiting future violations of the federal securities laws. The Commission intends to have these funds paid into a court account pursuant to the Fair Fund provisions of Section 308(a) of the Sarbanes-Oxley Act of 2002 for ultimate distribution to victims of the fraud. The four former Merrill Lynch executives named in the complaint, Robert S. Furst, Schuyler M. Tilney, Daniel H. Bayly and Thomas W. Davis, are contesting the matter.

Example 2: SEC enforcement press release example related to insider trading.

PRESS RELEASE

SEC Announces Charges Against Atlanta Man Accused of Insider Trading in Advance of Tender Offer

FOR IMMEDIATE RELEASE | 2015-29

Washington D.C., Feb. 11, 2015 — The Securities and Exchange Commission today announced charges against an Atlanta resident accused of insider trading in the stock of a technology company by exploiting nonpublic information he learned from the friend of a company executive.

The SEC's Enforcement Division alleges that Charles L. Hill Jr. made approximately $740,000 in illicit profits by trading in Radiant Systems stock on the basis of confidential inside information about an impending tender offer by NCR Corporation to buy the company. Hill was aware that his friend who shared this nonpublic information also was a friend of a Radiant Systems executive. Hill purchased approximately 100,000 Radiant Systems shares that were valued at nearly $2.2 million on the last trading day before the acquisition was publicly announced in July 2011. Hill had not purchased equity securities in the previous four years, and had never before bought Radiant Systems stock.

Example 3: SEC enforcement press release example related to market manipulation.

PRESS RELEASE

SEC Sanctions 19 Firms and Individual Trader for Short Selling Violations in Advance of Stock Offerings

FOR IMMEDIATE RELEASE | 2014-195

Washington D.C., Sept. 16, 2014 — The Securities and Exchange Commission today announced the latest sanctions in a continuing enforcement initiative uncovering certain hedge fund advisers and private equity firms that have illegally participated in an offering of a stock after short selling it during a restricted period.

The SEC last year announced the initiative to enhance enforcement of Rule 105 of Regulation M, which is designed to preserve the independent pricing mechanisms of the securities markets and prevent stock price manipulation. Rule 105 typically prohibits firms or individuals from short selling a stock within five business days of participating in an offering for that same stock. Such dual activity typically results in illicit profits for the firms or individuals while reducing the offering proceeds for a company by artificially depressing the market price shortly before the company prices the stock.

The SEC's investigations found that 19 firms and one individual trader charged in these latest cases engaged in short selling of particular stocks shortly before they bought shares from an underwriter, broker, or dealer participating in a follow-on public offering. Each firm and the individual trader have agreed to settle the SEC's charges and pay a combined total of more than $9 million in disgorgement, interest, and penalties.

Example 4: SEC enforcement press release example related to registration/disclosure violations.

PRESS RELEASE

General Electric Agrees to Pay $200 Million Penalty for Disclosure Violations

FOR IMMEDIATE RELEASE | 2020-312

Washington D.C., Dec. 9, 2020 — The Securities and Exchange Commission today announced that General Electric Co. (GE) has agreed to pay a $200 million penalty to settle charges for disclosure failures in its power and insurance businesses. In 2017 and 2018, GE's stock price fell almost 75% as challenges in its power and insurance businesses were disclosed to the public.

According to the SEC's order, GE misled investors by describing its GE Power profits without explaining that one-quarter of profits in 2016 and nearly half in the first three quarters of 2017 stemmed from reductions in its prior cost estimates. The order also finds that GE failed to tell investors that its reported increase in current industrial cash collections was coming at the expense of cash in future years and came primarily from internal receivable sales between GE Power and GE's financial services business, GE Capital. In addition, the order finds that from 2015 to 2017, GE lowered projected costs for claims against its long-term care insurance portfolio and failed to inform investors of the corresponding uncertainties resulting from lower estimates of future insurance liabilities at a time of rising costs from long-term health insurance claims.

A.2 AI-based classification of defendants in insider trading cases

To systematically determine whether SEC insider trading cases targeted organizations or only individuals, we develop a custom prompt for GPT-4o. The prompt was designed to emulate the analytical process of a financial analyst and SEC enforcement staff member, applying clear decision rules to identify defendants directly named in the enforcement action. The classification task consisted of two parts: (1) identifying whether any organization was a defendant and (2) extracting the organization name(s) when applicable. The rules were intentionally conservative, which ensures that organizations were classified as defendants only if explicitly named as direct objects of enforcement actions or if responsible for paying associated penalties or settlements. Table A.1 presents the exact prompt used in the training and classification process.

You are acting as a financial analyst and SEC enforcement staff member. Your task has TWO parts for the given text snippet: 1) Classify whether the defendant(s) include any ORGANIZATION. - Output 0 if ONLY individuals are defendants. - Output 1 if AT LEAST ONE organization is a defendant. 2) If an ORGANIZATION is a defendant, extract the organization name(s) (verbatim if possible). - If multiple org defendants appear, join with ‘;’. - If no org defendants, return an empty string. Decision rules (apply strictly): A) Enforcement triggers (non-exhaustive): “SEC sues”, “SEC charged”, “SEC charges”, “SEC files a complaint against”, “SEC brings an action against”, “SEC initiates/institutes proceedings against”, “SEC alleges”, “SEC settles with”, “SEC penalizes”, “SEC fines”, “SEC sanctions”, “SEC bars”, “SEC enters an order against”, “SEC obtains judgment against”, “SEC takes enforcement action against”. → Extract the DIRECT OBJECT(S) of these verbs as defendants. B) Affiliation ≠ defendant:

If an organization only appears as an affiliation marker (e.g., ‘at’, ‘from’, ‘of’, ‘formerly of’, ‘with’, ‘employed by’, ‘unit of’, ‘subsidiary of’), DO NOT mark that org as a defendant.
Examples:
- “SEC brings actions against three individuals at Goldman Sachs ...” → org is NOT a defendant.
- “SEC sues the Chairman of Grupo Mexicano de Desarrollo ...” → the chairman is a person defendant; the org is NOT a defendant unless separately charged.

C) Penalty/settlement payer heuristic:
If the text states who pays a penalty/settlement and that payer is a company/institution, the company IS a defendant. If the payer is a person, treat as an individual defendant.

D) Conjunction disambiguation:
If the headline/text says “against X and Y”, include Y as a defendant ONLY if the enforcement verb grammatically governs both X and Y (i.e., Y is also a direct object of the enforcement verb).

E) Default when ambiguous:
Only classify an organization as a defendant if it is explicitly a direct object of an enforcement action (A) or the payer under (C). Otherwise assume individual-only.

After running this procedure on 120 insider trading press releases, the AI classified only one case as involving a corporate defendant. We then manually reviewed the full SEC complaints for each case and identified five instances in which the defendant was, in fact, an organization. The close alignment between AI predictions and manual verification supports the robustness of the classification procedure, while also highlighting that corporate defendants in insider trading cases are rare.

A.3: Identifying whether individual defendants had already left the company

To assess whether individual defendants named in SEC insider trading enforcement press releases were still employed by the company at the time of enforcement, or had already left (e.g., resigned, retired, or been terminated), we developed a specialized prompt for GPT-4o. This classification task was designed to emulate the reasoning of SEC enforcement analysts, incorporating domain-specific heuristics and linguistic cues observed in the press releases.

Table A.2 presents the exact prompt used in the training and classification process.

You are an SEC enforcement analyst.

Your task is to determine whether the SEC text suggests that the named officer or employee defendant had already **left the company** (e.g., was fired, resigned, retired, terminated, or otherwise no longer employed) **before or at the time of the enforcement action**.

Return:
- 1 if the text explicitly or implicitly indicates the individual had **already left the company**.
- 0 **only** if the text clearly states the person is **still employed** or there is **no strong evidence** either way.

Assign 1 (“fired or left”) if **any of the following** conditions are met:
• Explicit departure phrases: “former”, “ex-”, “resigned”, “retired”, “terminated”, “departed”, “no longer with”, “left the company”, “had since left”, “after his resignation”, etc.
• Past-tense role: “was the CFO”, “previously served as”, “worked at”, “was employed by”, “was a VP during”, “after leaving”, “while at XYZ”, “had been employed”, “was responsible for X at”, etc.
• Employment window with an end date before enforcement: “CEO from 2015 to 2020”, “was employed until 2019”, etc.
• Indirect separation language: “during his time at”, “was then employed at”, “was associated with”, “following his tenure at”, “in his prior role at”, etc.

• Described solely as a trader or individual actor with **no current role or employer stated** (e.g., “opened a brokerage account”, “traded via personal account”, “resident of”, “acted through foreign entities”)
• Subject of emergency relief, asset freeze, or complaint **without current employment linkage**
• Conduct is clearly placed in the past, even without departure language (e.g., “engaged in conduct while at X”, “in 2016, when he was employed by…”)

Assign 0 (“still employed”) **only if**:
• The person is described in present tense with an active role: “is the CEO”, “serves as CFO”, “is currently employed at”, “still an executive at”, etc.
• There is **no job title or timeframe** at all, and the context does not imply employment separation.

Heuristic for ambiguous or unclear cases:
If the individual is charged **purely based on personal trading or offshore activity**, and **no job title or employer is mentioned**, assign 1 — assume the person is not currently employed by a firm at the time of enforcement.

Output format (STRICT JSON only):
{
  “officer_fired_or_left”: 0 or 1
}

The prompt instructed the model to evaluate whether the text *explicitly or implicitly* indicated that the individual had already left the company before or at the time of enforcement. The output was a binary classification: (1) 1 if the text provided evidence that the individual had departed, and (2) 0 if the person was either clearly still employed or if there was insufficient evidence of a departure.

After applying this method to 119 insider trading press releases (individual defendants’ cases), we find that the vast majority of individual defendants, nearly 80% (91 cases), were either explicitly described as no longer employed or inferred to have left based on temporal or structural clues in the text. This suggests that most enforcement actions target individuals after they have exited the firm, potentially limiting immediate reputational or financial damage to the employer, and reinforcing our broader interpretation that these enforcement events are personal in nature rather than organizational.

A.4 Accounting and financial market data

This appendix describes the accounting-based and market-based firm characteristics used in the empirical analysis. All variables are measured at the firm-month level unless otherwise stated:

- *Return on equity* (*RoE*): Following Haugen and Baker (1996), *RoE* is defined as net income divided by the book value of common equity. This variable serves as a proxy for firm profitability.
- *Leverage*: Following Bhandari (1988), *Leverage* is defined as total liabilities divided by the market value of equity. This variable reflects the firm's reliance on debt financing.
- *MAX*: Following Bali et al. (2011), *MAX* is defined as the maximum daily return within each calendar month. A minimum of 15 daily observations in a given month is required to compute this variable.
- *Idiosycratic volatility* (*IVOL*): Following Kumar (2009), *IVOL* is estimated as the standard deviation of daily residuals from the Fama-French-Carhart four-factor model. We use three months as estimation periods.
- *Idiosycratic skewness* (*ISKEW*): Following Kumar (2009), *ISKEW* is estimated as the skewness of daily residuals from the Fama-French-Carhart four-factor model. We use three months as estimation periods.
- *Market* beta (*Beta*): *Beta* is estimated using a 60-month rolling regression of stock excess returns on market excess return.
- Amihud's liquidity (*Amihud*): Following Amihud (2022), *Amihud* is defined as the average daily absolute return divided by dollar trading volume, computed over the prior 12 months.

- *Log of price* (*Prc_log*): Natural logarithm of the stock's closing price at the end of the month preceding each event.
- *Log of market cap* (*Mcap_log*): Natural logarithm of market capitalization measured at each firm's June fiscal year-end.
- *Momentum* (*MOM*): Following Jegadeesh and Titman (1993), *MOM* is calculated as the cumulative stock return from month *t*–12 to *t*–2.

To capture firms' speculative characteristics, a monthly Lottery-Like Index (LLI) is constructed as a standardized composite score based on six speculative features: *Mcap*, *MAX*, *IVOL*, *ISKEW*, *Amihud*, and *BM*. For each month, firms are ranked into percentiles (0–99) within the cross-section for each variable. The LLI is then computed as the average of the available percentile ranks, requiring at least three of the five inputs to be non-missing. The LLI for firm *i* in month *t* is defined as:

$$LLI_{i,t} = \frac{1}{N_{i,t}} \sum_{k=1}^{5} R_{i,k,t} + 1, \qquad \text{(A.1)}$$

where $R_{i,k,t}$ is the percentile rank of firm *i* on characteristic *k* in month *t*, and $N_{i,t}$ is the number of non-missing characteristics for firm *i* in that month, with a minimum requirement of three non-missing components. We add one to the LLI calculation to ensure that all index values are positive, which facilitates subsequent standardization and prevents issues with potential zero or negative values.

A.5 Option implied volatility

Following studies such as Patell and Wolfson (1979), and Hann et al. (2019), we use option implied volatility (IV) as a proxy for information uncertainty. We obtain options data from OptionMetrics, which provides end-of-day bid and ask prices, open interest, trading volume and implied volatilities. Prior studies (e.g., Gao et al., 2018) highlight that options data are extensive and noisy due to liquidity constraints and market microstructure issues. To address these issues, we follow Xing et al. (2010), and Gao et al. (2018) employ a multi-faceted filtering process. First, we remove options data with missing implied volatility, zero open interest, or zero bid or ask prices. The bid and ask prices must satisfy fundamental no-arbitrage boundaries.[11] We focus on at-the-money options, which are generally the most liquid. We define an option as at-the-money if its "moneyness", the ratio of strike price to stock price, falls between 0.9 and 1.1. Consistent with Roger et al. (2009), Bilings et al. (2015) and Hann et al. (2019), we calculate 30-day implied volatility as the average of call and put options IVs. We interpolate the IVs of 30-day maturity options using available contracts with varying strike prices and maturities.

A.6 Distance-to-default (DtD)

We follow Brogaard et al. (2017) and measure corporate default risk using Merton's distance-to-default (DtD) metric. We obtain DtD data from the Credit Research Initiative (CRI) at the National University of Singapore.

A.7 Abnormal trading volume (AVOL)

Following Cready and Hurtt (2002), and Beaver et al. (2020), we calculate AVOL by comparing the share trading volume during the [-10, 10] event window surrounding the SEC press releases to the average daily trading volume over the pre-event period [-130, -10].

[11] These boundaries include ask price > bid price, stock price ≥ bid price (for call options), strike price ≥ bid price (for put options), ask price ≥ max[0, stock price - strike price] (for call options) and ask price ≥ max[0, strike price - stock price] (for put options).

A.8 SEC EDGAR downloads

This appendix describes how SEC EDGAR downloads are measured. We analyze EDGAR server log files for the period from January 2003 to June 2017, obtained from the SEC's Division of Economic and Risk Analysis (DERA) website (https://www.sec.gov/data-research/sec-markets-data/edgar-log-file-data-sets). This time frame represents the full set of log data publicly released by the SEC's EDGAR system.

Each log file includes partially anonymized records of user access to SEC filings. Specifically, the logs capture the first three octets of a user's Internet Protocol (IP) address, while the fourth octet is masked with a three-character string that preserves the user's identification without disclosing the complete IP address. The log files also record accession numbers, which uniquely identify each individual filing request.

We focus on Form 8-K filings because they are used by firms to disclose timely, often unexpected, material information regarding significant changes in operations or financial condition that occur between periodic reports. Ben-Rephael et al. (2022) document that 8-K disclosures offer limited value to retail investors, but they attract significant attention from institutional investors. The SEC mandates public companies to file Form 8-K within four business days of a triggering event. This immediacy and informational significance make 8-Ks highly relevant in our analysis of investor responses to similarly unexpected SEC press releases. In addition, Drake et al. (2015), and Gibbons et al. (2021) identify 8-Ks as among the most frequently accessed filings on the EDGAR platform.

To ensure that our analysis reflects access by human users rather than automated systems, we apply a series of data filters consistent with prior research such as Lee et al. (2015), and Hollander and Litjens (2022). In particular, we remove all requests made by known web crawlers and omit requests referencing index pages (idx=1). We retain only entries with successful document retrievals (HTTP status code = 200). Finally, we exclude any IP address that downloads filings for more than 50 unique firms in a single day, which Lee et al. (2015) classify as robotic behaviour.

A.9 AIA

Following Ben-Rephael et al. (2017, 2021), and Chan and Smales (2025), we proxy institutional investor attention using abnormal institution attention (AIA), which reflects Bloomberg terminal usage pattern. Because Bloomberg terminals are predominantly used by institutional investors with substantial financial resources, AIA provides a credible and direct measure of institutional attention.

We retrieve AIA data directly from Bloomberg terminals, which provides a daily modified attention score based on user engagement with stock-specific news. In particular, Bloomberg tracks the number of times terminal users search for or read news related to stock *i*. These interactions are scored on a scale from 1 to 10, where a score of 10 reflects active searching and/or reading, and a score of 1 indicates passive reading only. These scores are aggregated into hourly interval. For each hour, Bloomberg computes a relative attention score by comparing the stock's average hourly engagement over the prior eight hours to all hourly engagement levels observed in the previous 30 days. A score of 0 is assigned if this rolling average is below the 80^{th} percentile, 1 if it falls between the 80^{th} and 90^{th} percentiles, 2 if it is between the 90^{th} and 94^{th} percentiles, 3 if it is between the 94^{th} and 96^{th} percentiles, and 4 if it is above the 96^{th} percentile. The maximum hourly score for each trading day becomes the stock's daily attention score.

Consistent with Ben-Rephael et al. (2017, 2021), we transform this continuous daily score into a binary variable, which is equal to 1 if the score is 3 or 4, and 0 otherwise. We define AIA over the event window [-10, +10] by comparing each day's binary attention indicator to its baseline average in the pre-event period [-70, -10].

Appendix B. Supplementary Figures

Figure B.1: Buy-and-Hold Abnormal Returns (BHARs) Around SEC Press Releases for Individual Firms

This figure plots BHARs over the event window [−1,+2] for two individual firms: Synchronoss Technologies Inc. (SNCR) and Oppenheimer Holdings Inc. (OPY). For each firm, the red line represents the cumulative abnormal return when the firm is mentioned in an SEC enforcement-related press release, while the blue line shows the firm's cumulative abnormal returns following a non-enforcement SEC disclosure. The x-axis denotes event time in trading days, and the y-axis shows cumulative abnormal returns in percentage terms. The sample period spans from 1999 to 2022.

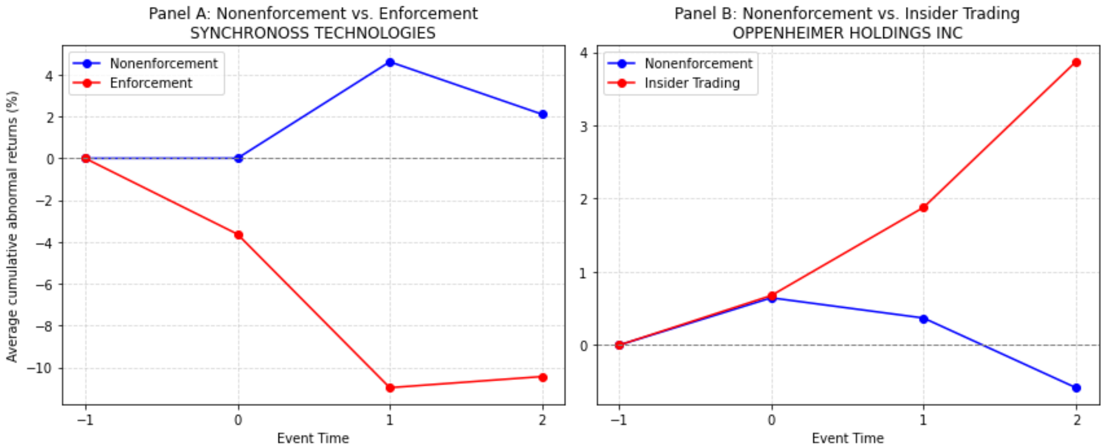


Figure B.2: Distribution of Similarity Scores Between SEC Enforcement Press Releases and Preceding WSJ Articles

This figure presents the distribution of similarity scores between each SEC enforcement press release and Wall Street Journal articles published in the four weeks prior to the release. Panel A displays cosine similarity, which captures directional similarity in word usage after adjusting for document length. Panel B shows Jaccard similarity, reflecting the proportion of overlapping vocabulary without accounting for term frequency. Panel C illustrates semantic similarity based on Sentence-BERT embeddings, which capture contextual meaning beyond surface wording. The sample period is January 1999 to December 2022.

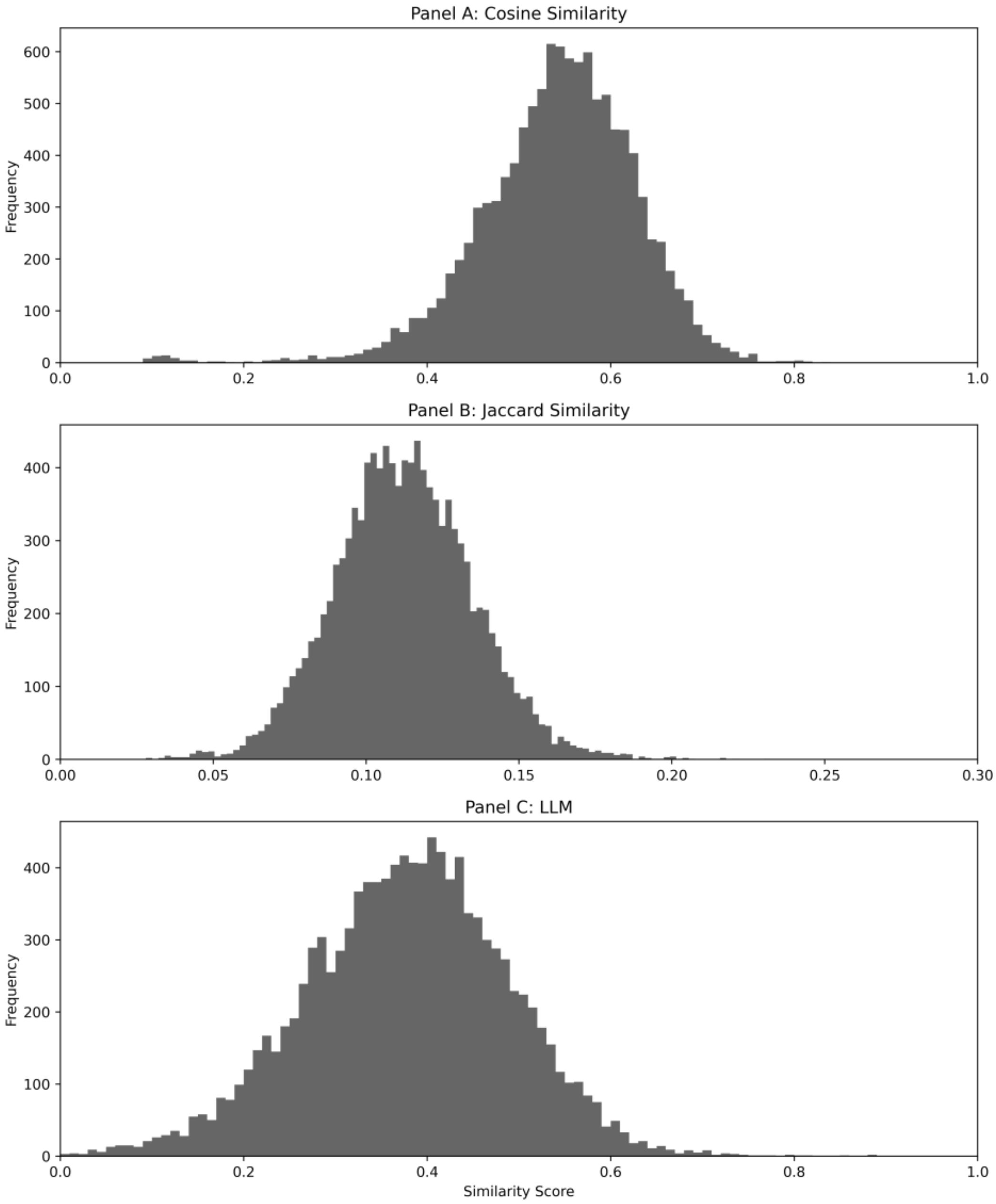
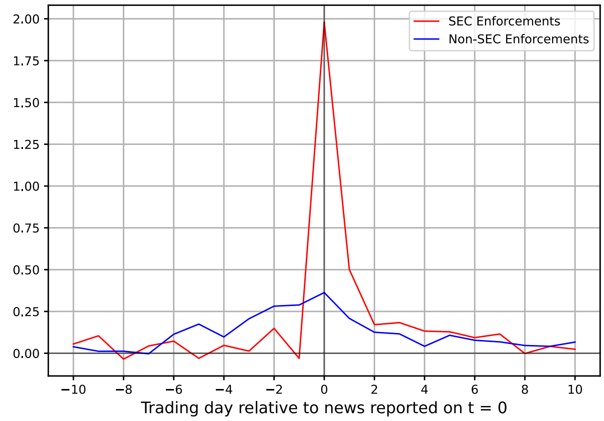


Figure B.3: AVOL and AIA

The figure plots the average abnormal volume (Panel A), and Bloomberg AIA metrics (Panel B) using an event window spanning [-10, +10] trading days. Due to data availability, the analysis covers from 1999 to 2022 for abnormal trading volume, and 2010 to 2022 for Bloomberg AIA metrics.

Panel A: Abnormal volume trading (AVOL)



Panel B: Bloomberg AIA

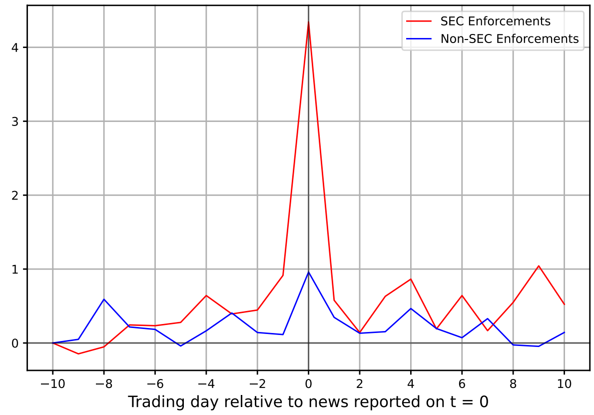


Figure B.4: Pooled Dynamic Event Study

This figure presents the dynamic treatment effect of SEC enforcement events on firm abnormal returns (BHAR) relative to matched non-enforcement firm announcements. The y-axis shows the difference in abnormal returns (treated minus control), and the x-axis denotes event days from 0 to 5. The red line represents the estimated daily enforcement effect, while the shaded region indicates the 95% confidence interval, with standard errors clustered at the industry level.