International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2025, 15(3), 18-28.

Does US Monetary Policy Affect Stock Market Behaviour Under Extreme Market Conditions? Evidence from COVID-19

Erdem Kilic[1]*, Sitki Sönmezer[2]

[1]Turkish-German University, Istanbul, Turkiye, [2]Istanbul Ticaret University, Istanbul, Turkiye. *Email: erdem.kilic@tau.edu.tr

Received: 23 October 2024 **Accepted:** 05 March 2025 **DOI:** https://doi.org/10.32479/ijefi.18286

ABSTRACT

We examine the short-term impact of Federal Open Market Committee (FOMC) announcements on technology stocks behavior. Using a modified continuous-time simulation model, we analyze high-frequency data for nine representative stocks from July 2019 to January 2021, covering ten FOMC announcement dates and the outbreak of COVID-19. High-frequency data provides more insight than lower frequent data. These insights enabled us to analyze the volatilities with higher incisiveness. Our results show differences in price jump patterns between mega-cap and second-tier large-cap stocks, varying degrees of noise dominance, and the presence of Brownian motion. Specifically, FOMC announcements increase market volatility and impact stock prices in different ways. Mega-cap stocks that are already financially strong appear to be less sensitive to interest rate increases than their smaller counterparts that rely on external financing.

Keywords: Monetary Policy, Stock Market Behaviour, COVID-19
JEL Classifications: C22, E49, G11

1. INTRODUCTION

FOMC announcements are crucial in determining the required rate of returns as risk-free rates are computed from treasury yields. As previous studies reveal (i.e. Andersen et al., 2003; Bernanke and Kuttner, 2005) the impact of these announcements increases when the announced information is unexpected. In financial markets, the FOMC strategically employs forward guidance to steer market dynamics (Bielecki et al., 2019). This practice has prompted an extensive investigation into the effects of US macroeconomic news releases on stock index returns and volatility.

In particular, US macroeconomic news announcements have imminent effects on both stock index returns and daily volatilities. These effects have been extensively analyzed in the literature. Some scholars have examined these effects using high-frequency 5-min data and found significant effects on the Canadian index return and volatility (Hussain and Omrane, 2021). Earlier studies have also conducted studies for the public releases of US and German regulatory bodies. They analyzed the effect of these announcements on currency volatility. Moreover, they provided evidence that adverse announcements have a greater impact due to information asymmetry. Andersen et al. (2003) used 5-min interval data for 1992-1998 to study the impact of German and US announcement surprises on the currencies' conditional means and volatilities. They provide evidence that although exchange rates react quickly to macro-news surprises, the response of conditional variance is relatively slow. They characterized the nature of the price response as asymmetric when adverse news is found to have a larger impact. Foreign equity indexes react to path surprises, as they have some financial linkage with the US economy. Moreover, foreign markets sometimes overreact to FOMC announcements because of the change in the perceived risk in the aforementioned linkage. The literature has stated that macroeconomic news releases trigger both volatility jumps and price jumps (Chan and Gray, 2018). Two hypotheses explain why jumps occur: First hypothesis claims that investors may evaluate the risk premium using different assumptions, and the announcements align these assumptions for that particular announcement date, causing jumps. The second hypothesis incorporates biases of irrational investor expectations or projections into the occurrence of jumps.

This behavioral camp explains jumps in terms of these investor biases (Jiang and Yao, 2013). Bernanke and Kuttner (2005) showed evidence that the unexpected monetary policy announcements have a greater impact on risk premiums; thus, the change in stock market returns and the volatility depend on the predictability of the FOMC moves.

When FOMC announces to decrease its target rate, stock returns diminish, and stock prices increase with an increase in target rates. The path of interest rates is an important factor for the valuations of stocks (Neuhierl and Weber, 2019). Their findings show that the path of interest rates matters for asset prices, and monetary policy affects asset prices continuously. Meanwhile, Tauchen and Zhou (2011) explained how characterizing the distribution and causes of jumps can improve asset pricing models, which motivates our study. Bomfim (2003) has provided evidence that positive news effects the volatility even more than negative news, which is found to be consistent with both the leverage and volatility-feedback hypotheses.

From early investigations into equity valuations and predictability to recent advances in high-frequency data and machine learning, a spectrum of research clusters informs our understanding of market behavior. Andersen and Bollerslev (1998) highlighted the utility of high-frequency data in resolving volatility disputes and its interactions with market microstructure features. Yan (2011) stated that option-implied volatility and high-frequency data provide better volatility forecasts than historical returns. Amini et al. (2010) demonstrated short-horizon stock returns' better prediction by past price movements, questioning autocorrelation reliability. Assets usually have trends, and they frequently have unexpected changes upon a piece of unexpected information released for their prices, known as jumps. Small stocks tend to have higher price jumps than large ones (Jiang and Yao, 2013).

Nakamura and Steinsson (2013) find evidence for the information effect of FOMC decision. They interpret the increase in expected output growth after a monetary tightening as evidence of a Fed information effect. When the Fed raises interest rates, this leads to increased optimism about economic fundamentals. Ignatieva and Ohashi (2024) find a not-lasting drift up of pre-FOMC announcement drift which becomes significant after the FOMC public announcement. Simultaneously, they observe a negative trend of the VIX Index after the announcement

Meanwhile, Bali and Peng (2006) explored the risk-return trade-off using multiple volatility estimators and find a positive relationship. Patel and Michayluk (2016) examined the predictability of returns following large price fluctuations, resulting in profitable trading strategies. Related newer studies applying machine learning models. Mücher (2022) used LSTM Recurrent Neural Networks to forecast daily volatility, achieving improvements.

Earlier scholars have studied market microstructure, asset-pricing dynamics, and the implications of monetary policy on financial markets from various aspects. This part aims to align these studies hereinafter. Easley and O'Hara (2003) pointed out the role played by microstructure factors in differentiating asset-pricing dynamics. The authors have studied the cross-correlation and autocorrelation structure of stocks, long-run returns, and premia associated with liquidity and informational asymmetries. Cohen et al. (1980) examined high-frequency market microstructure and the impacts of changes in this field, focusing specifically on how high-frequency trading strategies impact traders and market dynamics. Madhavan (2000) demonstrated that market transparency has a clarifying impact on price formation, price discovery, trading costs, and the integration of information over time. The interaction between market structure, design, and participants' ability to observe trading processes is also analyzed. Moreover, Lehalle and Laruelle's (2018) analysis of market microstructure in practice assesses the effects of regulatory changes on market design, electronic trading, and participant behaviors. Finally, Hu and Rocheteau (2015) explored the relationship between monetary policy, asset prices, and market structure in economies in which assets are traded. They have studied the formation and structures of bubbles in asset prices depending on the level of liquidity.

In recent years, the imminent FOMC announcement are likely to trigger speculation for stock returns. In the literature movements in stock prices before the announcements are called "pre-announcement drift" (Lucca and Moench, 2015). These studies can been considered to give evidence for the explanatory power of the expectations channel. Pre-announcement drifts are found present in various samples and mostly positive returns are detected by these previous studies (Hu et al., 2022; Bodilsen et al., 2021; Gu et al., 2018; Guo et al., 2021; Monaco and Murgia, 2023; Ai and Bansal, 2018; Guo et al., (2024); Ma, 2022; Brusa et al., 2020) which indicates a better outlook forecast for stocks in particular due to the announcement to be made. On the contrary, Sekandary and Bask (2023) found detected negative stock returns for the pre-announcement period.

Some scholars have studied uncertainty in the pre-announcement period and they provide evidence that volatility levels are low (Guo et al., 2021; Monaco and Murgia, 2023; Vähämaa and Äijö, 2011). Whereas, volatility levels may also increase upon announcements depending on the chosen sample (Sekandary and Bask, 2023; Gu et al., 2018). Cox et al. (2020) find higher volatility for the COVID-outbreak-period from Feburary to April 2020 driven more by sentiment then substance. Benchimol et al. (2021) describe the increased sentiment and uncertainty effects in the stock market with relation to FED's policy decisions during COVID period.

Despite the vast literature about preannouncement drift with respect to stock returns and volatility, there is no single study that analyses NASDAQ-listed technology stock returns and FOMC announcements that lead to drifts via high –frequency data for the COVID-19 period. Based on the previous research, our study explores the complex relationship between FOMC-driven market behavior, volatility jumps, and risk premiums, enhancing our understanding of the complex interplay that shapes financial markets via the expecations channel.

Another contribution of this study is that we utilize a modified version of the spectrogram model developed by Ait-Sahalia and Jacod (2012). Our model specification analyses the volatility dynamics in stock returns by differentiating various volatility aspects by incorporating continuous volatility components, alternative jump sizes, finite jumps, and infinite jumps. As a core interest, the significance of a structural change in the data around the FOMC meetings is analyzed. Our continuous-time model utilizes frequent data to analyze dynamics such as Brownian motion, jumps, and the intensity of jumps. Our main contribution is to provide a model that simultaneously segments the Brownian motion part, the noise part and the jump part in the stock returns. As a novelty, this segmentation model is implemented to analyze the effect of FOMC announcements on technology stocks in NASDAQ in the COVID-19 period.

The remainder of this paper is structured as follows. The next section explains the model settings, data, and assumptions. The third section discusses the results of our analyses.

2. METHODOLOGY AND HYPOTHESIS DEVELOPMENT

The following section describes the methodology for identifying the type of volatility and jumps in the stock returns. The methodology follows the spectrogram approach of Ait-Sahalia and Jacod (2009). According to some calculated threshold criteria, the volatility and jumps are classified as finite and infinite jumps, Brownian motion, continuous component, or dominating noise.

This continuous-time simulation method enables us to analyze the market reaction better as this study uses 5-s-interval data, as known as tick-data. The lower the interval, the higher the chance to detect market reaction for a material annoucement in particular Ait-Sahalia and Jacod (2012).

There are various price jump classifications in the literature. The general jump setting in our model uses a compound Poisson jump process which is semi-martingale property. The most relevant ones for our study are introduced below. Finite Activity Jumps occur at specific points in time and have a finite number of occurrences over a given period. They are uncommon yet impactful, representing major market disruptions. Infinite Activity Jumps occur continuously, making them more frequent but smaller in magnitude compared to finite jumps. These abrupt price movements signal a more subtle but follow the market trends. Additive noise is incorporated additively into a price process. It is the unexplained part of price movement. These different jump types and noise processes are hypothesized separately in the model.

2.1. Model Settings

Following our research motivation, we created a designed statistical measure to analyze specific parts of the distribution of highly frequent data returns. It is aimed to identify different components of the semi-martingale process to which the returns follow. The components of interest in the model are jumps, finite or infinite activity, and continuous components. Other macroeconomic variables that have an impact on stock prices are deliberately ignored as the sole aim is to distangle various components in the stock returns.

The following continuous model structure follows Ait-Sahalia and Jacod (2009). The asset price X follows the Ito semi-martingale process in eqs. (1)-(2).

$$X_t = X_0 + \int_0^t b_s + \int_0^t \sigma_s dW_s + Jumps \tag{1}$$

$$Jumps = \int_0^t \Big(\int_{\{|x| \le \varepsilon\}} x(\mu - \upsilon)(ds, dx) + \int_0^t \Big(\int_{\{|x| > \varepsilon\}} x\mu(ds, dx) \tag{2}$$

The first and second integrals in eq.(1) indicate the drift term and continuous part, respectively. Meanwhile, the first integral in eq.(2) shows the small jumps and the latter big jumps. W is a standard Brownian motion, μ is a pure jump process of X, ε indicates a cut-off level to distinguish between small and big jumps, υ is the Levy measure, where both μ and υ are random positive measures on $\mathbb{R}_+ \times \mathbb{R}$. From this the cut-off level $1 \geq \varepsilon > 0$ we define small and large jumps as given in Ait-Sahalia and Jacod (2012). Figure 1 summarizes the model components in brief.

The above specification then becomes a differential equation:

$$dX_t = b_t dt + \sigma_t dW_t + dJ_t \tag{3}$$

The model constructs power variations of the increments suitably truncated and sampled at different frequencies to determine the relative magnitude and check whether they are present. Thus, the methodology closely follows the spectrogram apporach as introduced by Ait-Sahalia and Jacod (2012). The different asymptotic behavior of the variation are explained by alterning the power p, truncation level u, and sampling frequency Δ as given in eq. (4).

The power tuning parameter p emphasizes continuous component for $p < 2$, jump components for $p > 2$, and puts equal weight for $p = 2$. With the help of the truncation level u, big jumps can be distinguished from small jumps. Modifying the values for the sample intervals Δ, the asymptotic behavior of the power variations is determined.[1] Incorporting alternative truncation levels enables our model to detect various volatility, jump and noise factors. Detection of these factors are hypothesized seperately in methodology section below.

From this definition, the combination of these parameters and the semi-martingale process of the asset return can be described as the parameter triplet in eq. (4).

$$B(p, u_n, \Delta_n) = \sum_{i=1}^{[T/\Delta_n]} |\Delta_i^n X|^p \, 1_{\{|\Delta_i^n X| \le u_n\}} \tag{4}$$

1 See Ait-Sahalia and Jacod (2009) for a formal derivation of the spectrogram approach for financial assets.

Figure 1: Interval selection in spectrogram model

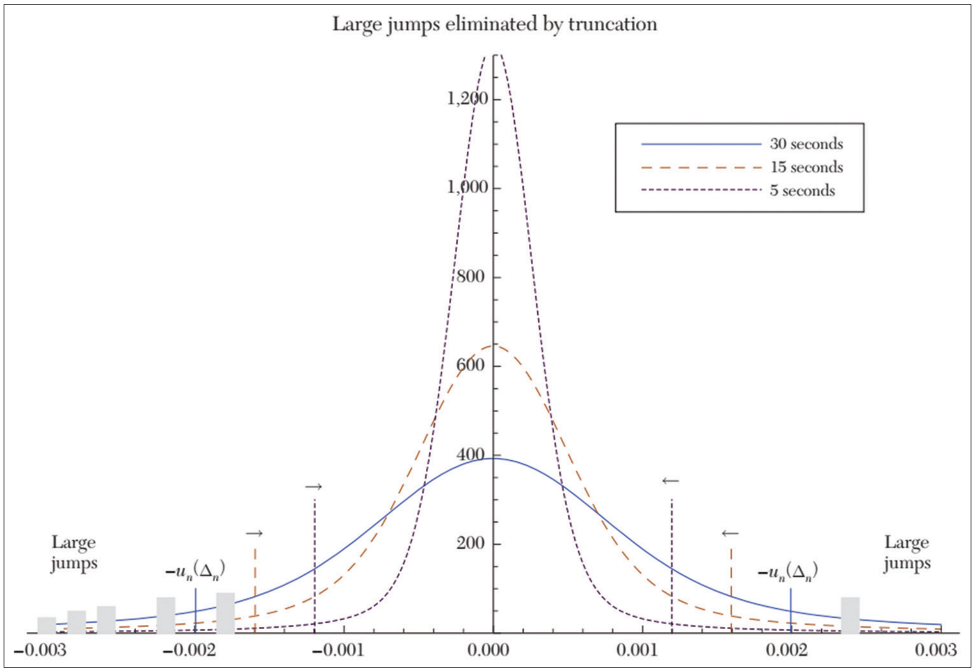


Figure 1 depicts the effect of using tick sizes on probability distribution of price movements. The model starts with at 30 s interval, continuouing with 15 s tick size and ending with 5 s, depending on the truncation level. The 5 s interval exhibits a higher kurtosis but thinner tails, eleminating the large jumps
Source: Ait-Sahalia and Jacod (2012) page 1016

where T is fixed, asymptotiscs are all with respect to $\Delta_n \to 0$, and u_n gives the truncation level of increments. To find increments larger than u, the triplet definition becomes eq. (5).

$$U(p,u_n,\Delta_n)=\sum_{i=1}^{[T/\Delta_n]} |\Delta_i^n X|^p \, 1_{\{|\Delta_i^n X|>u_n\}} \quad (5)$$

Definition 1.

For the $p > 2$ and k chosen from alternative sample interval values, the test statistic for existence of jumps in X is calculated as in eq. (6). Based on whether there are jumps or not, S_j delivers another behavior.

$$S_j(p,k,\Delta_n)=\frac{B(p,\infty,k\Delta_n)_T}{B(p,\infty,\Delta_n)_T} \quad (6)$$

For the integer choice $k \geq 2$ and $p > 2$ the following trunction S_{FA} in eq. (7) separates between different types of jumps, that is, finite and infinite jumps.

$$S_{FA}(p,u_n,k,\Delta_n)=\frac{B(p,u_n,k\Delta_n)}{B(p,u_n,\Delta_n)} \quad (7)$$

For $\gamma > 1$ and $p' > p > 2$, the test statistic S_{IA} describes infinite jump activity as in eq. (8).

$$S_{IA}(p,k,\Delta_n)=\frac{B(p',\gamma u_n,\Delta_n)B(p,u_n,\Delta_n)}{B(p',u_n,\Delta_n)B(p,\gamma u_n,\Delta_n)} \quad (8)$$

For the choice $k \geq 2$ and $p < 2$, the test statistic S_W in eq. (9) determines whether Brownian motion is present or not.

$$S_W(p,u_n,k,\Delta_n)=\frac{B(p,u_n,\Delta_n)}{B(p,u_n,k\Delta_n)} \quad (9)$$

Testing for a pure jump process simultaneously means to test for no Brownian motion in X. By chosing $\gamma > 1$ the related truncation ratio becomes as in eq. (10).

$$S_{noW}(p,u_n,\gamma,\Delta_n)=\frac{B(2,\gamma u_n,\Delta_n)U(0,u_n,\Delta_n)}{B(2,u_n,\Delta_n)U(0,\gamma u_n,\Delta_n)} \quad (10)$$

2.2. Spectrogram Model Tests

To test for the presence of jump activity, we apply the spectrogram methodology as introduced in Section 3.2. The test statistics operate in certain sets of particular:

$$\Omega_T^f = \{\omega : t \mapsto X_t(\omega)\} \quad (11)$$

has finitely many jumps in the interval [0, T].

$$\Omega_T^i = \{\omega : t \mapsto X_t(\omega)\} \quad (12)$$

has infinitely many jumps in the interval [0, T].

Moreover, the following sets are defined: $\big|_T^W$ consists entirely of a Wiener process, and $\big|_T^{noW}$ has no Wiener process, $\big|_T^c$ denotes set of continuous process, $\big|_T^j$ denotes set of jumps, and $\big|_T^c$ denotes set of continuous process. Set $\big|_T^c$ represents that X is continuous in [0, T], and set $\big|_T^c$ contains jump components of in [0, T]. Meanwhile, set $\big|_T^f$ indicates that X has finitely many jumps in [0, T], set $\big|_T^i$ indicates that X has infinitely many jumps in for [0, T], set $|_T^W$ indicates that X has a Wiener component for [0, T], and set $|_T^{noW}$ indicates that X has no Wiener process in [0, T].

To identify the structure of the stock return dynamics, we test the following hypotheses.[2]

2.2.1. Hypothesis 1. Jumps: Presence or not

Under the null hypothesis, set $|_T^c$ represents that X is continuous in [0, T], the set $|_T^j$ contains jump components of X in [0, T]. It is tested whether the stock returns exhibit jumps or not with the help of eq. (6).

$$H_0 : \Omega_T^c \quad H_1 : \Omega_T^j, where\, S_j : \begin{pmatrix} p > 2 \\ \infty \\ \Delta_n, k\Delta_n \end{pmatrix}$$

$$H_0 : |_T^j \quad H_1 : |_T^c$$

2.2.2. Hypothesis 2. Jumps: Finite or infinite activity

Under null hypothesis, set $|_T^f$ indicates that X has finitely many jumps in [0, T], set $|_T^i$ indicates that X has infinitely many jumps in for [0, T]. It is tested whether the stock returns exhibit finite or infinite activity by the help of eq. (7).

$$H_0 : \Omega_T^f \quad H_1 : \Omega_T^i \qquad S_{FA} : \begin{pmatrix} p > 2 \\ u_n \\ \Delta_n, k\Delta_n \end{pmatrix}$$

$$H_0 : \Omega_T^i \quad H_1 : \Omega_T^f \qquad S_j : \begin{pmatrix} p > 2, p' > 2 \\ u_n, \gamma u_n \\ \Delta_n \end{pmatrix}$$

2.2.3. Hypothesis 3. Brownian motion: Present or not

Under null hypothesis, set $|_T^W$ indicates that X has a Wiener component for [0, T], set $|_T^{noW}$ indicates that X has no Wiener process in [0, T]. It is tested whether the stock returns exhibit Brownian motion or not with the help of eq. (9).

$$H_0 : \Omega_T^W \quad H_1 : \Omega_T^{noW} \qquad S_W : \begin{pmatrix} p < 2 \\ u_n \\ \Delta_n, k\Delta_n \end{pmatrix}$$

$$H_0 : \Omega_T^{noW} \quad H_1 : \Omega_T^W \qquad S_{noW} : \begin{pmatrix} p = 0, p' = 2 \\ u_n, \gamma u_n \\ \Delta_n \end{pmatrix}$$

2.2.4. Hypothesis 4. Estimating the degree of jump activity β

Under null hypothesis $\hat{\beta}$, we estimate the degree of jump activity β by the help of eqs. (4) and (5).

$$\hat{\beta} : \begin{pmatrix} p = 0 \\ U : u_n, \gamma u_n \\ \Delta_n \end{pmatrix} \qquad \widehat{\beta'} : \begin{pmatrix} p = 0 \\ U : u_n \\ \Delta_n, k\Delta_n \end{pmatrix}$$

2.2.5. Hypothesis 5. Relative magnitude of the components

Under null hypothesis $\%QV$, we test the relative magnitude of the components by the help of eqs. (4) and (5).

$$\%QV : \begin{pmatrix} p = 2 \\ u_n \\ \Delta_n \end{pmatrix}$$

2.3. Determination of Limits of Test Statistics

We followed Ait-Sahalia and Jacod (2012) for the methodology of statistical limits. On the basis of the test computation in Section 3.3 and the definition of the spectrogram triplet in Section 3.2, the associated critical values of the test statistics are expressed via the limits of the test statistics (Table 1). The basic assumption for the triplet parameter specifications is expressed as follows: p denotes for power, u denotes truncation parameter, and Δ denotes sampling interval (Section 3.3). From the aforementioned methodology, the numerical values are given as follows $p \in [3,6]$ and $k \in [2,3]$, $\Delta \in [5\ s, 1\ min]$.[3]

For S_j, S_{FA}, S_W and QV, the test limits and critical values are given by the help of the decision boundries in Table 1.[4]

Once the truncation and scale parameters are identified, the special boundaries enable us to test the hypotheses. Here, explanatory

Table 1: Test statistics limits

Test parameter	Test parameter limits	Decision
S_j	$1/k$	additive noise dominates
	$1/k^{1/2}$	rounding error dominates (and jumps have finite activity)
	1	jumps present and no significant noise
	$k^{p/2-1}$	no jumps present and no significant noise
S_{FA}	1/k	additive noise dominates
	no limit	rounding error dominates
	1	infinite activity jumps present and no significant noise
	$k^{p/2-1}$	finite activity jumps present and no significant noise
S_W	$1/k$	additive noise dominates
	no limit	rounding error dominates
	1	no Brownian motion and no significant noise
	$k^{1-p/2}$	Brownian motion and no significant noise
Q_V	0	additive noise dominates
	actual fraction of QV	no significant noise

2 The relevant parameters are derived from simulation of the spectrogram model. These parameters are explained regarding to the benchmark parameters in section 4 one-by-one. For details of computation see [39].

3 The upper limit for has been lowered from 2 min to 1 min compared to Ait-Sahalia and Jacod (2012).

4 If noise is present in the data, the theoretical limits of $S_J(p,u,\Delta)$ become respectively $1/k$ and $1/k^{1/2}$ in the two polar cases of additive noise and noise due to rounding error on the whole set Ω [37].

hypotheses regarding jumps and jump densities are derived and can be applied to our data sample. Relevant results on interest rate decisions between 2019 and 2020 are described from a market pricing perspective in Section 4.

3. DATA AND SAMPLE PERIOD

Ten FOMC dates are identified due to the Federal Reserve FOMC statement releases (Table 2).

The focus is on the expansion and contraction of the federal funds rates.[5] The data period spans from July 2019 to March 2021, which encompasses the outbreak of the COVID-19 pandemic. Most announcements are made at 2:00 p.m. EST. We used 5-s interval Nasdaq data for the six representative companies chosen due to their various market cap rankings. We believe that market capitalization may play a role in perceiving the stock price risk and volatility. We select nine Nasdaq-listed stocks with different market capitalizations to identify potential diversity in the return dynamics: Apple (AAPL), Microsoft (MSFT), and Amazon (AMZN) (2.25, 1.8, and 1.6 trillion USD, respectively);[6], first-tier large-cap Cisco (CSCO), Pepsi (PEP), and Qualcomm (QCOM) (192, 182, 164 billion USD, respectively); and second-tier large-cap Fox Corporation (FOX), Incyte (INCY) and Check Point Software Technologies Ltd. (CHKP) (19.11, 17.71, and 16.25 billion USD, respectively). The stock prices in the model applications are expressed as percentage returns. Since the data has a 5-s high frequency, the sample size is set in a data-rich environment.[7]

4. RESULTS

In this section, we present model results for the effects of FOMC announcements on the behavior of the stock market by analyzing specific dates and their corresponding market responses. Each date offers potential insights into the connection between monetary policy decisions and the dynamics of the stock market. By analyzing the presence of jumps, noise patterns, and continuous components in stocks with varying market capitalizations, we intend to decipher the interactions between FOMC actions and market responses. This analysis offers a broad perspective on how various stocks react to FOMC announcements, contributing to a deeper understanding of the underlying factors driving market fluctuations. For each announcement date, effects are briefly analyzed and discussed below. Related results on interest rate decisions are presented in Appedix Tables A1 and A2.

4.1. Jumps and Volatility as of Announcement Dates

4.1.1. 31 July 2019

Throughout 2019, the US economy enjoyed a growth of 2.3% and inflation rate of 1.9% FOMC lowered rates despite growth that led to cheaper financing for firms in the market. When searching

5 See Table 2 for a compact illustration of the related FOMC announcements with relevant information about interest rate decisions. The date March 2020 announcement is delisted from our sample because it is related with pandemic issues and not directly arising from monetary policy concerns.

6 Market capitalization is given as of 2022 Refinitiv database records.

7 The normality tests for each announcement date are applied as Shapiro-Wilk Test and Kolmogorov-Smirnov Test. We observe that the test statistics violate the normality assumption for each announcement date and each individual stock. The simulation model is implemented at 5% significance-level. The parameters are interpreted according to the statistical limits from Table 1.

Table 2: FOMC announcements

Announcement date	Type of announcement	Interest rate decision	Policy change
January 27, 2021	Federal Reserve issues FOMC statement For release at 2:00 p.m. EST	Target for the fed funds rate at a range of 0%-0.25%.	No
December 15, 2020	Federal Reserve issues FOMC statement For release at 2:00 p.m. EST	Target for the fed funds rate at a range of 0%-0.25%. It also opted to continue its QE program and overnight repurchase (repo) agreement operations.	No
November 5, 2020	Implementation Note issued November 5, 2020	The fed funds rate at a range of 0%-0.25%. It also opted to continue its QE program and overnight repurchase (repo) agreement operations	No
September 16, 2020	September 16, 2020: FOMC Projections materials, accessible version	Target for the fed funds rate to a range of 0%-0.25%	No
July 29, 2020	Federal Reserve issues FOMC statement For release at 2:00 p.m. EDT	The committee said it would use its full range of tools until it is confident that the economy has weathered recent events and is on track to achieve its maximum employment and price stability goals.	No
June 10, 2020	Implementation Note issued June 10, 2020	For the fed funds rate to a range of 0%-0.25	No
April 29, 2020	Federal Reserve issues FOMC statement For release at 2:00 p.m. EDT	It kept the fed funds rate at a range of between 0% and 0.25%	No
October 30, 2019	For release at 2 p.m. EDT October 30, 2019	The FOMC lowered the target fed funds rate to a range between 1.5% and 1.75%. It was concerned that inflation was below its 2% target	Yes
September 18, 2019	For release at 2 p.m. EDT September 18, 2019	The Committee lowered its benchmark rate to a range between 1.75% and 2.0%	Yes
July 31, 2019	Federal Reserve issues FOMC statement For release at 2:00 p.m. EDT	The Committee lowered the fed funds rate to a range between 2.0% and 2.25%. It was the first rate cut since December 2008. It paused reducing its $3.8 trillion in holdings of securities amassed during QE.	Yes

for the presence of jumps, we realized jumps with no significant noise in mega-cap stocks of our sample, whereas the rest of the sample had no significant jumps. AMZN, INCY, and QCOM have a dominating additive noise, whereas AAPL has infinite activity jumps and no significant noise upon the announcement of FOMC. FOX and CHKP, second-tier large-cap companies of our sample, have no values for detecting Brownian motion. However, the remainder of the sample indicates Brownian motion and negligible noise. Our results demonstrate that the announcement has increased the market's overall volatility. AAPL, MSFT, and PEP have a continuous component, whereas the rest of the stocks lack dominant noise; jumps are less intense in the CHKP and INCY stocks.

4.1.2. 19 September 2019

FOMC announcements do not have unilateral results for stocks with varying market caps. The announcement of September 2019 has led to almost similar jumps for the stocks in our sample. Meanwhile, the Fed Funds rate was lowered from 2.25% to 2.00%, since the Fed was concerned about slowing growth. Looking at the imminent effects other than jumps, we also observed that finite jumps, Brownian motion, and continuous component are observed as well. However, when we observe finite jumps, we find that mega-cap stocks have relatively higher average values than the second-largest-cap stocks. Second-tier large-cap stocks have dominant additive noise, whereas AAPL and MSFT have infinite activity jumps and no significant noise. Meanwhile, AMZN has dominant additive noise. For this particular announcement, AAPL, Cisco, and MSFT have dominant continuous component, indicating a pattern where both Brownian motion and noise prevail. For our dataset, Brownian motion seems to fit our sample, and no significant noise can be observed.

4.1.3. 31 October 2019

Despite slow global growth and muted inflation, the FOMC has continued lowering interest rates of 0.25%. The new interest level was 1.75%, which lowered the firm's discount rate and valuation. Inevitably, the new interest rate impacted the prices and volatility of the company stocks under study. The vast majority of the firms in our sample exhibited neither jumps nor significant noise. The authors believe that this is due to the predictability of the decision's magnitude and timing. In other words, the decrease in interest rates has already been factored into share prices, so there have been no price increases. For this announcement, we observe Brownian motion and no significant noise for most stocks. On average, mega-cap stocks have higher noise domination values, indicating that CHKP, CSCO, and INCY lack noise domination.

4.1.4. 29 April 2020

Although FOMC has decided to decrease the interest rate from 1.75% to 1.25%% in March 2020, we excluded the announcement from our sample, as this date coincides with the outbreak of the COVID-19. Any inference to be made from this announcement might be problematic. On April 2020, FOMC has lowered interest rates radically to 0.25%, effectively 0%. The free money effects could have mutual effects on stock prices. Jumps were present for AAPL and AMZN with no significant noise, whereas MSFT and PEP had no jumps and no significant noise. Additive noise

Figure 2: Continuous and jump components in spectrogram model

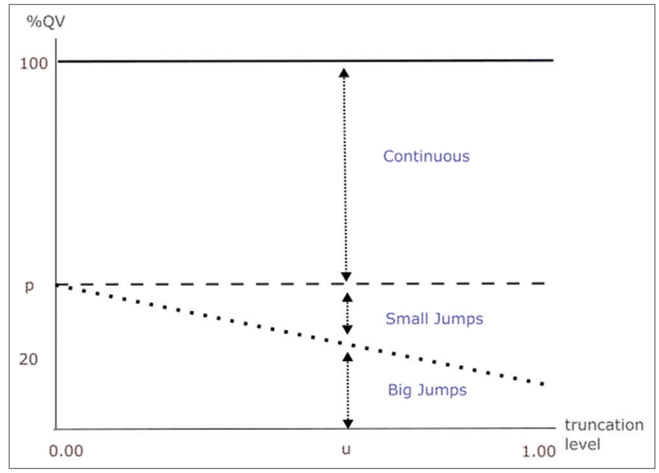


Figure 2 depicts the cut-off level to distinguish between continuous and jump parts. Our model in eq. (2) incorporates both small jumps and big jumps depending on the truncation level.

dominates in QCOM, PEP, and AMZN. For CSCO, jumps are present with no significant noise. All shares have Brownian motion and no significant noise. Moreover, the jump intensity is finite only in CHKP, FOX, and INCY.

4.1.5. 10 June 2020

In the early stage of the COVID-19 period, FOMC was expected to keep low interest rates. On this particular announcement date, only CSCO had a significant jump with no noise. The ambiguity about epidemic also affected prices; therefore, it is very hard to associate any jump with FOMC announcements. Interestingly, each of the second-tier large-cap companies was affected by additive noise. Despite Brownian motion being present in all firms, the significance is higher in second-tier large-cap companies. MFST, AAPL, and CSCO stocks have a continuous component upon the announcement.

4.1.6. 29 July 2020

For this date, the FOMC decided to keep the interest levels at the lowest levels of 0.25%. MSFT and CSCO have jumps and no significant noise. AMZN, FOX, INCY, PEP, and QCOM have dominating additive noise. Meanwhile, for MFST stock only, there are infinite activity jumps and no significant noise. Similarly, Brownian motion is present when interest rates are low. As in the earlier announcement, MFST, AAPL, and CSCO stocks have a continuous component.

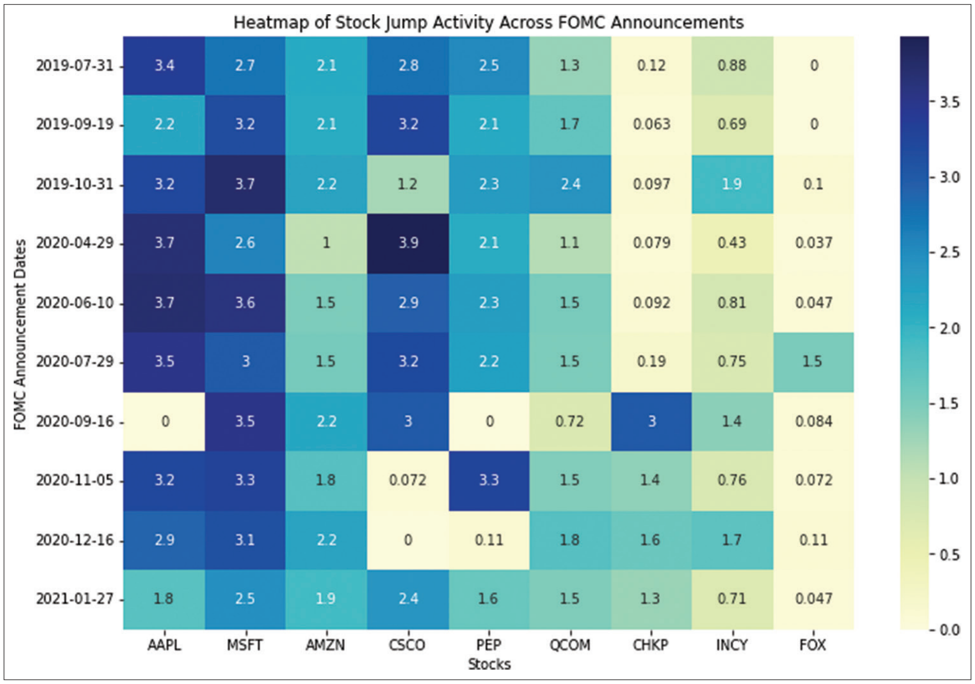
4.1.7. 16 September 2020

FOMC keeps interest rate levels at 0.25%. Only CHKP has a jump and no significant noise. The decision of FOMC appears to be foreseen by the market. AMZN and each of the second-tier large-cap companies in our data set have dominating noise. Only AMZN, INCY, and PEP have Brownian motion, whereas MFST, AAPL, and CSCO stocks have a continuous component as earlier.

4.1.8. 5 November 2020

FOMC has not changed the interest rates, and no jumps were detected by our model. One can infer that all relevant information

Figure 3: Heatmap of price jump likelihood



was incorporated into the prices. All stocks other than AAPL and MSFT have Brownian motion and no significant noise.

4.1.9. 16 December 2020

QCOM and INCY have jumps and no significant noise. AMZN and CHKP have dominating additive noise. Meanwhile, Brownian motion is present for all stocks except MSFT. After the announcement, AAPL, MSFT, CSCO, and PEP have a continuous component.

4.1.10. 27 January 2021

The FOMC kept the interest rates at the same level. As investors are accustomed to no change in policies, there were no jumps and no significant noise. Except for AAPL and MSFT, we detected Brownian motion in all stocks. MFST, AAPL, and CSCO stocks have a continuous component as earlier.

4.2. Market Perspective and Transaction Motive

Drawing some inference from the results about common patterns, we derive the following outcomes from a market perspective and transaction motive.

The first five announcements in our sample contain a decision to lower interest rate levels, whereas the final five announcements contain no change. In the first set of announcements, we observe jumps in mega-cap stocks, with AAPL and MSFT experiencing infinite activity jumps and no significant noise.

As we move toward the end of the announcements, we observe that jumps are only present in first-tier large-cap and second-tier large-cap stocks, which may be due to the perception that lowest levels of interest rates might help these companies with financing.

Mega-cap stocks enjoy the abundance of money from their retained earnings; therefore, a 0.25% interest rate may help them, which is less than that of companies requiring external funding. Moreover, we can see from our model the consequences of these announcements in terms of jumps. MFST, AAPL, and CSCO stocks have a continuous component, whereas the rest of the sample has dominating additive noise occurrences.

In Figure 3 a heatmap is formed to make our analysis results more compact and understandable. Beta values from the earlier Appedix Tables A1 and A2 are imported. Betas represent the likelihood of a large price jump, the higher the beta value, the lower the chance that there will be a large price jump. It is apparent that larger cap stocks tend to be more stable in terms of large price jumps. But on the contrary, small-cap firms are more likely to experience significant price fluctuations.

5. CONCLUSION AND POLICY IMPLICATIONS

We have gained valuable insights into the complex interaction between monetary policy decisions and stock market dynamics by examining particular dates and subsequent market responses beginning form the outbreak of the COVID-19 pandemic. Each FOMC announcement date provides an opportunity for a unique observation window of market fluctuations and stock market reactions. This study has not focused on the policy change direction but rather it deviates from the majority of the literature by shifting the focus to the drift dynamics in the market due to the event of a monetary policy change. By analyzing high-frequency data, this research provides a contribution to the understanding of how firms' market capitalization influences their price sensitivity to announcements.

Our paper supports expectation theories, as unexpected moves of FOMC lead to relatively more jumps for our sample with high-frequent data. Moreover, the FOMC announcements impacted stock market volatility, with some stocks experiencing significant price increases, whereas others remained relatively stable. The Brownian motion and noise in the data indicate the inherent randomness and fluctuations in the market. The continuous component in some stocks indicates certain predictable patterns in their price movements. Assuming cases where markets are not weak-form efficient, the presence of predictable patterns in MFST, AAPL, and CSCO may enable trading algorithms and technical analysis to outperform the rest of the stocks in our sample. Moreover, our findings suggest that at the lowest interest rate levels, second-tier large-cap stocks tend to exhibit a higher propensity for jumps, highlighting the importance of taking market capitalization into account. Alternative levels of internal financial strength and resilience to external shocks are exposed in the contextual interaction between market fluctuations and monetary policy. Large-cap stocks are found to be less sensitive to monetary policy changes, particularly to higher interest rates. Debt-financing can easily be replaced by internal financing in large-cap stocks that have idle cash available. Sustaining leverage levels is harder for smaller firms in our sample.

The study illuminates the relationship between monetary policy decisions and market reactions by providing empirical evidence of the multidimensional effects of FOMC announcements on stock behavior. During this period of increased economic uncertainty, market participants were more sensible to the Fed's signals regarding the economic recovery path. Unlike more stable times, the information effect likely played a more substantial role.

As outlined by Nakamura and Steinsson (2013), during periods of economic instability like the pandemic, investors may place greater emphasis on what the FED's policy decisions imply about the future state of the economy. The FED's forward guidance, in particular, offered important signals to markets about the anticipated trajectory of monetary policy and economic recovery.

These insights are essential for investors, and economists navigating the complexities of dynamic financial markets. Hereby, regulators shall take not only the imminent effects of their monetary decisions but also the long-term effects on various markets. The long-term effects of FOMC announcement are beyond the scope of the this study but can be analyzed in a further study.

Although our analysis provides a solid foundation, machine learning methods may be utilized in future research in analyzing the effects of monetary policy on the stock market. In the context of uncertainty in the stock markets, the role of monetary policy can be quantified in more detial. Future research could include model applications utilizing alternative methodologies, such as RNN, Lasso, SVM, and logistic models, thereby enhancing our understanding of the complex relationships governing market behavior.

REFERENCES

Ai, H., Bansal, R. (2018), Risk preferences and the macroeconomic announcement premium. Econometrica, 86(4), 1383-1430.

Aït-Sahalia, Y., Jacod, J. (2009), Testing for jumps in a discretely observed process. The Annals of Statistics, 2009, 184-222.

Aït-Sahalia, Y., Jacod, J. (2012), Analyzing the spectrum of asset returns: Jump and volatility components in high frequency data. Journal of Economic Literature, 50(4), 1007-1050.

Amini, S., Hudson, R., Keasey, K. (2010), Stock return predictability despite low autocorrelation. Economics Letters, 108(1), 101-103.

Andersen, T.G., Bollerslev, T. (1998), Towards a unified framework for high and low frequency return volatility modeling. Statistica Neerlandica, 52(3), 273-302.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Vega, C. (2003), Micro effects of macro announcements: Real-time price discovery in foreign exchange. American Economic Review, 93(1), 38-62.

Bali, T.G., Peng, L. (2006), Is there a risk-return trade□off? Evidence from high□frequency data. Journal of Applied Econometrics, 21(8), 1169-1198.

Benchimol, J., Kazinnik, S., Saadon, Y. (2021), Federal reserve communication and the COVID-19 pandemic. Covid Economics, 79, 218-256.

Bernanke, B.S., Kuttner, K.N. (2005), What explains the stock market's reaction to Federal Reserve policy? The Journal of Finance, 60(3), 1221-1257.

Bielecki, M., Brzoza-Brzezina, M., Kolasa, M. (2019), Comment on "The limits of forward guidance" by Jeffrey R. Campbell, Filippo Ferroni, Jonas Fisher, and Leonardo Melosi. Journal of Monetary Economics, 108, 135-139.

Bodilsen, S., Eriksen, J.N., Grønborg, N.S. (2021), Asset pricing and FOMC press conferences. Journal of Banking and Finance, 128, 106163.

Bomfim, A.N. (2003), Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. Journal of Banking and Finance, 27(1), 133-151.

Brusa, F., Savor, P., Wilson, M. (2020), One central bank to rule them all. Review of Finance, 24(2), 263-304.

Chan, K.F., Gray, P. (2018), Volatility jumps and macroeconomic news announcements. Journal of Futures Markets, 38(8), 881-897.

Cohen, K.J., Hawawini, G.A., Maier, S.F., Schwartz, R.A., Whitcomb, D.K. (1980), Implications of microstructure theory for empirical research on stock price behavior. The Journal of Finance, 35(2), 249-257.

Cox, J.D., Greenwald, L., Ludvigson, S.C. (2020), What Explains the COVID-19 Stock Market? United States: National Bureau of Economic Research.

Cutler, D.M., Poterba, J.M., Summers, L.H. (1990), Speculative Dynamics and the Role of Feedback Traders. Working Paper no 3243.

Easley, D., O'Hara, M. (2003), Microstructure and asset pricing. İn: Handbook of the Economics of Finance. Vol. 1. Netherlands: Elsevier, p1021-1051.

Gu, C., Kurov, A., Wolfe, M.H. (2018), Relief rallies after FOMC announcements as a resolution of uncertainty. Journal of Empirical Finance, 49, 1-18.

Guo, H., Hung, C.H.D., Kontonikas, A. (2021), Investor sentiment and the pre-FOMC announcement drift. Finance Research Letters, 38, 101443.

Guo, H., Hung, C.H.D., Kontonikas, A., Zeng, Y. (2024), Flight to lottery ahead of FOMC announcements: Institutional investors or retail investors? British Journal of Management, 35, 1076-1096.

Hu, G.X., Pan, J., Wang, J., Zhu, H. (2022), Premium for heightened uncertainty: Explaining pre-announcement market returns. Journal of Financial Economics, 145(3), 909-936.

Hu, T.W., Rocheteau, G. (2015), Monetary policy and asset prices: A mechanism design approach. Journal of Money, Credit and Banking, 47(S2), 39-76.

Hussain, S.M., Omrane, W.B. (2021), The effect of US macroeconomic news announcements on the Canadian stock market: Evidence using high-frequency data. Finance Research Letters, 38, 101450.

Ignatieva, K., Ohashi, K. (2024), The pre-FOMC announcement drift: Short-lived or long-lasting? Evidence from financial and volatility markets. Applied Economics, 2024, 1-17.

Jiang, G.J., Yao, T. (2013), Stock price jumps and cross-sectional return predictability. Journal of Financial and Quantitative Analysis, 48(5), 1519-1544.

Lehalle, C.A., Laruelle, S. (2018), Market Microstructure in Practice. Singapore: World Scientific.

Lucca, D.O., Moench, E. (2015), The pre-FOMC announcement drift. The Journal of Finance, 70(1), 329-371.

Ma, L. (2022), Three Essays in Monetary and Financial Economics. Ph.D. Thesis, Department of Economics, University of Alberta.

Madhavan, A. (2000), Market microstructure: A survey. Journal of Financial Markets, 3(3), 205-258.

Monaco, E., Murgia, L.M. (2023), Retail attention and the FOMC equity premium. Finance Research Letters, 53, 103597.

Mücher, C. (2022), Artificial neural network-based non-linear transformation of high-frequency returns for volatility forecasting. Frontiers in Artificial Intelligence, 4, 787534.

Nakamura, E., Steinsson, J. (2013), High-Frequency İdentification of Monetary Non-neutrality. United States: National Bureau of Economic Research.

Neuhierl, A., Weber, M. (2019), Monetary policy communication, policy slope, and the stock market. Journal of Monetary Economics, 108, 140-155.

Patel, V., Michayluk, D. (2016), Return predictability following different drivers of large price changes. International Review of Financial Analysis, 45, 202-214.

Sekandary, G., Bask, M. (2023), Monetary policy uncertainty, monetary policy surprises, and stock returns. Journal of Economics and Business, 124, 106106.

Tauchen, G., Zhou, H. (2011), Realized jumps on financial markets and predicting credit spreads. Journal of Econometrics, 160(1), 102-118.

Vähämaa, S., Äijö, J. (2011), The Fed's policy decisions and implied volatility. Journal of Futures Markets, 31(10), 995-1010.

Yan, S. (2011), Jump risk, stock returns, and slope of implied volatility smile. Journal of Financial Economics, 99(1), 216-233.

APPENDIX

Table A1: Test statistics results

			19 Aug		
Asset	S_j	S_{FA}	S_W	***QVSplit***	β
APPL	0.93	1.3699	1.4197	0.3222	3.3504
AMZN	1.035	0.4584	2.9082	0.0224	2.1044
CHKP	2.2332	0.7799	inf	0	0.1174
CSCO	1.4161	0.8268	1.6697	0.0938	2.7592
FOX	na	na	na	na	na
INCY	2.7123	0.2735	5.0135	0.0021	0.8819
MSFT	1.159	0.9775	1.4582	0.3979	2.7244
PEP	2.9604	0.6197	2.1223	0.1375	2.5274
QCOM	2.2369	0.531	2.472	0.0125	1.319
			19 Sep		
Asset	S_j	S_{FA}	S_W	***QVSplit***	β
APPL	2.1914	0.9836	1.5036	0.4484	2.1773
AMZN	3.3164	0.4025	3.3173	0.0486	2.0733
CHKP	2.3959	na	inf	0	0.063
CSCO	2.6741	0.9522	1.5513	0.3886	3.2434
FOX	na	na	na	na	na
INCY	1.9091	0.2152	inf	0	0.6948
MSFT	1.987	1.2365	1.3991	0.3717	3.1539
PEP	2.3412	0.5631	2.3288	0.0711	2.1309
QCOM	3.0712	0.4805	2.6342	0.0331	1.6775
			19 Oct		
Asset	S_j	S_{FA}	S_W	***QVSplit***	β
APPL	1.1291	1.2572	1.3409	0.4533	3.2206
AMZN	2.273	0.478	2.5799	0.0616	2.2042
CHKP	1.3745	inf	inf	0	0.0965
CSCO	7.6817	inf	inf	0.0064	1.2241
FOX	4.1169	1.0794	inf	na	0.104
INCY	2.2818	0.5776	2.1882	0.0749	1.91
MSFT	1.4107	1.3438	1.4107	0.553	3.7408
PEP	1.9176	0.6758	2.1164	0.1154	2.3032
QCOM	1.6442	0.8691	1.6317	0.1387	2.4113

(Contd..)

Table A1: ***(Continued)***

			20 Apr		
Asset	S_j	S_{FA}	S_W	***QVSplit***	β
APPL	1.0832	1.1419	1.5164	0.2722	3.6643
AMZN	1.0287	0.3503	3.5087	0.0049	1.04031
CHKP	0.7239	inf	inf	0	0.0786
CSCO	0.9015	1.0622	1.54	0.2504	3.9282
FOX	1.499	na	inf	na	0.0368
INCY	1.1479	1.1414	inf	0	0.4342
MSFT	2.3462	0.5371	2.4488	0.0922	2.5929
PEP	3.5967	0.4191	2.9073	0.0313	2.0828
QCOM	1.4076	0.3231	3.4399	0.0067	1.1168
			20 Jun		
Asset	S_j	S_{FA}	S_W	***QVSplit***	β
APPL	1.3368	1.1692	1.547	0.3661	3.7094
AMZN	1.6919	0.3266	3.8059	0.0109	1.479
CHKP	4.8703	inf	inf	0	0.0922
CSCO	1.0625	1.3397	1.401	0.2286	2.9327
FOX	1.1362	inf	inf	0	00.0467
INCY	1.3178	0.3391	4.4428	0.0034	0.8138
MSFT	1.7231	1.1947	1.4761	0.4246	3.5806
PEP	1.309	0.4347	3.1607	0.0369	2.2815
QCOM	1.4276	0.4126	3.1077	0.0121	1.5164
			20 Jul		
Asset	S_j	S_{FA}	S_W	***QVSplit***	β
APPL	1.1705	0.864	1.7256	0.2847	3.5048
AMZN	3.745	0.3759	3.2019	0.0039	1.5252
CHKP	2.3283	inf	inf	0	0.1949
CSCO	1.0387	1.1009	1.4822	0.2536	3.1781
FOX	1.554	0.4043	3.5243	0.01	1.5031
INCY	1.2146	0.3553	4.6203	0.0033	0.7525
MSFT	1	1.0482	1.518	0.3187	2.9858
PEP	2.1939	0.4287	2.7082	0.0859	2.2464
QCOM	2.219	0.4005	3.1518	0.0029	1.4767

na, dentoes no solution for the simulation model is avaiable, inf means infinitum in the model solution

Table A2: Test statistics results

Asset	S_j	S_{FA}	S_W	QVSplit	β
20 Sep					
APPL	0.8701	1.6137	1.3286	0.5787	-
AMZN	0.8917	0.419	2.9313	0.0275	2.1632
CHKP	1.0962	5.4823	inf	0	0.0383
CSCO	1.1862	1.3905	1.3561	0.4178	2.9998
FOX	1.8425	inf	inf	0	0.0838
INCY	1.3008	0.3341	3.7912	0.0064	1.3897
MSFT	0.9271	1.271	1.4042	0.4376	3.5118
PEP	1.3987	0.4852	2.6145	0.0517	na
QCOM	2.3217	0.3331	inf	0.0031	0.7241
20 Nov					
APPL	1.3101	1.3793	1.3622	0.2851	3.2103
AMZN	1.3319	0.4087	3.1113	0.0196	1.7852
CHKP	1.1061	0.3479	3.4677	0.0104	1.361
CSCO	1.1744	1.4095	1,4168	0,5788	3,2629
FOX	1.5383	inf	inf	na	0.0723
INCY	3.1633	0.3384	3.5527	0.0028	0.761
MSFT	0.9872	1.823	1.2991	0.2919	3.2924
PEP	1.3414	0.4587	2.9051	0.0724	2.1507
QCOM	5.898	0.435	2.8255	0.0039	1.4505
20 Dec					
APPL	1.5	2	1.6	0.71	2.89
AMZN	2.056	0.4852	2.626	0.0659	2.1961
CHKP	2.0338	0.3859	4.0281	0.0298	1.6258
CSCO	2.2637	0.7832	1.882	0.2618	inf
FOX	1.7454	inf	inf	0	0.1056
INCY	0.9906	0.3904	3.1882	0	1.7188
MSFT	1.8596	1.624	1.3258	0.7342	3.1076
PEP	1.4586	0.5202	2.4201	0.1093	0.1093
QCOM	1.036	0.4838	2.6694	0.0815	1.7814
21 Jan					
APPL	1.4	1.157	1.3785	0.4043	1.7553
AMZN	2.4619	0.3903	3.2593	0.0318	1.9139
CHKP	4.1226	0.2906	4.3648	0.0073	1.2948
CSCO	1.6473	1.2521	1.4408	0.473	2.3796
FOX	4.5462	na	inf	na	0.0472
INCY	3.6727	0.3452	4.3307	0.0019	0.7065
MSFT	2.5735	1.3949	1.3412	0.512	2.4575
PEP	3.678	0.415	2.8376	0.0343	1.6348
QCOM	4.1389	0.348	3.2541	0.0094	1.4643

See Table A1