

ADAPTIVE MARKETS AND ATTENTION- DRIVEN ANOMALIES IN TIMES OF CRISIS: A COVID-19 PERSPECTIVE

**REVISITING THE EFFECT OF FRIDAY INATTENTION AND POST-
EARNINGS ANNOUNCEMENT DRIFT IN THE U.S. MARKET**

EMMA LOVÉN

ELISE CRUTZE

Bachelor Thesis

Stockholm School of Economics

2024



Abstract

This study examines the impact of day-of-the-week effects, specifically Fridays, on post-earnings announcement drift (PEAD) in the U.S. stock market from 2016 to 2023, with a specific focus on the COVID-19 pandemic period. Our findings reveal significant challenges in isolating the effects of investor inattention from firm-specific characteristics and the strategic timing of earnings announcements. While previous literature, such as DellaVigna and Pollet (2009), attribute anomalies like reduced Friday reactions to investor inattention, our results suggest that these patterns may instead arise from unobserved biases and external market factors. During the COVID-19 pandemic, shifts in market dynamics were observed, however, the evidence remains inconclusive regarding the persistence of traditional anomalies.

Our analysis underscores the methodological challenges posed by non-random announcement distributions and selection biases, complicating the attribution of observed trends to specific behavioral or market inefficiencies. These limitations constrain the ability to draw definitive conclusions for market participants, highlighting the need for future research to explore broader datasets, alternative market contexts, and randomized announcement tests to address these issues. As financial markets are expected to face increasing volatility due to the growing likelihood of pandemics and similar systemic disruptions, understanding these dynamics is crucial for researchers, investors, and corporate managers.

Keywords

Investor Inattention, Earnings Announcements, Behavioral Finance, COVID-19, Day-of-the-week effect, Efficient Market Hypothesis, Anomalies

Authors

Emma Lovén (25679)

Elise Crutze (25611)

Tutor

Marieke Bos, Deputy Director, Swedish House of Finance Researcher, Swedish House of Finance

Examiner

Ramin Baghai, Professor, Department of Finance, Stockholm School of Economics

Bachelor Thesis

Bachelor Program in Business and Economics Stockholm School of Economics

© Emma Lovén & Elise Crutze, 2024

1. Introduction

Traditional financial theory assumes that stock prices fully reflect all available information, punching investors to respond immediately to new information. Behavioral theorists like Kahneman (1973) argue that attention is a limited resource, influencing how investors process information. This concept is expanded by Huberman and Regev (2001), who suggest that stock prices only incorporate new information when investors actively attend to it. The ability to process information is further constrained by cognitive limits, underscored by Cherry (2024). Context heavily influences where and how investors allocate their attention, leading to diverse research into how attention varies across different settings such as weekdays, specific times of day, seasonal changes, and political cycles (Kim and Verghese, 2012).

Building on these insights, this study examines how investor attention around earnings announcements affects the U.S. stock market prices, with a particular focus on variations between Fridays and non-Fridays. By analyzing the post-earnings announcement drift (PEAD) before and during the COVID-19 crisis, we aim to determine if inattention-driven anomalies previously observed continue to exist, adapt, or reappear under changed market conditions. The COVID-19 pandemic, which has significantly altered economic landscapes and market behaviors due to its unpredictable disruptions and heightened uncertainty, provides an interesting context to explore these concepts further. The topic offers a timely and relevant perspective, given the increasing likelihood of pandemics (Haileamlak, 2022) and their direct and indirect impact on global financial markets. The COVID-19 pandemic has notably shifted the dynamics of traditional working weeks. Where there once was a strict alignment with the market week, we now see a more flexible arrangement, which we hypothesize might weaken investors' attention to market signals, further amplified by an information overload during the crisis. This shift motivates our research on PEAD around earnings announcements on different weekdays in times of crises.

DellaVigna and Pollet's (2009) research presents a new perspective to the study of investor attention by exploring the impact of weekend distractions on the U.S stock market. Their focus is on how the anticipation of the weekend might affect investor responses to earnings announcements on Fridays compared to other weekdays. Earnings announcements, which introduce new information into the market, are a common economic event for observing investor attention, as they require a significant cognitive effort to influence stock prices. Through an analysis of data spanning from 1994 to 2006, DellaVigna and Pollet observed that announcements made on Fridays received a 15% lower immediate response and underwent 70% greater PEAD relative to other weekdays. These findings support the idea that limited cognitive resources and situational distractions influence observable market inefficiencies.

Post-earnings announcement drift (PEAD) refers to the tendency of a firm's stock price to drift in the direction of its earnings surprise over time (Fink 2021). Since Ball and Brown (1968) first highlighted the relationship between earnings surprises and stock market reactions, and Bernard and Thomas (1989) further demonstrated PEAD, this anomaly has been widely studied. Various mechanisms have been proposed to explain PEAD, including trading frictions (Jeffrey, Rusticus, and Verdi, 2008), arbitrage opportunities (Mendenhall, 2004), investor inattention and behavioral biases (DellaVigna and Pollet, 2009, Hirshleifer, Lim, and Teoh, 2009) and market illiquidity (Chordia, Goyal, Sadka, and Shivakumar, 2009). However, no single theory has been able to fully account for it (Fink 2021). Recent research, such as Martineau (2021), suggests that PEAD is diminishing in modern markets as earnings surprises are incorporated into stock prices, driven by reduced transaction costs, increased liquidity,

enhanced price discovery through technological advancements, and the adaptive behavior of markets. These improvements in market efficiency tend to diminish the observability of anomalies like PEAD over time.

While existing literature has traditionally examined the drivers of PEAD under typical market conditions, recent research by Fang (2024) explores how systemic shocks like the COVID-19 pandemic affect PEAD on the U.S stock market. During the period from March to December 2020, Fang observed that PEAD continued to persist, despite previous studies suggesting a decline. Similar to how DellaVigna and Pollet explain increased drift on Fridays, Fang attributes the persistence of PEAD during COVID-19 to increased investor inattention and an overwhelmed cognitive capacity, as investors struggled to process the substantial increase of financial disclosure during the pandemic.

The COVID-19 pandemic triggered a global systematic shock that extended beyond its initial health crisis. In the early 2020, stock markets plummeted, and the world experienced its deepest recession since the Great Depression of 1929 (International Monetary Fund, 2020). In the U.S., the crisis prompted extraordinary fiscal and monetary interventions, including stimulus packages under the Biden administration, further contributing to the constant stream of information already dominated by pandemic updates and frequent press conferences. This created a unique and complex environment for investors to navigate, marked by an abundance of new information. In line with the findings of Fang (2024), Fabrizi, Ipino, Longhin, and Parbonetti (2023) argue that during the pandemic, investors behaved irrationally due to increased reliance on alternative sources of information, beyond earnings announcements. This shift is explained by significant regulatory interventions and the diminished reliability of corporate earnings forecasts during the pandemic. Bolek, Gniadkowska-Szymańska and Lyroudi (2022), on the other hand, suggest that investors tend to behave more rationally in times of crisis.

The adaptive market hypothesis (AMH) blends the efficient market hypothesis (EMH) with behavioral finance by suggesting that market behaviors evolve as investors respond to changing conditions (Lo, 2004). Although DellaVigna and Pollets (2009) findings have gained traction, it is essential to revisit such studies to observe if these anomalies still persist in today's market environment. Particularly, given the disruption caused by the COVID-19 pandemic, examining these market anomalies can reveal whether they persist or have changed. Our study aims to explore these issues, focusing on how the pandemic might have influenced market behaviors documented in previous research.

- I. *Does the magnitude of abnormal returns and abnormal trading volume following earnings surprises differ on Fridays compared to non-Fridays in modern financial markets?*
- II. *Does post earnings announcement drift (PEAD) persist, adapt or reappear in unstable markets, specifically during the COVID-19 crisis?*

Our study utilizes an event study methodology, closely following the model set by DellaVigna and Pollet (2009), to evaluate how stock returns react to earnings surprises across multiple event windows. Specifically, we analyse cumulative abnormal returns (CAR) during the immediate period following an earnings announcement (0 to 1 day), and a longer period to capture delayed market reactions (2 to 75 days), and the total drift throughout the entire quarter (0 to 75 days). To provide a nuanced understanding of market behaviors, we categorise earnings

announcements into quantiles based on the magnitude and direction of the earnings surprise, with a focus on extreme quantiles to assess strong market responses. Additionally, our methodology incorporates cross-sectional regressions to explore the determinants of cumulative abnormal returns and abnormal trading volume, highlighting variations in investor reactions across different market conditions and timeframes, including the impact of the COVID-19 pandemic.

In an ideal setting, earnings announcements would be randomly distributed across weekdays to isolate the effect of investor attention. However, firms strategically choose their announcement days, which may introduce selection bias and endogeneity into our models (Boulland and Dessaint, 2017). For example, companies could release earnings news of a certain nature on certain days of the week. To address this issue, we conduct our analysis using a homogeneous sample comprising firms that distribute their announcements more evenly across the week. This approach helps ensure that our findings are not excessively influenced by the strategic timing of earnings releases.

Our analysis indicates that extremely positive surprises lead to increased returns in the short-term irrespective of the announcement day, contradicting DellaVigna and Pollet's (2009) hypothesis of diminished effects for Friday announcements. However, we observe no consistent patterns in long-term responses, with non-Friday announcements showing insignificant differences after accounting for potential selection biases. This suggests that external factors such as firm-specific characteristics or strategic management decisions, may drive observed anomalies, rather than systematic investor inattention as traditionally hypothesized.

During the COVID-19 pandemic, our analysis highlights shifts in market dynamics, particularly in responses to earnings announcements made on Fridays. While these announcements exhibit delayed reactions, suggesting potential drift, the evidence remains inconclusive. These patterns seem to be driven more by market disruptions and external factors than by investor inattention. This finding aligns with previous research by Fang (2024), which highlights the impact of major crises on investor behavior and the challenges of understanding anomalies during such periods.

Our research contributes to several areas of financial literature. Initially, we revisit the classic theory of market efficiency, underscored by Fama's Efficient Market Hypothesis (1998), which suggests that stock prices reflect all available information. This study challenges the robustness of this hypothesis under unstable market conditions, specifically during global health crises which are expected to become more common (Haileamlak, 2022). In such periods, marked by heightened uncertainty and an overload of information, we examine market anomalies such as PEAD, traditionally seen as evidence of market inefficiency. This exploration is enriched by integrating behavioral finance perspectives, notably Kahneman's (1973) theories on the cognitive limitations of investors impacting their attention to and processing of information.

Our analysis is further deepened by examining how PEAD, as originally identified by Bernard and Thomas (1989), behaves during turbulent periods, extending our understanding of market anomalies during systemic shocks like the COVID-19 pandemic. Extending beyond DellaVigna and Pollet's (2009) work on weekend distractions, our study considers more recent data from 2016 to 2023. This allows us to observe the effects of evolving market technologies and strategies as discussed by Martineau (2021), and to consider the significant disruptions caused by the COVID-19 pandemic. Studying the unique market disruptions caused by the COVID-19 pandemic, builds on Fang's (2024) research of PEAD during systemic shocks.

Unlike Fang, however, our study is structured to analyze market reactions across two distinct phases: pre-crisis and during the crisis. This temporal framework enables us to observe the adaptability or evolution of market anomalies under varied conditions, aligning with the Adaptive Market Hypothesis by Lo (2004).

Overall, our research combines insights from a progression of theoretical to empirical studies, enhancing our understanding of how traditional market theories and behavioral finance coexist and respond to unexpected market conditions. Our research also underscores the practical implications for corporate management. Specifically, our study explores whether managers could strategically time their earnings announcements to optimize market reactions, particularly in an era where pandemics may become more frequent, affecting investor attention and market dynamics. Understanding these patterns can enable more informed decision-making, helping to navigate the complexities of modern financial markets marked by both technological advancement and potential epidemiological crises.

The remainder of our study proceeds as follows: Section 2 presents and motivates our predictions. Section 3 defines the data and key variables used in the analysis. Section 4 describes the methodology applied. Section 5 presents the main results. Section 6 discusses the findings, along with their implications and limitations. Finally, Section 7 provides concluding remarks.

2. Hypotheses

H1: We predict no significant difference in immediate market response to earnings announcements made on Fridays compared to earnings announcements made on other weekdays.

Lo (2004) suggests that financial markets are adaptive, with participants learning based on past successes and failures. In line with this theory, we believe that the previously documented inattentive behavior has been arbitrated away through more immediate responses driven by the dynamic learning and adaptation of market participants.

H2: We expect no significant difference in delayed response to earnings announcements made on Fridays compared to earnings announcements made on other weekdays.

Martineau (2021) suggests that PEAD has declined in recent years due to arbitrage of anomalies and increasing market efficiency due to new technologies and adaptive behavior. In line with this, we anticipate a similar development for the Friday inattention-anomaly. As we believe the immediate response to earnings announcements is now fully pronounced, we expect the delayed reaction to be negligible.

H3: We expect the immediate response to earnings announcements made on Fridays to be significantly lower than announcements made on other days during COVID-19, and anticipate the delayed reaction to be significant.

Similar to Fang (2024) we expect PEAD to exist under COVID-19 attributing this to investors' cognitive limits combined with the increased flow of information during the pandemic. Fabrizi et al. (2023) suggest that investors relied on alternative information sources rather than earnings announcements during the pandemic, further supporting the likelihood of a delayed response to earnings announcements under COVID-19. Additionally, we believe that the disruption of the conventional working week during the pandemic blurred the distinction between weekdays and weekends, and that it further contributed to delays in fully processing and acting upon earnings announcements.

3. Data

3.1 Quarterly Earnings Announcements

Following the methodology used by DellaVigna and Pollet, we focus our study on earnings announcements. A quarterly earnings announcement is an official public statement of a company's profitability (Investopedia, 2021), nearly standardized across publicly traded firms and consistently published, making it an ideal subject for research. Its defined release dates and impact on stock prices make it particularly effective for studying investor attention, providing distinct events to analyze market reactions.

In an ideal scenario, we would replicate DellaVigna and Pollet's methodology by using the same data sources and filtering criteria to ensure comparability across time, attributing any differences to changes in market behavior rather than variations in the sample or data collection approach. Additionally, we would collect data from their original time period to validate the accuracy of our model and ensure alignment with their findings before applying it to a more recent context. DellaVigna and Pollet analyzed earnings announcements from all publicly traded companies in the U.S. between 1994 to 2006, listed in the Compustat database. However, due to limitations in data availability and the scope of our study, this approach was not feasible. Instead, we focus on the stocks included in the S&P 500, which serves as a recognized proxy for the U.S. equity market and representative of the large-cap segment. Together, the companies account for approximately 80% of the total market capitalization. Although inclusion in the index is primarily based on market capitalization, other factors such as liquidity and industry balance also play an important role in the selection process (S&P Global, 2024).

Our analysis examines earnings announcements published between March 2016, and December, 2023, incorporating the most recent data available and aligning with the objective of understanding today's market. Due to limited availability of earnings announcement data in our selected database prior to 2012, we are unable to replicate the initial time frame used by DellaVigna and Pollet. This prevents us from directly comparing and analyzing our results to those of DellaVigna and Pollet, limiting us to more speculative conclusions about the development of the anomaly.

The specific data points associated with earnings announcements relevant for this study include the reported earnings per share (EPS), the consensus forecasted EPS, and the date of the earnings announcement, consistent with the approach of DellaVigna and Pollet. To retrieve these data points for each earnings announcement, we use Refinitiv Eikon and the time series request function. Specifically, we extract two data types: the date of the interim earnings announcement made by a company, and the earnings surprise defined as the difference between the actual EPS reported by the company and the consensus analyst forecast¹. We limit the sample to announcements made on weekdays (Monday through Friday), as the market is closed on weekends, preventing the measurement of immediate investor reactions. After filtering for weekdays and matching the necessary data points, the resulting sample includes 13,897 quarterly earnings announcements from March 29, 2016, to September 14, 2023.

¹ The Average EPS estimate is commonly known as the "consensus forecast". It is calculated by adding the Current EPS estimate data for the specified fiscal time period from all Contributing Firms and dividing this figure by the number of EPS estimates that enter into the calculation. (I/B/E/S, 2010)

3.2 Variables

3.2.1 Dependent Variables

We extract daily trading volumes and closing prices from Refinitiv Eikon. Following DellaVigna and Pollet (2009), we focus on returns and trading volumes as the dependent variables in our analysis.

3.2.1.1 Abnormal Returns

Return (R) is calculated as the percentage change in daily closing price for the stocks. Let P represent the price of a given stock i , and n denote a specific day:

$$R_{i,n} = \frac{P_{i,n} - P_{i,n-1}}{P_{i,n-1}} * 100$$

To calculate abnormal returns, we use the Fama-French three-factor model (FF3). This approach deviates from DellaVigna and Pollet (2009), who apply only a single factor model. We base our decision on the fact that multifactor models offer a more detailed view of risk by incorporating multiple factors (CFA Institute, 2024). We use the FF3 model to calculate excess return, which is computed by subtracting the risk-free rate ($R_{f,n}$) from the stock return ($R_{i,n}$) for stock i on day n :

$$Excess\ Return = R_{i,n} - R_{f,n} = \alpha + \beta_{Mkt}(Mkt - R_f) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \epsilon_{i,n}$$

We obtain factor data from Eugene F. Fama and Kenneth R. French's Data Library (2024). Yearly coefficients are estimated through a linear regression, as we calculate the FF3 factors annually rather than updating them per earnings announcements, as done in DellaVigna and Pollet (2009). This methodological choice is based on the most similar approach to DellaVigna within the scope of our analysis, which limits us to yearly factor estimates. In the model, $Mkt - R_f$ denotes the market risk premium, SMB the small-minus-big factor, and HML the high-minus-low factor. The residual term $\epsilon_{i,n}$ represents the portion of a stock's return that is not explained by the three factors. We calculate the expected return by plugging in the estimated yearly coefficients into the FF3 model.

$$Expected\ Return = \beta_1(Mkt - R_f) + \beta_2(SMB) + \beta_3(HML)$$

We then compute abnormal returns (α) as the difference between the excess return and the expected return.

$$\alpha = Excess\ Return - Expected\ Return$$

The Cumulative Abnormal Return (CAR) metric captures the total effect of earnings surprises over the event window. To calculate CAR, we sum the daily abnormal returns over the specified period.

$$CAR_{(T_1, T_2)} = \sum_{t=T_1}^{T_2} \alpha_{i,t}$$

where (T_1, T_2) defines the bounds of each event window relative to the earnings announcement day.

3.2.1.2 Volume

Following DellaVigna and Pollet (2009), we calculate abnormal volume as the percentage change in trading volume relative to a pre-announcement baseline. Volume ($V_{i,n,t}$) is defined as the total traded shares for stock i on day n in quarter t . The pre-announcement period, spanning trading days -20 to -11 prior to the announcement, defines the baseline for normal trading activity and is calculated as the average logarithm of daily trading volume during this period. For the announcement window, we compute the average natural logarithm of daily trading volume from day h to H (e.g., $[0,1]$, which includes the announcement day and the following day). Abnormal volume is then calculated as the difference between the average volume in the announcement window and the pre-announcement baseline.

$$Abnormal\ Volume_{i,n,t} = \left(\frac{1}{H-h+1} \sum_{u=h}^H \log(V_{i,n,t}) \right) - \frac{1}{10} \sum_{u=t-20}^{t-11} \log(V_{i,n,t})$$

After computing the calculations for abnormal volume around each of the 13,897 earnings announcements, the data sample of abnormal volume consists of 13,895 observations.

Descriptive Statistics Dependent Variables

Interval	N	Mean	SD	Min	Max
AbnormalReturn					
0-1	13897	0.0022	0.0538	-0.3515	0.4862
0-75	13897	0.0038	0.1062	-1.4537	1.3676
2-75	13897	0.0016	0.0907	-1.4672	1.1469
AbnormalVolume					
0-1	13895	0.6631	0.4489	-2.3026	2.9457

Table 1 presents the descriptive statistics for the dependent variables used in the analysis: Abnormal Return and Abnormal Volume. Abnormal Return measures the deviation of the stock's return from the expected return during different event windows (0-1, 0-75, and 2-75 days after the earnings announcement). It includes 13,897 observations. Abnormal Volume captures the deviation of the stock's trading volume from the expected volume during the event window (0-1 days). It includes 13,895 observations. The table provides the mean, standard deviation (SD), minimum, and maximum for each variable across the respective intervals.

3.2.2 Independent Variables

3.2.2.1 Earnings surprise

Earnings surprises are the primary driver of PEAD and capture the value of the new information provided to investors through the earnings announcement. Using daily closing price data, we divide each earnings surprise by the stock price five days prior to the announcement. Let $e_{i,t}$ represent the earnings per share announced in quarter t for company i , and let $\hat{e}_{i,t}$ denote the corresponding consensus analyst forecast. $P_{i,(t-5)}$ is the price of the shares of company i 5 trading days prior to the announcement in quarter t . The normalized earnings surprise is calculated as:

$$S_{i,t} = \frac{e_{i,t} - \hat{e}_{i,t}}{P_{i,(t-5)}}$$

A positive value for $S_{i,t}$ implies earnings that were higher than expected while a negative value implies lower-than-expected earnings. This measure standardizes the surprise relative to the stock's pre-announcement value, aligning with the methodology used by DellaVigna and Pollet (2009). By scaling the surprise, we account for differences in stock value.

3.2.2.2 Day of the Week indicator

Each earnings announcement is categorized as either "Friday" or "non-Friday," with Friday announcements representing only 7.0% of the total. This classification is a key independent variable in our analysis, allowing us to examine differences in investor attention and PEAD across Fridays and non-Fridays. As illustrated in Appendix A, most announcements are concentrated in the middle of the week, particularly on Thursdays (33.5%), followed by Wednesdays and Tuesdays, each at 26.5%.

3.2.2.3 COVID-19 Indicator

To capture the effect of the COVID-19 pandemic, we include a COVID-19 dummy variable in our COVID-19 analysis. This variable is designed to account for the changes in market behavior during the pandemic period. The COVID-19 dummy is a binary variable, which takes the value of 1 during the period of the pandemic (01-01-2020 to 05-05-2023) and 0 during the pre-pandemic period (2016-01-01 to 31-12-2019). This indicator allows us to examine how earnings announcements and stock responses during the pandemic differ from those during the pre-pandemic period. The inclusion of the COVID-19 dummy enables us to isolate the effects of the pandemic from other factors, providing insight into whether the market response to earnings announcements was significantly different during the crisis compared to normal conditions. After filtering the baseline dataset for this period, we end up with 13,398 observations.

3.2.2.4 Standard Controls

In line with the methodology by DellaVigna and Pollet (2009), our analysis incorporates a set of standard control variables to account for border economic and market trends that could influence stock returns and trading volume. These control variables are included in all of our regression models to isolate the specific impact of earnings announcements.

To control for macroeconomic fluctuations, seasonal trends, and other time-specific factors, we include fixed effects for year and month in all models. These fixed effects account for

factors that are common across all companies in a given year or month, ensuring that any observed relationship between earnings announcements and stock returns is not confounded by these broader influences. Year fixed effects control for global or macroeconomic trends that could affect all firms in a given year, including economic policy and interest rates. Month fixed effects account for seasonality, such as month-specific market patterns including fiscal year-end effects or holiday-related volatility.

Market capitalization is another key control variable in our analysis. Larger firms often attract more investor attention, and their earnings announcements may exhibit different market responses compared to smaller firms. To account for these variations, we include market capitalization as a control variable in our regressions. To standardize firm size and reduce the influence of extreme values or outliers, we calculate the natural logarithm of each firm i 's market capitalization in quarter t . This helps in comparing firms of various sizes on a common scale. Each firm's log market capitalization is then compared to the average of all firms in the same quarter.

$$\Delta \log(\text{MarketCap})_{i,t} = \log(\text{MarketCap}_{i,t}) - \frac{1}{N_t} \sum_{i=1}^{N_t} \log(\text{MarketCap}_{i,t})$$

The resulting values $\Delta \log(\text{MarketCap})_{i,t}$ are used to categorize firms into market capitalization deciles. These deciles are used as control variables to adjust for differences in stock returns due to firm size.

3.2.2.5 Company Fixed Effects

In addition to the standard control variable, we also include company fixed effects in the model for examining short-term response in abnormal volume to control for time-invariant, company-specific factors that could influence market reactions.

To evaluate the presence of multicollinearity among independent variables in our regression model, we utilized the Variance Inflation Factor (VIF) test (Appendix B). As all VIF values fall below the commonly accepted threshold of 10, we conclude that multicollinearity does not pose a significant concern for our regression model (Pallant, 2013).

Descriptive Statistics Independent Variables						
Variable	N	Proportion of Fridays	Mean	SD	Min	Max
Earnings Surprise	13,897	NA	0.0012	0.0065	-0.2934	0.1627
Friday Dummy	967	0.0696	NA	NA	NA	NA
Market Cap (million USD)	13,897	NA	0.0587	0.1374	0.0001	2.9888

Table 2 presents descriptive statistics for the independent variables used in the analysis. Earnings Surprise is the normalized earnings surprise, calculated as the difference between actual earnings per share and the consensus forecast, scaled by the stock price prior to the earnings announcement. The Friday Dummy is a binary variable indicating whether the earnings announcement occurred on a Friday (1) or on another day (0). Market Cap represents the market capitalization of the companies in the sample, measured in million USD. The

column for Friday Dummy shows the number of earnings announcements made on Fridays, while the columns for Earnings Surprise and Market Cap show the statistics for the respective variables across all earnings announcements in the sample.

4. Methodology

4.1 Event Study

We employ an event study methodology, following the approach of DellaVigna and Pollet (2009), to examine the market response of stock returns to earnings surprises. An event study examines the impact of a specific event on the performance of a security, particularly changes in a company's stock value (Investopedia, 2024). Our analysis focuses on CAR over multiple event windows surrounding the earnings announcement date (Day 0). Consistent with DellaVigna and Pollet (2009), we define the following event windows to capture both immediate and delayed market responses:

- [0, 1]: Captures the immediate price reaction over the announcement day and the following day.
- [2, 75]: Assesses the delayed cumulative price reaction following the announcement.
- [0, 75]: Examines total drift over the entire quarter.

4.1.2 Quantile Division

Following DellaVigna and Pollet (2009) we divide the earnings announcements into 11 quantiles based on their quality, defined as magnitude and direction of the earnings surprise:

- Quantiles 1–5: Represent negative surprises, ranging from extreme to moderate.
- Quantile 6: Represents surprises that are equal to zero.
- Quantiles 7–11: Represents positive surprises, ranging from moderate to extreme.

The boundaries for each quantile are determined separately for each year to ensure a balanced representation of surprises across quantiles. Since positive surprises are four times more prevalent than negative surprises in our dataset, quantiles 7–11 include four times as many observations as quantiles 1–5. Within each quantile, the average earnings surprises for Friday and non-Friday announcements are nearly identical. However, differences arise in the top and bottom quantiles, where the average earnings surprise for Friday announcements is 10% larger and 44% smaller, respectively (Appendix C).

We focus most of our study on the top and bottom quantiles, aligning with DellaVigna and Pollet (2009), for two main reasons: (i) extreme quantiles typically exhibit the strongest market responses, facilitating the identification of behavioral biases such as underreaction and delayed responses, which may be less observable in intermediate quantiles, and (ii) the use of quantiles allows for nonparametric analysis, avoiding model assumptions like linearity and ensuring results are driven by the observed data patterns. This becomes particularly important when observing the S-shaped relationship between earnings surprises and returns (Appendix D).

4.2 Cross-Sectional Regression

Consistent with DellaVigna and Pollet (2009), we conduct cross-sectional OLS regression analysis to examine the cross-sectional determinants of CAR and abnormal trading volume.

Our analysis includes two types of regressions: quantile-based regressions, focusing on the top and bottom quantiles of earnings surprise, and regressions that treat earnings surprises as a categorical variable across all earnings announcements.

4.2.1 Regressions of Quantiles

The quantile regression analysis is performed to assess the impact of earnings surprise on cumulative abnormal returns (CAR) over different event windows: [0, 1], [2, 75] and [0, 75]. The focus is on the top and bottom earnings surprise quantiles (quantile 1 and 11) to examine the effects of extreme earnings surprises.

The regression specification for CAR is as follows:

$$CAR_{i,n}^{(h,H)} = \beta_0 + \beta_1 TopGroup + \beta_2 TopGroup * Year + \beta_3 TopGroup * Month + \beta_4 FridayDummy + \beta_5 TopGroup * FridayDummy + \beta_6 MarketCapDecile + \beta_7 TopGroup * MarketCapDecile + \gamma Year + \gamma Month + \epsilon_{i,n}$$

Eq 1.

Where:

CAR = The cumulative abnormal return over the specified event window [h, H].

TopGroup = A binary variable for the top quantile (quantile 11).

FridayDummy = A binary variable indicating if the earnings announcement occurred on a Friday.

Year and *Month* fixed effects = Control for year- and month-specific factors.

MarketCapDecile = A control for firm size, as measured by market capitalization deciles.

Standard errors are clustered by announcement date to account for potential correlations among earnings announcements made on the same day.

For robustness, we perform the same regressions using the top two and bottom two quantiles to ensure that our results are not driven by extreme values.

4.2.1.1 Delayed Response Ratio (DRR)

To consolidate the insights from the CAR regression into a single interpretable measure, we calculate the Delayed Response Ratio (DRR), as proposed by DellaVigna and Pollet (2009). The DRR measures the proportion of the total market response that is attributable to the delayed reaction, distinguishing between Friday and non-Friday announcements in the top and bottom quantiles.

The DRR is computed for Friday and non-Friday announcements as the ratio of delayed fractions to the total market response. This is calculated using the difference between CAR over the event window [2, 75] and [0, 75] for the top and bottom quantiles:

$$\begin{aligned}
DRR_{Friday} &= \frac{E(R_{i,t}^{(2,75)} | d_{i,t}^{top}=1, d_{i,t}^F=1) - E(R_{i,t}^{(2,75)} | d_{i,t}^{top}=0, d_{i,t}^F=1)}{E(R_{i,t}^{(0,75)} | d_{i,t}^{top}=1, d_{i,t}^F=1) - E(R_{i,t}^{(0,75)} | d_{i,t}^{top}=0, d_{i,t}^F=1)} = \frac{\phi_{T-B}^{(2,75)} + \phi_{T-B}^{F(2,75)}}{\phi_{T-B}^{(0,75)} + \phi_{T-B}^{F(2,75)}} \\
DRR_{Non-Friday} &= \frac{E(R_{i,t}^{(2,75)} | d_{i,t}^{top}=1, d_{i,t}^F=0) - E(R_{i,t}^{(2,75)} | d_{i,t}^{top}=0, d_{i,t}^F=0)}{E(R_{i,t}^{(0,75)} | d_{i,t}^{top}=1, d_{i,t}^F=0) - E(R_{i,t}^{(0,75)} | d_{i,t}^{top}=0, d_{i,t}^F=0)} = \frac{\phi_{T-B}^{(2,75)}}{\phi_{T-B}^{(0,75)}}
\end{aligned}$$

Where $\phi_{T-B}^{(2,75)}$ is the coefficient ϕ_{T-B} estimated in (Eq. 9) with $R_{i,t}^{(2,75)}$ as dependent variable, and for $\phi_{T-B}^{(0,75)}$. We then test whether DRR is significantly higher for Friday announcements by calculating the difference between the DRRs for Friday and non-Friday announcements:

$$\begin{aligned}
DRR_{Difference} &= DRR_{Non-Friday} - DRR_{Friday} \\
&\text{Eq. 2}
\end{aligned}$$

The results are tested for statistical significance to determine whether the delayed response to earnings announcements differs significantly on Fridays compared to non-Fridays.

4.2.2.2 Regressions Including All Announcements

In addition to the quantile regressions, we perform OLS regressions using all earnings announcements across two event windows: [0,1] and [2, 75] with CAR as the dependent variable. The regression specification is as follows:

$$\begin{aligned}
CAR_{i,n}^{(h,H)} &= \beta_0 + \beta_1 SurpriseQuantile + \beta_2 SurpriseQuantile * Year + \\
&\beta_3 SurpriseQuantile * Month + \beta_4 FridayDummy + \beta_5 SurpriseQuantile * FridayDummy \\
&\beta_6 MarketCapDecile + \beta_7 SurpriseQuantile * MarketCapDecile + \gamma Year + \gamma Month + \epsilon_{i,n}
\end{aligned}$$

$$\text{Eq. 3}$$

Where:

SurpriseQuantile = The earnings surprise quantile (coded as a categorical variable for quantiles 1 to 11).

FridayDummy = Captures the effect of earnings announcements occurring on Fridays.

Year and *Month* fixed effects = Control for year- and month-specific factors.

MarketCapDecile = A control for firm size, as measured by market capitalization deciles.

As with the quantile regressions, standard errors are clustered by announcement date. The regression uses non-Friday announcements as the baseline, allowing comparisons between Friday and non-Friday announcements. The model also includes interaction terms to investigate whether the impact of earnings surprises differs between Fridays and non-Fridays.

4.2.2.3 Trading Volume

As a complement to our analysis of stock returns, we examine the abnormal trading volume surrounding earnings announcements. Following the methodology of DellaVigna and Pollet

(2009), we focus on the event window $[-2, 5]$, which captures the abnormal trading volume for a few days before and after the earnings announcement. This window is chosen to allow us to assess the market's volume response across the entire trading week following the earnings announcement, and to compare Fridays with non-Fridays. To test the determinants of abnormal trading volume, we perform OLS regression models for the event window $[0, 1]$ with abnormal volume as the dependent variable. The regression models are as follows:

$$AbnormalVolume = \beta_0 + \beta_1 SurpriseQuantile + \beta_2 FridayDummy + \beta_3 MarketCapDecile + \gamma Year + \gamma Month + \epsilon_{i,n}$$

Eq. 4

Where:

SurpriseQuantile = measures the impact of earnings surprise quantiles.

FridayDummy = indicates whether the earnings announcement occurred on a Friday.

MarketCapDecile = controls for firm size.

Year and *Month* fixed effects = account for time-specific variations.

In a second regression model, we include Company fixed effects to control for company-specific factors.

$$AbnormalVolume = \beta_0 + \beta_1 SurpriseQuantile + \beta_2 FridayDummy + \beta_3 MarketCapDecile + \gamma Year + \gamma Month + \gamma Company + \epsilon_{i,n}$$

Eq. 5

Both regressions aim to identify the relationship between abnormal trading volume and earnings surprise, while controlling for other factors such as firm size and time-specific effects. Clustered standard errors are calculated by the announcement date to account for potential autocorrelation in trading volume across different announcements made on the same day.

4.3 Temporal Dimension

We incorporate a temporal dimension into our study to assess the impact of COVID-19 on investor attention and the Friday anomaly. This approach expands upon the methodology of DellaVigna and Pollet (2009) by including a period marked by high volatility and economic uncertainty. Analyzing events in such turbulent times presents challenges, as the high volatility increases the risk that observed changes in stock prices may reflect broader market fluctuations rather than the specific effect of earnings announcements. However, since the purpose of our extension is to examine the potential impact of an uncertain period, specifically COVID-19, it is essential to include it in our analysis.

Segmenting the analysis into pre-, during-, and post-COVID-19 periods allows us to evaluate whether the anomaly persisted before the pandemic, how it changed during the crisis, and whether the market adapted in its aftermath. However, due to the recent conclusion of the pandemic, data limitations restrict our ability to conduct a full post-pandemic analysis, limiting our study to focus on the pre- and during- COVID-19 periods. We define the pre-period as spanning from January 1, 2016, to December 31, 2019. In January 2020, growing news coverage about COVID-19 began to attract significant attention, culminating when the World

Health Organization (WHO) declared the outbreak a Public Health emergency on January 30, 2020 (World Health Organization, 2024). Given our study's focus on investor attention, we include the entire month of January 2020 in the during-period, which is defined to run from January 1, 2020, to May 5, 2023, when WHO officially declared the pandemic's end (World Health Organization, 2024).

4.3.1 Regressions for COVID

The temporal dimension includes 13,338 observations of earnings announcements, with 6,780 observations in the Pre-COVID window and 6,558 in the During-COVID window. While we apply a similar methodology to the COVID-19 analysis as in the baseline sample, we make certain adaptations. Specifically, we include a COVID-19 dummy variable to indicate whether the earnings announcement date falls within the pandemic timeframe, as well as an interaction term between the Friday dummy and COVID-19 dummy.

4.3.1.1. Return regressions:

Regression 6 and 7 correspond to Regression 1 and 3, respectively, with the addition of the COVID-19 independent variables.

$$CAR_{i,n}^{(h,H)} = \beta_0 + \beta_1 TopGroup + \beta_2 TopGroup * Year + \beta_3 TopGroup * Month + \beta_4 FridayDummy + \beta_5 TopGroup * FridayDummy + \beta_6 TopGroup * MarketCapDecile + \beta_7 CovidDummy + \beta_8 CovidDummy * FridayDummy + \beta_9 MarketCapDecile + \gamma Year + \gamma Month + \epsilon_{i,n}$$

Eq. 6

$$CAR_{i,n}^{(h,H)} = \beta_0 + \beta_1 SurpriseQuantile + \beta_2 SurpriseQuantile * Year + \beta_3 SurpriseQuantile * Month + \beta_4 FridayDummy + \beta_5 SurpriseQuantile * FridayDummy + \beta_6 MarketCapDecile + \beta_7 SurpriseQuantile * MarketCapDecile + \beta_8 CovidDummy + \beta_9 CovidDummy * FridayDummy + \gamma Year + \gamma Month + \epsilon_{i,n}$$

Eq. 7

Where:

CovidDummy = A binary variable indicating if the announcement was during COVID.

4.3.1.2. Volume regressions:

Regressions 8 and 9 correspond to Equations 4 and 5, respectively, with the addition of the COVID-19 independent variables.

$$AbnormalVolume = \beta_0 + \beta_1 SurpriseQuantile + \beta_2 FridayDummy + \beta_3 MarketCapDecile + \beta_4 CovidDummy + \gamma Year + \gamma Month + \epsilon_{i,n}$$

Eq. 8

$$\begin{aligned}
AbnormalVolume = & \beta_0 + \beta_1 SurpriseQuantile + \beta_2 FridayDummy + \beta_3 MarketCapDecile \\
& + \beta_4 CovidDummy + \beta_5 CovidDummy * FridayDummy + \gamma Year + \gamma Month \\
& + \gamma Company + \epsilon_{i,n}
\end{aligned}$$

Eq. 9

Where:

CovidDummy = A binary variable indicating if the announcement was during COVID.

4.4 Robustness

4.4.1 Homogeneous Sample

To address the potential selection bias associated with firms choosing to announce their earnings on Fridays, we construct a homogeneous sample following the methodology of DellaVigna and Pollet (2009). Specifically, we exclude companies that make fewer than 5% or more than 95% of their earnings announcements on Fridays, creating a sample of firms that distribute announcements relatively evenly across weekdays. While DellaVigna and Pollet (2009) adopt a stricter criterion, limiting their sample to firms with 10% to 90% of their earnings announcements on Fridays, our initial sample size constraints led us to adopt a broader range. This reduces the robustness of the homogeneous sample slightly, though we proceed with this approach to explore the potential effects of selection bias.

To construct the homogenous sample, we filter out earnings announcements from firms that fall outside the 5% to 95% range and re-categorize them into market capitalization deciles and earnings surprise quantiles, specifically calculated for this sample. We then apply the methodology steps 4.1 to 4.3 on the homogeneous sample.

Table 3 presents the mean earnings surprise and market capitalization for both Friday and non-Friday announcements across the baseline and homogeneous samples. While there are statistically significant differences in mean earnings surprise between Friday and non-Friday announcements in both samples, the magnitude of these differences is small, suggesting that the samples are comparable. Specifically, Friday announcements in the baseline sample show a slightly lower earnings surprise compared to non-Fridays, with a statistically significant difference at the 1% level. In the homogeneous sample, Friday announcements exhibit a slightly higher earnings surprise than non-Fridays, with the difference also statistically significant. The difference in market capitalization between Friday and non-Friday announcements remains consistent across both samples. Given this, we control for market capitalization in the homogeneous sample as well to account for potential biases stemming from firm size.

Ideally, incorporating the temporal dimension into the analysis of the homogenous sample analysis would enhance the robustness of our findings. However, due to the significant reduction in sample size and the insufficient observations when dividing into subgroups and quantiles, this additional layer of analysis is not feasible. This could reduce the depth of our analysis regarding the potential impact of COVID-19 on investor inattention and behavioral anomalies. Despite this constraint, the results from the homogeneous sample show similar trends to those in the baseline sample, suggesting consistent findings across the different subsamples.

Differences between Surprises on Friday and Other Weekdays for Baseline and Homogeneous Samples

	Baseline Sample			Homogeneous Sample		
	Friday	Non-Friday	Difference	Friday	Non-Friday	Difference
Earnings Surprise	0.001 (0.0105)	0.0013 (0.0061)	-3e-04 (3e-04) ***	0.001 (0.0111)	9e-04 (0.01)	1e-04 (4e-04) ***
Market Cap (\$M)	0.0753 (0.0924)	0.0575 (0.1401)	0.0178 (0.0032) ***	0.073 (0.0924)	0.0561 (0.0714)	0.0169 (0.0035) ***
Year	2019.38 (2.18)	2019.57 (2.18)	-0.19 (0.0727) *	2019.36 (2.16)	2019.57 (2.19)	-0.21 (0.0868) *
Month 1 in Quarter	0.0011 (0.0033)	0.0014 (0.0042)	-3e-04 (1e-04) ***	0.0011 (0.0032)	0.0012 (0.0034)	-1e-04 (1e-04) ***
Month 2 in Quarter	8e-04 (0.0179)	0.0012 (0.0068)	-4e-04 (6e-04) ***	8e-04 (0.019)	9e-04 (0.0115)	-1e-04 (7e-04) ***
Month 3 in Quarter	-2e-04 (0.0067)	6e-04 (0.012)	-8e-04 (2e-04) ***	-3e-04 (0.0071)	-0.0015 (0.0261)	0.0012 (6e-04) ***
Observations	967	12930	13897	859	2274	3133

Table 3 compares the mean earnings surprise and market capitalization between Friday and non-Friday earnings announcements for the baseline and homogeneous sample. The homogeneous sample includes companies which announce within the range of 5% to 95% of their earnings announcements on Fridays. The data consists of 13,897 observations in the baseline sample and 3,133 observations in the homogeneous sample. The mean surprise is displayed with standard deviations in parentheses. The difference between the mean surprise on Fridays vs non-Fridays is next to its standard error in parentheses. The table shows that there is a slight difference in mean surprise between Friday and non-Friday announcements in both samples.

***p-value<0.01, **p-value<0.05, *p-value<0.1

5. Empirical Results

5.1 Stock Return Response

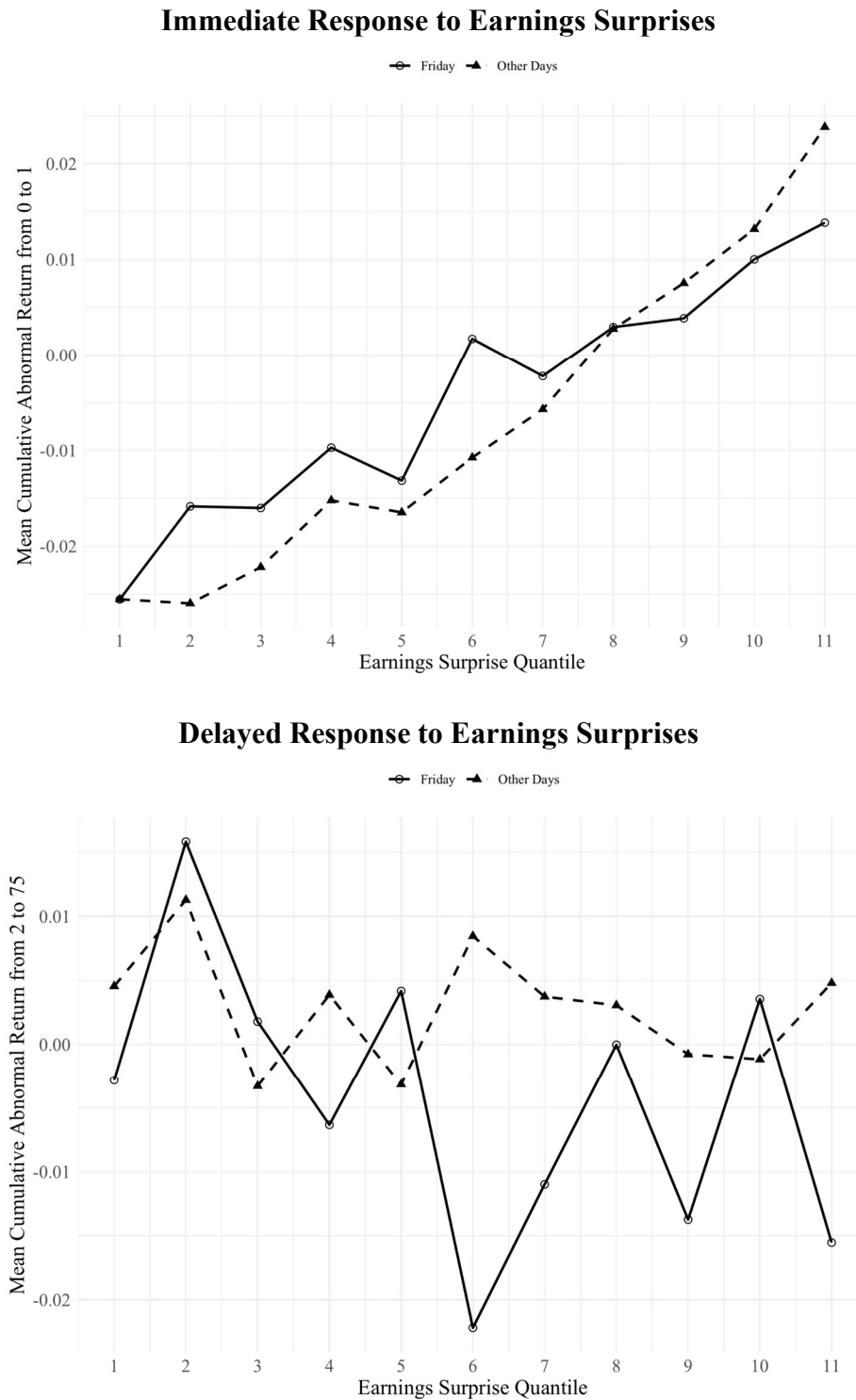


Figure 1a presents the immediate response for Friday and non-Friday announcements across all earnings surprise quantiles. Immediate return is measured in the mean of CAR from 0 to 1 days. **Figure 1b** presents the delayed response for Friday and non-Friday announcements across all earnings surprise quantiles. Immediate return is measured in the mean of CAR from

2 to 75 days. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles.

Figure 1a captures the short-term market response on the announcement day and the following day. The graph reveals an approximately linear relationship between returns and earnings surprise quantiles, with Friday announcements exhibiting greater variability. Non-friday announcements display a more pronounced responsiveness, with more negative returns in the lower quantiles, shifting to stronger positive returns by the 8th quantile. Figure 1b presents the delayed reaction of stock returns to Friday and non-Friday announcements across all earnings surprise quantiles. The graph displays no clear trends, but non-Friday announcements show less variation than Friday announcements. For the non-friday announcements, returns are positive for the majority of quantiles, ranking from the lowest to the highest quantile. Friday announcements exhibit more volatile returns and the majority are negative. The immediate response seems to exhibit a more clear direction compared to the delayed response across earnings surprise quantiles.

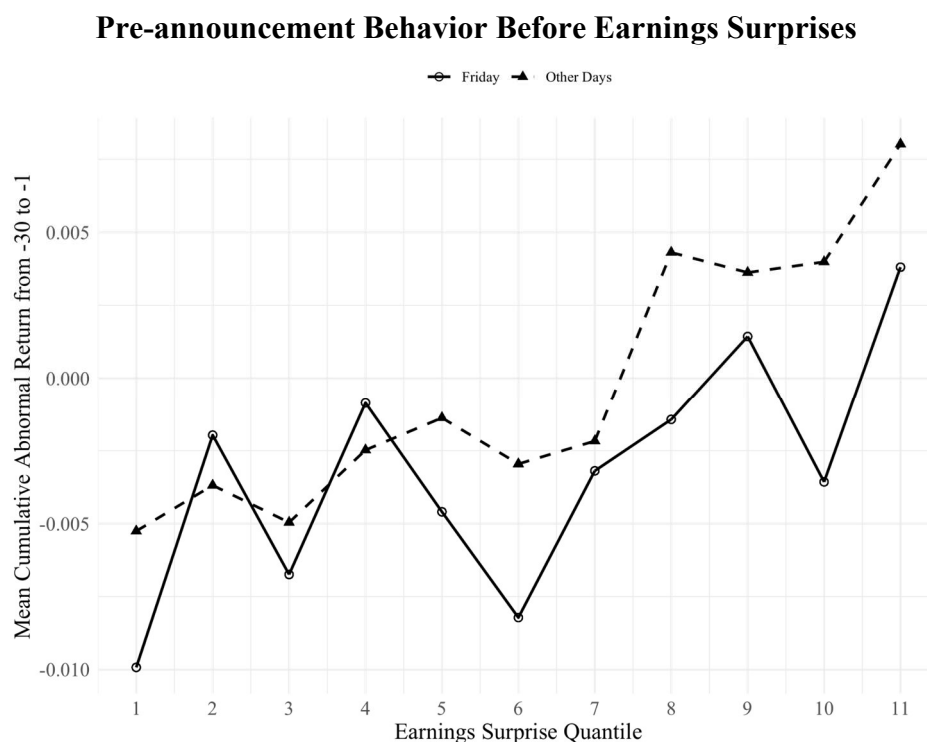


Figure 1c presents the market behavior before the earnings announcement across each quantile for Friday and non-Friday announcements. The market behavior is explained by the mean CAR from -30 to -1 days prior to the announcement. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles.

The figure illustrates a weak positive trend between return and earnings surprise quantiles for both Friday and non-Friday announcements, one month prior to the announcement. The trend is stronger for non-Friday announcements while Friday announcements show greater volatility and lower returns across the majority of earnings surprise quantiles.

Stock Price Response to Earnings Announcements for the Top and Bottom Quantiles

Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)	Total CAR (0-75 days)
(Intercept)	-0.0126 (0.0161)	0.0073 (0.0265)	-0.0053 (0.0312)
Top_Group	0.0634 (0.0176)***	0.025 (0.0294)	0.0883 (0.0354)*
FridayDummy	-0.0141 (0.0124)	0.0033 (0.0216)	-0.0108 (0.0246)
Top_Group:FridayDummy	-0.0153 (0.0113)	0.0337 (0.0179)	0.0184 (0.0206)
Standard Controls	X	X	X
Number of Observations	2762	2762	2762
Adjusted R ²	11.93%	1.36%	4.91%

Table 4 reports the regression results for the immediate, delayed, and total return response for the top and bottom quantiles with CAR as the dependent variable (Eq. 1). The data consists of 2,762 observations of earnings announcements for each interval. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles. The standard controls include market cap decile, and month and year fixed effects. Standard controls included in the regression are also interacted with the indicator variable for the top quantile. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 4 presents the regression results for stock return responses to earnings announcements, focusing on top and bottom quantiles across three event windows; immediate, delayed and total. The coefficient intercept, representing the bottom quantile for non-Friday announcements, is negative in the immediate period and turns slightly positive in the delayed period. The total effect on return is negative as indicated by the total CAR. However, the intercept coefficients are not statistically significant. The top quantile coefficient is positive across all event windows. It is statistically significant at the 1% level in the immediate period and at the 10% level in the total period, while statistically insignificant in the delayed period. This indicates that higher earnings surprises have a significant positive impact on abnormal returns in the immediate window. The Friday dummy coefficient is negative in the immediate and total periods, suggesting a negative impact on abnormal returns, but slightly positive in the delayed period. However, the insignificance of the coefficients in all three periods implies the model does not capture any systematic difference in returns between Friday and non-Friday announcements. While the top quantile coefficient is statistically significant in the immediate and total window, it is insignificant when interacted with the Friday dummy. The regression analysis for delayed CAR reveals no statistically significant variables and a very low R², indicating that the model accounts for only a limited proportion of the variance. In contrast, the regression for the immediate interval identified one statistically significant variable and demonstrates a higher R², suggesting that the model is more effective in explaining the immediate response than the delayed response.

We perform the same regressions on the top and bottom two quantiles to account for potential limitations of the quantile division (Appendix E). The results reveal no contradictions regarding the explanatory power of the independent variables used in the model, further supporting the robustness of the findings. We also perform the regressions on the homogenous sample, as a robustness test to assess whether the results are significantly affected by firms announcing

exclusively on Fridays or non-Fridays (Appendix F). The results are generally consistent with what we observed for the top and bottom quantiles in the baseline sample. The immediate top quantile coefficient remains the only statistically significant coefficient, albeit now significant at the 10% level. Additionally, R^2 values increase slightly across all three event windows but remain low, reflecting limited predictive power overall. These findings align with the results from the two previously analyzed samples.

Delayed Response Ratio (DRR) of Extreme Quantiles

Variable	Estimate
DRR (Friday)	0.2228 (0.012)*
DRR (Non-Friday)	0.2743 (0.0152)*
Difference in DRR (Friday - Non-Friday)	-0.0515 (-0.0033)*
Standard Controls	X
Number of Observations	2762

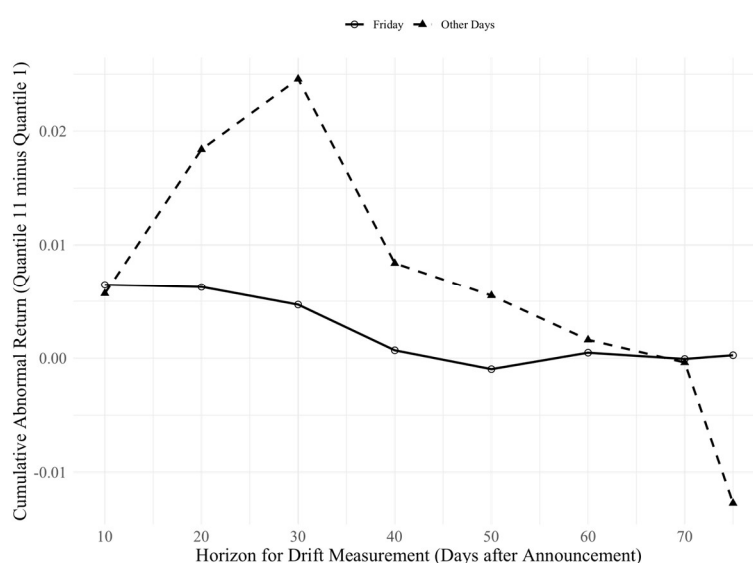
Table 5 reports the DRR for the extreme quantiles, capturing the proportion of the CAR that can be attributed to delayed reactions (Eq. 2). The data consists of 2,762 observations of earnings announcements. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles. The standard controls include market cap decile, and month and year fixed effects. Standard controls included in the regression are also interacted with the Friday dummy. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 5 reports the DRR for earnings announcements in the extreme quantiles, capturing the proportion of the total CAR attributable to delayed reactions. The DRR for Friday announcements implies that 22.28% of the total response to earnings surprises is observed in the delayed window. The DRR for non-Friday announcements is higher at 27.43%, indicating a greater proportion of the total response is delayed. The difference between the DRR for Friday and non-Friday announcements, signifies that the delayed response is approximately 5.15 percentage points lower for Friday announcements. The difference is statistically significant at the 10% level.

Testing the DRR model on the homogeneous sample, we observe results consistent with the baseline sample (see Appendix Table G). The DRR for Fridays and non-Fridays are both negative while the Friday DRR is less pronounced, indicating lower drift. However, the results are not statistically significant, limiting further interpretation.

Performance of Drift at Different Horizons



Plot 2 illustrates the performance of drift from 10 to 75 days after the day of announcement. The data consists of 2,762 observations of earnings announcements. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles.

Plot 2 illustrates the performance drift over various horizons for Friday and non-Friday announcements. For non-Friday announcements the drift is initially positive, peaking approximately 30 days after the announcement. Subsequently, it gradually moves toward zero, before turning negative by day 70. In contrast, for Friday announcements, the drift is slightly positive during the first 30 days but then trends toward zero, remaining nearly flat the entire period.

Stock Price Response to All Earnings Announcements

Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)
Surprise_Quantile	0.0049 (0.0010)***	-0.0001 (0.0018)
FridayDummy	0.0110 (0.0051)*	0.0010 (0.0090)
Surprise_Quantile:FridayDummy	-0.0014 (0.0006)*	-0.0008 (0.0010)
Standard Controls	X	X
Number of Observations	13897	13897
Adjusted R ²	7.96%	1.66%

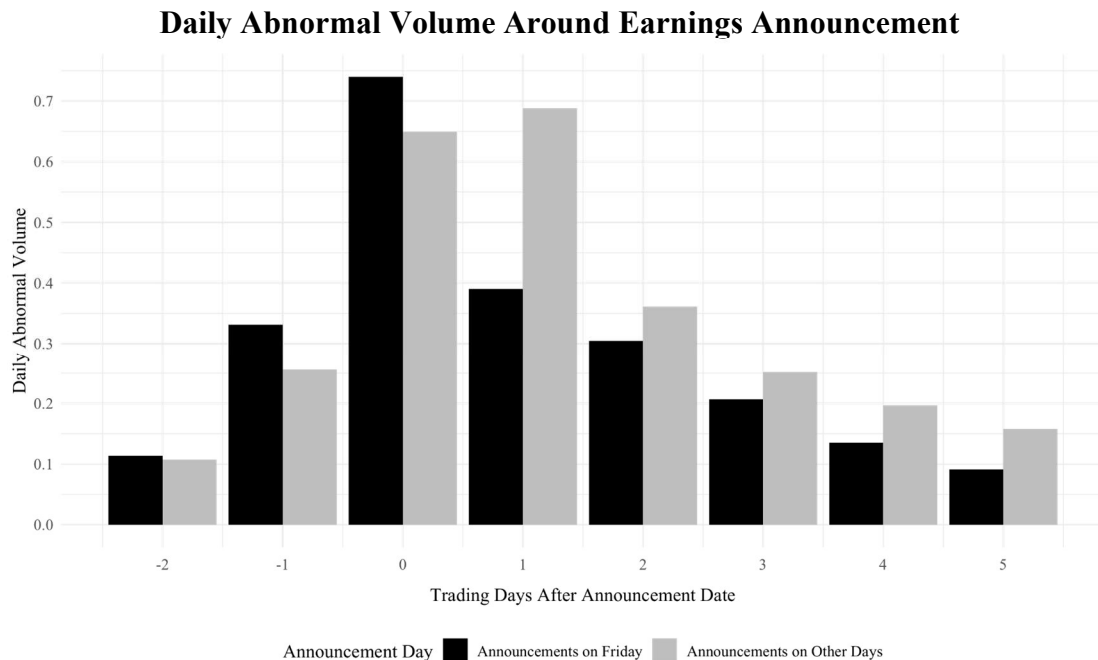
Table 6 reports the regression results for the immediate and delayed return response for all earnings announcements with CAR as the dependent variable (Eq. 3). The data consists of 13,897 observations of earnings announcements for each interval. The standard controls include market cap decile, and month and year fixed effects. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 6 presents the regression results for immediate and delayed stock return responses to all earnings announcements. The surprise quantile coefficient is positive and statistically significant at the 1% level for the immediate response while the effect is inconclusive for the delayed response window due to the variables statistical insignificance. For the immediate response, this signals that for each increase in surprise quantile, the CAR increases marginally. The Friday dummy coefficient is positive in both the immediate and delayed periods, albeit only statistically significant for the immediate reaction at the 10% level. The coefficients for the interaction term between surprise quantile and Friday dummy is negative for both intervals. The negative coefficients indicate that the impact of surprise quantile on the CAR is more negative for Friday announcements. The effect is statistically significant at the 10% level for the immediate response and insignificant for the delayed reaction. When including all announcements in the model, it still only accounts for a limited proportion of the variance in delayed CAR as seen by the low R^2 .

We conduct the same regressions for all announcements in the homogeneous sample (see Appendix Table H). The results show that the Friday dummy remains positive, although not significant for either interval. Moreover, the R^2 value exhibits a slight increase in both intervals. This finding contrasts with the results of the regression performed on the baseline sample for immediate CAR. Consequently, the regression on the homogeneous sample implies that there is no significant difference between Friday and non-Friday announcements.

5.2 Volume Response



Plot 3 presents the daily abnormal volume surrounding earnings announcements for Fridays and non-Fridays. The data consists of 13,895 observations of earnings announcements for each interval.

In Plot 3, we observe the daily abnormal volume surrounding the day of the earnings announcements. For non-Fridays, the abnormal volume is approximately 65% on the

announcement day, rising modestly on the following day. Subsequently, the magnitude of abnormal volume declines each day, although it remains above normal levels. One trading week after the announcement, the abnormal volume is approximately 14% higher than normal. Fridays follow a similar pattern of abnormal volume but exhibit significantly lower levels in the [0, 1] event window.²

Short-Term Volume Response to an Earnings Announcement

Variable	Estimate	Estimate
FridayDummy	-0.0652 (0.0202)**	0.0201 (0.0227)
Surprise Quantile	X	X
Standard Controls	X	X
Company Fixed Effects		X
Number of Observations	13895	13895
Adjusted R ²	7.82%	32.92%

Table 7 reports the regression results for the short-term volume response to an earnings announcement with the dependent variable as abnormal volume in event time from 0 to 1 (Eq. 4). The data consists of 13,895 observations of earnings announcements. The standard controls include market cap decile, and month and year fixed effects (Eq. 5). One model includes company fixed effects. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 7 presents the regression results for the abnormal volume response to earnings announcements made on Fridays and non-Fridays, focusing on the immediate period. The Friday coefficient is negative and significant at the 5% level when company fixed effects are not included, indicating a negative relationship between immediate abnormal volume and announcements made on Fridays, consistent with the pattern we observe in Plot 3. However, when controlling for company fixed effects, the Friday dummy coefficient changes direction, becoming positive and statistically insignificant. This suggests that the significant result observed in the simpler model may have been driven by confounding variables related to the company-specific characteristics. The significantly higher R² in the model that includes company fixed effects further support this interpretation.

When the regression is performed on the homogeneous sample, the Friday dummy coefficient is not statistically significant, regardless of whether company fixed effects are included (see Appendix Table I). This pattern is consistent with the results observed when performing the regression including all earnings announcements on the homogenous sample, where the Friday dummy also became insignificant.

² To account for potential biases arising from after hours announcements on non-fridays we analyze (0,0) and (1,1) together, following DellaVigna and Pollet (2009).

5.3 COVID-19 Time-frame

Stock Price Response to Earnings Announcements for the Top and Bottom Quantiles (COVID-19)

Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)	Total CAR (0-75 days)
(Intercept)	-0.0139 (0.0148)	0.0217 (0.0105)*	0.056 (0.0131)***
Top_Group	0.061 (0.0163)***	-0.002 (0.0172)	5e-04 (0.0194)
FridayDummy	0.0048 (0.0111)	-0.0453 (0.0205)*	-0.0515 (0.0237)*
Top_Group:FridayDummy	0.002 (0.0099)	-0.0322 (0.0218)	-0.0267 (0.0245)
CovidDummy	0.0123 (0.0099)	-0.0336 (0.0208)	-0.0244 (0.0242)
FridayDummy:CovidDummy	0.0143 (0.0107)	-0.0565 (0.0233)*	-0.068 (0.0273)*
Standard Controls	X	X	X
Number of Observations	2651	2651	2651
Adjusted R ²	12.39%	1.3%	4.73%

Table 8 reports the regression results for the immediate, delayed, and total return response for the top and bottom quantiles with CAR as the dependent variable (Eq. 6). The data consists of 2,651 observations of earnings announcements for each interval. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles. The standard controls include market cap decile, and month and year fixed effects. Standard controls included in the regression are also interacted with the indicator variable for the top quantile. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

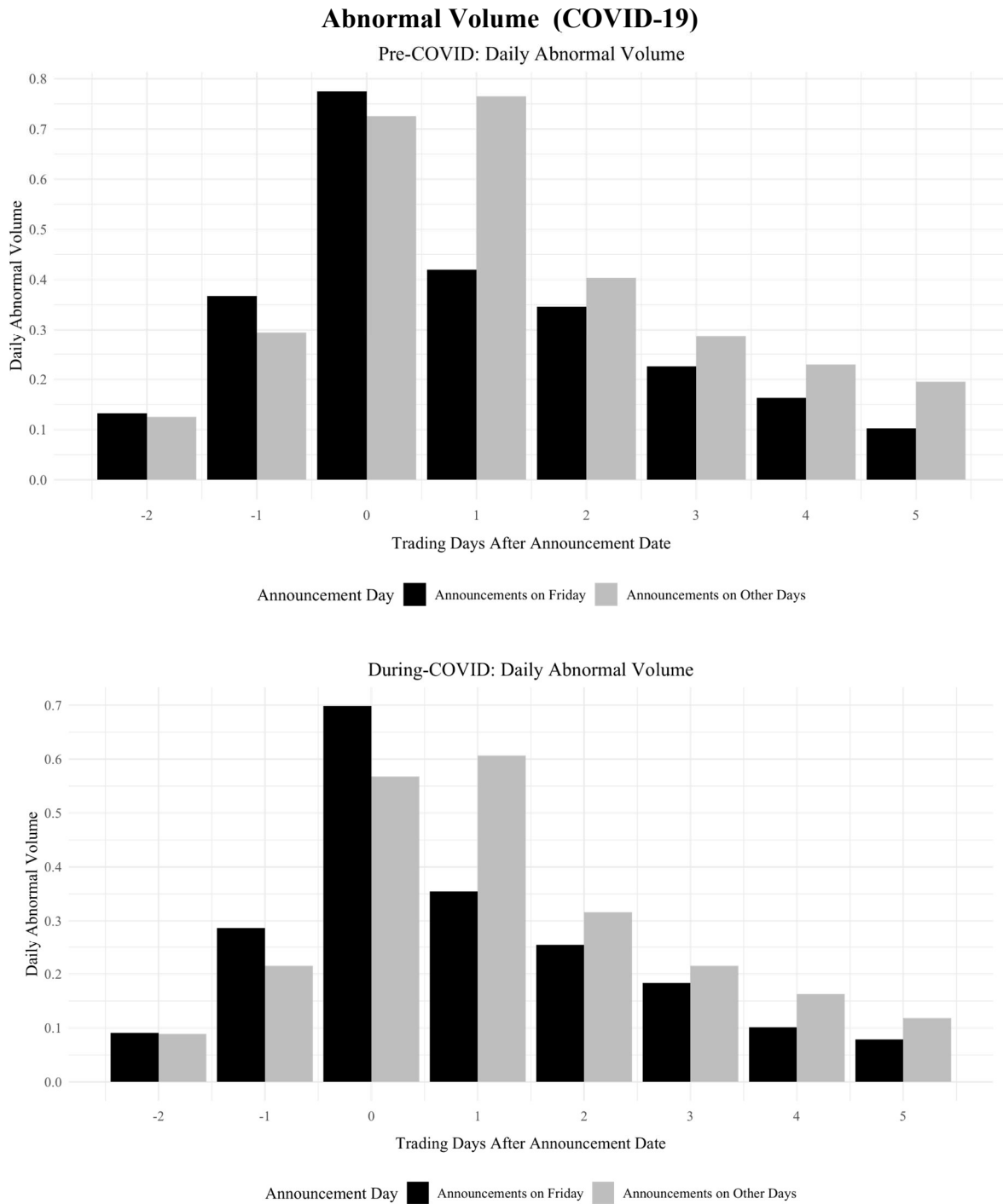
Table 8 presents the regression results for stock return responses to earnings announcements, focusing on top and bottom quantiles across event windows; immediate, delayed and total, while controlling for COVID-19. The coefficient intercept, representing the bottom quantile for non-Friday announcements pre-COVID, is negative in the immediate period and positive in the delayed- and total period. The statistically significant coefficient at a 10% level for the delayed response indicates a positive delayed impact on CAR. The top quantile coefficient is positive and statistically significant at the 1% level in the immediate period while statistically insignificant in the delayed and total period. This signals that the highest earnings surprises have a significant positive impact on abnormal returns in the immediate window. The Friday dummy coefficient is positive in the immediate period, but insignificant, and negative in the delayed and total periods and significant at the 10% level. This suggests Friday announcements have a negative impact on delayed abnormal returns. The coefficient for the Covid dummy is positive in the immediate window and negative in the delayed and total period, albeit not statistically significant. The coefficient for the interaction term between Friday dummy and Covid dummy is statistically significant at the 10% level for delayed and total CAR where they indicate a negative effect. This indicates that Friday announcements during COVID-19 resulted in lower delayed return compared to announcements on other days. Although the delayed

model exhibits more significant independent variables, it has a very low R^2 , explaining a limited proportion of the variance in delayed CAR.

Stock Price Response to All Earnings Announcements (COVID-19)		
Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)
Surprise_Quantile	0.0052 (0.0009)***	-0.0001 (0.0017)
FridayDummy	0.0033 (0.0061)	-0.0015 (0.0103)
Surprise_Quantile:FridayDummy	0.0027 (0.0057)	0.0221 (0.0103)*
CovidDummy	-0.0007 (0.0053)	0.0198 (0.0097)*
FridayDummy:CovidDummy	0.0100 (0.0054)	0.0207 (0.0103)*
Standard Controls	X	X
Number of Observations	13338	13338
Adjusted R^2	7.99%	1.62%

Table 9 reports the regression results for the immediate and delayed return response for all earnings announcements with CAR as the dependent variable (Eq. 7). The data consists of 13,897 observations of earnings announcements for each interval. The standard controls include market cap decile, and month and year fixed effects. Standard errors are in parenthesis. ***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 9 presents the regression results for stock return responses to all earnings announcements for the immediate and delayed intervals, while controlling for COVID-19. The surprise quantile coefficient is positive and statistically significant at the 1% level for the immediate response while the effect is inconclusive for the delayed response window due to the variables statistical insignificance. The interaction term between surprise quantile and Friday dummy shows a positive statistically significant relationship at the 10% level for the delayed model, indicating a positive effect of surprise quantile on the delayed CAR for Friday announcements. The Covid dummy coefficient is positive and statistically significant at the 10% level. It suggests that announcements during COVID-19 have a positive impact on delayed CAR. The interaction term between Covid dummy and Friday dummy is also positive and statistically significant at the 10% level for the delayed model, indicating that Friday announcements during COVID-19 exhibit stronger impact on delayed CAR. Like in the model performed for the extreme quantile, the R^2 for the delayed CAR is lower compared to the explanatory power of the immediate CAR.



Plot 4a and 4b presents the daily abnormal volume surrounding earnings announcements for Fridays and non-Fridays before and during COVID-19. The data consists of 13,895 observations of earnings announcements for each interval.

In the plots, we observe the daily abnormal volume surrounding the day of the earnings announcements, for the pre-COVID and during-COVID periods, respectively. The patterns of abnormal volume are nearly identical across the two plots, however, the during-COVID period exhibits an overall lower magnitude of abnormal volume. When comparing Fridays and non-Fridays within the immediate event window $[0, 1]$, Fridays experience significantly lower

levels of abnormal volume in both periods, with the level being more pronounced during the COVID period.³

Short-Term Volume Response to an Earnings Announcement (COVID-19)

Variable	Estimate	Estimate
FridayDummy	-0.117 (0.026)***	-0.0259 (0.027)
CovidDummy	-0.0149 (0.0302)	0.0016 (0.0262)
FridayDummy:CovidDummy	0.1056 (0.0402)**	0.0921 (0.0374)*
Surprise Quantile	X	X
Standard Controls	X	X
Company Fixed Effects		X
Number of Observations	13336	13336
Adjusted R ²	7.99%	32.58%

Table 10 reports the regression results for the short-term volume response to an earnings announcement with the dependent variable as abnormal volume in event time from 0 to 1 (Eq. 8). The data consists of 13,336 observations of earnings announcements. The standard controls include market cap decile, and month and year fixed effects. One model includes company fixed effects (Eq. 9). Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 10 presents the regression results for the abnormal volume response to earnings announcements made on Fridays and non-Fridays, controlling for COVID-19. The Friday coefficient is negative and significant at the 1% level when company fixed effects are excluded, indicating a negative relationship between immediate abnormal volume and announcements made on Fridays. However, when controlling for company fixed effects, the Friday dummy coefficient is statistically insignificant, indicating confounding variables related to company-specific characteristics. The Covid dummy is insignificant for both models. Notably, the interaction term between Covid dummy and Friday dummy is positive and statistically significant for both models, and of approximately the same magnitude. This suggests that Friday announcements during COVID-19 result in a greater abnormal volume, when excluding and including company fixed effects. The significantly higher R² when includes company fixed effects gives further support for confounding variables relate

³ To account for potential biases arising from the higher frequency of after hours announcements on non-fridays we analyze (0,0) and (1,1) together, following DellaVigna and Pollet (2009).

6. Discussion

6.1 Analysis

As reported in the empirical results, our findings reveal some contradictions between the models.

The return regression focused on the top quantiles is limited to explaining that, in the short run, extremely positive surprises contribute to increased returns, regardless of the day of the week. This aligns with our H1, where we predicted no difference in immediate response between Friday and non-Friday announcements. When all announcements are included in the same model, however, we observe lower immediate returns for announcements made on Fridays. This broader model, which provides a more comprehensive perspective, reveals that while the higher surprises continue to explain increases in abnormal returns, Friday announcements tend to slightly weaken this positive effect. Both observations align with the findings of DellaVigna and Pollet (2009), who argue that Friday announcements result in a lower immediate response. They attribute their findings of lower immediate response to investor inattention on Fridays, which, according to their findings, leads to a delayed response in returns during the subsequent quarter. However, we cannot rely on the same explanation of investor inattention, as our models do not indicate any drift in abnormal returns for Fridays. Furthermore, our findings raise the question of whether earnings announcements generate any persistent drift in returns at all, as the reactions in our results appear to be short-lived regardless of the day of the week.

Intuitively, isolating the effect of earnings announcements over a longer period is more challenging, since the market is affected by and adapting to a lot of other factors. This could suggest the presence of potential omitted variables in our analysis. Although not directly comparable due to differences in dataset and adjustments in methodology, DellaVigna and Pollet's (2009) findings indicate a delayed response to Friday announcements, whereas the model applied to our modern market does not exhibit the same pattern. This raises the question of whether the modern market and our chosen time period is noisier and more complex. As visualized in the result section, the immediate relationship between surprise quantile and return appears to be linear (Plot 1a), while the delayed period (Plot 1b) exhibits no clear patterns. This further supports the notion that our simple linear model may be insufficient to capture the complexities of longer time periods.

Another explanation for the absence in drift could be, as suggested by the slightly positive slope in Plot 1c, that investor's expectations are aligned with the actual outcomes of earnings surprises beforehand. This interpretation aligns with the findings of Martineau (2021), who suggest that modern financial markets have become more efficient, absorbing the PEAD anomaly. Increased information availability and technological advancements, combined with investor's ability to adapt to changing environments, have facilitated the faster incorporation of information into stock prices. This phenomenon is further explained by Lo's (2004) Adaptive Market Hypothesis, and would be in line with what we hypothesized in our H2. Notably, however, Plot 1c exhibits a less distinct trend concerning Friday announcements. Investor's behavior a month prior to the announcement should not be influenced by inattention on the day of the announcement, indicating the existence of additional underlying factors.

In contrast to our expectations in H2 and the models above, as presented in our results, the DRR analysis indicates the presence of a drift for both Friday and non-Friday announcements,

that is more pronounced on non-Fridays. As observed in Plot F, Friday announcements exhibit close to zero drift, whereas a noticeable drift is observed for non-Fridays. Interestingly, this finding contradicts the results of DellaVigna and Pollet (2009), who reported a delayed response specifically for Friday announcements.

Complementing this with our volume analysis, we observe further evidence of underlying factors influencing the results. Specifically, the model indicates lower trading volumes on Fridays, but only when company-specific effects are not controlled for. This finding suggests that underlying company characteristics, rather than day of the week, may explain the observed differences in trading volume. These results suggest that similar confounding factors may also be present in the other models discussed.

From our homogenous sample analysis, designed to minimize selection bias and endogeneity, we find that when controlling for such biases, the previously observed patterns related to the day of the week disappear, both in terms of returns and trading volume. This finding highlights the importance of considering firm-specific announcement behaviors in analyses influenced by non-random choices by companies, especially since other observed patterns, such as investor reacting more strongly to extreme surprises, continue to persist. Interestingly, even though DellaVigna and Pollet (2009) applied stricter limitations to their homogenous sample, they still observed the Friday-inattention patterns across both their baseline and homogenous samples. It is important to note, however, that our homogenous sample consists of a significantly smaller set of earnings announcements, which may impact the robustness of our findings.

In our COVID-19 analysis, the short-term window revealed no significant impact of either the day of the announcement or the occurrence of the COVID-19 pandemic on returns. This is not in line with what we predicted in H3, where we anticipated a negative impact on Fridays due to potential disruptions in the conventional working week caused by the pandemic. Speculating, the flexible scheduling might have allowed investors more time to process information and react immediately to it. This could also suggest that short-term market reactions were primarily driven by the nature of the earnings' surprise, rather than external factors such as the pandemic or the timing of the announcement. Relating back to the changing dynamic of a working-week under the pandemic, what we predicted would have a negative effect on investor attention, could actually prove the inverse relationship. One could speculate in investors having more time on their hands to react to earnings announcements due to the earlier weekend. However, in the quantile analysis, we observe that earnings announcements made on Fridays during the COVID-19 pandemic had a negative impact on returns in the delayed window. This suggests that extreme positive surprises may have been met with skepticism or heightened sensitivity during periods of crisis. Conversely, when considering all announcements, our findings indicate a generally positive contribution of COVID-19 to returns, particularly for announcements made on Fridays during the pandemic. These seemingly contradictory observations indicate elements of irrational investment behavior. This could be supported with the research of Fabrizi et. al (2023), who suggests that during the pandemic, investors relied more heavily on external information signals rather than focusing on companies' own reports, potentially leading to inconsistencies in market reactions.

Complementing the analysis with abnormal volume provides insights into short-term trends that could not be fully explained through the analysis of returns. Overall, we observe a generally lower trading volume during the COVID-19 period in Plot 4b. As presented in our results, we find evidence suggesting that while the pandemic itself did not significantly affect trading volume across all days, it specifically influenced trading volume positively on Fridays.

When controlling for company-specific effects, this Friday effect slightly decreases in magnitude, indicating that a proportion of the observed effect can be attributed to individual company characteristics. This suggests that while a day-of-the-week effect is evident during the COVID-19 period, in the short term, it is not solely driven by market uncertainties but is also shaped by how individual firms are perceived and how their specific circumstances interact with broader market sentiment. While indicating a specific pattern for Fridays, it contradicts our hypothesis of COVID-19 having a negative impact on the immediate reaction.

6.2 Limitations

While we have included control variables and analyzed a homogeneous sample to mitigate biases, fully isolating the effects of earnings announcements remains challenging. The COVID-19 pandemic introduced significant market and company uncertainties, which could influence the observed significance in our results.

The multitude of information sources with regards to company earnings complicates the isolation of the effects from earnings announcements. Ideally, our analysis would occur in an environment where earnings reports are the sole source of information about a company's financial performance, ensuring that market reactions are not influenced by prior speculations or information leakage that could lead to the pre-announcement pricing of effects.

Moreover, the non-random distribution of earnings announcement days introduces additional complexity into our study. Companies often strategically choose their announcement dates, potentially to align with favorable market conditions or to avoid periods of expected high volatility. This selection bias could distort the true effect of earnings announcements as observed in our analyses. By choosing specific days for announcements, companies might intentionally or unintentionally influence investor attention and market reactions, complicating the isolation of announcement effects from other market activities. This challenge could be addressed by conducting a placebo test where the announcements would be randomly assigned to test the robustness of our models. Additionally, a more in-depth analysis of the reasons behind the timing of announcements and their impacts on investor behavior and market performance could add value.

Our study is limited by the available observations, especially in the COVID-19 sample, which is too small to allow for comprehensive pattern observation using a homogeneous filtering. As explained in the methodology section, the optimal analysis would be conducted solely on a homogeneous sample to account for the biases. Furthermore, focusing solely on the S&P 500 may not fully represent the broader market dynamic, as it excludes mid and small-cap stocks. This potentially skews our perspective of the overall market behavior.

The low R^2 values in our models, particularly when examining delayed stock returns responses, indicate that our linear regression captures only a fraction of the market's complexities. Despite efforts to control for selection bias and omitted variables through company fixed effects, which improved the R^2 in our volume analysis, our study still faces significant limitations in accounting for unobserved heterogeneity and industry-specific effects.

7. Concluding Remarks

7.1 Conclusion

Our study reexamines the post-earnings announcement drift (PEAD) and the day-of-the-week effects in the U.S. stock market, focusing on Friday inattention, both during regular market conditions and throughout the COVID-19 pandemic. While we observe variations in market reactions, such as lower immediate responses to Friday announcements and shifts during the pandemic, our findings are constrained by methodological challenges, including potential selection biases from the strategic timing of earnings announcements and unobserved firm-specific factors.

The lack of consistent patterns in long-term drifts and the limited explanatory power of our models suggest that the observed anomalies may not primarily stem from systematic investor inattention, as traditionally hypothesized. Instead, these patterns seem to be influenced by a combination of firm-specific dynamics, external market conditions, and broader economic disruptions. As a result, our findings remain inconclusive regarding the persistence or evolution of traditional anomalies such as PEAD.

An ideal research scenario would involve a more randomized and controlled dataset, such as companies being required to distribute their earnings announcements evenly across days of the week, thereby reducing selection bias. This could help isolate the true drivers of observed anomalies, whether behavioral or structural. Furthermore, analyzing smaller firms, incorporating diverse market conditions, and employing experimental designs could offer deeper insights into the persistence of market inefficiencies and investor behavior.

Given the increasing likelihood of systemic disruptions like pandemics, markets are expected to exhibit greater volatility. To understand the nuanced effects of these crises on market dynamics, future research must address the limitations identified in this study. Such efforts are essential for drawing more definitive conclusions and providing practical implications for corporate managers and investors operating in an evolving and unpredictable financial landscape.

References

- Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, 6(2), 159–178.
- Bernard, V. L., & Thomas, J. K. (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research*, 27, 1–36.
- Bolek, M., Lyrouti, K., Gniadkowska-Szymańska, A. (2022). Covid-19 Pandemic and Day-of-the-week Anomaly in Omx Markets. *Central European economic journal*, 9 (56), 158–177.
- Boulland, R., Dessaint, O. (2017). Announcing the announcement. *Journal of banking & finance*, 82, 59–79
- CFA Institute. (2024). *Using Multifactor Models*. Retrieved from CFA Institute: <https://www.cfainstitute.org/insights/professional-learning/refresher-readings/2024>
- Cherry, K., (2024). *What Attention Means in Psychology*. Retrieved from VeryWellMind: <https://www.verywellmind.com/what-is-attention-2795009>
- Chordia, T., Sadka, R., Goyal, A., Sadka, G., & Shivakumar, L. (August 5, 2009). Liquidity and the Post-Earnings-Announcement Drift. *Financial Analysts Journal*, 65(4), 18–32.
- DellaVigna, S., & Pollet, J. M. (2009). Investor Inattention and Friday Earnings Announcements. *The Journal of Finance*, 64(2), 709–749.
- Fabrizi, M., Ipino, E., Longhin, F., Parbonetti, A. (2023). The informativeness of earnings announcements during times of global uncertainty: Evidence from the Covid-19 pandemic. *Corporate Governance: An International Review*, 31 (5), 795–813.
- Fama, Eugene F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics*, 49 (3), 283–306.
- Fama, E. F., & French, K. R. (2024). *Data library*. Retrieved from: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- Fang, D. (February 16, 2024) Post-Earnings Announcement Drift, Systemic Shock, and Limited Attention: Evidence from COVID-19 Pandemic. NCCU Working Paper. 2–25.
- Fink, J. (2021). A review of the Post-Earnings-Announcement Drift. *Journal of behavioral and experimental finance*, 29, 2–9.
- Haileamlak, A. (2022). Pandemics Will be More Frequent. *Ethiopian Journal of Health Sciences*, 32 (2), 228.
- Hirshleifer, D., Lim, S.S., & Teoh, S.H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance* 64, 2289–2325.

Huberman, G., & Regev, T. (2001). Contagious Speculation and a Cure for Cancer: A Nonevent That Made Stock Prices Soar. *The Journal of Finance*, 56(1), 387–396.

I/B/E/S (2010). *I/B/E/S on Datastream: User guide* (Version 5.0). Retrieved from I/B/E/S: https://libapp.lib.ncku.edu.tw/libref/handout/20110107_IBES_user_guide.pdf

International Monetary Fund. (2020). *IMF Annual Report 2020*. Washington, D.C.: International Monetary Fund.

Investopedia. (2021). *Earnings Announcement: Definition and Impact on Market*. Retrieved from Investopedia: <https://www.investopedia.com>

Investopedia. (2024). *Event Study: Definition, Methods, Uses in Investing and Economics*. Retrieved from Investopedia: <https://www.investopedia.com/terms/e/eventstudy.asp>

Jeffrey, N. G., Rusticus, T. O., & Verdi, R. S. (2008). Implications of Transaction Costs for the Post-Earnings Announcement Drift. *Journal of Accounting Research*, 46(3), 661–696.

Kahneman, D. (1973). *Attention and Effort* (Prentice-Hall, Englewood Cliffs, NJ).

Kim, Y., Verghese, P. (August 29, 2012). The Selectivity of Task-Dependent Attention Varies with Surrounding Context. *Journal of Neuroscience*, 32 (35), 12180–12191.

Lo, Andrew W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *Journal of Portfolio Management*, Forthcoming, 1-24.

Martineau, C. (March 27, 2021). Rest in Peace Post-Earnings Announcement Drift. *Critical Finance Review*, Forthcoming, 5–22.

Mendenhall, R. R. (2004). Arbitrage Risk and Post-Earnings-Announcement Drift. *The Journal of Business*, 77(4), 875–894.

Pallant, J. (2013). *SPSS Survival Manual: A step by step guide to data analysis using SPSS*. Open University Press.

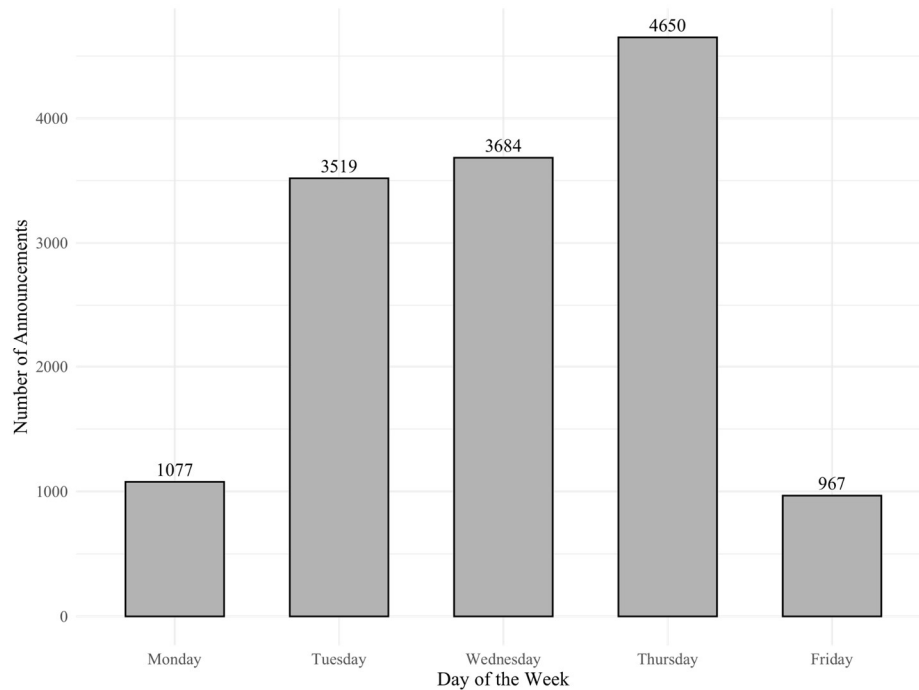
S&P Global. (2024). *S&P U.S. Indices Methodology*. Retrieved from S&P Global: <https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-us-indices.pdf>

World Health Organization. (2024). *Coronavirus disease (COVID-19) pandemic*. Retrieved from World Health Organization: <https://www.who.int/europe/emergencies/situations/covid-19>

Appendix

Appendix A

Distribution of Earnings Announcements by Day of the Week



The figure shows the distribution of earnings announcements by day of the week for the baseline sample.

Appendix B

Correlation Matrix of Independent Variables

Variable	Normalized_Surprise	LogMarketCap	Year	Month	FridayDummy	CovidDummy	VIF
Normalized_Surprise	NA	0.0021	0.0197	0.0210	-0.0117	0.0466	1.0044
LogMarketCap	0.0021	NA	0.1921	-0.0440	0.0986	0.1639	1.0499
Year	0.0197	0.1921	NA	-0.1762	-0.0200	0.8671	4.1990
Month	0.0210	-0.0440	-0.1762	NA	-0.0168	-0.1057	1.0424
FridayDummy	-0.0117	0.0986	-0.0200	-0.0168	NA	-0.0145	1.0120
CovidDummy	0.0466	0.1639	0.8671	-0.1057	-0.0145	NA	4.0796

To assess the potential issue of multicollinearity among our independent variables, we calculate the Variance Inflation Factors (VIFs).

Appendix C

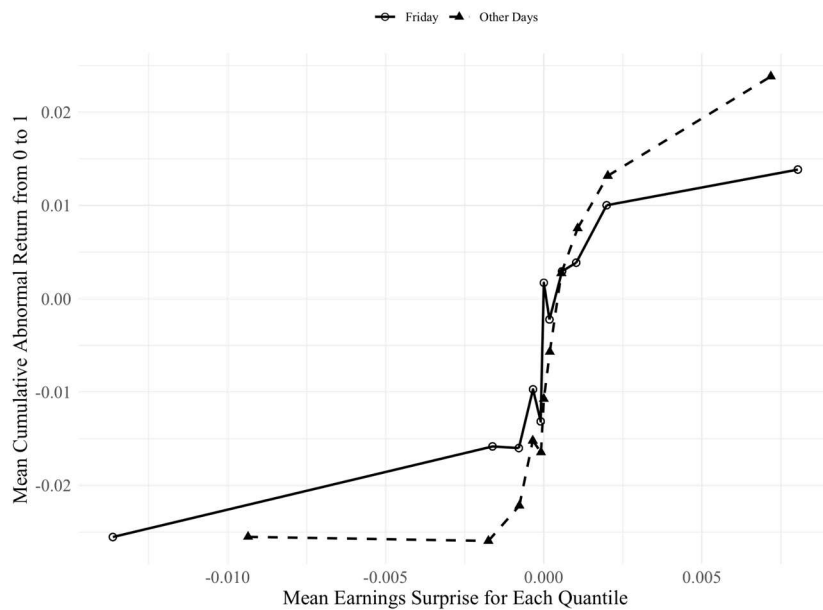
Average Surprise by Earnings Surprise Quantile

Quantile	Friday		Other Days	
	Mean	N	Mean	N
1	-0.0136	53	-0.0094	509
2	-0.0016	48	-0.0018	513
3	-0.0008	46	-0.0008	514
4	-0.0003	32	-0.0004	525
5	-0.0001	40	-0.0001	515
6	0.0000	8	0.0000	82
7	0.0002	140	0.0002	2,065
8	0.0006	167	0.0006	2,036
9	0.0010	134	0.0011	2,069
10	0.0020	145	0.0020	2,056
11	0.0080	154	0.0072	2,046

The table displays the average earnings surprise along with the number of observations for both Friday and non-Friday announcements across each quantile.

Appendix D

Nonlinear Form of the Immediate Response to Earnings Surprises



The Figure illustrates the relationship between earnings surprises and the immediate response in mean CAR from 0 to 1 days after the announcements for Friday and non-Friday announcements. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles.

Appendix E

Stock Price Response to Earnings Announcements for the Top Two and Bottom Two Quantiles

Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)	Total CAR (0-75 days)
(Intercept)	-0.0146 (0.0105)	0.0076 (0.0203)	-0.0070 (0.0235)
GroupTop_Two_Groups	0.0351 (0.0104)***	0.0227 (0.0208)	0.0578 (0.0238)*
FridayDummy	0.0070 (0.0068)	0.0017 (0.0114)	0.0087 (0.0122)
GroupTop_Two_Groups:FridayDummy	0.0005 (0.0081)	0.0098 (0.0141)	0.0103 (0.0154)
Standard Controls	X	X	X
Number of Observations	5524	5524	5524
Adjusted R ²	10.4%	1.61%	3.95%

The table reports the regression results for the immediate, delayed, and total return response for the top two and bottom two quantiles of the baseline sample with CAR as the dependent variable. The data consists of 5524 observations of earnings announcements for each interval. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles. The standard controls include market cap decile, and month and year fixed effects. Standard controls included in the regression are also interacted with the indicator variable for the top two quantiles. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Appendix F

Stock Price Response to Earnings Announcements for the Top and Bottom Quantiles (Homogeneous Sample)

Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)	Total CAR (0-75 days)
(Intercept)	0.003 (0.0234)	-0.0199 (0.0458)	-0.0168 (0.0522)
Top_Group	0.0514 (0.026)*	0.021 (0.0491)	0.0724 (0.0565)
FridayDummy	-0.0479 (0.0253)	0.0413 (0.0387)	-0.0066 (0.0492)
Top_Group:FridayDummy	-0.036 (0.0191)	0.0612 (0.0369)	0.0252 (0.0462)
Standard Controls	X	X	X
Number of Observations	622	622	622
Adjusted R ²	18.25%	3.15%	7.79%

The table reports the regression results for the immediate, delayed, and total return response for the top and bottom quantiles for the homogeneous sample with CAR as the dependent variable. The homogeneous sample includes companies which announce inside the range of 5% to 95% of their earnings announcements on Fridays. The data consists of 622 observations of earnings announcements for each interval. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles. The standard controls include market cap decile, and month and year fixed effects. Standard controls included in the regression are also interacted with the indicator variable for the top quantile. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Appendix G

Delayed Response Ratio (DRR) for Extreme Quantiles (Homogeneous Sample)

Variable	Estimate
DRR (Friday)	-0.2795 (0.0221)
DRR (Non-Friday)	-0.3565 (0.028)
Difference in DRR (Friday - Non-Friday)	0.077 (-0.0059)
Standard Controls	X
Number of Observations	622

The table reports the DRR for the extreme quantiles of the homogeneous sample, capturing the proportion of the CAR that can be attributed to delayed reactions. The homogeneous sample

includes companies which announce inside the range of 5% to 95% of their earnings announcements on Fridays. The data consists of 622 observations of earnings announcements. Quantiles 1 to 5 include the negative earnings surprises, quantile 6 includes the zero earnings surprises, and quantiles 7 to 11 include the positive earnings surprises. Each year determines the breakpoints for the quantiles. The standard controls include market cap decile, and month and year fixed effects. Standard controls included in the regression are also interacted with the Friday dummy. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Appendix H

Stock Price Response to All Earnings Announcements (Homogeneous Sample)

Variable	Immediate CAR (0-1 days)	Delayed CAR (2-75 days)
Surprise_Quantile	0.0054 (0.0018)**	-0.0017 (0.0031)
FridayDummy	0.0055 (0.0059)	0.0025 (0.0109)
Surprise_Quantile:FridayDummy	-0.0008 (0.0007)	-0.0008 (0.0013)
Standard Controls	X	X
Number of Observations	3133	3133
Adjusted R ²	8.68%	2.24%

The table reports the regression results for the immediate and delayed return response for all earnings announcements in the homogeneous sample with CAR as the dependent variable. The homogeneous sample includes companies which announce inside the range of 5% to 95% of their earnings announcements on Fridays. The data consists of 3,133 observations of earnings announcements for each interval. The standard controls include market cap decile, and month and year fixed effects. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

Appendix I

Short-Term Volume Response to an Earnings Announcement (Homogeneous Sample)

Variable	Estimate	Estimate
FridayDummy	-0.0116 (0.0214)	0.0135 (0.023)
Surprise Quantile	X	X
Standard Controls	X	X
Company Fixed Effects		X
Number of Observations	3131	3131
Adjusted R ²	7.88%	26.65%

The table reports the regression results for the short-term volume response to an earnings announcement in the homogeneous sample with the dependent variable as abnormal volume in event time from 0 to 1. The homogeneous sample includes companies which announce inside the range of 5% to 95% of their earnings announcements on Fridays. The data consists of 3131 observations of earnings announcements. The standard controls include market cap decile, and month and year fixed effects. One model includes company fixed effects. Standard errors are in parenthesis.

***p-value<0.01, **p-value<0.05, *p-value<0.1

AI Appendix

The AI tool Chat GPT 4 has been used to improve the grammar in the writing of this bachelor's thesis in order to improve the readability. The tool has not been used to write any parts of the paper or provide any results. Additionally, it has been used for improving and searching for errors in the R code.