The Differential Impact of Monetary Policy Shocks on Growth and Value Stocks

Evidence from an Event Study Approach

KRISTOFERS GERKENS

EDWIN SANDBORG

Bachelor Thesis

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Abstract:

We attempt to measure mispricing in different types of equities during macroeconomic shocks. Building on previous research establishing the relationship between stock returns and macroeconomic conditions and behavioural finance perspectives of investor sentiment, we show that responses of two distinct samples, namely, growth and value-oriented equities respond heterogeneously to policy shocks. Further, we empirically test the explanatory power of firm characteristics and sentiment as determinant of stock return response. The findings show that growth equities experience stronger, but not necessarily more directional, mispricing around the Federal Open Market Committee's (FOMC) decisions, during 2022 – 2023. Investor sentiment exhibits statistical significance in explaining this difference only in the ± 2 day observation window. The research provides meaningful extensions to multiple previous finance research papers, among them, Barberis et al. *A Model of Investor Sentiment* (1998), Da et al. *In Search of Attention* (2011), and Fama & French *A five-factor asset pricing model* (2015)

Keywords: Monetary policy, Behavioural finance, Event study, Investor sentiment, Abnormal returns

Authors:

Kristofers Gerkens (26084)

Edwin Sandborg (25988)

Tutor:

Marieke Bos, Deputy Director, Swedish House of Finance

Examiner:

Ramin P. Baghai, Professor, Department of Finance

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Stockholm School of Economics

1. Introduction

Behavioural finance, as a field of study within the broader science, has become increasingly popular in recent years, as more irregularities present themselves within financial markets. The field rejects the notion that market participants always act rationally by introducing psychological bias as a key determinant of decision-making (Barberis, Shleifer & Vishny, 1998). Further, it posits that the transmission of information is rarely efficient, conversely, it is misinterpreted and skewed, leading to divergence in market movements from what traditional theory would suggest. The question then becomes how market mechanisms interplay with human psychology, and if it is possible to model this relationship. Fama & French (2015) highlight that the rise of speculative investment strategies, mostly due to rapid technological development, has caused a widening gap between returns of different groups of equities, namely, growth and value stocks – the unique characteristics of which will be outlined further on. In addition, this gap intensifies during periods of economic uncertainty and monetary policy shocks (Lettau, Ludvigson & Manoel, 2020).

Understanding the drivers of this gap has important implications for predicting future returns of equities, and, further, how markets react overall to expansionary/contractionary policy. This can, not only help investors structure their portfolio according to their risk appetite but also help economists examine the possible effects of specific policies aimed at producing desirable economic conditions. As such, the proposed research question is outlined as:

Did growth equities experience stronger mispricing, as opposed to value equities, during the Federal Reserve's post-Covid interest rate hike cycle, and was this reaction amplified by investor sentiment?

During the Covid-19 pandemic, the American central bank (further, the Fed) was forced to dramatically slash interest rates to stimulate demand. Ludvigson, Ma & Ng (2021) show how these circumstances result in favourable conditions for growth for firms that rely on debt to finance their investments, in this instance causing a growing rate of return all throughout the pandemic period. Once the health crisis was subdued, these same conditions were the basis of rapid inflation (Jorda, Singh & Taylor, 2022), which the Fed was forced to combat by raising borrowing costs, causing rapid repricing market-wide. We posit that the characteristics of growth firms make them especially sensitive to these types of monetary policy shocks, based on the theoretical evidence of Lettau & Wachter (2007). Further, Barberis et al (1998) argue that the psychology of investors extrapolates downside risk for all equities, which is a key driver of mispricing during the period.

Monetary policy shocks move asset prices via two distinct channels – a pure monetary-policy (MP) shock and a central bank information (CBI) shock (Jarocinski and Karadi, 2020). A MP shock has a direct effect, as a rate change fundamentally alters discount rates, which are used to calculate the present value of companies, and subsequently the fair value of their shares. A CBI shock has a more indirect, albeit possibly more profound effect on sentiment – it signals to investors what the outlook of the economy is: rate tightening means elevated recession risk, while the lowering of rates signals a positive outlook on business growth. Equities respond heterogeneously to this shock based on their sensitivity to interest rate changes (Bernanke & Kuttner, 2005). Growth firms typically base a significant proportion of their valuation on positive cash flows in the future, and higher interest rates increase the discount factor used to calculate present value, as shown by Lettau & Wachter (2007). Additionally, our paper builds on the Book-to-Market ratio (further, B/M ratio) as being a statistically robust predictor of stock returns, empirically tested by Fama & French (1992), even shown to have higher statistical power than β. The paper identifies and classifies growth and value by fundamentals. Growth firms (low B/M) typically have low expected returns, strong recent performance and optimism-driven pricing. Analogous, value firms (high B/M) exhibit depressed prices, high expected returns and weak fundamentals. Lastly, the cross-sectional impact of investor sentiment needs to be acknowledged. Baker & Wugler (2006) find that sentiment is a key driver of mispricing in inefficient markets, due to investor overreaction to macroeconomic changes when attention is elevated. Further, they show that this sentiment-induced mispricing is stronger for growth firms due to their valuation being derived from intangible and uncertain cash flows. Understanding these mechanisms could lead to developing models with accurate predictive power, which is especially relevant for policymakers and money managers in the recent, growth-dominated market cycles. Taking the justification of existing literature we, therefore, propose the following hypotheses:

H_1: Growth equities will exhibit larger abnormal returns around the Fed's announcements than value equities.

H2: Higher investor sentiment to the topic "interest rate" on Google Trends increases the magnitude of mispricing (CAR) during FOMC announcements.

H3: Growth stocks exhibit stronger sensitivity to sentiment for the topic "interest rate" on Google Trends than the control (value) portfolio during FOMC announcements.

1.2. Conceptual Framework: Google Trends as a Measurement of Investor Attention

An aspect of this study explores whether investor attention leads to the amplification of abnormal returns, specifically overreactions to monetary policy decisions by the Federal Open Market Committee (FOMC). While these interest rate shocks change discount rates and thus company valuations, the actual market impact of this information can vary depending on the amount of attention it receives. Preis et al. (2013) stipulates that investor sentiment on the Google search topic "debt" correlates with market volatility and negative cumulative abnormal returns (CARs). Thus, investor attention toward that topic has a downward effect on equity returns, and, in a broader sense, interest in macroeconomic terms in general is a predictor of market sentiment. Furthermore, Barberis et al. (1998) show conclusive evidence that the salience of information proceeding macroeconomic events, and monetary policy fluctuations, in particular, have an impact on how strongly the market reacts. Fundamentally, both the aforementioned papers demonstrate a meaningful relationship between investor sentiment on macroeconomic topics and CARs, where higher attention rates predict larger market movements.

When attention is high, investors trade with higher volumes, as it is an indication of high salience to monetary policy. This leads to price change amplification, particularly overreactions to interest rate shocks, especially, in the case of growth-oriented firms, as mentioned previously. Since these firms are characterized by a low B/M ratio, discount rates on their financial fundamentals experience more volatility, as cash-flows are typically concentrated in the future. In our setting, Google Trends does not replace monetary policy decisions as an explanatory variable for market reactions; rather, it is an information channel that serves as a moderator, possibly amplifying investor sentiment. Essentially, the attention variable modulates how salient the information signal is, which can create overreactions in the market, especially with negative signals leading to worse outlooks on the market and investor sentiment.

1.3. Ideal Methodology and Practical Implementation

The ideal experiment would require several specific conditions, some of which we are able to establish in our approach. Most notably, it would require a random assignment of firms to either a growth or value portfolio, and the underlying characteristics for the firms across both would be the same, as argued by Barberis et al. (1998). Therefore, any observed difference between the portfolios would isolate the treatment effect perfectly and remove confounding. However, style portfolio's, such as we intend to construct, differ due to inherent traits. Next, the timing of monetary policy shocks would be unrelated to market conditions and arrive as exogenous shocks with unpredictable timing (Kuttner, 2001). In reality, Romer & Romer (2004) argue, macro shocks are a product of broader economic conditions, which makes them partially predictable. Further, the shock itself must be unambiguous in direction and uniform in magnitude across the population (Barberis et al. 1998). Through this, the psychological bias, particularly, the representativeness heuristic[1] can be used to argue why such mispricing occurs. The paper posits that investors operate in a belief-updating regime and tend to extrapolate news of any kind – they believe that what is currently happening will continue to happen in the future. Thus, a negative monetary policy shock is an ideal event to test this mechanism.

The actual setup for testing the proposed hypothesis differs from the ideal, nevertheless, it holds statistical merit in isolating the desired effects. Growth and value are not randomly assigned, a population of firms is sorted by their B/M ratios (Fama & French, 1992), and the top/bottom percentile is assigned to a value/growth portfolio, respectively. This causes selection bias to some degree, when assessing the effects of sentiment, as the difference in CARs partially arises from differences in inherent characteristics, such as duration risk (Lettau & Wachter, 2007), which could confound sentiment effects. However, firm-specific betas are estimated in a pre-event period, partially absorbing systemic differences, and helping isolate the desired effect. Nevertheless, the anchor literature posits that these differences arise exactly due to structural differences of firms and their sensitivity to policy shocks (Bernanke & Kuttner, 2005; Lettau & Wachter, 2007), therefore we can observe divergence in CARs, while limiting noise, by taking this approach. Additionally, the Fed's meeting dates are known and are correlated with macroeconomic conditions, thus, Nakamura & Steinsson (2018) remark that markets expect policy actions and investors can pre-emptively position themselves in anticipation of likely effects. They show the creation of unnecessary noise that poses a challenge in isolating pure mispricing. The approach used again addresses this by calculating expected returns in the pre-event period, helping isolate deviations from these expectations, not risk differences. Further, a fixed-effects (FE) dummy is included that removes cross-event noise and isolates within-event variation. The events themselves are also not independent but correlated, as the sample consists of a sequence of events in an underlining economic environment. Obviously, The Google Trends Index as an imperfect proxy for investor attention needs to be taken into consideration, however, Da, Engleberg & Gao (2011) outline its accuracy and relevance in this regard. Overall, the conditions surrounding the experiment's setup are not ideal, however, the approach reasonably limits noise, and the setting remains quasi-natural due to its ability to isolate shocks, accurately proxy investor attention and divide the firm samples based on sensitivity to discount rates.

1.4. Methodological Divergence from Anchor Literature

The proposed methodology anchors to, but somewhat differs from, a combination of empirical methods proposed in previously mentioned research papers. The conceptual behaviour model is an interpretation of Barberis et al. (1998), in that their proposed mechanism is stress-tested under real-world conditions. The conditions of their set-up, namely, random sampling and purely exogenous shocks, are described in the previous section. Additionally, their sentiment measure and its volatility is theoretical, while our model uses data and a sentiment proxy.

[1] As defined by Tversky and Kahneman (1974): "A person who follows this heuristic evaluates the probability of an uncertain event, or a sample, by the degree to which it is (i) similar in its essential properties to the parent population (ii) reflects the salient features of the process by which it is generated" (p. 33)

Da et al. (2011)'s methodology presents an individual firm-level sentiment analysis where SVI from google trends is used as a proxy for attention. It differs in that it measures firm specific attention movements rather than aggregate level macroeconomic sentiment fluctuations. Specific firm tickers are used from the Russel 3000 index, where firm specific news triggers CARs. Our methodology shares Google trends as a proxy though not through an index but rather through a large sample of US firms. Nevertheless, Da et al. (2011) serves as a methodological base for our analysis as it demonstrates significant correlation between investor sentiment and firm-specific CARs.

Preis et al. (2013) offers another methodological parallel to our paper, particularly through their use of a specific search topic on Google trends as we do, specifically "debt". The paper focuses on the broader scope of market-wide, non-event specific outcomes of firms reacting to macroeconomic sentiment. Our paper differs, in that we focus on monetary policy communication through an event study. Preis et al. (2013) presents a meaningful relationship between sentiment in the topic "debt" and CARs market-wide using indexes, whereas we use the topic "interest rate" to measure reactions from monetary policy events of the FOMC, and, thus, the effect of investor attention to the topic on CARs. Hence, our paper presents a meaningful extension to the literature in the form of how different firms type equities (growth versus value) react to investor sentiment on the topic "interest rate" on specific monetary policy changes made by the FOMC in the US.

Lastly, the empirical basis used for expected return estimation can be found in Fama & French (2015). The expanded 5-factor model produces firm-specific exposure to systemic risk factors. Our application is largely faithful, however, differences arise. The estimation windows conceptually differ, in that the model was originally designed for cross-sectional pricing with a running, long-term estimation, while our study utilises it over a relatively short window. Further, Zhang (2005) shows that the factor estimates themselves may contain macroeconomic information, such as policy shocks, especially through the market factor. However, our estimation widow is relatively stable, and exhibits quite static market condition, which negate said risk.

1.5. Paper Structure

We continue with describing our dataset and outlining the methodology applied to test the proposed hypothesis. Further on, the results are presented and analysed. Then, diagnostic tests are performed to interpret the robustness of regression results. Finally, conclusions are drawn and a decision on whether to accept/reject the hypotheses is made.

2. Data Description

2.1. Data Sources

The data used divides into three distinct subsets, namely, company-specific information, macro-level data, and a sentiment proxy. Company-specific information, taken from The *Wharton Research Data Services* (further, *WRDS*), consists of components needed to compile a list of testable equities, approximate their expected return and observe actual returns.

The *Financial Ratios Suite by WRDS* is used to construct both sample groups. The database is useful, as it offers pre-calculated financial ratios for all listed companies in the US for a given time period (usually, financial quarters), which, as will be made clear in the next section, is of paramount importance for our study. Further, the *Capital IQ* (*CIQ*) Compustat database is utilised, and quarterly fundamentals are pulled for numerous companies. Here, fundamentals are defined as the core financial and operational aspects of a business that determine its health, value and potential for future growth[2]. Apart from identifying information (company name, ticker, identification codes, etc.), each company's total asset, liability and cash holdings amounts are pulled, as well as various income statement items, such as operating income, R&D expenses and SGA expenses. The role of this data will be described in detail, in the model set-up section below. For robustness, the date range for this data encompasses not only our event period (roughly, early 2022 – late 2023) but also quarterly reports for 2021, 2020, and 2019 – this being an important component of expected return estimation during the event period. Additionally, the CRSP database is used to gather daily stock returns throughout both periods for each company.

The Fama-French 5 (FF5) model will be later used to estimate expected returns for the companies in the samples, thus, daily returns for each factor is required. This data is acquired through the Fama-French Portfolios database. The Five-Factor model builds on its predecessor and offers two additional factors to explain stock returns. Although the model was developed some time ago, it has remained a cornerstone of empirical asset pricing and beats similar models in accuracy (Fama & French, 2015). The aim is to estimate each firm's expected (normal) returns; therefore, Fama & French (2015) argue that a long sample of data is required, here the period is taken as the 3 years before the start of the event window.

Since Google trends has been used as a valid proxy for investor attention, it will be used as a measure of investor attention, where the specific search topic "interest rate" serves as a high frequency term in relation to monetary policy information. Google trends topics differ from search terms in that they encapsulate all related queries to "interest rate" for instance, where all related searches are reflected in the measurement of attention. It is important to note that this is a United States based study, meaning all sentiment data gathered will be specific to the US. The database measures sentiment based on the search volume index (SVI). The SVI is a relative measure of search volumes scaled from 0-100. It is not an absolute unit; hence it is a useful value to approximate attention spikes surrounding monetary policy events.

2.2. Sample Construction

The refinement procedure is as follows: the database of companies is sorted, in decreasing value, by their average BM ratio during 2019-2023, and the top/bottom 30% of companies are labelled as value/growth, respectively – each sample contains *~1350* companies. This approach attempts to omit equities, which may exhibit both growth *and* value characteristics, therefore, the middle 40% of companies in the database are discarded – this approach is argued by Fama & French (1993). To measure 'mispricing', it needs to be outlined, what the 'correct' return for each firm would be on a particular day. This will be calculated for each firm by running a time-series regression, utilising returns from the FF5 model in the pre-event period, and the actual returns for each firm (Fama & French, 1993).

In addition to the ideal setup's, and our deviations from it, description in the introductory section, another implication materialises here. Firms with incomplete fundamentals and/or returns data are omitted from the samples, so to maximise the fullness of information, when analysing individual firms in aggregate. This improves the statistical significance of the results, while decreasing sample size, as outlined by Fama & French (2015). The excluded firms might have an impact on the reported differences in abnormal returns due to extreme characteristics, yet they are sure to decrease the robustness of the results. Nevertheless, sample size remains large.

[2] https://www.investopedia.com/terms/f/fundamentals.asp

2.3.Variable Construction

The following tables describe the variables, which will be used throughout the analysis to test the outlined hypotheses. They contain the name and equation (if applicable) of each variable, as well as a contextual description.

Variable	**Description**
Independent Variables	
Investor Sentiment ($Attention_t$)	Approximated, conceptually, by measuring Investor Attention using a normalised Search Volume Index (SVI) with topic 'Interest Rate'. See appendix for mathematical approach.
Monetary Policy Shocks	Policy decisions and signals conveyed by the Fed in the event period (2022-2023). See appendix.
Dependent Variables	
Raw Return ($R_{i,t}$)	The stock return for firm i on date t, expressed as a %
Excess Return ($R_{i,t} - R_{f,t}$)	The stock return for firm i over the risk-free rate on date t, expressed as a %. The risk-free rate is pulled from the Fama-French Portfolio database.
Expected Return ($\hat{E}(R_{i,t})$)	The return for stock i that is expected under normal market circumstances on date t. It is expressed as a % and derived from the Fama-French 5-Factor model.
Abnormal Return (AR)	Calculated as $AR_{i,t} = R_{i,t} - \hat{E}(R_{i,t})$ and expressed as a %, this variable denotes how much the return for stock i differs from what is expected on date t.
Cumulative Abnormal Return (CAR)	Calculated as $CAR_{i,e} = \sum AR_i$ and expressed as a %, the variable expresses the sum of abnormal returns for firm i around event e for a particular observation window ($\pm 1; \pm 2; \pm 5, etc.$).

Figure 1: Independent and Dependent Variables

Variable	Description
Control Variables	
Firm Fundamentals	Characteristics for each firm *i* across the event period that control for cross-sectional differences in financial strength and risk that affect individual returns. See appendix.
Fixed Effects Dummy	Represents an unobserved, time-invariant characteristic specific to a group[3]. In the context of this paper, each event represents its own group – the dummy will control for the macro-level shock that all firms in the sample experience, regardless of attention or firm type.
Growth Dummy	= 1 for growth firms, = 0 for value firms
Factor Variables	
Fama-French Model Terms	Explains expected stock returns using 5 systemic risk factors – market, size, value, profitability, and investment. See appendix.
Interaction Variables	
Growth x Sentiment	Captures whether the relationship between investor sentiment and CARs differs between the growth and value firms.

Figure 2: Explanatory and Control Variables

2.4. Summary Statistics of Primary Variables and Sample Size Analysis

	Sample Size (No of Observations)	
	Growth	**Value**
Initial Population	4357	
Initial Sample	1307	1307

Figure 3: Population and Initial Sample

The initial population contains the entire CRSP database of firms, as pursuant to constraint specification (B/M ratio availability within the estimation/event window). Each calculation step (ordered) reduces the sample size somewhat – for growth, the final sample used for CAR calculations signifies a 12,3948 % decrease from the intial sample, while for value this figure is an 18,7452 % decrease. The sample reductions were implemeted to ensure reliability of results.

The drop in sample size from the raw returns to the expected returns was caused be a requirement set forth, that a firm needs at least 24 months (out of 36) of complete data for beta estimation (following the empirical methodology of Fama & French (1992)) – those firms, which did not meet this requirement, were considered unreliable and were dropped from the sample. Next, to calculate abnormal returns for a firm, it needs to have both expected returns and actual returns on days around the event dates – if one or more is missing, the firms gets dropped from the sample. The same logic follows for CARs calculations, thus, the sample decrease between these steps is negligible. Overall, the sample size remains large enough to have representativeness, and the constraints implemented that cause sample size decrease only help to improve statistical significance by analysing continuously traded firms throughout the period (Kothari & Warner, 2007).

[3] https://ds4ps.org/PROG-EVAL-III/FixedEffects.html#:~:text=A%20fixed%20effect%20model%20better,characteristics%20that%20change%20over%20time

Figure 4 below describes the summary statistics of our dependant and independent variables.

variable	mean	median	min	max	n_obs	n_unique_firms
Raw returns (Growth)	0,0006	0,0000	-0,9448	9,9835	1327544	1305
Raw returns (Controls)	0,0006	0,0000	-0,9088	5,8500	1368923	1304
Expected returns (Growth)	0,0023	0,0025	-0,2335	0,4300	621741	1241
Expected returns (Controls)	0,0022	0,0021	-0,3298	0,4216	635769	1269
Abnormal returns (Growth)	-0,0027	-0,0031	-0,9340	8,3311	548662	1145
Abnormal returns (Controls)	-0,0022	-0,0026	-0,8907	3,0742	500214	1066
CARs (Growth)	-0,0119	-0,0124	-1,4475	2,6986	52552	1145
CARs (Controls)	-0,0113	-0,0109	-1,3012	2,9755	47905	1062
Google Trends SVI	40,2083	37	12	100	288	-

Figure 4: Summary Statistics of Independent and Dependant Variables

3. Methodology

3.1 Model Specification

3.1.1 Time-Series Estimation of $\boldsymbol{\beta}$ estimation (Firm-level)

Using Ordinary Least Squares (OLS) estimation of the FF5 model for each firm. The model is set up, as follows:

$$\boldsymbol{R_{i,t} - R_{f,t} = \alpha_i + \beta_{mkt,i}(MKT_t - R_{f,t}) + \beta_{smb,i}SMB_t + \beta_{hml,i}HML_t + \beta_{rmw,i}RMW_t + \beta_{cma,i}CMA_t} \quad \mathbf{(1)}$$

Equation (1) estimates factor loadings (β) for each firm i using a 2-year pre-event period. The aim is to estimate expected returns under normal market circumstances, given the FF5 returns on a particular day. Each β estimate represent a firm's exposure to a specific systemic risk factor that the FF5 model accounts for. This model is key in determining what the returns of each firm *should* be during the event dates.

3.1.2 Event-Study Analysis – Abnormal Returns

Using the factor loadings, estimated using pre-event data, an out-of-sample estimation is utilized to estimate the expected returns for firm i on date t. The set-up is as follows:

$$\boldsymbol{\widehat{E}(R_{i,t}) = R_{f,t} + \widehat{\alpha}_i + \textstyle\sum_k \widehat{\beta}_{k,i} F_{k,t}} \quad \mathbf{(2)} \text{ , where}$$

$\boldsymbol{R_{f,t}}$ is the risk-free rate on day t

$\widehat{\boldsymbol{\alpha}}_{\boldsymbol{i}}$ is the average excess return unexplained by the FF5 model for firm i

$\widehat{\boldsymbol{\beta}}_{\boldsymbol{k,i}}$ is the estimated sensitivity of firm i to factor k (SMB, MKT, HML, etc.)

$\boldsymbol{F}_{\boldsymbol{k,t}}$ is the actual daily return for factor k on day t

Model (2) estimates the expected return for each firm on each day around a pre-specified event-window. It serves as the baseline. From which abnormal returns are calculated.

Once expected returns are calculated, ARs and, further, CARs can be calculated around each event t, as specified in the previous section. Formally, the equation is outlined as:

$$\sum \widehat{\boldsymbol{E}}(\boldsymbol{R}_{\boldsymbol{i,t}}) = \boldsymbol{R}_{\boldsymbol{f,t}} + \widehat{\boldsymbol{\alpha}}_{\boldsymbol{i}} + \sum_{\boldsymbol{k}} \widehat{\boldsymbol{\beta}}_{\boldsymbol{k,i}} \boldsymbol{F}_{\boldsymbol{k,t}} \quad \textbf{(3)}, \text{ over a specified observation window.}$$

3.1.3 Cross-Sectional Model (Behavioural Regression)

Once CARs around event-windows are calculated, it is necessary to tie the results together with our main explanatory variable, i.e., attention/sentiment. To do this, a cross-sectional regression is set up, using the developed measures for attention, sector type and their interaction. Additionally, firm-specific fundamentals are added, as control variables. The model is set up as follows:

$$\begin{aligned}\boldsymbol{CAR}_{\boldsymbol{i,e}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\boldsymbol{1}}\boldsymbol{Attention}_{\boldsymbol{e}} + \boldsymbol{\beta}_{\boldsymbol{2}}\boldsymbol{Growth}_{\boldsymbol{1}} + \boldsymbol{\beta}_{\boldsymbol{3}}(\boldsymbol{Attention}_{\boldsymbol{e}} \times \boldsymbol{Growth}_{\boldsymbol{i}}) \\ + \boldsymbol{\gamma}_{\boldsymbol{1}}\boldsymbol{Size}_{\boldsymbol{i,e-1}} + \boldsymbol{\gamma}_{\boldsymbol{2}}\boldsymbol{BM}_{\boldsymbol{i,e-1}} + \boldsymbol{\gamma}_{\boldsymbol{3}}\boldsymbol{Lev}_{\boldsymbol{i,e-1}} + \boldsymbol{\gamma}_{\boldsymbol{4}}\boldsymbol{Prof}_{\boldsymbol{i,e-1}} + \boldsymbol{\gamma}_{\boldsymbol{5}}\boldsymbol{Cash}_{\boldsymbol{i,e-1}} + \boldsymbol{\gamma}_{\boldsymbol{6}}\boldsymbol{Inv}_{\boldsymbol{i,e-1}} \\ + \boldsymbol{\sigma}_{\boldsymbol{e}} + \boldsymbol{\varepsilon}_{\boldsymbol{i,e}} \quad \textbf{(4)}\end{aligned}$$

Equation (4) is paramount in assessing, whether attention amplifies mispricing at all, and, further, if this case is growth-orientation specific. Two important distinctions offer robustness and statistical significance here. Firstly, the inclusion of fundamentals helps control for the different financial structures and business models of the firms in both the treatment and control samples. Inherently, firms with differences in the aforementioned parameters are *rationally* expected to react differently to the same macroeconomic shocks, even within their respective groups, for example, a firm with higher leverage will react more strongly to interest rate hikes, as this increases their interest payments, subsequently lowering profits and share price. Analogous logic can be applied to the other variables.

The inclusion of these controls helps absorb firm-level heterogeneity so the interaction term can isolate behavioural, rather than structural differences. Without their inclusion, the interaction term would pick up variance in CARs that have no relation to attention, as an amplification mechanism. Each fundamental is lagged one period (for an event happening on day t the model would apply fundamentals from the last reported quarter before t), to avoid look-ahead bias: future information, not available at the time, being used to analyse said period. The goal is to mimic the information available to investors pre-event in an attempt to statistically incorporate their expectations about the firms' future outlook. Further, some fundamentals, such as firm size, are transformed to log-scale to minimize huge differences between these variables in different firms, and make the results represent proportional, not absolute, effects.

4. Empirical Results

4.1. **Market Environment Analysis**

	Factor Average					
Period	***mktrf***	***smb***	***hml***	***rmw***	***cma***	***rf***
Estimation (2019-2021)	0,00099	0,00002	-0,00027	0,00030	-0,00003	0,00072
Event (2022-2023)	-0,00001	-0,00009	0,00032	0,00022	0,00017	0,00262

Figure 5: FF5 Model Average Loadings during the Estimation/Event Period

The above figure allows for comparison between the pre-event, i.e., *normal* and the *event* environment. These calculations utilise Equation (5) on a market-wide basis (see appendix.) The transition of each factor between these two states is pivotal, as it allows for analysis of the underlying risk factor environment and its implications. In a sense, a dissertation of the macro-environment and, further, investor mentality is possible.

Market excess return *mktrf* represents the average reward to investors for holding risky assets (equities), as defined in Fama & French (1993). Although both periods exhibit near-zero averages, the nominal values are not so much of interest here, as is the directional change. The drop in the event period signifies that investors, in aggregate, no longer received compensation for holding risky securities, and their general risk-appetite weakened (Bekaert, Hoerova, Lo Duca, 2013). This is in line with macroeconomic theory described by Jarocinski & Karadi (2020), as the event represents a monetary policy tightening cycle, signalling near-term uncertainty, stemming from a period of low interest rates – resulting in the deterioration of market conditions and a loss of equity momentum (Brunnermeier & Koby, 2018). The likely strategy for investors during this time is risk offloading and a shift towards more safe investments, such as bonds, real estate, and legacy companies. The implication for this study is that conditions for growth deteriorated market-wide (Jarocinski & Karadi, 2020), so negative CARs could, at least partially, be the result of systematic, not type–specific factors.

The *smb* factor signals investor preference of small-cap (positive) or large-cap (negative) firms as investments (Fama & French, 1993). The reversal from a positive loading to a negative one signifies that larger firms outperformed smaller ones during the event period – in line with what intuition would suggest. Small-cap firms are more illiquid and credit-dependent than their large-cap counterparts (Kashyap, Stein & Wilcox, 1993), thus, they are likely to underperform during periods of tight monetary policy. Investors prefer relative safety, thus, they flock towards less-speculative, blue-chip stocks as a defensive mechanism, in an attempt to limit downside exposure, as demonstrated in Albuquerque, Eichenbaum, Luo & Rebelo (2020). Similarly, the *hml* loading had an analogous sign change that has a similar economic interpretation as the *smb* factor shift. Mathematically, the factor shows the difference in returns between a *value* stock and a *growth* stock portfolio, which helps visualise investor mentality during both periods (Fama & French, 1993). During expansionary regimes, much like the one The US economy experiences during the pandemic, investors pay for growth potential due to favourable conditions for said potential to come to fruition (Hanson & Stein, 2015) but during tightening cycles, they prioritise stability and tangibility, because growth is limited (Albuquerque et al., 2020). The exhibited factor loadings help support this thesis.

The change in the *rmw* factor signals, in essence, that investors prioritise profitability less during the event period (Fama & French, 2015). However, there is no sign change and the decrease is marginal, meaning it is still a deciding factor but other differentiators, such as liquidity or sector exposure, become more important in resource allocation decision-making, this is empirically outlined in Koijen, Moskowitz, Pedersen & Vrugt (2020).

The *cma* factor exhibits an increase, which aligns with the shift in the macro environment. Investors preferred low-investment, disciplined firms due to their perceived resilience in market downturns – a fact supported in Belo, Lin & Bazdresch (2014). Additionally, high volume investment-oriented firms become especially exposed, when interest rates rise due to much of the investment being financed through debt (Ottonello & Winberry, 2020), meaning their interest payments increase and profit decreases.

The risk-free rate exhibits a massive hike, which is to be expected, given the monetary policy environment. The important distinction is that the risk-free rate depresses all equity valuations (due to the time value of money) but especially those, whose positive cash-flows are projected in the future (Belo, Collin-Dufresne & Goldstein, 2015), i.e., what investors classify as *growth stocks*, meaning this variable could be thought of as an anchor in the model and an indirect driver of the other variables, which is empirically outlined in Cochrane (2011).

In sum, these statistics imply that the event period took place during a system shift from a growth-friendly, low-rate environment to a defensive and value-oriented regime. The transition likely amplified the negative CARs growth firms experienced, since macro factors, such as interest rates and risk sentiment moved against them simultaneously (Cochrane, 2011).

4.2. Sample Characteristics during the Estimation Period

Factor	Growth (Mean)	Controls (Mean)
$\boldsymbol{\alpha}$	-0,0000	-0,0005
$\boldsymbol{\beta_{mkt}}$	0,9586	0,8458
$\boldsymbol{\beta_{smb}}$	0,6135	0,7241
$\boldsymbol{\beta_{hml}}$	-0,1978	0,5377
$\boldsymbol{\beta_{rmw}}$	-0,5823	-0,2519
$\boldsymbol{\beta_{cma}}$	-0,1927	-0,1965

Figure 6: FF5 Model Factor Average Loadings by Sample Type (Estimation Period)

Using Equation (1), we estimate factor loadings of each FF5 model term by sample. There is practically zero abnormal performance based on the model factors. This is an ideal set-up for analysing their returns during the event period, as investors did not systematically award premiums to either group (Fama & French, 2015), based on sentiment or momentum, meaning any mispricing found around the Fed policy shocks is less likely to be explained as structural bias or trend differences (Kuttner, 2011). Additionally, these loadings give strength to positing this period as exhibiting *normal* market conditions.

The *mkt* factor loading suggests that both samples react with less magnitude than the market itself, as explained by Fama & French (1993). The important distinction here is that the market beta for the *growth* portfolio is higher, thus, the treatment group's structural peculiarities expose it to cyclical changes and market-wide shocks to a higher degree (Fama & French, 1992). In essence, during a bull market, gains are amplified, and, during a bear market – losses are. Economically, Baker &

Wurgler (2006) suggest that this signals that growth investors tend to operate in an optimistic and highly reactive manner, particularly when it comes to interest rate changes and liquidity.

The size factor indicates that both groups are skewed towards a small market capitalisation, with the control sample more so. Gertler & Gilchrist (1994) posit that smaller firms are more sensitive to economic shocks, particularly when these shocks impact their liquidity, which is a key determinant in this study. However, since the loading is similarly positive for both groups, it is unlikely that this variable will have strong explanatory power (Fama & French, 1993), when analysing CARs.

The *hml* loading is crucial in examining the applicability of the samples to this study, and it confirms their fit, respectively. The growth portfolio is tilted towards firms whose value is derived from future expectations and long-duration cash flows – in line with most intrinsic definitions of *growth* firms (Fama & French, 1993) -, while the control sample is anchored in current fundamentals, and low growth expectations. This creates the ideal conditions for testing the outlined hypothesis, as it would be more likely that the *growth*-oriented portfolio investors overreact to policy shocks (Cochrane, 2011), as they have a more profound and material impact on their portfolio.

Profitability across the board is low, although the treatment sample exhibits worse profit conditions still (Fama & French, 2015). The negative rmw loading suggests that both samples consist of firms that have high reinvestment rates (Hou, Xue & Zhang, 2015), therefore, attracting capital off of the promise of high future returns. Ideally, the control sample would have robust profitability, as this measure can also be considered a key differentiator between the two types. However, in this instance, the previous loading is a more accurate indicator of robust sample construction.

Similarly, the cma factor confirms that both samples consist of investment-heavy firms, meaning, as suggested in Zhang (2015), that they have high real-option value and tend to be more cyclical in performance. However, since the loadings are practically equal, this factor is unlikely to drive differences between CARs, more so it reiterates the possibility of sample construction improvement.

4.3. Expected Returns

group	mean_exp_ret	median_exp_ret	sd_exp_ret	min_exp_ret	max_exp_ret
Controls	0,2151%	0,2131%	1,8091%	-32,9822%	42,1604%
Growth	0,2339%	0,2451%	2,2092%	-23,3491%	42,9966%

Figure 7: Summary Statistics of Expected Returns by Sample Type (Event Period)

The control sample exhibits lower mean and median expected daily returns during the event period, in line with classic asset-pricing models, as these firms typically deliver a steady, cash flow-driven performance, and their valuation is more tied to current fundamentals than potential upside (Fama & French, 2015). Further, the standard deviation of their returns is lower, implying lower sensitivity to model-based revision and less exposure to aggregate shocks, as outlined in Cochrane (2011). Interestingly, the minimum observed expected return is lower for this group than for the treatment, however, Campbell, Lettau, Malkiel & Xu (2001) teaches us that the volatility difference indicates that this is an isolated distressed observation, rather than systemic instability. Overall, these limited measures showcase that the control group does act like a *value*-oriented portfolio, providing a natural benchmark for evaluating the response of *growth* firms to market shocks.

In comparison, the treatment group, while having higher expected returns on average, showcase higher volatility as well – both pointing to the sample being, at the very least, **more** *growth*-oriented than the controls, as justified by Gormsen & Koijen (2020). The heightened standard deviation implies a greater sensitivity to earnings revisions and higher impact of macroeconomic conditions for their valuation (Campbell & Vuolteenaho, 2004). Additionally, the sample has a higher minimum expected return and an almost equal maximum expected return, demonstrating fewer extreme downturns, while having similar upside potential. Campbell, Lettau, Malkiel & Xu (2001) suggests that, due to this, *growth* firms exhibit broad, systematic uncertainty, rather than idiosyncratic risk, in line with the examined *mkt* loading in the previous section.

4.4. Abnormal Returns

Group	**Average Abnormal Return**
Controls	-0,2216%
Growth	-0,2677%

Figure 8: Average Abnormal Return by Sample Type (Event Period)

Utilising Equation (2), we are able to derive ARs for each sample. On average, both samples return a negative abnormal return across the *event* period. This fact helps support the proposed effect on the market as a whole, during the Fed's rate hike cycle, which Kuttner (2001) suggests is overreaction to market shocks. Inferring on what psychological bias drove the decision-making of investors over the course of this period, the hawkish signals from the Fed regarding economic outlook, coupled with a general rising fear of inflation – while obviously causing some downward pressure on equity prices – caused pessimism to rise among their ranks and extrapolate said pressure (Barberis et al., 1998). Additionally, the treatment group had a more negative return, in line with expectations. The risk profile of *growth* firms presented a large uncertainty for investors, thus, more chose to shift to a more stable portfolio by selling off *growth* stocks (Rigobon & Sack, 2004).

4.4.1. Cumulative Abnormal Signed Returns

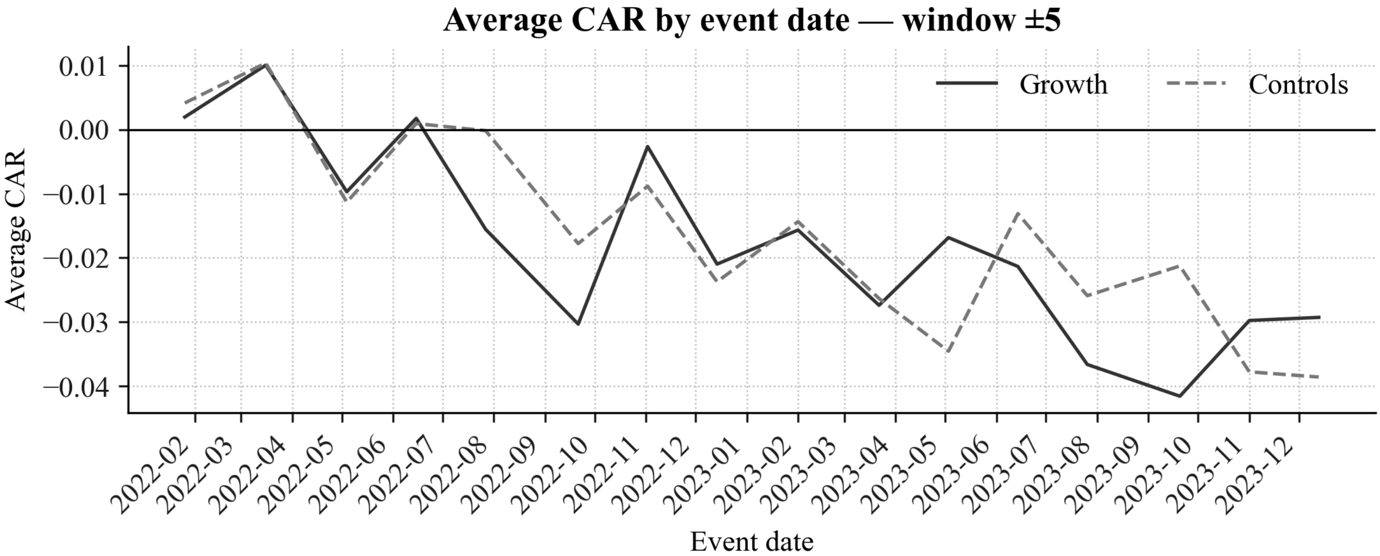

Figure 9: Average CARs During the Event Period by Sample

The overall movement of CARs for both groups coincides for most of the event period, implying that the drivers of mispricing here are systematic, not idiosyncratic. Additionally, asymmetric variance is noticeable, notably, during 2023 tightening shocks caused larger negative CARs across the board than easing signals did positive CARs. Here, two main causes are outlined. Firstly, information saturation, with each new rate hike or other policy tightening instrument, signalled the persistence of restrictive policy (Gurkaynak, Sack & Swanson, 2005). Where some investors may have initially thought that this stance is short-term, its persistence became evidence for a structural regime change at the federal level. Secondly, Gurkaynak (2005) shows that the value of *good news* became marginally less valuable over time. At the start of the tightening cycle, each instance of good news holds a lot of value, because it potentially changes the trajectory of future rates, however, as the cycle progresses, markets internalize the new, tighter regime, until it becomes the baseline expectation. At this point, any easing signals have less marginal value (Nakamura & Steinsson, 2018), as investors discount them as rhetorical, rather than foundational.

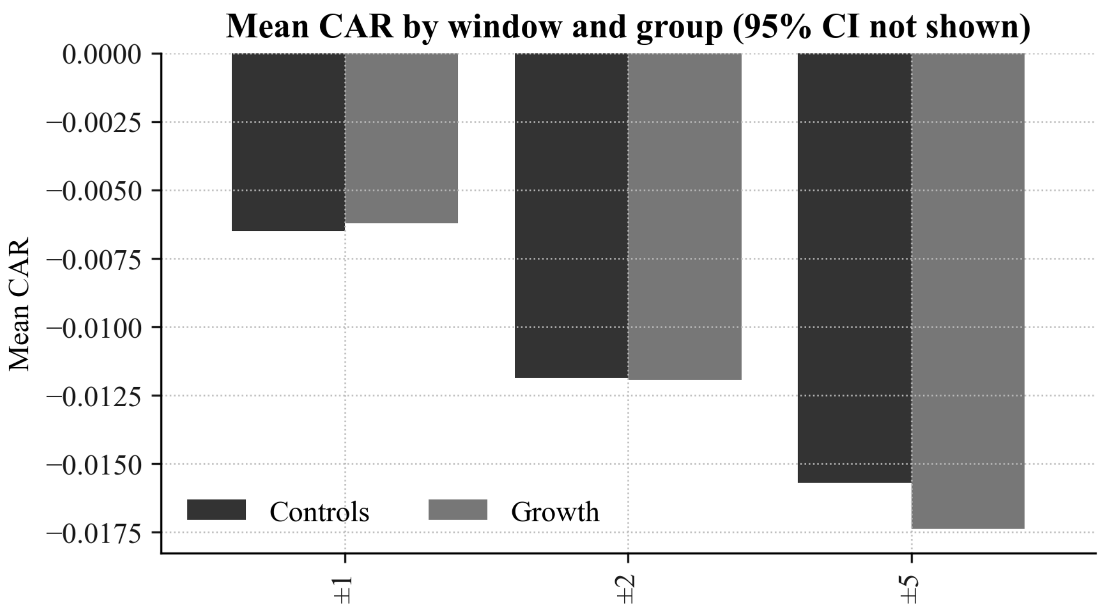

Figure 10: Average CARs by Observation Window and Sample

Figure 10 formally outlines some conclusions drawn from the cross-event time series, namely, that, on average, the *growth* portfolio experiences stronger mispricing. Interestingly, in the immediate period following/proceeding a policy shock, the *control* sample reacts more strongly but this relationship is reversed, as the observation window increases, and the biggest gap between abnormal returns manifests in the longest (±5 days) within-event observation period.

4.4.1.2. Statistical Significance of Signed Results

window	*n_growth*	*n_ctrl*	*mean_growth*	*mean_ctrl*	*t_stat*	*p_value*	*cohens_d*	*Significance Level*
+/-1	17514	15962	-0,6213%	-0,6489%	0,3440	0,7308	0,0037	***n.s.***
+/-2	17518	15967	-1,1950%	-1,1864%	-0,0835	0,9334	-0,0009	***n.s.***
+/-5	17520	15976	-1,7390%	-1,5691%	-1,4417	0,1494	-0,0156	***n.s.***

Figure 11: Mean Statistic Significance Table

The above table is used to summarise the statistical significance of the results presented on the mispricing direction and magnitude. Mean analysis, conducted above, shall be disregarded here. The *t-statistic* measures how many standard errors apart the means of the two sample groups are. The *p value* is the probability that the data above occurred via random chance under the null hypothesis, while *Cohen's d* measures the magnitude of the difference between the means. The three measures provide the statistical backbone of the analysis (Wooldridge, 2010).

Unfortunately, the results appear to be statistically insignificant. Further, the observation count reinforces this notion, as typically with large samples, Deaton & Cartwright (2018) show that even small differences in results would show up as statistically significant – the fact that it does not here adds to the interpretation of real-world insignificance. The *t-stat* confirms that estimated differences between the two groups are practically non-existent. At a 5% confidence level, the rule of thumb is $|t| > 1{,}96$ to confirm significance (Wooldridge, 2010), yet here, none of the values are close to this level. Further, for the two shorter windows, the difference is small, even relative to the miniscule standard error. The *p-value* confirms – in fact, it is so large for the shorter windows that there is essentially no evidence of statistical significance between the difference of both means. Overall, any difference in reaction is statistically zero and indistinguishable from general noise. The likely cause is that positive and negative reactions offset each other to the point that, even if reactions are large, they average out and become statistically flat (Andersen, Bollerslev, Diebold & Vega, 2007).

The *Cohen's d* adds an additional layer by showing the economic insignificance of the results, meaning, even if they had been statistically significant, their economic impact would regardless be negligible (Harvey, Liu & Zhu, 2016). The sign change, as the observation window expands, offers little-to-no meaningful information, as the values are practically zero, from a statistical standpoint.

There can be multiple underlying factors that reduce the significance of type classification on mispricing around shocks. Namely, it is likely that, due to the sheer size of this specific tightening cycle, systematic repricing dominated firm-sensitivity. Andersen et al. (2007) posits that the equity market reaction to monetary policy shocks exhibit differences based on characteristics immediately after the shock (minutes, sometimes hours) but, as the information diffuses, markets price the risk in systemically. A possible extension of this paper would be adjusting the observation-windows to intra-day lengths to capture said mechanism.

Additionally, it may be the case that classification affects reaction strength, and not necessarily direction. This means that the magnitude of mispricing may be significantly different, even if signed CARs are not – this test does not contradict the behavioural implications outlined in the hypothesis but helps suggest that they may manifest as volatility amplification, rather than directional mispricing. We examine this possibility in the following section. Further, sentiment may dominate channels over a longer term. Barberis et al. (1998) suggests that investors update their beliefs slowly, rather than instantaneously, therefore, a divergence in stock price from a behavioural perspective may be more significant over longer windows. Therein lies the delicate balance of observing this mechanism, while trying to limit noise. All in all, the results remain meaningful, even if statistically insignificant, as it contributes to existing literature by showing that not all macroeconomic shocks produce cross-sectional divergence in over/underreaction, given extreme overall uncertainty in the market.

4.4.2. Absolute Cumulative Abnormal Returns

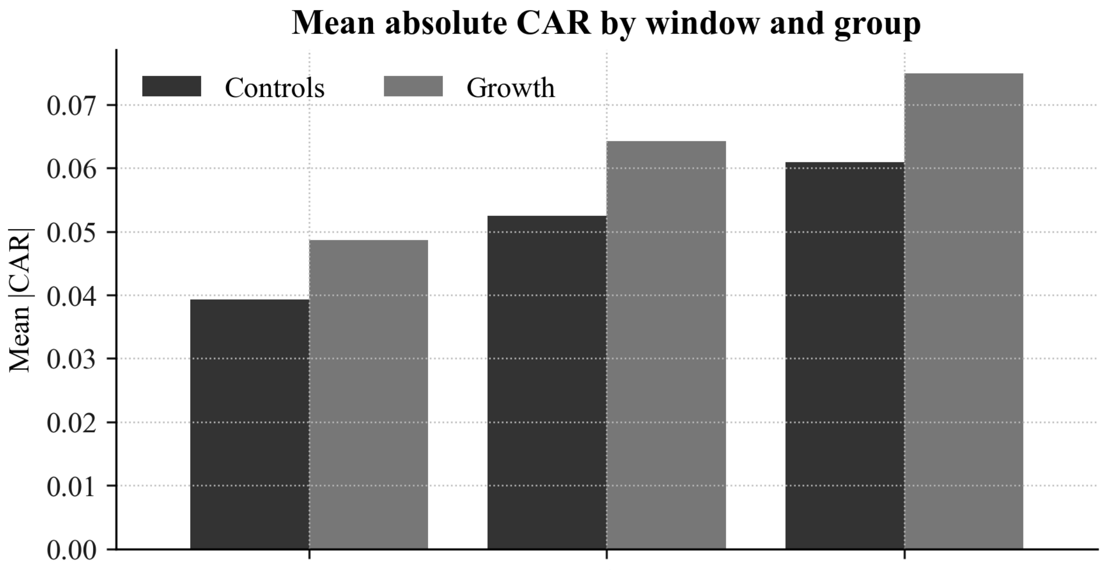

Figure 12: Average Mean Absolute CARs by Sample

Absolute values allow for the dissertation of mispricing by each group regardless of direction. Although the event period can be generally classified as a downward pressure on market prices, the contradictory events cannot be disregarded. Barberis et al. (1998) posits that a negative policy shock may result in an immediate drop in equity prices below what theory suggests but the positive *rebound* after the fact can offer insight as well.

Across the board, the *growth* sample exhibits systematically higher absolute CARs, suggesting that *growth* equities experience stronger revaluation pressure than *value* stocks. This observation is in line with generally accepted mechanisms, notably, that *growth* stocks, more existentially dependant on cash flows far off in the future, present uncertainty in the minds of investors (Lettau & Wachter, 2007). Thus, it follows that a market shock of any kind would more severely impact these types of equities when compared to stable, dividend-paying companies. Accordingly, the gap between overall mispricing between the two groups widens, as the observation window is expanded. While it is a straightforward process to revalue fundamentals, effectively providing a mathematically justified change in the market capitalisation of a *value* stock, most *growth* equities, especially since the start of the AI epidemic, rely on concepts like narrative and sentiment as a benchmark of their value (Barberis, Greenwood, Jin & Shleifer, 2015). Therefore, the information provided by a shock from the central bank has a prolonged diffusion period in *growth* stock prices, mostly due to the slower updating of beliefs, as opposed to a change in financial metrics.

4.4.2.2. Statistical Significance of Absolute Results

window	n_growth	n_value	t_stat	p_value	cohen_d	ci_low_diff	ci_high_diff	Significance Level
+/-1	17514	15962	14,3394	0,0000	0,1557	0,0080	0,0106	***
+/-2	17518	15967	14,5601	0,0000	0,1580	0,0102	0,0134	***
+/-5	17520	15976	14,9682	0,0000	0,1621	0,0121	0,0158	***

Figure 13: Abnormal Mean Significance Results

The statistics for absolute abnormal returns present a completely different picture than those, which describe signed values. Both the t-stat and p-value confirm with overwhelming confidence that the difference in absolute CARs between growth and value are not due to random sampling and are statistically significant. This implies that growth CARs experience systemically stronger mispricing, as opposed to value CARs. Further, Cohen's D remains small, however, in the context of our thesis (and the broader science) the effect could be non-trivial due to values being expressed in %, where even small values can have implications on large volumes (Fama & French, 1993).

4.5. Real-World Implications of Significance Results

The combination of statistically insignificant results for signed outputs, while the absolute values remain extremely significant creates a holistic environment for combined analysis. The FOMC signals do not consistently push growth/value firms' prices up or down – this varies by individual firms/sectors/fundamentals, etc. However, growth firms consistently react more strongly, regardless of the implied direction of the shock – consistent with our theoretical foundation and anchor papers.

These results have material real-world implications for firms, policymakers, and money managers, mainly due to the inference we can make on the effect of policy signals on volatility. First, while average returns might be indifferent between the two portfolios, growth-oriented portfolios are more exposed to macroeconomic volatility, especially around shocks, such as this one – a claim supported by evidence from Barroso & Santa-Clara (2015). This has massive implications for how fund managers approach and implement their risk strategy, especially for fund's who operate under volatility targets, and risk-parity strategies. Even if long-run returns are unaffected, an assessment of risk capital allocation needs to be made to avoid unwanted short-term volatility. Additionally, the correlation of growth stocks with other assets becomes unstable under this narrative (Adrian & Brunnermeier, 2016), this being relevant for multi-asset funds and sovereign funds, whose models rely on maintaining a stable and uniform cross-asset volatility level.

Secondly, the findings posit that growth equities are affected by policy shocks through volatility, not direction, directly tying into the mechanism outlined by Jarocinski & Karadi (2020), where they outline how the two types of shocks contained in a central bank signal (a MP shock and a CBI shock) can have opposite effects on prices, suggesting information disagreement, and a divergence in decision-making among investors. This mechanism has material consequences for policymakers and financial regulators, as it can allow for a more accurate inference of the consequences of different decisions. Thirdly, growth stocks are positioned to be attractive investments around policy decisions. Nakamura & Steinsson (2015) posit that, since real-world policy shocks are not entirely sudden (FOMC meetings are known beforehand), volatility/short-term traders can position themselves in growth stocks around these decisions, as a large shift (as seen here) can be immensely profitable (Lucca & Moench, 2015). Obviously, the risk of predicting a wrong signal remains, although empirical evidence from Barber, Huang & Odean (2021) shows that retail investors have, on aggregate, increased their predictive power of such events. Further, liquidity providers face higher risk around such shocks, as there exists a higher degree of price misallocations and larger bid-ask spread adjustments, causing liquidity to deteriorate sharply around shocks, increasing transaction costs (Fleming & Piazzesi, 2005).

4.6. Sentiment as an Explanatory Variable

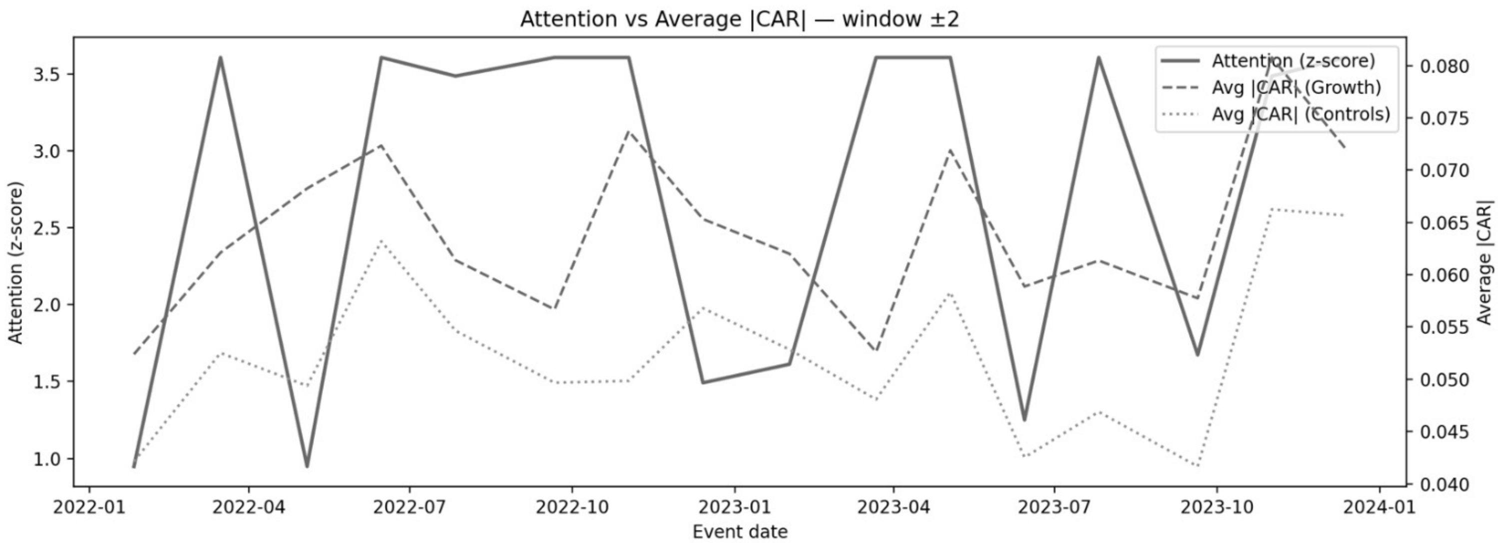

Figure 14: Time-Series of Investor Sentiment and absolute CARs (2-Day Observation Window)

window	group	beta_attention	SE_attention	p_value	R_squared	N_obs	Significance Level
±1	Growth	0.0014	0.0015	0.3822	0.0550	16	n.s.
±1	Controls	0.0018	0.0015	0.2442	0.0955	16	n.s.
±2	Growth	0.0024	0.0018	0.1939	0.1174	16	n.s.
±2	Controls	0.0035	0.0016	0.0445	0.2582	16	**
±5	Growth	0.0017	0.0025	0.4965	0.0336	16	n.s.
±5	Controls	0.0033	0.0018	0.0956	0.1857	16	*

Figure 15: Statistical Significance of Investor Sentiment on absolute Abnormal Returns

Outputs demonstrate no significant relationship between signed aggregate CAR values and sentiment. However, when assessing absolute aggregate CAR values, there is a single significant relationship at p-value: 0.0445. Interestingly, this refers to the controls at a ±2-day window. The results indicate that we can only accept $H_2$for controls at the ±2-day window of the FOMC announcements at a 95% confidence level, and with a beta of 0.0035. Hence, a one standard deviation increase in investor sentiment for the topic "interest rate" predicts an increase in CAR magnitude by 0.35%. A diagnostic conducted (Figure 18) solidifies this relationship, where a permutation test with 10000 permuted series shows that only 4.55% of events show an observed beta of 0.0035 or higher. This result mimics the general findings in Preis et al. (2013), where sentiment does act as a predictor for amplifying volatility in the short run. The behavioural nature of the mispricing both increasing and decreasing throughout the duration of the event study does not indicate purely pessimism about firm valuation, but rather reflects investor uncertainty, which is confirmed by the control group at the ±2-day window.

Apart from this significant relationship, we cannot reject the null hypothesis (H_{02}) at any other independent variable configuration. Since our results do not present any significant relationship between the growth portfolio and sentiment, we cannot reject the null hypothesis (H_{03}) at the interaction level, meaning we cannot prove whether the chosen growth portfolio has a stronger relationship with sentiment than the control portfolio. Additionally, the signed CAR results do not indicate that the growth group has a more negative relationship with sentiment than the control group, despite confirming that growth stocks are systematically more mispriced in absolute terms.

This contrasts the findings in Da et al. (2011), where the paper reports stronger and consistent findings of correlation between abnormal sentiment and firm-level returns. However, this is likely due to using the SVI to capture idiosyncratic movements which are firm specific, rather than investigating macro-level attention on an aggregate firm-level. Macro attention to the topic "interest rate" isn't investor specific and is prone to attention from a broader non-investor audience, weakening the cross-sectional relationship between sentiment and abnormal returns. This is illustrated in Boguth et al. (2019), where they present significant findings pertaining to macro-level shocks on the aggregate market. The difference in our methods likely explains the divergence in findings, where the paper used a "Michigan consumer sentiment" survey rather than SVI. The survey was directly administered to their sample and thus did not encounter the level of noise macro-SVI contains. This difference, along with the use of specifically monetary policy "surprises" may have led to their results having stronger significance than ours. We instead opted for the analysis of all macro-signals during our chosen period, which may have led to confounding announcements, where some signals mattered more, and were more predictable than others.

Furthermore, papers examining the growth-value firm relationships find that growth firms do react stronger to monetary policy shocks due to their duration risk (Barberis et al., 1998). While our results are congruent with these papers, the sentiment analysis extension, and the lack of findings, particularly for growth stock sensitivity to sentiment could be explained by the following. A recent body of research has shown that during periods of macroeconomic turbulence (characterized by sudden and meaningful monetary policy shocks), abnormal returns are fundamentally driven by the macro shocks themselves due to stronger uncertainty and adaptation to inflation expectations (Jarocinski et al., 2020). Hence, during periods, such as we observe here, fundamentals drown out any significant relationship between sentiment and CARs. Our chosen period of analysis (2022-2023) presents strong macroeconomic instability primarily due to inflation post-covid, leading to the unexpected tightening cycle. The aforementioned paper then helps justify the insignificance of our findings.

Overall, the analysis finds that the link between sentiment and CARs is insignificant, apart from the ±2-day observation window. The main limitations to the method are the low frequency and scheduled nature of FOMC announcements, as argued by Lucca et al (2015), outlining how announcement acts as its own quasi-exogenous shock experiment. The high noise during the tightening cycle, characterized by a turbulent period, presents further difficulty to find a significant relationship between sentiment and CARs. Finally, portfolio aggregation may mask firm-level heterogeneity. Da et al. (2011) attained consistently significant findings at the firm-level, where our method aggregated the firms into two segments instead. This is not necessarily a limitation, but rather a finding that sentiment and abnormal returns may be a more firm-specific relationship, and that firms respond differently to sentiment leading to insignificant relationships at an aggregate level.

5. DIAGNOSTICS

window	n_growth	n_controls	true_mean_g	true_mean_c	true_diff	perm_mean_diff	perm_sd_diff	p_two_sided
+/-1	17514	15962	-0,0062	-0,0065	0,0003	0,0000	0,0008	0,7271
+/-2	17518	15967	-0,0119	-0,0119	-0,0001	0,0000	0,0010	0,9359
+/-5	17520	15976	-0,0174	-0,0157	-0,0017	0,0000	0,0012	0,1548

Figure 16: Sample Classification Permutation Test

A permutation test is a non-parametric robustness check of the difference in baseline means of both groups (Fisher, 1935). Essentially, if there exists no meaningful difference between the CARs of both groups, then, whether each observation being labelled is trivial. The test, therefore, randomly assigns the group-type labels, while leaving the underlying results the same – it then recalculates the difference in means, as specified in Barber, Jin & Liu (2021). The shuffle is done for thousands of times (here, 20 000) and generates a distribution of differences that arise purely from chance. The observed difference is compared to said distribution, and, if there is a significant difference between the results, a meaningful difference between the CARs of both samples can be concluded.

The results indicate that the differences observed between the two samples arise due to chance. Across all three event windows, the two-sided p-values are extremely high, implying that randomly assigned groups frequently produce mean differences of equal or greater magnitude. The findings compliment the earlier t-test by showing that the insignificance of the results is not a product of normality or model specification. This adds strength to the point that firm classification itself is not a driver of difference between abnormal returns. The differences, therefore, could be explained by other factors, such as the event period or the CAR properties themselves.

window_pre	n_events_used	mean_diff_g_minus_c	sd_diff	t_stat	p_two_sided
[-20,-5]	16	-0,0007	0,0013	-2,1045	0,0526

Figure 17: Pre-Event Balance Test

The pre-event balance test, as defined in MacKinlay (1997), looks at the differences between the two samples in the period preceding the event (from -20 to -5 days). Over this period, the average abnormal return for each group is calculated and differences are compared, then pooled. The test highlights any trends or pre-event drifts that occur before an event that could be used to explain the observed differences in CARs during the event (Kothari & Warner, 2007).

There is a slight difference in mean abnormal returns observed, with the growth portfolio performing slightly worse than its value counterpart, although this difference is extremely small, almost negligible. The corresponding t-stat and p-value imply weak significance at the 10% but not the 5% level (Kim & Ji, 2015). Overall, the observed differences are too small to account for the significant event drift observed between the samples, indicating that the observed events do cause volatile repricing and suggest that the divergence of CARs could be attributable to monetary policy shocks.

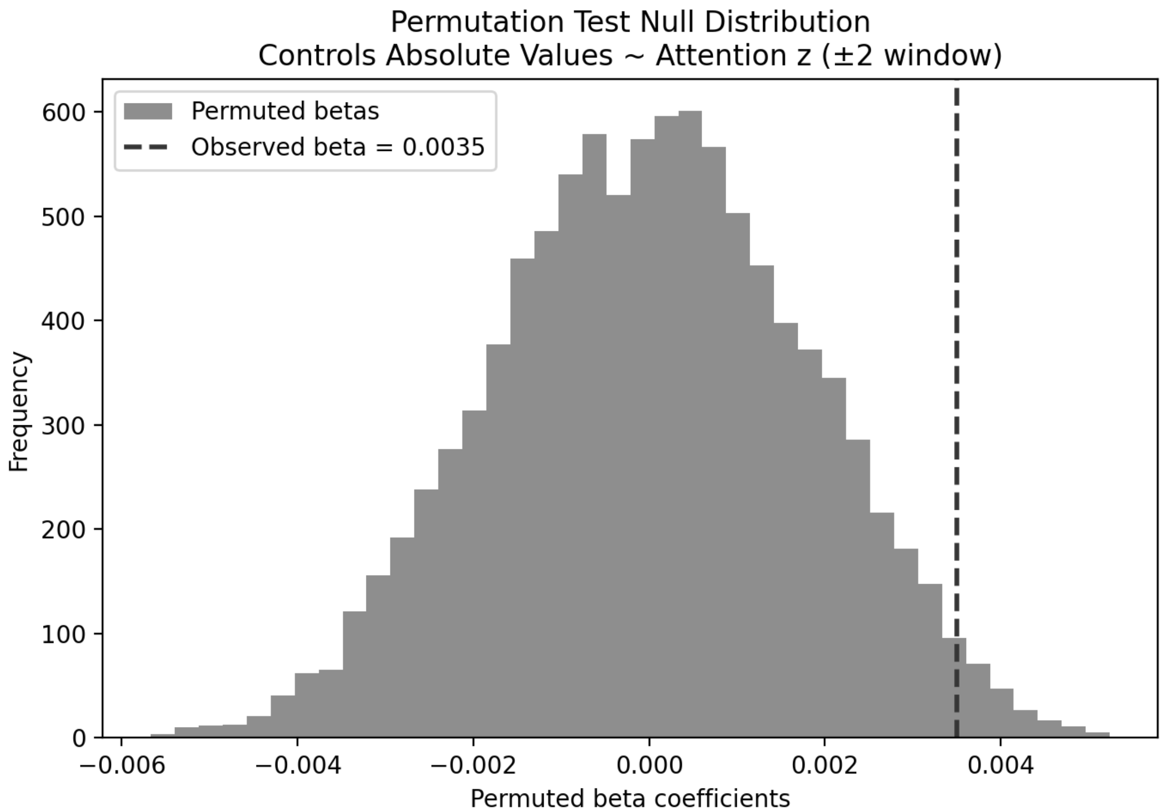

Figure 18: Permutation test estimating the slope of the control groups absolute CAR on investor sentiment at +/-2 day window from FOMC announcements. The distribution contains 10000 randomized permutations to check the robustness of the significant result.

The placebo permutation test visualized in figure 18, provides additional robustness for the significant result of the control group at the $\pm$2-day window from the sentiment analysis. The relationship's significance is robust and unlikely to be due to noise in the sample data. The test confirms the significance of the observed beta (0.0035), meaning a single standard deviation increase in sentiment corresponds to a 0.35% CAR increase for $\pm$2-day window control group. The initial analysis provided a p-value of 0.0445, and the permutation test solidified the relationship with a new p-value of 0.0455. Hence, only 4.55% of permuted coefficients at random were above the observed beta, making the result unlikely due to chance or noise.

6. Conclusion

This paper examined how U.S. monetary policy affects market equity mispricing and whether investor sentiment has any correlation or amplifies the impact of the MP changes through the scope of growth and value stocks. We chose to conduct this study through the tightening cycle in the years 2022-2023, as this period was characterized by numerous unexpected MP shocks. Hence, it was interesting to look into this period and study the behavioural effects on investors, given the nature of macroeconomic instability during this time. Initially, CARs for both growth and value firms were produced on an aggregate level and showed that growth stocks were consistently more mispriced in absolute terms than value stocks around FOMC announcements, enabling the rejection of the null hypothesis H_{01} in absolute terms. However, no significant results were found for the conventional signed analysis of CARs, indicating that although mispricing was higher for growth stocks, it is unclear whether the mispricing is generally more positive or negative. Thus, the takeaway from H_1 appears to be that the volatility of mispricing is stronger for growth firms.

The second part of the paper examines the effect of sentiment on these CARs, using the proxy topic "interest rate" from Google Trends around the FOMC announcement dates. Analysis shows one significant result for the control firms at a $\pm$2-day window. This was later scrutinized with a permutation test that confirmed the significance of the result, demonstrating a small positive amplification of control firms in relation to investor sentiment. This resulted in a partial rejection of H_{02} only for the aforementioned conditions, while the rest of the results for both controls and growth firms had insignificant relationships with sentiment. Furthermore, given the insignificance of the results we were unable to reject the null hypothesis H_{03} meaning we have no evidence that growth firms are more sensitive to sentiment than controls. These findings are in line with Jarocinski et al. (2020), where it is evident that during the turbulent macroeconomic period of 2022-2023, mispricing was more reflective of the fundamental MP changes rather than behavioural channels. Essentially, powerful economic fluctuations overshadowed our sentiment analysis, revealing only partial evidence of mispricing driven by sentiment.

Despite the limitations of the study mentioned in the paper, this thesis makes several contributions. The empirical verification of growth stocks being systematically more mispriced than value stocks in the scope of monetary policy fluctuations extends literature analysing B/M value, such as Fama & French (1992). The extension to behavioural mechanisms bridges empirical monetary policy research with behavioural theory by Barberis et al. (1998), demonstrating investor sentiment interactions with policy shocks in a cross-sectional event study. In sum, while the results to H2 and H3 provide little evidence of sentiment driven amplification for growth stocks, there is still a relationship between controls and sentiment which solidifies the behavioural mechanism studied even during turbulent macroeconomic conditions. This study demonstrates the potential and limitations of using Google Trends as a measure of investor sentiment, as well as the overall complexity of monetary policy interactions with behavioural theories during a high instability period.

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Appendix

Factor	Abbreviation	Definition	Economic Interpretation
Market	*Mkt*	Market portfolio return minus the risk-free rate	Captures broad market risk
Size	*Smb*	Return of small-cap portfolios minus large-cap portfolios	Measures the *size premium*
Value	*Hml*	Return of high B/M (value) firms minus low B/M (growth) firms	Distinguishes value from growth orientation
Profitability	*Rmw*	Return of firms with robust profitability minus weak profitability	Reflects the profitability premium
Investment	*Cma*	Return of firms with a conservative investment minus aggressive investment style	Indicates investment discipline

Figure 19: FF5 Model Terms and Their Definition

Mathematical Interpretation of the Model:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_i + h_i HML_i + r_i RMW_i + c_i CMA_i + e_{it} \quad (5)$$

Fundamental	Name, as presented in Compustat	Definition
Total Assets (quarterly)	*atq*	Sum of all assets owned by the firm
Common/Ordinary Equity (quarterly)	*ceqq*	Shareholders' equity attributable to common stockholders
Cash (quarterly)	*chq*	Cash and cash equivalents available to the firm
Common Shares Outstanding (quarterly)	*cshoq*	Number of common shares currently issued and held by investors
Depreciation and Amortization (quaterly)	*dpq*	Non-cash expense reducing asset book values over time
Earnings per Share - Excluding Extraordinary Items (quarterly)	*epspxq*	Profit per share from normal operations, excluding unusual gains/losses
Income Before Extraordinary Items (quarterly)	*ibq*	Net income from ongoing operations before exceptional items
Liabilities Total (quarterly)	*ltq*	Total obligations owed to creditors
Net Income (quarterly)	*niq*	Bottom-line profit after all expenses, taxes, and interest
Operating Income After Depreciation (quarterly)	*oiadpq*	Earnings from core operations after depreciation and amortisation
Net Sales (quarterly)	*saleq*	Revenue from goods and services, net of returns and discounts
Research and Development Expense (quarterly)	*xrdq*	Spending on product and technology innovation
Capital Expenditures (yearly)	*capxy*	Funds used to acquire or upgrade fixed assets
Price Close (quarter)	*prccq*	Market closing price of the firm's stock at quarter-end

Figure 20: Firm Information Pulled from WRDS, and Interpretation

Variable	**Formula**	**Definition**
Size	$\ln{(prccq \times cshoq)}$	Natural logarithm of market capitalisation
Book-to-Market Ratio	$\frac{ceq}{(prccq \times cshoq)}$	Ratio of book value of equity to market capitalisation
Leverage	$\frac{ltq}{atq}$	Total liabilities divided by total assets
Profitability	$\frac{oibdp}{atq}$	Operating income (loss) scaled by total assets
Cash	$\frac{cheq}{atq}$	Cash and cash equivalents divided by total assets
Investment	$\frac{capxy}{atq\_lag)}$	Capital expenditures relative to lagged assets

Figure 21: Firm Fundamentals, used as Control Variables. Formulas for calculating them

$$Attention_t = \frac{SVI_t - \mu_{22-23}}{\sigma_{22-23}} \quad (6)$$

$$\mu_{22-23} = \frac{1}{T} \sum_{t \epsilon 2022-2023}^{t} SVI_t \quad (7)$$

$$\sigma_{22-23} = \sqrt{\frac{1}{T-1} \sum_{t \epsilon 2022-2023}^{t} (SVI_t - \mu_{22-23})^2} \quad (8)$$

Preis et al. (2013) for equations 6, 7, 8.

event_date	*event_description*	*group*	*avg_car*
26/01/2022	FOMC policy decision (start-of-year stance, pre-hike cycle)	**Controls**	**0,4121%**
26/01/2022		Growth	0,1938%
16/03/2022	FOMC policy decision; first 25 bp hike begins tightening cycle	**Controls**	**1,0344%**
16/03/2022		Growth	1,0017%
04/05/2022	FOMC policy decision; continued hikes and guidance	**Controls**	**-1,1321%**
04/05/2022		Growth	-0,9702%
15/06/2022	FOMC policy decision; first 75 bp hike (major shock)	Controls	0,0918%
15/06/2022		**Growth**	**0,1732%**
27/07/2022	FOMC policy decision; large hike, guidance watched	Controls	-0,0188%
27/07/2022		**Growth**	**-1,5555%**
21/09/2022	FOMC policy decision; hawkish stance ('higher for longer') building	Controls	-1,7778%
21/09/2022		**Growth**	**-3,0302%**
02/11/2022	FOMC policy decision; fourth straight 75 bp hike	**Controls**	**-0,8827%**
02/11/2022		Growth	-0,2662%
14/12/2022	FOMC policy decision; 'higher for longer' message emphasized	**Controls**	**-2,3713%**
14/12/2022		Growth	-2,0965%
01/02/2023	FOMC policy decision; ongoing tightening cycle	Controls	-1,4346%
01/02/2023		**Growth**	**-1,5662%**
22/03/2023	FOMC policy decision amid banking stress; guidance crucial	Controls	-2,6320%
22/03/2023		**Growth**	**-2,7375%**
03/05/2023	FOMC policy decision; terminal rate debate intensifies	**Controls**	**-3,4529%**
03/05/2023		Growth	-1,6836%
14/06/2023	FOMC policy decision; pause/skip discussion and dot-plot focus	Controls	-1,3105%
14/06/2023		**Growth**	**-2,1332%**
26/07/2023	FOMC policy decision; potential final hikes and guidance	Controls	-2,5883%
26/07/2023		**Growth**	**-3,6602%**
20/09/2023	FOMC policy decision; 'higher for longer' expectations assessed	Controls	-2,1255%
20/09/2023		**Growth**	**-4,1535%**
01/11/2023	FOMC policy decision; policy path and growth/inflation outlook	**Controls**	**-3,7740%**
01/11/2023		Growth	-2,9747%
13/12/2023	FOMC policy decision; year-end guidance and dot-plot	**Controls**	**-3,8549%**
13/12/2023		Growth	-2,9262%

Figure 22: Policy Shocks, and Corresponding Average Cumulative Abnormal Returns by Sample

AI Appendix

Generative AI (ChatGPT) was used for help with coding errors.