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Effects of interest rate changes on the performance of technology stocks in the COVID-19 era – an event study

Master's thesis

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Declaration of Authorship

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Abstract

This thesis examines the impact of interest rate changes on the stock performance of technology firms during the COVID-19 era, using an event study methodology. The research investigates the sensitivity of technology stocks, particularly those with high leverage, to monetary policy adjustments - particularly in regard to changes in Fed Funds Effective Rate and Fed Funds Rate Futures. The study finds that technology firms in the NASDAQ 100 have on average higher returns around a change in interest rates than the broader market. The study also finds that stocks with higher leverage and price to book ratio react more negatively to changes in interest rates than other firms.

JEL Classification	C10, C12, F21, G14, L25, M2, O16
Keywords	Interest rates, Technology Stocks, Event Study, COVID-19, Fed Fund Rates
Title	Effects of interest rate changes on the performance of technology stocks in the COVID-19 era – an event study

Abstrakt

Tato práce zkoumá vliv změn úrokových sazeb na výkonnost akcií technologických firem během období COVID-19 pomocí metodologie studie události. Výzkum zkoumá citlivost technologických akcií, zejména těch s vysokou finanční pákou, na úpravy měnové politiky - zejména s ohledem na změny efektivní sazby Fed Funds a Fed Funds Rate Futures. Studie zjišťuje, že technologické firmy v NASDAQ 100 mají v průměru vyšší výnosy kolem změny úrokových sazeb než širší trh. Studie také zjišťuje, že akcie s vyšší finanční pákou a poměrem ceny k účetní hodnotě reagují na změny úrokových sazeb negativněji než ostatní firmy.

JEL Klasifikace	C10, C12, F21, G14, L25, M2, O16
Klíčová slova	Úroková míra, Technologické Akcie, Studie Události, COVID-19, Fed Fund Rates
Název	Účinky změn úrokových sazeb na výkonnost technologických akcií v době pandemie COVID-19 – studie události

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Acronyms

DCF Discounted Cash Flow

CAPM Capital Asset Pricing Model

APT Arbitrage Pricing Theory

WACC average Cost of Capital

IV Instrumental variables

GMM Generalized Method of Moments

VAR Vector Autoregressive

FFR Federal Funds Rate

FFeR Federal Funds Effective Rate

FFRF Federal Funds Rate Futures

AR Abnormal Return

CAR Cumulative Abnormal Returns

FOMC Federal Open Market Committee

NDX NASDAQ 100

SPY S&P 500

Chapter 1

Introduction

On the 11th of March 2020, the World Health Organization officially declared COVID-19 a global pandemic, marking the beginning of a period characterized by widespread societal upheaval (WHO 2020). This unprecedented health crisis, which has claimed approximately 6.9 million lives worldwide (WHO 2023), instigated a series of comprehensive government interventions. To curb the spread of the virus, governments globally implemented stringent lock-downs and social distancing measures, inadvertently triggering a cascade of economic repercussions. The economic effects of lock-downs have been significant, with immediate and dramatic impacts on various activities and aggregate output Chen *et al.* (2020). These effects have spilled over into adjacent economies, resulting in a shift in the regional economic landscape (Dyason *et al.* 2021). However, while the effects of the lockdown have been significant, they are generally proportional to the population affected (Asahi *et al.* 2021). Additionally, not all sectors of the economy were impacted equally. A study by He *et al.* (2020) found that mining, electric and heating, and environmental industries were negatively affected, whereas manufacturing, information technology, education, and health industries responded positively. Parsoya & Perwej (2021) identified education (EdTech), e-retail, banking, financial services, insurance, medical, and information technology as industries that benefited from the pandemic. Narayan *et al.* (2022) further found that health, information technology and consumer staples were among sectors that also benefited. Whilst Ishak *et al.* (2021) highlighted the negative impact on cyclical industries such as tourism, airlines, restaurants, and transportation. But even though some industries benefited, such as the technology industry, the overall consensus is that COVID-19 has had a significant negative impact on the economy. When observing the stock market, which can serve as a proxy for the economy as a whole (Krchniva 2016; Laopodis & Papastamou 2016), it can be observed that COVID had negative effects on both the returns and volatility. Apergis & Apergis (2020) and (Zhang *et al.* 2020) each found that increases in COVID-19 cases were associated with lower stock returns, with Apergis also noting an increase in volatility. Chatjuthamard *et al.* (2021) further supported this, finding that an increase in confirmed cases led to higher volatility and lower returns as did the finding by Curto & Serrasqueiro (2022). Khatatbeh *et al.* (2020) also found a significant negative impact on stock market returns following the announcement of the first confirmed COVID-19 case and the declaration of a global pandemic. Governments thus tried various measures to boost the economy and the stock market. Narayan *et al.* (2021; 2022) explored the effects of these policies on the stock market and found that "lock-downs, travel bans, and economic stimulus packages all had a positive effect on the G7 stock markets". This means that while the lock-downs had a negative impact on the economy as a whole , they did boost investor confidence in the ability of governments to manage the crisis. Capelle-Blancard & Desroziers (2020) further show that "credit facilities and government guarantees, lower policy interest rates, and lockdown measures mitigated the decline in domestic stock prices". **?** expanded on their findings by focusing on which financiers found that the stock market was more significantly affected than the bond market, with fiscal policy responses having a more positive effect on the former and monetary policy responses on the latter. As expected the monetary policy of low interest rates thus had stimulating effects on the stock market and on the economy as a whole (**?**Blanchard 2019; Lian *et al.* 2019). With the stimulus packages and lowering interest rates it is crucial to also consider the broader economic implications of these policies. One key aspect, often intertwined with expansive monetary strategies, is inflation - a phenomenon that can significantly alter the economic landscape and influence long-term investment decisions. Generous fiscal support has increased demand for consumption goods, while industrial production has struggled to keep up, leading to a demand-supply imbalance (Soyres *et al.* 2022). This imbalance has been further exacerbated by changes in consumer expenditure patterns, with increased spending on food and other categories with rising inflation (Cavallo 2020). Additionally upward pressure on prices was generated by disrupted supply chains as noted by Giovanni *et al.* (2022) and Santacreu & LaBelle (2022), although once again they showed that industries such as manufacturing were more affected than those like services. On the other hand, it's important to note that the pandemic has also caused a significant drop in consumer demand, which has had a larger impact on inflation than supply constraints, pushing inflation down (Shapiro 2020). Eldomiaty *et al.* (2020) then show the negative effects of inflation on the stock prices and their volatility. Since March 2022, the Federal Reserve has executed a series of interest rate hikes, totaling 11 adjustments, signaling a substantial shift in monetary policy in the post-COVID-19 era. These hikes mark a departure from the low-interest environment that characterized much of the pandemic's economic response. While the broad effects of interest rate fluctuations on the economy and stock markets have been extensively studied in the past (Gunardi *et al.* 2023; Alzoubi 2022; Lobo 2000; Bernanke & Kuttner 2005), the specific implications of these recent increases (past 2020), particularly in the context of a recovering global economy from the COVID-19 pandemic, remain less explored. A study by Kim (2023) sheds light on how these interest rate hikes impacted firms in Korea, revealing a trend where investors gravitated towards companies with higher exports, greater foreign ownership, and larger sizes, indicating a preference for 'quality' firms in times of financial uncertainty. This behavior underscores the resilience of certain firms to monetary policy changes in the U.S. However, the focus on Korean companies leaves a knowledge gap regarding the impact on U.S.-based firms, especially within the technology sector. The technology sector, as highlighted in previous studies (He *et al.* 2020), has not only withstood the economic turmoil of the pandemic but has also emerged as a dominant force in the stock market. In 2023, a mere seven technology companies contributed to over 110% of the total returns of the S&P 500 (Lewis *et al.* 2023), with five companies alone accounting for a quarter of the S&P 500's value (Pisani 2023). This concentration of market power within a handful of technology firms raises questions about their susceptibility or resilience to the recent interest rate hikes, particularly as these rates reach levels not seen in two decades. This research paper seeks to explore the nuanced and complex dynamics of how technology firms, a sector characterized by rapid growth, innovation, and significant market influence, respond to the challenges posed by the Federal Reserve's monetary policy shifts. By analyzing the interplay between interest rate hikes and technology firms' stock' performance, this study aims to contribute to a deeper understanding of sector-specific responses in the face of macroeconomic changes. This understanding is essential not only for investors and policymakers but also for comprehending the broader economic trajectory in a post-pandemic world.

Chapter 2

Theoretical Background

2.1 Valuation Theory

The relationship between interest rates and stock valuations is fundamental in financial theory and practice. This section delves into key theoretical frameworks that elucidate this relationship, focusing on the Discounted Cash Flow (DCF) model, the Capital Asset Pricing Model (CAPM), and the Arbitrage Pricing Theory (APT).

2.1.1 Discounted Cash Flow Model

DCF model is a cornerstone of valuation theory, premised on the idea that the value of an asset is the present value of its expected future cash flows. Interest rates play a crucial role in this model as they are used to discount future cash flows to their present value. When interest rates rise, the discount rate increases, leading to a lower present value of future cash flows, and consequently, a lower stock valuation. Conversely, when interest rates fall, the discount rate decreases, resulting in a higher present value of future cash flows and a higher stock valuation (Damodaran 2012). The mathematical representation of the DCF model is:

$$PV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t}$$

Where PV is the present value, CF_t represents the cash flow at time t, and r is the discount rate/Cost of capital, often influenced by the prevailing interest rates.

Interest Rates and Cost of Capital

Company's cost of capital is the rate of return required to make a capital budgeting project, such as building a new factory or investing in a new company, worthwhile. The cost of capital consists of the cost of equity and the cost of debt, both of which are influenced by changes in interest rates.

Cost of Equity The cost of equity represents the return that investors require for investing in a company's equity. It is influenced by the risk-free rate, which is typically proxied by government bond yields. As interest rates rise, the risk-free rate increases, leading to a higher cost of equity. This relationship is articulated in the CAPM (formula in the next section). An increase in R_f raises $E(R_i)$, as investors demand higher returns to compensate for the increased risk-free rate. This, in turn, elevates the overall cost of equity capital for firms, making equity financing more expensive.

Cost of Debt The cost of debt refers to the effective rate that a company pays on its borrowed funds. It is directly influenced by market interest rates. When interest rates rise, the cost of borrowing increases, resulting in higher interest expenses for firms with existing variable-rate debt or new debt issuance. The cost of debt can be expressed as:

$$R_d = R_f + credit\ spread$$

Where R_d is the cost of debt, R_f is the risk-free rate, and the credit spread reflects the additional risk premium required by lenders (Damodaran 2012). Rising interest rates increase R_f , leading to higher R_d.

Weighted average Cost of Capital (WACC) WACC is a blend of the cost of equity and the cost of debt is represented by the formula below:

$$WACC = (\frac{E}{V}R_e) + (\frac{D}{V}R_d(1-T))$$

Where E is the market value of equity, D is the market value of debt, V is the total value of capital (equity plus debt), R_e is the cost of equity, R_d is the cost of debt, and T is the corporate tax rate. An increase in R_d raises the WACC, making all forms of capital more expensive and potentially leading to a reduction in corporate investment (Modigliani & Miller 1958).

2.1.2 The Capital Asset Pricing Model CAPM

CAPM is another fundamental framework that describes the relationship between systematic risk and expected return for assets, particularly stocks. The model asserts that the expected return on an asset is a function of the risk-free rate, the asset's beta (which measures its sensitivity to market movements), and the market risk premium. The CAPM formula is given by:

$$E[R_i] = R_f + \beta_i(E[R_m] - R_f)$$

Where $E[R_i]$ is the expected return on the asset, R_f is the risk-free rate (typically represented by government bond yields), β_i is the asset's beta/correlation with the market, and $E[R_m] - Rf$ is the market risk premium (Sharpe 1964). Interest rates directly influence the risk-free rate component of the CAPM. An increase in interest rates raises the risk-free rate, which in turn increases the expected return required by investors. This can depress stock-prices in two ways, firstly by making the risk-free assets, such as T-bonds, more attractive to an investorâ€™s portfolio and secondly by influencing the discount rate. Thus, CAPM illustrates how changes in interest rates impact stock valuations through the risk-free rate component (Fama & French 2004).

2.1.3 Arbitrage Pricing Theory

APT offers a more flexible approach compared to CAPM, allowing for multiple factors to influence an asset's return. Developed by Ross (1976), APT posits that asset returns can be predicted using a linear relationship of various macroeconomic factors, including interest rates. The APT model can be represented as:

$$E[R_i] = R_f + \sum_{j=1}^{n} \beta_{ij} F_j$$

Where $E[R_i]$ is the expected return on the asset, R_f is the risk-free rate, Î²$_{ij}$ represents the sensitivity of the asset to factor j, and F_j represents the factor risk premium. Interest rates are one of the key factors in APT. Changes in interest rates can affect various aspects of the economy, such as inflation expectations and economic growth, which in turn influence stock valuations. APT highlights that interest rates are part of a broader set of economic variables that collectively impact stock prices, providing a multifaceted view of how interest rate changes can affect market valuations.

2.2 Historical Context and Empirical Evidence

The theoretical framework outlined above has been substantiated by multiple studies. Thorbecke & Alami (1994) investigated the influence of monetary policy on stock prices from September 1974 to September 1979, prior to the Federal Reserve's procedural changes in October 1979. This study specifically examined the impact of alterations in the federal funds rate target on stock prices, aiming to elucidate the connection between monetary policy and the stock market in the pre-1979 period. Utilizing an event study approach, the researchers analyzed stock price changes in response to shifts in the federal funds rate target. The findings revealed a significant negative correlation between changes in the federal funds rate target and stock prices. Specifically, a 100 basis point increase in the federal funds rate target resulted in an average decline of 1.2% in the DJIA, 1.3% in the SPCA, and 1.4% in the DJCA. During this period, the Federal Reserve's strict control over the federal funds rate target allowed market participants to promptly detect changes. The results support the notion that stock market participants anticipated monetary tightening to raise real interest rates and depress stock prices, contradicting assertion made by Fama (1981) that monetary policy did not affect real stock returns during this period. Consequently, the study demonstrates a clear liquidity effect in the pre-1979 era, underscoring a direct link between monetary policy and stock market performance.

A significant change in the Federal Reserve's disclosure practices occurred in February 1994 when the FOMC began announcing its decisions on the intended federal funds rate on the same day as its meetings. Previously, markets had to infer the intended rate from the nature and magnitude of the Federal Reserve's open market operations until the decision was officially published after the next FOMC meeting. This shift allowed Lobo (2000) to investigate the behavior of stock prices around the time of the announcements during the 1990s. Lobo employed an ASAR-EGARCH model to capture the asymmetric nature of stock price adjustments and volatility changes in response to interest rate change announcements. The model assesses the persistence of stock returns and volatility before and after these announcements.

Lobo's study provides several key insights. First, there are asymmetric price adjustments: positive stock returns, which correct overpricing, persist more before rate change announcements, particularly before joint target and discount rate changes. Negative returns are negatively autocorrelated, indicating a quicker correction for overreaction to bad news. Second, volatility patterns reveal that volatility significantly increases before joint target and discount rate changes, indicating higher market uncertainty. After announcements, volatility decreases, suggesting that uncertainty is resolved; however, it rises post-announcement for unilateral target changes, reflecting ongoing uncertainty. Third, the FOMC's shift to immediate disclosure of rate changes in February 1994 led to increased volatility after announcements compared to the previous delayed disclosure policy. Fourth, the market reaction to different announcements varies: joint announcements of target and discount rate changes provide clearer signals to the market than unilateral target changes. Rate increases (bad news) tend to cause overreaction and increased volatility, while rate cuts (good news) are better anticipated and integrated into prices. In conclusion, Lobo's study demonstrates that changes in the federal funds rate target significantly affect stock returns and market volatility. The asymmetric adjustment of stock prices indicates that investors react more quickly to bad news than to good news, reflecting a higher aversion to downside risk. The findings also highlight the significant impact of the FOMC's immediate disclosure policy on market behavior.

Bernanke & Kuttner (2005) further explored the relationship between monetary policy and equity prices. They distinguished between expected and unexpected policy actions, employing a method proposed by Kuttner (2001) that uses Federal funds futures data to identify "surprise" rate changes. The analysis utilized a vector autoregression (VAR) model, adapted from Campbell & Ammer (1991) and Campbell & Ammer (1993), to calculate revisions in expectations of future interest rates, dividends, and excess returns. This approach allowed the authors to isolate the effects of unanticipated monetary policy actions on expected excess returns, which account for most of the stock price response. The study found that the stock market reacts significantly to unanticipated changes in the Federal funds rate. An unexpected 25-basis-point cut in the rate target is associated with about a 1% increase in broad stock indices, such as the CRSP value-weighted index. They also demonstrated that anticipated rate changes had a small effect, highlighting the significance of surprise elements in monetary policy actions. The primary driver of the stock market's response is the impact of policy surprises on expected future excess returns. While some effects are due to revisions in cash flow forecasts, very little is directly attributable to changes in expected real interest rates. The findings suggest that monetary policy surprises are linked to changes in the equity premium, directly connecting the results to the theoretical framework set out in the previous section. Rigobon & Sack (2003) validate the results of Bernanke and Kuttner while introducing a novel methodology that distinguishes their study from previous research. Unlike earlier studies that used T-bills or federal funds futures rates without considering their simultaneous effects on asset prices, Rigobon and Sack isolate the effects of policy shocks, innovating the traditional event study approach. They develop a new estimator leveraging the heteroskedasticity in high-frequency data, demonstrating that asset price responses to monetary policy can be identified by the increased variance of policy shocks on days of FOMC meetings and the Chairman's semi-annual monetary policy testimony to Congress. This method requires fewer assumptions than the OLS regressions used in event studies, which can lead to biased estimates.

Rigobon and Sack's alternative identification strategy, based on heteroskedasticity, compares the covariance matrices of changes in interest rates and asset prices between high-variance (policy) and low-variance (non-policy) periods. The key assumptions for this methodology are:

- The variance of policy shocks increases on policy dates.
- The variances of other shocks (affecting asset prices and interest rates) remain unchanged across these periods.
- The parameters describing the relationship between interest rates and asset prices are stable over time.

The final parameters are derived using instrumental variables (IV) regression or the generalized method of moments (GMM). Their results indicate that an unexpected rise in short-term interest rates significantly reduces stock prices. For instance, the heteroskedasticity-based estimate shows that an unanticipated 25-basis-point increase in the short-term interest rate results in a 1.7% decrease in the S&P 500 index. This pattern is consistent across other stock market indices, including the Wilshire 5000, with the Nasdaq showing an even greater decline of 2.4%, likely due to technology stocks' reliance on future cash flows. Conversely, the Dow Jones Industrial Average experiences a smaller decline, possibly due to its composition of companies with more immediate cash flows. Chen (2007) investigates the asymmetric effects of monetary policy on stock returns from January 1965 to November 2004, using monthly returns from the S&P's 500 price index. Employing a Markov-switching model, Chen explores whether monetary policy impacts stock returns differently during bull and bear markets. The study examines various measures of monetary policy stance, including money aggregates (M2 growth rate), interest rates (changes in Federal funds rates and discount rates), and VAR-based measures (orthogonalized innovations to the Federal funds rate).

Chen's findings reveal that contractionary monetary policy generally lowers stock returns in both bull and bear markets, with more pronounced effects during bear markets. For example, a 1% increase in the discount rate leads to a 2.58% decrease in returns during bull markets and a 6.12% decrease during bear markets. Similarly, a 1% increase in the Federal funds rate reduces stock returns by 1.13% in bull markets and 3.54% in bear markets. VAR-based measures corroborate these results, showing significant impacts on stock returns in both market states, with larger effects during bear markets. To ensure robustness, Chen includes dividends in the return calculations and uses an event-study approach to account for market expectations and potential endogeneity. The study consistently finds that monetary policy has stronger impacts during bear markets.

Additionally, the time-varying-transition-probability Markov-switching model demonstrates that contractionary monetary policy increases the likelihood of switching to a bear-market regime and decreases the likelihood of remaining in a bull-market regime. Although Rigobon and Sack introduced a new estimator using heteroskedasticity in high-frequency data to address the simultaneous effects of policy shocks on asset prices, subsequent studies, including Chen's, returned to event studies or GARCH approaches to explore the impacts of monetary policy. Chen's research contributes robust empirical evidence that monetary policy has asymmetric effects on stock returns, with more significant impacts during bear markets. This highlights the importance of considering market conditions in monetary policy design and enhances the understanding of the relationship between monetary policy and stock market performance.

Studies by Ioannidis & Kontonikas (2008), Alam & Uddin (2009), Kasman *et al.* (2011), and Alzoubi (2022) affirm that the relationship between interest rates and stock prices is consistent across various countries, not just within the US and its stock market.

Ioannidis and Kontonikas investigated the relationship between monetary policy and stock returns across 13 OECD countries from 1972 to 2002. They aimed to understand the effect of monetary policy shifts on stock returns, thereby contributing to the understanding of the monetary policy transmission mechanism through financial markets. To ensure robustness, they used various measures of stock returns, including nominal, real, dividend-adjusted, and non-adjusted returns, and adjusted for the non-normal distribution of stock returns. Their regression model related stock returns to measures of monetary policy, focusing on interest rate and discount rate changes. The key findings indicated that monetary policy shifts significantly affect stock returns, with expansionary policies, such as lowering interest rates, boosting stock prices, and contractionary policies, like raising interest rates, depressing them. In countries such as the UK, France, Canada, and Italy, stock returns were significantly negatively related to interest rate increases. This impact was robust across different measures of returns and various econometric methods. The study also found that restrictive monetary policies decreased expected stock returns, highlighting the predictive power of monetary policy indicators on future stock market performance.

Alam and Uddin examined the relationship between interest rates and stock prices in fifteen developed and developing countries from January 1988 to March 2003. They assumed that stock prices would follow a random walk and would not be correlated with interest rates. However, their empirical findings indicated that none of the stock markets followed the random walk model, implying they were not weak-form efficient. This was supported by significant values obtained from unit root tests for all countries, suggesting serial dependencies in stock returns. Panel data analysis revealed a significant negative relationship between interest rates and share prices across the countries studied. Specifically, the one-way fixed effect model showed that a 1% increase in the interest rate led to a decrease in share prices by 2.08 units, while the two-way fixed effects model showed a smaller but still negative relationship. Country-wise time series analysis further supported these findings, showing significant negative relationships between interest rates and share prices for most countries. However, exceptions included Japan, where interest rates had a positive relationship with share prices, and Malaysia, where changes in interest rates negatively impacted changes in share prices but not the levels of share prices.

Kasmat et al. examined the impact of interest rate and exchange rate volatility on the stock returns and volatility of Turkish banks. Utilizing Ordinary Least Squares (OLS) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, they analyzed daily data from thirteen Turkish banks listed on the Istanbul Stock Exchange from July 27, 1999, to April 9, 2009. Their findings indicated that changes in interest rates and exchange rates had a significant negative impact on conditional bank stock returns. The study also revealed that the volatilities of interest rates and exchange rates were major determinants of the volatility in bank stock returns. This implies that fluctuations in interest and exchange rates significantly contribute to the volatility of bank stocks, highlighting their importance in the risk profile of banks. These results are particularly relevant for emerging markets like Turkey, which lack robust derivative markets for hedging interest and exchange rate risks.

Alzoubi (2022) examined the relationship between macroeconomic variables and stock market performance, focusing on the Amman Stock Exchange (ASE) from 1991 to 2020. The methodology employed was the autoregressive distributed lag bounds test, chosen for its efficiency with small sample sizes and its ability to handle variables of different integration orders. The primary variables analyzed included the consumer price index (CPI), interest rate, domestic credit to the private sector as a percentage of GDP, and real economic activity. The dependent variable was the ASE general index, representing stock market performance. The study revealed that both CPI and interest rates were highly significant with the expected negative signs. A 1 percent increase in CPI led to a 1.6 percent decrease in stock prices, and a 1 percent increase in the interest rate resulted in a 5 percent decrease in stock prices.

These four studies indicate that the negative correlation between stock prices and interest rates holds across different countries and central banks.

Next important contributions to this body of literature came from several papers authored by Maio. First, Maio (2013a) investigates the impact of monetary policy changes on the cross-section of equity returns. Building upon existing theoretical frameworks, this research suggests that monetary policy shifts differentially affect firms based on their characteristics, such as size and book-to-market ratios, due to the credit transmission channel. The study employs a VAR methodology, similar to Bernanke and Kutnerâ€™s work, to analyze how changes in the FFR influence stock returns, focusing particularly on cash-flow news and discount rate news as components of stock returns. The findings indicate that monetary policy changes, specifically monthly FFR variations, have a more pronounced impact on small and value stocks compared to large and growth stocks. This greater sensitivity among financially constrained stocks underscores their vulnerability to monetary policy shifts. The study's results suggest that the negative effect of FFR changes on stock returns primarily stems from a corresponding negative impact on future expected cash flows rather than future equity risk premia. This implies that cash-flow news is the main driver of the return response to monetary policy changes. Moreover, the study finds that the dispersion in return responses to monetary shocks across different stocks is explained by a similar dispersion in cash-flow news effects, which outweighs the dispersion in discount rate news betas. These findings are robust across different VAR specifications and alternative monetary policy measures. Secondly, Maio (2013b) examines the FFR as a predictor for excess equity returns and evaluates the effectiveness of dynamic trading strategies based on this relationship. The primary hypothesis posits that changes in the FFR serve as important signals for investors, influencing their stock market decisions and risk-taking behaviors. The study develops two main types of equity market-timing strategies utilizing information from FFR changes: a non-parametric rule based on the magnitude and direction of FFR changes and a parametric strategy based on out-of-sample predictive regressions of the equity premium on FFR changes. The non-parametric strategy involves taking long positions in the stock index if the FFR decreases below a specific threshold and short positions if it increases above another threshold, suggesting that a reduction in the FFR (indicating expansionary monetary policy) is beneficial for the stock market. This straightforward approach aims to circumvent the low statistical power often found in out-of-sample predictive regressions. Conversely, the parametric strategy uses the forecasted excess return from a predictive regression model to guide investment decisions, adopting long positions when the predicted return is positive and short positions when it is negative. Empirical findings show that both strategies significantly outperform a passive buy-and-hold strategy that merely maintains the stock index. The non-parametric market-timing strategy achieves an annual Sharpe ratio of 0.55 and a certainty equivalent return (CER) gain of 3.37% per year, compared to a Sharpe ratio of 0.41 for the passive strategy. The regression-based market-timing strategy records a Sharpe ratio of 0.39 and a CER gain of 1.84% per year, highlighting the economic significance of these strategies. Thirdly, Maio & Philip (2014) assess whether incorporating macroeconomic variables into the variance decomposition of stock returns could enhance the predictability and explanatory power of stock return components. They employed a first-order VAR model to analyze the unexpected excess stock market return by decomposing it into three components: cash-flow news, discount-rate news, and interest-rate news. The state vector in their VAR model included variables such as the log market return, log dividend-to-price ratio, aggregate dividend growth, and a set of six macroeconomic factors derived from a panel of 124 macro variables. The study first evaluated the contributions of these components using a benchmark VAR model that excluded the macro factors and then compared the results with an augmented VAR model that included the macro factors. Their study indicates that other macro factors did not add substantial incremental forecasting power beyond what was already captured by the financial state variables like the aggregate dividend yield and short-term interest rate. This study thus helps with correct model specification.

Finally, Maio & Santa-Clara (2017) developed a two-factor model to address several CAPM anomalies by focusing on the relationship between stock returns and short-term interest rates. One of the key insights from the study is the heightened sensitivity of stocks with high valuations and long durations to changes in short-term interest rates. These stocks, which often rely on future growth potential and external financing, are particularly vulnerable to interest rate increases that can restrict their investment capabilities and future cash flow growth. Although the paper does not name specific examples, technology stocks often fit this description as they rely on future cash flow growth to justify their valuations. Maio and Santa-Clara's study highlights the integral role of short-term interest rates in asset pricing and their substantial impact on stock returns. The two-factor model not only addresses CAPM anomalies but also provides deeper insight into the dynamic interplay between stock returns and macroeconomic variables, particularly the critical influence of interest rate changes on stocks with specific characteristics like high valuations and long durations. In recent studies, researchers have increasingly focused on how different types of companies react to changes in interest rates, particularly in relation to the COVID-19 pandemic.

Kakhkharov & Bianchi (2022) examined the impacts of various policy responses on the stock prices of banks and FinTech companies in Australia. Their study aimed to discern the effects of COVID-19-related announcements, monetary policy interventions by the Reserve Bank of Australia (RBA), and macroeconomic policies implemented by the Australian government during the early stages of the pandemic in 2020. Using an event study methodology, they analyzed daily stock returns to measure abnormal returns (ARs) and cumulative abnormal returns (CARs). The findings revealed that banks showed a more immediate and significant response to COVID-19-related news and government macroeconomic announcements compared to FinTech stocks. Bank stocks exhibited higher sensitivity to these announcements, consistent with previous financial crises where banks are typically more reactive to broad economic measures. In contrast, FinTech stocks demonstrated a delayed but stronger reaction to containment measures and monetary policy announcements, reflecting their unique business models and market positioning.

Secondly, O'Donnell *et al.* (2024) conducted an empirical investigation to analyze the impact of monetary policy interventions on banking sector stocks during the COVID-19 crisis. Using a quantitative event study methodology over a five-day window, they examined the effects of 188 monetary policy announcements from central banks in China, the U.S., and Europe. The study aimed to understand how different monetary policy mechanisms influenced market reactions throughout the pandemic. The results indicated diverse market responses to monetary policy interventions. In the U.S., cuts in interest rates and the maintenance of a low-interest rate environment by the Federal Reserve resulted in negative abnormal returns for banking stocks, while the effects in the EU and China were insignificant. The researchers suggest that this is due to the already low interest rate environment before the pandemic, which may have nullified some expected effects. Additionally, they found that in Europe, the ECB's inflation target announcements resulted in negative returns, and Chinese banking stocks responded positively to foreign exchange policies. These findings underscore the importance of understanding regional differences and the specific economic mechanisms targeted by monetary interventions, thereby informing policymakers on effective strategies for future economic disruptions.

The consistent findings across various studies on the relationship between monetary policy and stock prices reveal several overarching themes. Firstly, changes in interest rates have a significant impact on stock returns. Expansionary monetary policies, such as lowering interest rates, generally boost stock prices, while contractionary policies, such as raising interest rates, tend to depress them. This relationship holds true across different countries and various types of companies, including banks and FinTech firms. Notably, the impact of monetary policy shifts is not uniform across all stocks. Small and value stocks are typically more sensitive to these changes compared to large and growth stocks, with financially constrained stocks being particularly vulnerable.

Many studies utilize event study methodologies to analyze the effects of policy announcements on stock prices, measuring abnormal returns ARs and cumulative abnormal returns CARs. This approach effectively captures the immediate reactions of stock prices to monetary policy announcements. However, the response to monetary policy interventions can vary significantly by region and sector. Furthermore, monetary policy indicators, such as changes in the federal funds rate, possess strong predictive power for future stock market performance. These indicators influence investor behavior and risk-taking, affecting stock market decisions. Incorporating macroeconomic variables into models of stock returns can enhance the understanding and predictability of stock return components. However, the addition of these variables often does not provide substantial incremental forecasting power beyond existing financial state variables like dividend yields and interest rates.

The effects of monetary policy can also be asymmetric, with more pronounced impacts during bear markets compared to bull markets. Contractionary policies tend to have a stronger negative impact during bear markets. Additionally, stocks with high valuations and long durations, such as technology stocks, are particularly sensitive to changes in short-term interest rates. These stocks rely heavily on future growth potential and external financing, making them vulnerable to interest rate increases.

These findings underscore the significant role of monetary policy in influencing stock market behavior, the importance of considering firm-specific and macroeconomic factors, and the need for tailored policy responses based on regional and sectoral differences. This comprehensive understanding sets the stage for further exploration of how monetary policy impacts financial markets

Chapter 3

Hypothesis formulation

This section formulates hypotheses that are going to be tested later on in the paper and explains the reasoning behind them. These hypotheses delve into the nuances of market reactions to interest rate changes, the influence of Federal Open Market Committee (FOMC) meetings on stock volatility, and the comparative resilience of tech firms in the face of economic shifts, particularly in the context of their performance during the COVID-19 pandemic.

Hypothesis 1: *Stock prices of technology firms with higher levels of debt reacted more negatively to changes in interest rates*

This hypothesis finds support in various economic and financial studies. Notably, the research by Maio and Santa-Clara aligns with this hypothesis, as it highlights the heightened sensitivity of stocks with high valuations and long durations to changes in short-term interest rates. Technology firms, which often rely on future growth potential and external financing, fit this description and are thus particularly vulnerable to interest rate increases that can restrict their investment capabilities and future cash flow growth.

Insights (2020) provides further context, noting that before the COVID-19 pandemic, corporate debt in the U.S., especially in sectors like information technology and communication services, had reached new highs relative to the economy's size. This increase in debt was not uniformly accompanied by a proportional increase in investments, indicating potential risks if debt levels became unsustainable.

The Reserve (2017) also supports this hypothesis by explaining how interest rate hikes impact corporate debt. Higher interest expenses can arise from new debt issued at higher rates or from higher rates on existing floating-rate debt. Approximately 85% of corporate loans have variable interest rates, making them susceptible to interest rate changes. Even fixed-rate loans, which constitute a smaller fraction of corporate debt, are not immune due to their relatively short maturities. The Federal Reserve's study projects that an increase in the federal funds rate could significantly raise interest expenses for corporations, especially those in high-leverage sectors like technology.

These insights collectively suggest that technology firms, particularly those with high levels of debt, are especially vulnerable to interest rate hikes. The increased cost of debt servicing due to higher interest rates directly impacts their financial stability and investor perceptions, potentially leading to more volatile stock prices. Furthermore, the sectorâ€™s growth-oriented nature, which focuses on reinvesting profits for development rather than dividend payouts, could be hampered by rising borrowing costs, further affecting company valuations and stock performance.

Hypothesis 2: *Technology firms' stock prices are more resilient to interest rate hikes than other stocks due to their strong performance during the COVID-19 pandemic*

Research suggests that technology firms' stock prices may indeed exhibit greater resilience to interest rate hikes, a notion supported by their robust performance during the COVID-19 pandemic. Studies by Ding *et al.* (2020) and He *et al.* (2020) underscore the resilience of sectors with high levels of digital transformation, particularly the information technology sector, against negative market sentiment during the pandemic. Ding et al. discovered that sectors deeply embedded in digital transformation, such as information technology, exhibited notable resilience. Similarly, He et al. observed that the information technology industry was among those that effectively withstood the pandemic's impact on stock prices.

While interest rates significantly affect the cost of corporate borrowing, their impact on the cost of equity is less pronounced, as suggested by a 20-year study by McKinsey (2021). Technology companies, often growth-oriented and heavily invested in research and development, typically reinvest profits back into the firm, usually maintaining lower cash reserves. This reliance on borrowing renders these companies more sensitive to rising interest rates.

The impact of interest rate hikes on tech stocks has varied over time. For instance, during the dot-com bust in 2000 and the subsequent rise in interest rates until 2007, the tech sector did not underperform compared to the S&P 500 (Schmidt 2023). Conversely, during the low-rate environment following the Global Financial Crisis, tech stocks outperformed the S&P 500. The patterns during and after the COVID-19 pandemic reflect this complexity. While tech stocks initially outperformed the market with near-zero rates during the pandemic, they began to languish as rates rose rapidly in 2022 but showed signs of recovery in 2023 as the pace of rate hikes slowed.

These observations suggest that while technology firms are not immune to interest rate hikes, their strong performance during the COVID-19 pandemic indicates a level of resilience not observed in other sectors. This resilience could be attributed to their digital transformation and innovation capabilities, which allow them to adapt more readily to changing economic conditions. Therefore, the hypothesis that technology firms' stock prices are more resilient to interest rate hikes than those of other sectors finds substantial support in recent research and historical patterns.

Chapter 4

Research Design

In this section, we will outline the methodology used to explore the impact of the US Federal Reserve's monetary policy on technology firms post-COVID-19. This includes the rationale behind our chosen methods, data collection processes, and analytical techniques. We will also detail the specific data gathered, its sources, and how it was processed and analyzed, providing a clear foundation for understanding the study's findings and conclusions.

4.1 Data Sample

4.1.1 Stocks Information

To validate or disprove the hypotheses set out in the previous section, this analysis leverages a dataset comprising companies listed in the NASDAQ 100 (NDX) index. The NDX is predominantly composed of the largest technology companies listed on the Nasdaq stock exchange, with a total capitalization of approximately 22 trillion USD. This index represents nearly 50% of the S&P 500, which itself accounts for about 80%-85% of the U.S. stock market, thus providing a comprehensive proxy for the overall market (Gunzberg & Edwards 2018). The choice of the NDX is particularly relevant given its concentration in technology stocks, a sector of interest for this study.

Dataset and Period

The study period spans from January 1, 2019, to December 31, 2023. This timeframe captures a range of significant economic events, including the onset of the COVID-19 pandemic, which led to unprecedented government interventions, changes in monetary policy, and fluctuations in market sentiment. The inclusion of a 15-month pre-pandemic window provides a baseline for understanding pre-crisis trends and allows for a comparative analysis with the pandemic and post-pandemic periods.

Data Sources and Metrics

Data for company stock prices were sourced from LSEG Workspace, which also provided information about company specific attributed described below. Daily stock prices were extracted to compute daily returns, which are fundamental for the event study methodology employed in this analysis. Beyond just individual company information we've also extracted closing price and therefrom returns for the NDX and SPY indices were utilized as benchmarks to calculate expected market returns, providing a comparative framework for assessing abnormal returns. As the NDX is composed of the firms used in this analysis it shows the effects of portfolio composition on individual stock price performance. The SPY index then serves as a benchmark for wider stock market trends.

In addition to stock price data, detailed company-specific information was collected, including:

Total Debt to Enterprise Value (EV) Ratio: This metric helps assess the leverage and financial risk of each company. Higher leverage might indicate a higher sensitivity to interest rate changes, as interest expenses constitute a larger proportion of total costs. The relationship of this metric should then help us answer the Hypothesis 1 set out in the previous section. One would therefore expect companies with high Total Debt to EV ratios are expected to show perform worse folloing a change to interest rate.

GICS Code: The Global Industry Classification Standard (GICS) code categorizes companies into sectors and industries, enabling sector-specific analyses. Although, we use SPY as the benchmark to judge whether technology stocks react differently to interest rate changes than other sectors, the inclusion of GICS codes should give us a better understanding if particular subsectors performed differently within the technology sectors. These are: Information Technology, Industrials, Utilities, Health Care, Energy, Consumer Staples, Communication Services, Consumer Discretionary, Real Estate, Financials, Materials The IT subsector should serve as the as the representation for the purest technology driven firms.

Market Capitalization: Market capitalization of individual firms was also collected to understand the differential impact of monetary policy across companies of different sizes. We then transformed this variable to it logarithmic form, this should make it clearer how percentage increases in size affect the stock's performance following an interest rate change.

Price-to-Earnings (P/E) and Price-to-Book (P/B) Ratios: These valuation metrics distinguish between growth and value stocks, providing insights into how different valuation models may affect sensitivity to interest rate changes. From previous research discussed in Chapter 4, we could expect that value stocks should perform better as they are less impacted by changes in interest rates.

Return on Average Common Equity (ROcE): This efficiency metric indicates how effectively a company uses equity to generate profits, reflecting operational efficiency. One would expect that the changes that more capital efficient firm would react more positively to changes in interest rate as the ROcE implies a less of a need for external financing or also that these firm's can justify to take on debt at different interest rates.

R&D as a Percentage of Total Revenue: This metric indicates a company's investment in innovation, a critical factor for technology firms that heavily rely on future growth potential.

4.1.2 Interest rate information

Lastly, to track interest rates this analysis uses Fed Funds Rate Future (FFRF) and Fed Funds Effective Rate (FFeR). The FFRF measures the market expectation about futurue interest rates, meaning a change in it should have a more pronounced impact on stock returns as it prsents an exogenous shock to the system. FFeR then show the changes to actual interest rates. These changes are expected by the market and should, therefore, be priced into the stock returns. On the other hand, an unexpected change (one that deviates from FFRF) should prompt a market reaction. Additionally, after the change or slightly before the change, some investors may choose to reprice their portfolios to reflect the new expected interest rate. This means that some effect should be capture within the event window. Together these two interest rate metrics should help in differentiating between expected and unexpected changes in interest rates. Table 4.1 shows all changes in FFeR and the Fed Funds target rate bound. The changes usually occur day of or after the FOMC meetings, this means that the change in FFeR also serves as a proxy for FOMC meetings.

Table 4.1: Changes in Fed Fund Effective Rate from March 2020 to July 2023

FOMC Meeting Date	*Rate Change (bps)*	*Federal Funds Rate*
July 27, 2023	25	5.25% to 5.50%
May 4, 2023	25	5.00% to 5.25%
March 23, 2023	25	4.75% to 5.00%
Feb 2, 2023	25	4.50% to 4.75%
Dec 15, 2022	50	4.25% to 4.50%
Nov 3, 2022	75	3.75% to 4.00%
Sept 22, 2022	75	3.00% to 3.25%
July 28, 2022	75	2.25% to 2.50%
June 16, 2022	75	1.50% to 1.75%
May 5, 2022	50	0.75% to 1.00%
March 17, 2022	25	0.25% to 0.50%
March 16, 2020	-85	0% to 0.25%
March 4, 2020	-50	1.0% to 1.25%
October 31, 2019	-24	1.50% to 1.75%
September 19, 2019	-35	1.75% to 2.0%
August 1, 2019	-26	2.0% to 2.25%

4.2 Methodology - Stock Returns during FOMC

To understand the effect of interest rate hikes on stock prices and to validate Hypotheses 1 and 2, we employ an event study methodology. Event studies, such as those described in seminal works by MacKinlay (1997) or subsequent studies like Kakhkharov & Bianchi (2022), Kim (2023), and O'Donnell *et al.* (2024), are invaluable for assessing the impact of specific events on stock prices. This methodology is grounded in analyzing abnormal returnsâ€”returns that deviate from what would typically be expectedâ€”around the time of the event. By focusing on the period immediately before and after the Federal Reserve's announcements of interest rate changes, we can discern the direct impact of such policy decisions on the stock prices of technology firms.

We begin by calculating the daily return on day t, given price p:

$$R_{it} = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{4.1}$$

Next, we calculate the abnormal returns surrounding the interest rate hikes. Abnormal returns are defined as the difference between a stock's actual return and its expected return, based on a benchmark or market model. This expected return typically reflects the performance of the broader market or a comparable index, such as the NDX and SPY Index. As MacKinlay (1997) highlights, abnormal returns are crucial for identifying the specific impact of an event on a stock, separate from general market movements. To calculate abnormal returns, we use the following formula:

$$R_{it}^{\text{abn}} = R_{it} - E[R_{it}], \tag{4.2}$$

where R_{it}^{abn} represents the abnormal return of stock i on day t, R_{it} is the actual stock return, and $E[R_{it}]$ is the expected return, calculated using:

$$E[R_{it}] = \alpha_i + \beta_i R_{mt} + \epsilon_{it}, \tag{4.3}$$

The parameters α_i and β_i are estimated over a 250-day estimation window prior, ending 20 days before the event date t_0 (Kim 2023), with R_{mt} representing the return of the broader market, specifically the NDX and SPY indices for robustness. The CAPM-adjusted return for stock i on day t is thus:

$$R_{it}^{\text{abn}} = R_{it} - (\alpha_i + \beta_i R_{mt} + \epsilon_{it}) \tag{4.4}$$

The expected value of R_{it}^{abn}should then be equal to 0 if the event has no effect on expected returns (Figure A.1 and A.2).By aggregating these abnormal returns, we compute the Cumulative Abnormal Returns (CAR), which measure the total impact of the event over a specified time window (t_1, t_2).

$$CAR_{it}^{\text{abn}}(t_1, t_2) = \sum_{t=t_1}^{t_2} R_{it}^{\text{abn}} \tag{4.5}$$

For this study, we initially select a 5-day event window (-1, +3), aligning with the common practice in financial event studies as noted by Oler *et al.* (2007). This window allows us to capture immediate market reactions before and after the event, minimizing the confounding influences of unrelated market movements.

To further substantiate our findings, we extend the event window and conduct robustness checks, including varying the estimation window, using alternative benchmarks, and applying different market models. Additionally, we analyze the results separately for positive and negative interest rate changes to investigate potential asymmetries in market responses.

Finally, we conduct a cross-sectional regression analysis to examine the heterogeneous effects of the Fed's rate policy on firm-level stock returns. The model is specified as follows:

$$\begin{aligned} \text{cumulative returns}_i(t_1, t_2) = \beta_0 + \beta_1 \frac{TD}{EV} + \beta_2 \text{ Industry effect} \\ + \beta_i \text{ Controls} + \gamma_{t_0} \Delta FFR + \epsilon_i \end{aligned} \tag{4.6}$$

In this regression, the dependent variable is the cumulative return of stock i over the event window (t_1, t_2). The independent variables include the Total Debt to Enterprise Value ratio ($\frac{TD}{EV}$), which assesses the firm's leverage and sensitivity to interest rate changes. The "Industry effect" captures sector-specific factors, particularly distinguishing between technology firms and others. The "Controls" encompass additional financial metrics, such as market capitalization, P/E ratio, and R&D expenditure, which may influence stock price reactions. The term ΔFFR represents the change in the Federal Funds Rate, a key variable of interest, while ϵ_i denotes the error term.

By including these variables, we aim to uncover the nuanced effects of capital structure and industry characteristics on stock price performance during periods of monetary policy adjustments. This comprehensive approach allows us to test the robustness of our hypotheses and provides insights into the differential impacts of rate changes on various firm-specific attributes.

4.3 Limitations

While the event study methodology and dataset employed in this analysis provide significant insights, several limitations must be acknowledged:

Data Availability and Quality : The analysis relies on publicly available financial data, which may not capture all market reactions such as sentiment or internal company dynamics. Additionally, the financial metrics are calculated using the latest reported data. This means that the financial structure of the firm could have changed in between the the last reporting period and the event date.

Event Window Selection : The choice of a 5-day event window may not entirely capture the market's reaction to interest rate changes, especially if reactions are delayed or anticipatory trading occurs. An expanded window partially addresses this but risks confounding effects from other concurrent events. For robustness we will therefore also calculate a 10-day window starting 3 days prior to the even and ending 6 days after. This should on one hand capture most of the effect on the event but on the other also the other concurrent events. On average the daily return will be around 0 meaning in a long enough event window we would just capture the usual returns of the firms.

Benchmark Selection and Model Specification : The use of the NDX and SPY indices as benchmarks presumes these indices accurately reflect expected returns absent the event. However, extraneous market movements specific to these indices could introduce bias. Moreover, the CAPM model's linear risk-return assumption may not fully encapsulate stock price complexities, especially in volatile markets.

Sector and Firm-Specific Factors : While controlling for variables such as leverage and R&D expenditure, the analysis may omit other unobserved factors like company-specific news or managerial decisions that can independently influence stock prices. This once again relates to the data about sentiment analysis

Macroeconomic Environment : The study period's inclusion of the COVID-19 pandemic introduces a unique macroeconomic context, possibly leading to atypical market behavior. This period's extraordinary conditions, such as significant government interventions, could skew the effects of interest rate changes, limiting the findings' applicability to other periods.

Market Efficiency Assumptions : The event study assumes market efficiency, suggesting immediate incorporation of all available information into stock prices. However, information dissemination and investor reactions can vary, potentially leading to delayed market responses.

Chapter 5

Results

5.1 Event Study

Firstly, we assessed whether changes in the FFR have an effect on stock market returns. To do this, we differentiate between two types of events:

- Changes in the Federal Funds Rate Futures (FFRF)
- Changes in the Federal Funds Effective Rate (FFeR)

As previously discussed, the FFRF reflects the market's reaction to anticipated changes in interest rates, while the FFeR measures the response to actual changes, typically occurring on the day of or the day after a FOMC meeting. Table 5.1 details the magnitude and dates of each significant change (exceeding 0.1 percentage point) in either FFRF or FFeR from 2019 to the end of 2023. During this period, there were 26 significant changes in FFRF and 17 significant changes in FFeR. These events are considered influential factors on stock market returns. Additionally, it was observed that on some dates, when either FFRF or FFeR experienced a significant change, there was also a minor change in the other rate. For instance, on August 1, 2019, both FFRF and FFeR decreased by approximately 0.25 percentage points.

To analyze the impact of these events on stock returns, we calculated the CAR for each company over the event window. Figure 5.1 presents the CAR surrounding the announcement of changes to the FFR. The plot spans a five-day window, with the relative date 0 marking the event date. The vertical dashed line at relative date 0 indicates the timing of the policy announcement. The blue line represents the average CAR, while the shaded region denotes

Table 5.1: Changes in FFRF and FFeR with Descriptive Statistics

Date	**Δ FFRF**	**Δ FFeR**	**Date**	**Δ FFRF**	**Δ FFeR**
02.01.2019	0.13		01.06.2022	0.31	
01.08.2019	-0.25	-0.26	16.06.2022		0.7
03.09.2019	-0.12		01.07.2022	0.46	
16.09.2019	0.02	0.11	28.07.2022		0.75
19.09.2019	-0.01	-0.35	01.08.2022	0.65	0.01
01.10.2019	-0.20	-0.02	01.09.2022	0.21	
31.10.2019		-0.24	22.09.2022		0.75
01.11.2019	-0.25	-0.01	03.10.2022	0.52	
02.03.2020	-0.29	0.01	01.11.2022	0.70	
03.03.2020	-0.28		03.11.2022		0.75
04.03.2020	0.02	-0.50	01.12.2022	0.34	
09.03.2020	-0.13		15.12.2022		0.50
10.03.2020	0.12		03.01.2023	0.23	
11.03.2020	-0.13		01.02.2023	0.24	
16.03.2020	-0.06	-0.85	02.02.2023		0.25
01.04.2020	-0.58	-0.02	23.03.2023		0.25
01.03.2022	0.13		03.04.2023	0.17	
17.03.2022		0.25	01.05.2023	0.21	
01.04.2022	0.14		04.05.2023		0.25
02.05.2022	0.45		27.07.2023		0.25
05.05.2022		0.50	01.08.2023	0.21	
N ($0.1<\Delta$)	26	17	Mean	0.10	0.14
N (Total)	30	22	Median	0.13	0.18

the confidence interval, highlighting the statistical uncertainty surrounding the estimated CAR.

The data indicate that the CAR remains close to zero on day -1, suggesting no significant anticipation effects prior to the announcement. However, following the announcement (from day 0 onwards), there is a noticeable decline in CAR, indicating a negative market reaction to the policy change. This trend continues through to day 3, with CAR values significantly below zero. The expanding confidence interval post-event suggests increasing variability in market reactions over time.

Figure 5.1: CAR over a 5-day window surrounding change in FFeR

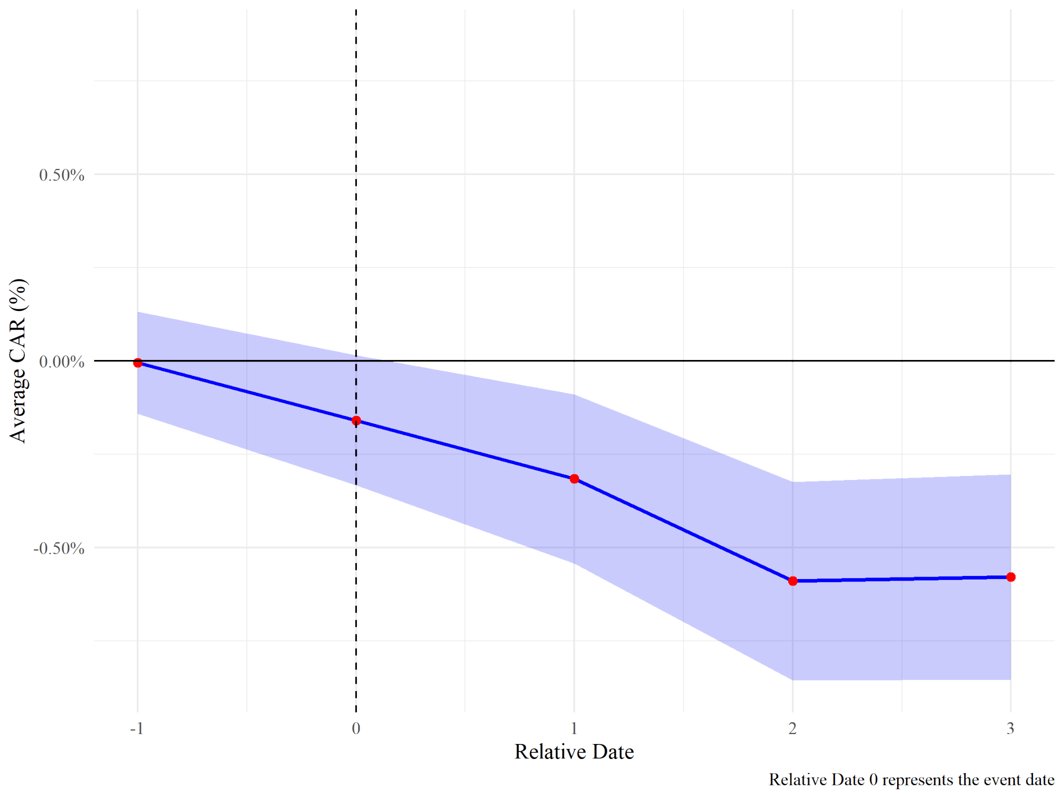
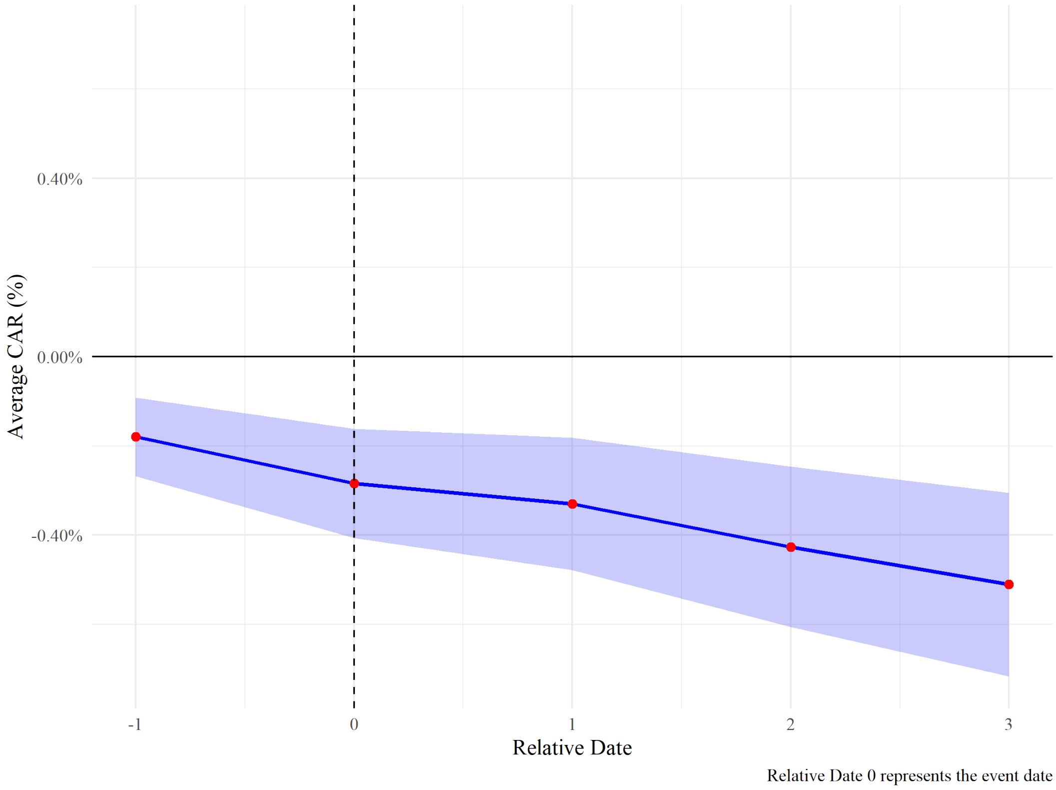


Figure 5.2 shows the CAR associated with changes in the FFRF within a five-day event window. Similar to Figure 5.1, the plot includes a vertical dashed line at the event date (relative date 0) and a shaded area representing the confidence interval.

In contrast to the market response observed for changes in FFeR, the reaction to changes in FFRF shows a more pronounced decline beginning on day -1. This suggests that the market may have anticipated the changes in the futures rate, indicating that the event window might be too narrow to fully capture the market's response. The CAR continues to decline consistently after the event date, indicating a prevailing negative sentiment in the market's reaction. The steady decline in CAR, accompanied by a slight widening of the confidence interval, reflects an increased uncertainty in market reactions as time progresses.

Figure 5.2: CAR over a 5-day window surrounding change in FFRF



To verify our assumption regarding the market's reaction to changes in both the FFeR and FFRF, we conducted a t-test analysis. The results of this analysis are presented in Table 5.2. This table summarizes the average CAR over the event window for both FFeR and FFRF events, along with their corresponding levels of statistical significance.

The results indicate that the market did not exhibit a significant reaction to changes in the FFeR on the day before the announcement (relative date -1), with an average CAR of 0.00%, which is not statistically significant. However, post-announcement, a significant negative reaction is observed. On the event day (relative date 0), the average CAR drops to -0.19%, significant at the 10% level ($p < .1$), indicating that the market begins to incorporate the new information. This negative trend continues, with the CAR reaching -0.65% by

Table 5.2: Average CAR over the Event window

Relative Date	*Average CAR (%) FFeR*	*Average CAR (%) FFRF*
-1	0.00	-0.18***
0	-0.19*	-0.28***
1	-0.37**	-0.33***
2	-0.65***	-0.43***
3	-0.62***	-0.52***

*p < .1; **p < .05; ***p < .01.

relative date 2, remaining significant at the 1% level ($p < .01$), suggesting a robust negative reaction to the rate change.

In contrast, the market's response to changes in the FFRF, as shown in the same table, begins to manifest even before the event. The average CAR at relative date -1 is -0.18%, significant at the 1% level ($p < .01$), suggesting that investors anticipated the policy changes. This anticipation effect is further confirmed on the event day (relative date 0), where the CAR declines further to -0.28%, maintaining its significance ($p < .01$). The negative reaction deepens over the following days, with the CAR reaching -0.52% by relative date 3, all maintaining high levels of statistical significance. These results suggest that the event window may need to be expanded to capture the full effect of changes in FFRF.

5.1.1 Expanded Event Window

The results obtained after expanding the event window to 10 days, from $t_1 = -3$ to $t_2 = 6$, indicate a significant market response to changes in the FFRF. As depicted in Figure 5.3, the average CAR begins to deviate from zero prior to the event, suggesting that the stock market anticipates these changes. The CAR exhibits a marked decline starting three days before the event, with a statistically significant deviation from zero at $p < 0.001$ on day -1 (Table 5.3). This pattern implies that market participants adjust their positions in anticipation of the expected rate changes.

Following the event date (relative date 0), the negative CAR trend continues and becomes more pronounced. The persistence of negative CARs through to day 6 highlights a lasting impact from the rate change announcement. This extended negative response suggests that the effects of adjustments in the FFRF

Figure 5.3: CAR over a 10-day window surrounding change in FFRF

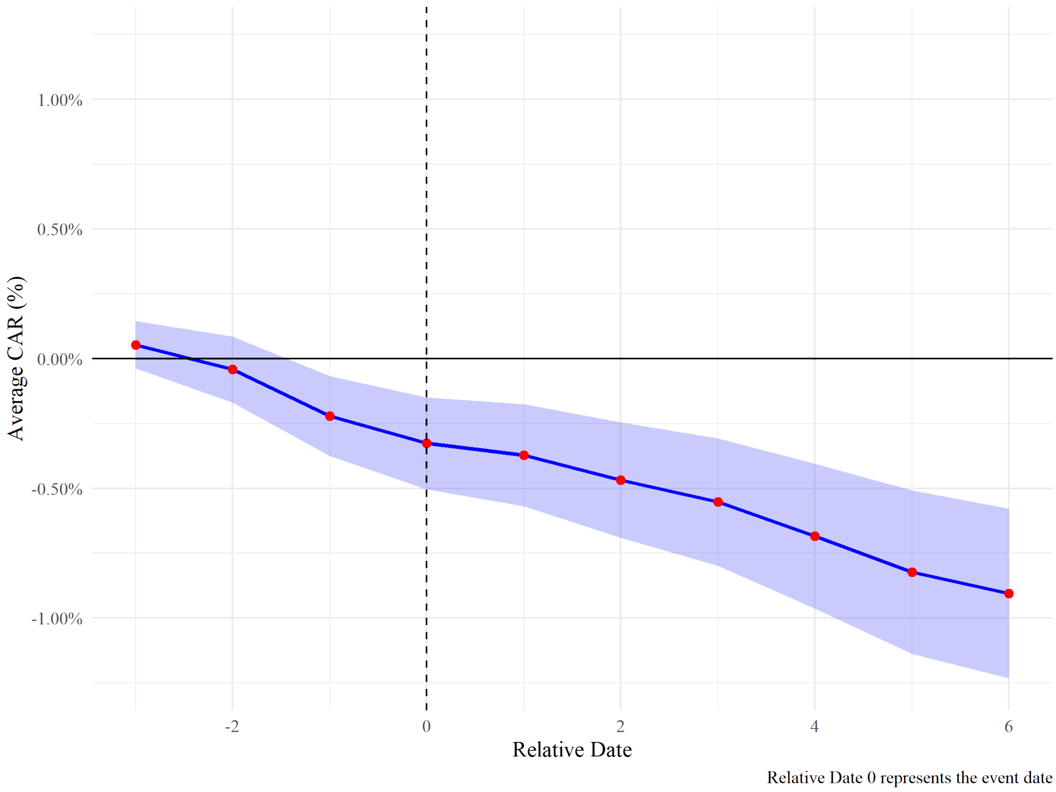


Table 5.3: Average CAR over the expanded Event window

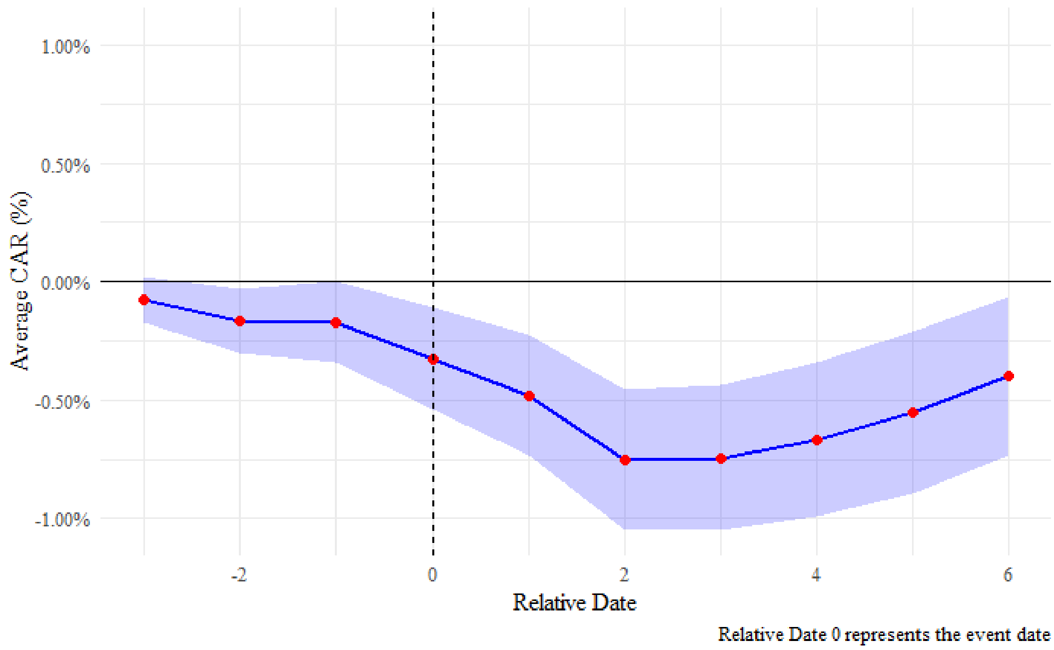
Relative Date	*Average CAR (%)*
-3	0.05
-2	-0.04
-1	-0.22***
0	-0.33***
1	-0.37***
2	-0.47***
3	-0.55***
4	-0.68***
5	-0.82***
6	-0.90***

*p < .1; **p < .05; ***p < .01.

on stock prices are both immediate and prolonged, indicating ongoing investor reassessment of the economic and financial implications of these changes.

For robustness, we also expanded the window for changes in FFeR, as illustrated in Figure 5.4. In this extended window, a minor correction is observed as the CAR decreases for three consecutive days. However, as the window is further expanded, it becomes increasingly challenging to ascertain whether the observed movements are directly related to the event or are merely random market fluctuations.

Figure 5.4: CAR over a 10-day window surrounding change in FFeR



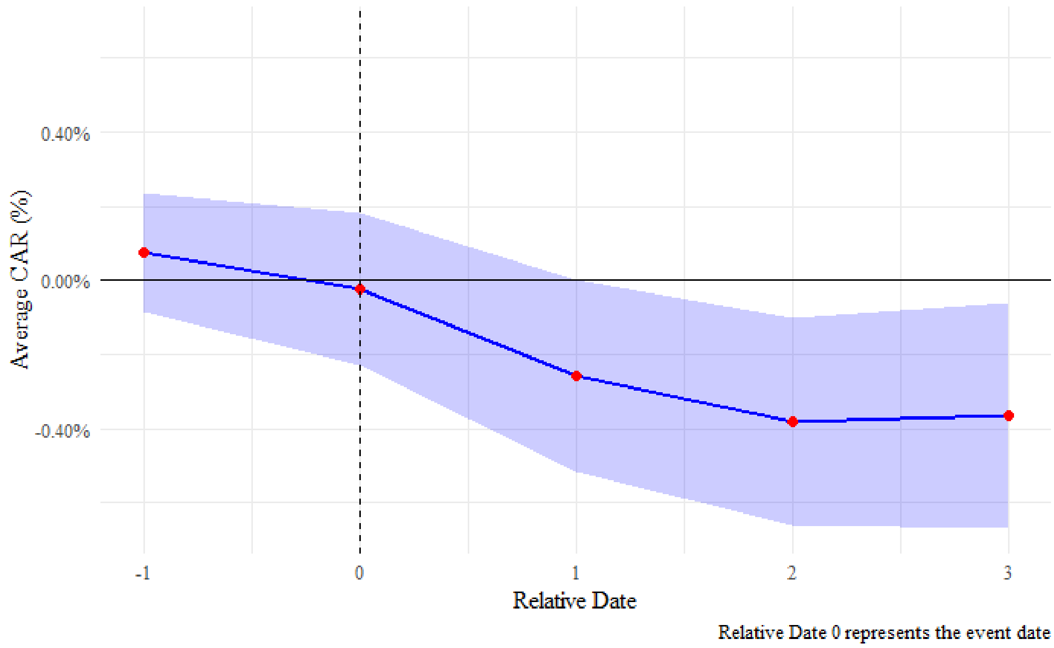
5.1.2 Effect depending on event type

Next, we differentiate between interest rate increases and decreases. In this section, we specifically analyze days/events associated with increases in FFeR and FFRF, and contrast them with days/events involving decreases in rates. This distinction allows for a more nuanced understanding of how the stock market reacts to changes in interest rates, depending on the direction of the change.

Figures 5.5 and 5.6 demonstrate the average reaction of firms in the NDX 100 to increases in interest rates. The data show that increases in both actual and expected interest rates do not fundamentally affect CAR. For increases in FFeR, the CAR becomes significantly different from zero only on day 2, after which it declines. This suggests that the impact of the rate increase is short-lived and limited in magnitude.

Similarly, for increases in FFRF, the CAR does not significantly deviate from zero for most days within the event window. This indicates that increases in FFRF have minimal to no effect on stock market returns, suggesting that the market may not perceive these anticipated rate increases as a significant driver of stock price changes.

Figure 5.5: CAR over a 5-day window surrounding increases in FFeR



Figures 5.7 and 5.8 show the market's reaction to decreases in actual and expected interest rates. Both graphs reveal a decline in CAR for both rates, indicating that market participants possibly perceived the decreases in FFeR and FFRF as signals of unfavorable economic conditions or lower future returns, leading to negative abnormal returns.

Following the initial decline, the returns on the subsequent day are negligible; however, there is another decrease thereafter, which then stabilizes. This pattern suggests that the market's adjustment to the new information may not be immediate, reflecting continued uncertainty or reassessment by investors. It is also notable that the stock market reacts more strongly to decreases in interest rates compared to increases, indicating a more pronounced concern or negative sentiment towards rate cuts.

Figure 5.6: CAR over a 5-day window surrounding increases in FFRF

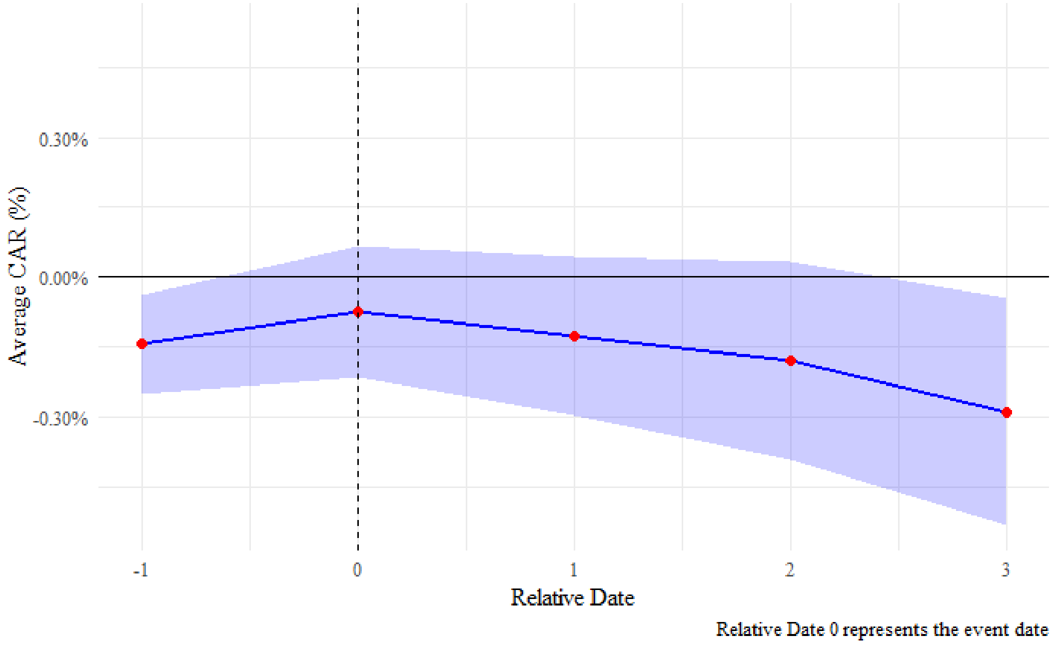


Figure 5.7: CAR over a 5-day window surrounding decreases in FFeR

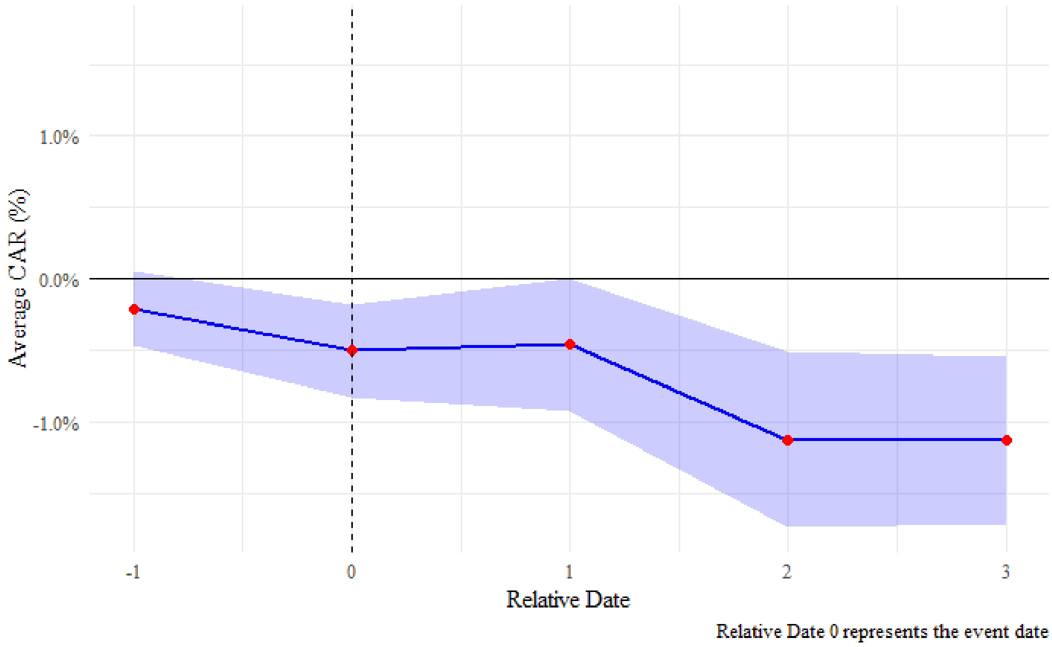
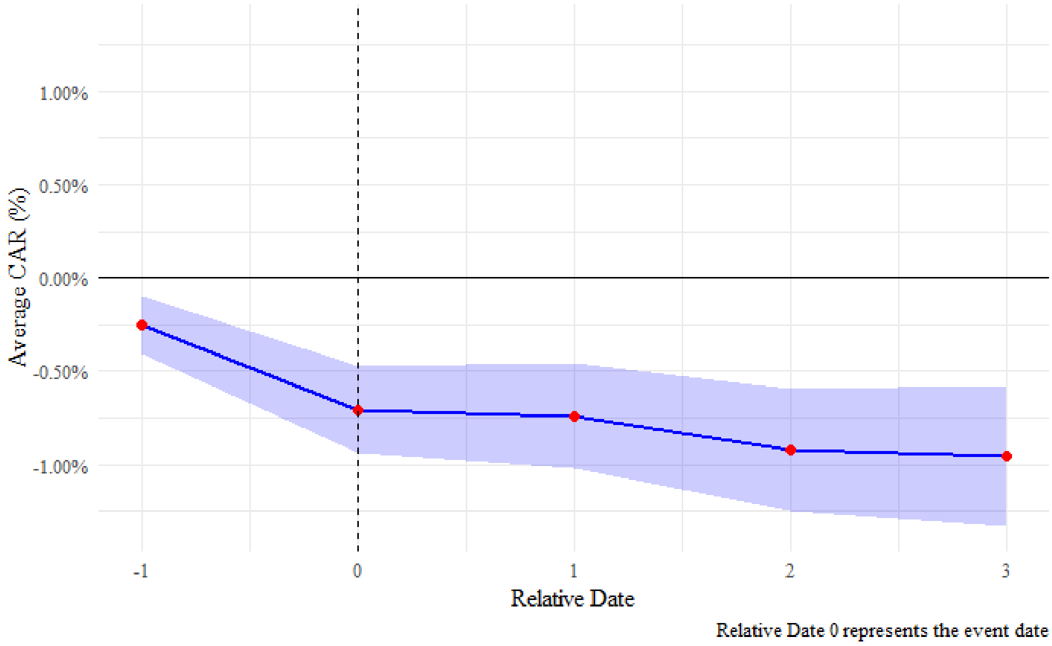


Figure 5.8: CAR over a 5-day window surrounding decreases in FFRF



5.1.3 Effect of SPY as a benchamark

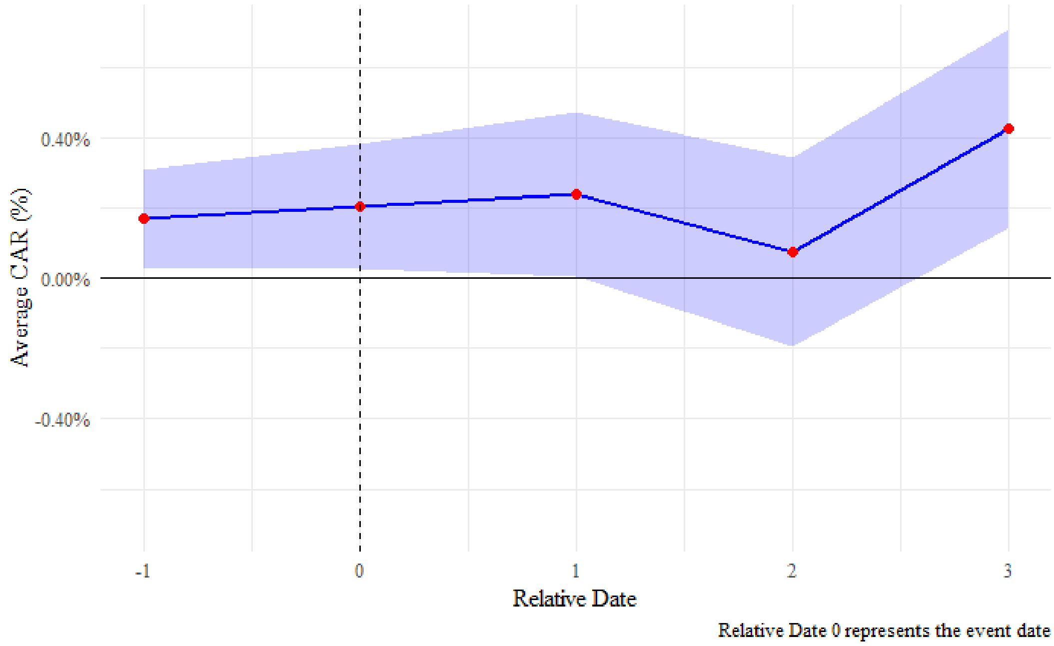
In this section, we present the results of the event study using the SPY as a benchmark. This approach helps to distinctly separate the broader market's effects from those specifically impacting technology stocks within the Nasdaq 100.

Figures 5.9 and 5.10 illustrate the CAR surrounding changes in the FFR effective rate and futures rate, respectively, with SPY as the benchmark. Compared to Figures 5.1 and 5.2, which use the Nasdaq 100, we observe a generally positive CAR, though it is mostly insignificant.

For changes in the FFeR, prior to the change in effective rates, technology stocks in the Nasdaq 100 exhibit positive returns, which continue into the day of the event. Both of these CARs are statistically significant at the 5% level ($p < 0.05$). Following the event, the confidence interval widens considerably, and CAR returns to the mean. This indicates some initial positive response followed by increasing uncertainty.

Regarding changes in the FFRF, the CAR initially starts at approximately zero, indicating no strong anticipatory movement. However, returns accumulate slowly over the event day and the subsequent day. The CAR on the first day following the event is also statistically significant. These results suggest that firms in the NDX exhibit a more positive reaction to changes in interest rates compared to firms in the broader SPY index.

Figure 5.9: CAR over a 5-day window surrounding change in FFeR - SPY Benchmark



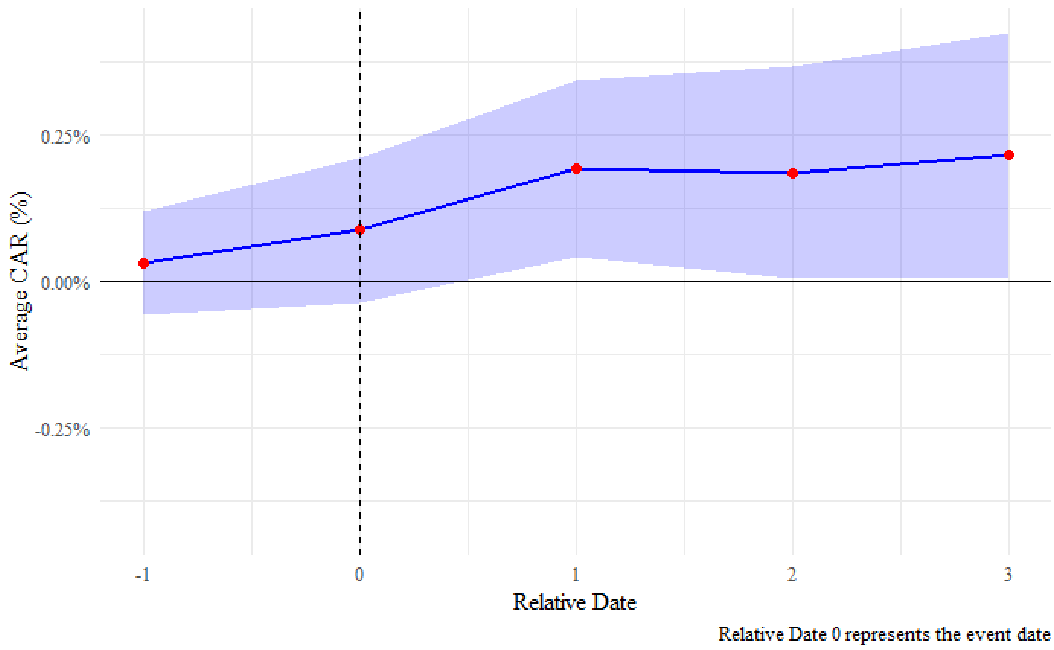
5.1.4 Effect depending on event type - SPY as a benchmark

Since we did not observe substantial effects warranting a broader event window, we will now explore whether the direction of the interest rate changeâ€”whether an increase or decrease-affects abnormal returns.

Figures 5.11 and 5.12 illustrate the market's reaction to increases in the FFeR and FFRF, respectively. Prior to the change in the FFeR, there is already a positive CAR, suggesting that returns reacted in anticipation of the rate increase. On the event day, the CAR does not increase significantly but remains positive, continuing into the day after the event. This indicates that stocks in the NDX index are more resilient to increases in interest rates compared to firms in the broader SPY index.

Regarding changes in the FFRF, the CAR does not show an immediate positive response on the event day. However, it increases on the day following the event. This suggests that the stocks did not initially reflect expectations of the changes but responded positively once the change occurred. This de-

Figure 5.10: CAR over a 5-day window surrounding change in FFRF - SPY Benchmark



layed positive reaction indicates that NDX firms may react more favorably to increases in the FFRF compared to firms in the SPY index.

Figures 5.13 and 5.14 show the market's reaction to decreases in the FFeR and FFRF, respectively. The data indicate that technology stocks, represented by the NDX, do not fundamentally react differently to decreases in interest rates compared to stocks in the broader SPY index. The CAR patterns for both indices are similar, suggesting that the negative sentiment associated with rate decreases is uniformly reflected across both technology and non-technology sectors.

5.2 Event Study - Regression

First let us consider the regression model that was specified in the previous section:

$$\begin{aligned}\text{cumulative returns}_i(t_1, t_2) = \beta_0 + \beta_1 \frac{TD}{EV} + \beta_2 \text{ Industry effect} \\ + \beta_i \text{ Controls} + \gamma_{t_0} \Delta FFR + \epsilon_i \quad (5.1)\end{aligned}$$

Figure 5.11: CAR over a 5-day window surrounding increases in FFeR - SPY Benchmark

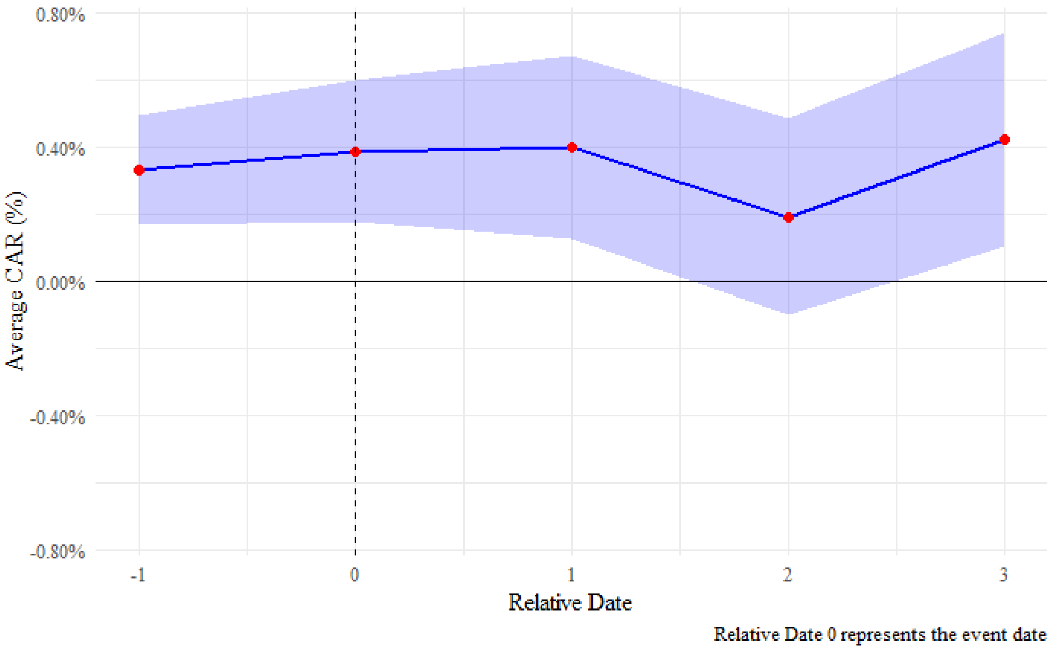


Figure 5.12: CAR over a 5-day window surrounding increases in FFRF - SPY Benchmark

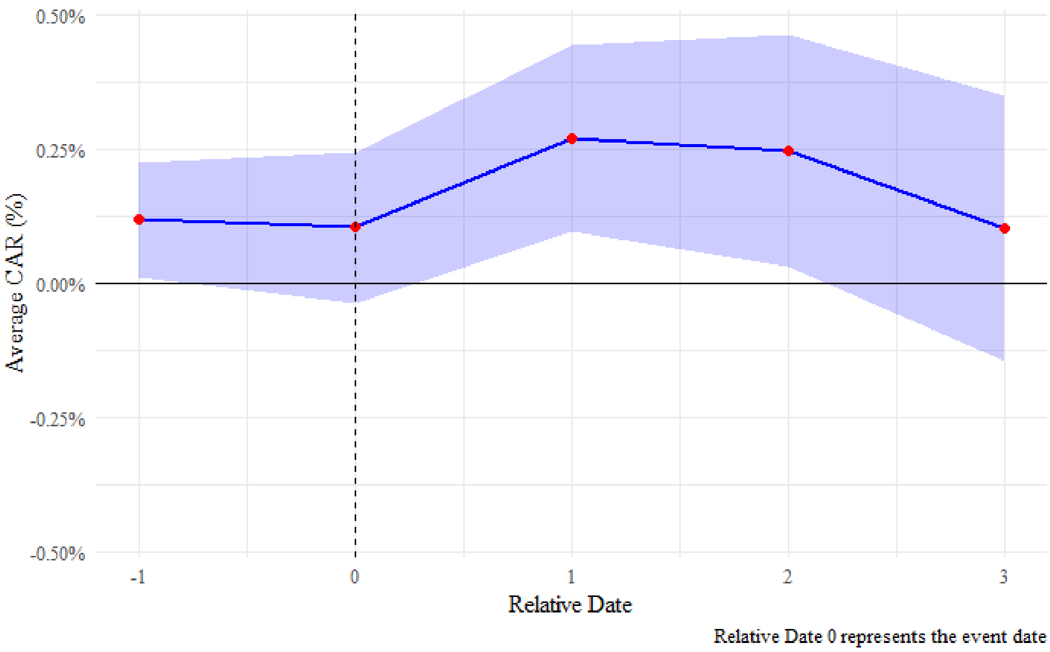


Figure 5.13: CAR over a 5-day window surrounding decreases in FFeR - SPY Benchmark

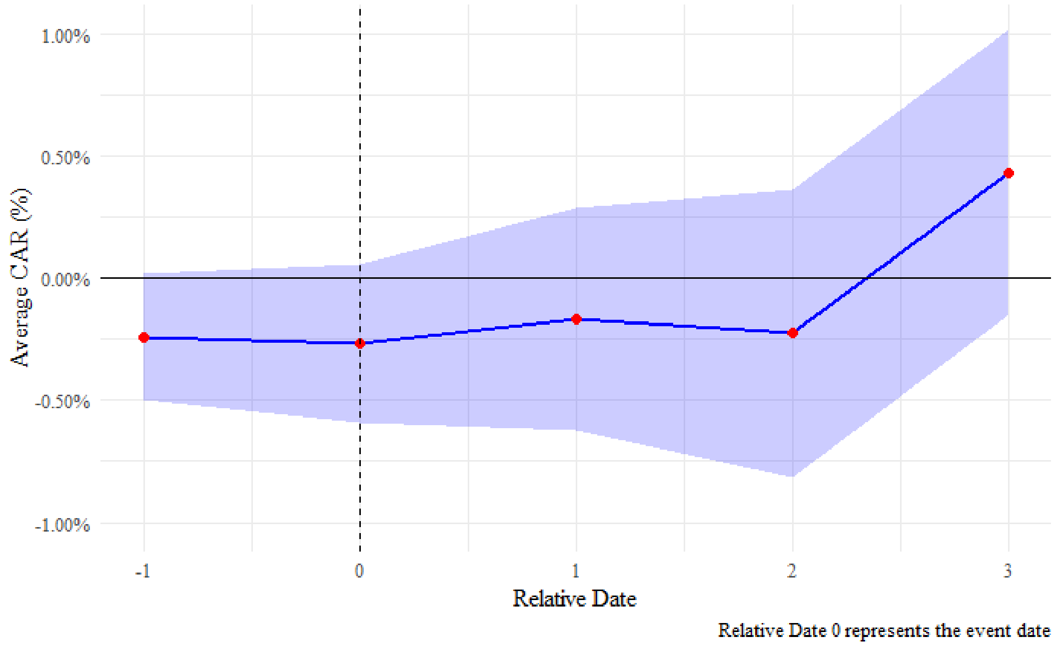
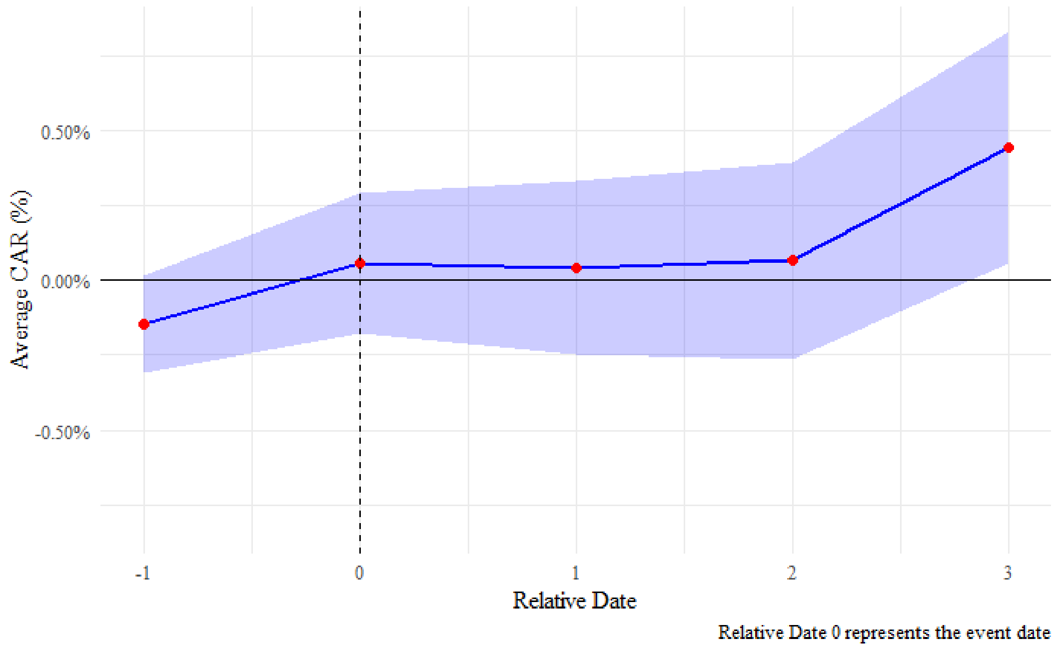


Figure 5.14: CAR over a 5-day window surrounding decreases in FFRF - SPY Benchmark



Having calculated the CAR for both changes in the FFeR and FFRF, we can now conduct multiple regression analyses to determine if the results differ depending on whether the change was expected (FFRF) or actual (FFeR). Table 5.4 presents the results of these regressions. The first column displays the regression of CAR on control variables for events involving changes in the FFeR, while the second column presents the regression results for events involving changes in the FFRF.

In the analysis, we observe that the coefficient for the change in FFRF is statistically significant at the 10% level, indicating some predictive power regarding CAR. However, the overall explanatory power of the models, as reflected by the low R-squared values, is weak. This suggests that the variables included in the model do not sufficiently explain the variations in CAR.

One possible explanation for this limitation is the occurrence of structural changes in the relationship between CAR and interest rates. Notably, prior to the COVID-19 pandemic, there were gradual decreases in interest rates approaching the Zero Lower Bound (ZLB), with a significant cut in the FFR by -0.85 percentage points on March 16, 2020, bringing it near zero. Additionally, on April 1, 2022, we observed the last decrease in the FFRF during this period.

Given these considerations, we will split the data into two time frames: pre-COVID and during COVID. This division is also supported by the results of the Chow test, which suggest that a structural change occurred in the model, thereby justifying the segmentation of the data.

Two-period Regression model

As breakpoints, we selected the WHO's announcement on March 11, 2022, declaring COVID-19 as a global pandemic. We subsequently conducted multiple regression analyses, with the results summarized in Table 5.5, highlighting several noteworthy findings. The coefficient for the Total Debt/EV Ratio is negative and significant before COVID for both FFeR and FFRF events, indicating that higher leverage was associated with lower CAR over the event window. However, this effect becomes non-significant during the COVID period, suggesting a possible shift in market reactions to leverage amid a global crisis. The sectoral dummy variables present mixed results, with none being statistically significant, except for the Health Care sector in the Pre-COVID FFeR regression, which is significant at the 10% level ($p < 0.1$). The absence of significance in other periods suggests that the Health Care sector's impact

Table 5.4: Regression Results: Determinants of CAR

	ΔFFeR	**ΔFFRF**
Total Debt/EV Ratio	-0.0154	-0.0060
	(0.0214)	(0.0161)
GICS - Consumer Discretionary	-0.1786	0.8931
	(0.8225)	(0.6364)
GICS - Consumer Staples	0.7625	-0.8244
	(0.9299)	(0.7097)
GICS - Energy	-2.0310	-1.5940
	(1.8310)	(1.3610)
GICS - Financials	0.1507	0.8228
	(1.3240)	(1.0130)
GICS - Health Care	0.4903	0.3563
	(0.6689)	(0.5112)
GICS - Industrials	-0.4714	-0.2322
	(0.8660)	(0.6576)
GICS - Information Technology	0.2576	-0.2483
	(0.5497)	(0.4211)
GICS - Materials	-0.1066	-1.6800
	(1.3690)	(1.0480)
GICS - Real Estate	0.0346	-0.1673
	(1.3300)	(1.0180)
Market Capitalization	-0.0537	-0.0487
	(0.1480)	(0.1117)
P/E Ratio	0.0000	0.0000
	(0.0000)	(0.0000)
Price to Book Ratio	0.0009	-0.0047***
	(0.0009)	(0.0010)
R&D as % of Revenue	0.0093	0.0081
	(0.0231)	(0.0176)
ROcE	-0.0028	0.0023
	(0.0033)	(0.0026)
$\Delta FFeR$	0.4246	-
	(0.3570)	-
$\Delta FFRF$	-	0.9700*
	-	(0.4072)
Constant	0.8836	0.9271
	(3.6950)	(2.7900)
Residual standard error	5.067 on 969 DF	4.798 on 1497 DF
Adjusted R-squared	-0.0071	0.0232

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001; .p<.1.

on CAR may have been limited. The Market Capitalization of companies does not appear to have a significant effect on CAR following the events. Regarding financial ratios, the P/B Ratio remains significant and negative across all periods and event types, except for FFeR events during COVID. This suggests that companies with higher market valuations relative to their book value tend to experience lower CAR, partially confirming the assumption that growth stocks are more sensitive to increases in interest rates. In contrast, the P/E ratio's effect is both insignificant and small, indicating it plays no role in influencing CAR. The coefficient for ROcE is positive and significant in the Pre-COVID period for both FFeR and FFRF changes, suggesting that more capital-efficient firms benefited from changes in interest rates. Lastly, R&D as a percentage of revenue was found to be insignificant in both periods and across both models, indicating it lacks predictive power in this context.

Regarding the changes in interest rates, we observe that the coefficients for ΔFFeR in the Pre-COVID period were negative and not significant. However, during the COVID period, the coefficient became positive and significant ($p < .05$). This suggests that during the COVID period, an increase in the FFeR was associated with an increase in cumulative abnormal returns. Similarly, for the FFRF, the results show a negative coefficient ($p < .05$) in the Pre-COVID period, indicating that anticipated rate hikes were generally viewed negatively. However, during the COVID period, the coefficient turned positive and significant, suggesting a positive market response to anticipated rate hikes at that time. The positive response to both actual (FFeR) and anticipated (FFRF) rate increases during the COVID period could be interpreted as markets viewing these rate hikes as indicators of economic stabilization. In an environment marked by uncertainty and economic downturns, rate increases might have been perceived as a vote of confidence by the Federal Reserve in the resilience and recovery of the economy. This positive perception could potentially outweigh traditional concerns about the restrictive effects of higher interest rates. Given that many coefficients remain statistically insignificant, further refinement of the model is necessary.

Reduced Two-period Regression model

First, we removed all variables that were statistically insignificant across all four regressions. Specifically, this means excluding Market Capitalization, P/E Ratio, and R&D as a percentage of Revenue. Second, we simplified the sector

Table 5.5: Regression Results: Determinants of CAR - Pre-COVID and COVID

	ΔFFeR		ΔFFRF	
	Pre-COVID	**COVID**	**Pre-COVID**	**COVID**
Total Debt/EV Ratio	-0.0765**	0.0092	-0.0649*	0.0213
	(0.0290)	(0.0279)	(0.0260)	(0.0208)
GICS - Consumer Discretionary	0.9442	-0.1955	1.9059	0.6650
	(1.8030)	(0.9783)	(1.7074)	(0.7213)
GICS - Consumer Staples	-0.6062	0.7981	-0.3591	-1.2930
	(1.3079)	(1.1700)	(1.2317)	(0.8587)
GICS - Energy	0.0281	-4.1860	-1.9272	0.0331
	(1.9350)	(2.8510)	(1.8517)	(1.9650)
GICS - Financials	-1.2148	0.5280	1.5728	0.3674
	(1.7871)	(1.6870)	(1.6935)	(1.2410)
GICS - Health Care	1.6616 .	0.0587	0.6233	0.1737
	(0.9442)	(0.8381)	(0.8798)	(0.6195)
GICS - Industrials	-0.1642	-0.7483	0.7054	-0.7331
	(1.2391)	(1.0800)	(1.1445)	(0.7932)
GICS - Information Technology	-0.1925	0.4810	0.5082	-0.5710
	(0.7812)	(0.6937)	(0.7328)	(0.5121)
GICS - Materials	-0.9827	-0.1218	-1.3893	-2.0030
	(1.8521)	(1.7440)	(1.7619)	(1.2830)
GICS - Real Estate	0.1002	-0.2054	0.9030	-0.6936
	(1.8072)	(1.6900)	(1.7136)	(1.2440)
Market Cap	0.2401	-0.1246	0.0607	-0.0772
	(0.2520)	(0.1790)	(0.2227)	(0.1314)
P/E Ratio	-0.0011	0.0000	-0.0004	0.0000
	(0.0018)	(0.0000)	(0.0020)	(0.0000)
P/B Ratio	-0.1123*	0.0017	-0.1238**	-0.0043***
	(0.0467)	(0.0012)	(0.0456)	(0.0011)
R&D as % of Revenue	0.0458	-0.0165	0.0408	-0.0086
	(0.0329)	(0.0292)	(0.0308)	(0.0214)
ROcE	0.0230*	-0.0067	0.0305**	0.0004
	(0.0107)	(0.0051)	(0.0105)	(0.0037)
Δ FFeR	-0.8203	1.2060*	-	-
	(1.1416)	(0.4918)	-	-
Δ FFRF	-	-	-5.0868**	1.6230**
	-	-	(1.6872)	(0.5350)
Constant	-5.7611	2.4630	-2.9566	1.7930
	(6.0695)	(4.5280)	(5.3662)	(3.3230)
Residual standard error	3.693 on 240 DF	5.413 on 712 DF	4.445 on 403 DF	4.884 on 1077 DF
Adjusted R-squared	0.0785	-0.0019	0.0601	0.0272

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001; .p<.1.

analysis by focusing solely on whether a firm belongs to the Information Technology (IT) sector. The results of this refined analysis are presented in Table 5.6.

Table 5.6: Reduced Regression Model: Determinants of CAR - Pre-COVID and COVID

	ΔFFeR		ΔFFRF	
	Pre-COVID	**COVID**	**Pre-COVID**	**COVID**
Total Debt/EV Ratio	-0.0453*	-0.0362*	-0.0664***	-0.0012
	(0.0183)	(0.0144)	(0.0161)	(0.0101)
GICS - Other than IT	-0.1775	-0.1736	-0.6385	0.7164 **
	(0.4968)	(0.3867)	(0.4479)	(0.2685)
Price to Book Ratio	-0.0150	0.0016	-0.0456**	-0.0048***
	(0.0174)	(0.0011)	(0.0173)	(0.0010)
ROcE	0.0055	-0.0072 *	0.0149**	0.0028
	(0.0053)	(0.0035)	(0.0049)	(0.0024)
Δ FFeR	1.8911	1.1239 *	-	-
	(1.1538)	(0.4427)	-	-
Δ FFRF	-	-	-8.8464***	1.2720 **
	-	-	(1.6506)	(0.4553)
Constant	0.6910	-0.3252	-1.3102**	-0.9766***
	(0.5392)	(0.3723)	(0.5019)	(0.2565)
Residual standard error	4.753 on 412 DF	6.129 on 1117 DF	5.467 on 670 DF	5.203 on 1672 DF
Adjusted R-squared	0.0121	0.0127	0.0702	0.0214

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001; .p<.1.

Firstly, the effect of the Total Debt/EV Ratio remained significant and negative during the Pre-COVID period, indicating that higher leverage was associated with lower CAR. This negative relationship persisted during the COVID period for changes in FFeR, but not for FFRF. This suggests that actual changes in interest rates negatively impact highly leveraged firms, while anticipated changes (FFRF) do not have the same effect. It implies that investors may only consider a firm's leverage when the change in interest rates actually materializes. The coefficient for non-IT sectors was generally not significant across most specifications, with the exception of changes in FFRF during the COVID period, where a positive and significant effect was observed. This indicates that, during the COVID period, sectors outside of IT experienced higher abnormal returns following changes in FFRF compared to the IT sector. One possible explanation is that investor sentiment was highly volatile during this period, with risk perceptions varying widely across sectors. The IT sector, which appeared promising even amidst the pandemic, might not have experienced the same relief or confidence boost from rate changes as other sectors. Post-pandemic, changes and expected changes in interest rates might have been interpreted as signs of economic recovery or stabilization, leading to significant positive abnormal returns in non-IT sectors. Next, the Price to Book Ratio consistently showed a negative and significant relationship with CAR during both periods for FFRF events, though it lost significance for changes in FFeR. This suggests that value stocks performed better following changes in FFRF. The effect of ROcE became less pronounced in the pre-COVID period regressions. It also lost its significance for changes in FFeR, with the effect size being negligible, indicating that capital efficiency did not have a strong influence on CAR. Regarding changes in interest rates, the coefficient for ΔFFeR was only statistically significant during the COVID period, indicating that investors did not pay much attention to actual changes before the pandemic was declared a global crisis. This could be due to the significant impact of futures rate changes, which had a large and statistically significant effect size. Specifically, a 1 percentage point change in FFRF resulted in a negative 8.85 percentage point effect on CAR over the five-day window, suggesting that investors closely monitored expected interest rate changes during the pre-COVID period. Post-pandemic, the coefficients for both ΔFFRF and ΔFFeR became positive and statistically significant. This suggests that investors perceived rate decreases as a signal of economic recovery during the pandemic, while increases were seen as a potential precursor to a recession. Finally, the constant term for changes in FFeR was insignificant in both periods, while it was negative and statistically significant for changes in FFRF. This indicates a general negative reaction of stocks to both actual and anticipated interest rate changes.

Effect of SPY as a benchmark

Finally, we conducted similar analyses using the SPY as a benchmark. The regression results, presented in Table 5.7, highlight several interesting patterns. Similar to the naive regression model in the previous section, most variables exhibit statistically insignificant coefficients. The only two statistically significant coefficients are for the P/B Ratio and ΔFFRF. The effect of the P/B Ratio remains consistent in both direction and magnitude, indicating that this relationship holds across different model specifications.

The negative coefficient for ΔFFeR suggests that the returns of technology stocks, compared to the broader SPY index, react in the opposite direction to changes in the effective Federal Funds Rate. However, this effect warrants further examination, as the overall model fit is not particularly strong. The results of the Chow Test support this observation, suggesting structural differences across periods. Consequently, we conducted a two-period regression analysis to better understand these dynamics.

Two-period Regression model The regression results for the pre-COVID and COVID periods, as shown in Table 5.8, provide several notable insights. First, the Total Debt/EV Ratio demonstrates a significant negative effect in the pre-COVID period for both FFeR and FFRF events (albeit only at $p < .1$), indicating that higher leverage was associated with lower abnormal returns. This effect dissipates during the COVID period, indicating a shift in market perception of leverage during the pandemic. This finding aligns with previous results (Table 5.5), suggesting consistency across both benchmarks.

The analysis of GICS sectors once again shows mixed results, with none of the coefficients achieving statistical significance and some even changing signs between the Pre-COVID and COVID periods. This suggests that the sector classification of firms had little to no effect on abnormal returns during these periods.

Similarly, Market Capitalization continues to be insignificant across all models, reinforcing the notion that firm size did not play a significant role in explaining abnormal returns. The P/B Ratio consistently exhibits a negative relationship with CAR, particularly significant for FFRF changes, highlighting a preference for value stocks during these events.

The ROcE coefficient suggests that more efficient companies experienced better abnormal returns in the pre-COVID period, particularly for FFRF events. This indicates that market participants rewarded capital efficiency during times of lower uncertainty. However, the significance and effect size of ROcE diminish during the pandemic, suggesting that investors placed less emphasis on capital efficiency during this period.

Notably, the coefficients for ΔFFeR and ΔFFRF reveal contrasting effects across periods. The negative and significant coefficient for ΔFFeR in the pre-COVID period suggests that anticipated rate hikes were viewed negatively by the market. In contrast, the coefficient for ΔFFRF remains positive and significant during both periods. This divergence in the sign of the ΔFFRF coefficient across benchmarks is intriguing. It may suggest that while individual firms react to changes in expected interest rates predictably in isolation, they generally fare better than most firms when compared to the broader market (such as the SPY). Conversely, decreases in expected interest rates tend to benefit the broader market more than individual technology firms.

Table 5.7: Regression Results - SPY as a benchmark: Determinants of CAR

	ΔFFeR	ΔFFRF
Total Debt/EV Ratio	-0.0172	0.0106
	(0.0219)	(0.0169)
GICS - Consumer Discretionary	0.2459	0.7921
	(0.8427)	(0.6675)
GICS - Consumer Staples	0.2645	-1.2120
	(0.9527)	(0.7444)
GICS - Energy	-2.0460	-1.3730
	(1.8760)	(1.4270)
GICS - Financials	0.3416	0.8175
	(1.3570)	(1.0620)
GICS - Health Care	0.2298	0.2134
	(0.6853)	(0.5362)
GICS - Industrials	-0.6129	-0.1324
	(0.8871)	(0.6897)
GICS - Information Technology	0.5250	-0.0553
	(0.5632)	(0.4417)
GICS - Materials	-0.2706	-1.6160
	(1.4030)	(1.0990)
GICS - Real Estate	-0.0956	-0.1424
	(1.3630)	(1.0680)
Market Capitalization	-0.0249	-0.1439
	(0.1516)	(0.1172)
P/E Ratio	0.0000	0.0000*
	(0.0000)	(0.0000)
Price to Book Ratio	0.0008	-0.0048***
	(0.0010)	(0.0010)
R&D as % of Revenue	0.0156	0.0185
	(0.0237)	(0.0184)
ROcE	-0.0026	0.0023
	(0.0034)	(0.0027)
$\Delta FFeR$	-0.7310*	-
	(0.3657)	-
$\Delta FFRF$	-	-0.3363
	-	(0.4271)
Constant	1.3540	3.9110
	(3.7850)	(2.9260)
Residual standard error	5.191 on 969 DF	5.033 on 1497 DF
Adjusted R-squared	-0.0020	0.0206

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001; .p<.1.

Table 5.8: Regression Results - SPY as a benchmark: Determinants of CAR - Pre-COVID and COVID

	ΔFFeR		ΔFFRF	
	Pre-COVID	**COVID**	**Pre-COVID**	**COVID**
Total Debt/EV Ratio	-0.0702*	0.0043	-0.0521 .	0.0306
	(0.0318)	(0.0282)	(0.0288)	(0.0212)
GICS - Consumer Discretionary	0.6748	0.0311	1.4777	0.6996
	(1.9727)	(0.9900)	(1.8903)	(0.7348)
GICS - Consumer Staples	-0.3875	-0.0468	-0.8905	-1.5770.
	(1.4310)	(1.1840)	(1.3636)	(0.8747)
GICS - Energy	0.4878	-4.1710	-1.7109	0.2361
	(2.1170)	(2.8850)	(2.0500)	(2.0010)
GICS - Financials	-1.0744	0.7328	1.7147	0.3303
	(1.9552)	(1.7070)	(1.8750)	(1.2640)
GICS - Health Care	1.9244.	-0.4016	0.4580	0.0840
	(1.0331)	(0.8480)	(0.9741)	(0.6311)
GICS - Industrials	0.4906	-1.2750	1.0713	-0.7441
	(1.3557)	(1.0930)	(1.2672)	(0.8080)
GICS - Information Technology	0.3007	0.6143	1.1188	-0.4930
	(0.8547)	(0.7020)	(0.8113)	(0.5217)
GICS - Materials	-0.3964	-0.6210	-1.2333	-2.0150
	(2.0264)	(1.7650)	(1.9506)	(1.3070)
GICS - Real Estate	0.2473	-0.4453	0.8048	-0.6951
	(1.9772)	(1.7100)	(1.8971)	(1.2670)
Market Cap	0.2374	-0.1384	0.0214	-0.1308
	(0.2758)	(0.1812)	(0.2465)	(0.1339)
P/E Ratio	-0.0008	0.0000	-0.0006	0.0000*
	(0.0020)	(0.0000)	(0.0022)	(0.0000)
P/B Ratio	-0.1044*	0.0014	-0.1131*	-0.0044***
	(0.0510)	(0.0012)	(0.0504)	(0.0011)
R&D as % of Revenue	0.0533	-0.0130	0.0568	-0.0068
	(0.0359)	(0.0295)	(0.0341)	(0.0218)
ROcE	0.0214 .	-0.0067	0.0286*	0.0001
	(0.0117)	(0.0051)	(0.0116)	(0.0038)
Δ FFeR	-5.5265***	-0.6351	-	-
	(1.2490)	(0.4976)	-	-
Δ FFRF	-	-	8.5722***	2.5860
	-	-	(1.8679)	(0.5450)
Constant	-6.6080	4.7700	1.5562	3.7600
	(6.6407)	(4.5810)	(5.9410)	(3.3850)
Residual standard error	4.041 on 240 DF	5.478 on 712 DF	4.921 on 403 DF	4.975 on 1077 DF
Adjusted R-squared	0.1180	-0.0042	0.0863	0.0231

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001; .p<.1.

Reduced Two-period Regression model Finally, we further refined the model to include only its most significant components. The reduced model results (Table 5.9) consistently showed that the Total Debt/EV Ratio had a significant negative relationship with abnormal returns in the pre-COVID period across both benchmarks (SPY and NDX). This finding suggests that high leverage was detrimental to firm performance in anticipation of, or during, actual rate changes. However, during the COVID period, while this negative impact persisted for changes in FFeR, it was not significant for changes in FFRF. This implies that investors were more concerned with realized rather than expected rate changes when assessing leveraged firms.

The effect of the IT sector, as compared to non-IT sectors, remained largely insignificant across most specifications. Nonetheless, a notable positive effect for non-IT sectors was observed during the COVID period in relation to changes in FFRF. This suggests that, during the pandemic, investors viewed sectors outside of IT as having greater potential for recovery or stabilization, potentially due to the generally stable outlook for the IT sector. The significant positive abnormal returns in non-IT sectors following changes in FFRF indicate a possible shift in investor sentiment, favoring these sectors as more responsive to rate changes during a period of economic uncertainty.

The Price to Book Ratio continued to show a negative and significant relationship with abnormal returns during FFRF events, both before and during the COVID period. This consistency across both benchmarks reinforces the preference for value stocks during times of anticipated rate changes, while the effect was less pronounced for actual changes (FFeR).

The influence of ROcE was generally minimal and mostly insignificant, except for some minor significance in certain COVID-period models. This suggests that capital efficiency was not a major factor influencing abnormal returns during the periods analyzed.

The most contrasting findings between the benchmarks emerged in the interpretation of interest rate changes. For the SPY benchmark, changes in FFRF had a notable negative impact in the pre-COVID period, a pattern not as pronounced for the NDX benchmark. However, during the COVID period, both benchmarks exhibited positive and significant coefficients for both FFeR and FFRF. This indicates a shift in investor sentiment, where rate changesâ€"both actual and expectedâ€"were seen as positive signals of economic recovery. This could reflect a general optimism regarding the economic outlook or confidence in the central bank's policies during the pandemic.

Overall, these results demonstrate that while certain factors, such as leverage and sector classification, had consistent effects across different benchmarks and periods, investor reactions to interest rate changes varied depending on the benchmark used.

Table 5.9: Reduced Regression Model - SPY as a benchmark: Determinants of CAR - Pre-COVID and COVID

	ΔFFeR		ΔFFRF	
	Pre-COVID	**COVID**	**Pre-COVID**	**COVID**
Total Debt/EV Ratio	-0.0449*	-0.0503***	-0.0707***	-0.0016
	(0.0185)	(0.0147)	(0.0167)	(0.0103)
GICS - Other than IT	-0.3673	-0.6342	-1.2504**	0.6238*
	(0.5028)	(0.3947)	(0.4660)	(0.2749)
Price to Book Ratio	-0.0209	0.0016	-0.0543**	-0.0050***
	(0.0176)	(0.0011)	(0.0180)	(0.0010)
ROcE	0.0073	-0.0091*	0.0170***	0.0029
	(0.0054)	(0.0036)	(0.0051)	(0.0024)
Δ FFeR	-2.4948*	-0.5514	-	-
	(1.1679)	(0.4520)	-	-
Δ FFRF	-	-	3.8101*	-0.0332
	-	-	(1.7173)	(0.4662)
Constant	0.5073	1.9010***	3.0308***	-0.2111
	(0.5458)	(0.3801)	(0.5221)	(0.2626)
Residual standard error	4.811 on 412 DF	6.257 on 1117 DF	5.688 on 670 DF	5.327 on 1672 DF
Adjusted R-squared	0.0191	0.0180	0.0506	0.0166

Note: Standard errors are in parentheses. *p < .05; **p < .01; ***p < .001; .p<.1.

5.3 Discussion

The results of this analysis shine light on the complex relationship between, both actual and anticipated, changes Federal Funds and stock market returns. It shows that both FFRF (expected) and FFeR (actual) changes significantly influence market reactions, with notable differences before and during the COVID-19 pandemic. Specifically, we observed that market reactions to unanticipated rate changes in FFRF tend to be more pronounced and predictive than reactions to actual changes (ΔFFeR), particularly in the pre-COVID period. This indicates that market participants may have been more responsive to forward-looking information, potentially due to the uncertain economic environment during that time.

A key observation is the shift in market dynamics during the COVID period, where both anticipated and actual rate changes were viewed more positively by investors. This suggests a change in sentiment, possibly reflecting increased optimism about economic recovery and confidence in monetary policy measures.

However, this sentiment shift might not be fully grounded in fundamental analysis. One example, could be the rally behind GameStop (GME), where stock prices surged largely due to market sentiment and speculative trading rather than changes in fundamental value.

5.3.1 Limitations

Several limitations must be considered when interpreting these results. The primary limitation is the relatively low explanatory power of the models, as indicated by the low R-squared values. This suggests that other unaccounted factors, possibly including macroeconomic variables or investor sentiment, could significantly influence stock returns. The exclusion of sentiment analysis and broader macroeconomic factors (which were partially incorporated but showed no significant effect) further limits the scope of the study. Future research could integrate sentiment analysis using social media and news data to quantify the influence of market sentiment. This approach could elucidate the extent to which sentiment drives market reactions compared to fundamental factors. Incorporating a broader range of macroeconomic variables, such as inflation expectations and GDP growth forecasts, may also enhance the models' predictive power. This could help differentiate between market reactions driven by fundamental economic shifts and those driven by speculative sentiment.

Moreover, this analysis only made use of daily returns. More granular data - intra-day prices - may show more subtle market dynamics, especially during periods of heightened volatility or speculative trading, following the change in interest rates.

Chapter 6

Conclusion

This thesis explored the impact of interest rate changes on technology stocks during the COVID-19 era using an event study methodology. The central research question addressed was whether and how these interest rate fluctuations influenced the stock performance of technology firms, especially compared to the broader market, amidst the unprecedented economic disruptions caused by the pandemic. The study employed a robust theoretical framework, calculating abnormal returns different from those implied by a CAPM model, and accumulating these over a short window around specific changes in interest rates, either actual (FFeR) or anticipated (FFRF).

Firstly, it was shown that individual stocks in the NASDAQ 100 reacted more negatively to interest rate changes than the NDX index itself, indicating that the weights of each stock in the index influence the overall effect of interest rate changes. This was evident as the average cumulative abnormal return (CAR) for individual stocks during FFRF changes was approximately -0.45% (3rd day), compared to a lesser reaction in the NDX index.

Secondly, the effect was more pronounced for changes in FFRF, which appeared even before the actual changes. This suggests that individual technology stocks have some predictive power regarding interest rate changes. Notably, while increases in interest rates showed a limited impact on individual stock performance, the effect of interest rate decreases was significantly stronger, with an average CAR of -0.65% (3rd day) following rate cuts.

Comparing the returns to the broader market (SPY), technology stocks generally exhibited higher returns around interest rate changes than the broader market. This effect was particularly notable for increases in both FFeR and FFRF, where technology stocks outperformed compared to the SPY index.

When examining specific variables influencing cumulative abnormal returns, it was consistently found that firms with high leverage, indicated by their Total Debt to Enterprise Value ratio, experienced more negative returns than other firms. This was particularly significant in the pre-COVID period. However, during the COVID-19 period, this variable lost some of its predictive significance.

Additionally, the Price to Book ratio played a significant role across various model specifications, especially concerning unexpected changes in interest rates. This finding suggests that value stocks are generally less affected by sudden interest rate changes, regardless of direction.

Future research should further explore how sentiment and non-fundamental variables affect stock returns following specific changes in interest rates. Investigating the role of investor sentiment and behavioral factors could provide deeper insights into the market dynamics observed during periods of monetary policy shifts.

In conclusion, this thesis contributes to the literature by offering a detailed sector-specific analysis of the effects of interest rate changes on technology stocks. It emphasizes the sector's unique characteristics and the broader economic implications of monetary policy in a post-pandemic world. The findings highlight the complex interplay between market expectations, firm-specific characteristics, and macroeconomic factors in shaping stock market responses to monetary policy changes.

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Appendix A

Appendix

Figure A.1: AR distribution - NDX benchmark

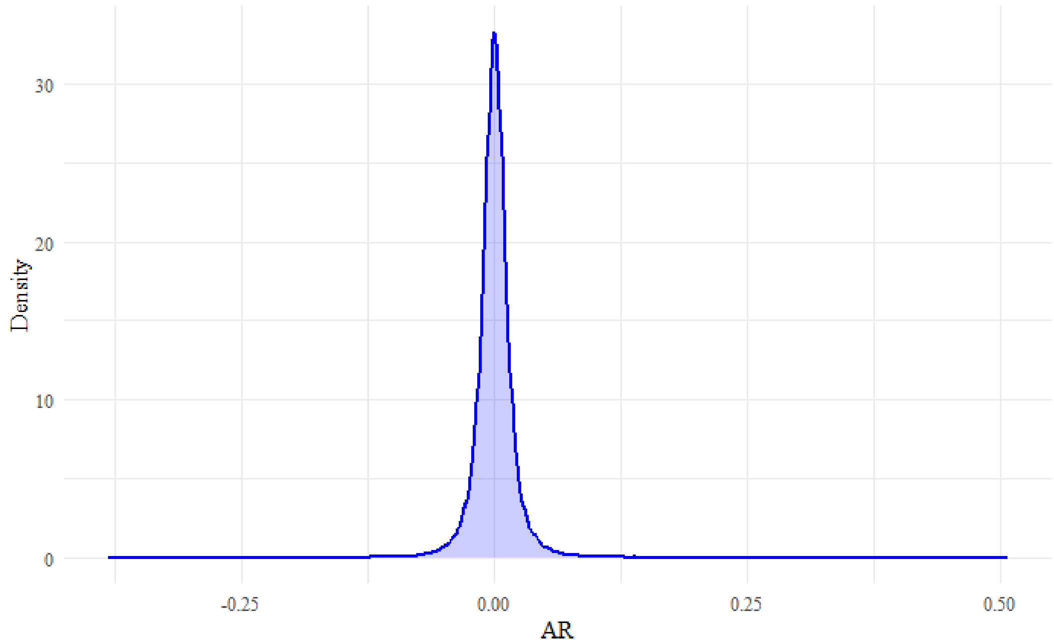

Figure A.2: AR distribution - SPY benchmark