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# The Impact of Monetary Policy on the Cryptocurrency Market


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Abstract [1]

This paper examines the impact of Federal Reserve (Fed) monetary policy announcements on the cryptocurrency market, focusing on immediate market reactions. Using a sample of 57 monetary policy announcements from January 2018 to September 2024, the analysis distinguishes between expected and unexpected rate changes and isolates the unexpected component, constructing a measure of “surprise” rate changes with Federal funds futures data. The results indicate that unexpected policy changes exert a moderate negative effect on cryptocurrency returns, whereas expected changes have a small impact. The findings contribute to the literature by extending event-study methodologies to cryptocurrencies and, within the cryptocurrency literature, by focusing on the broad cryptocurrency market to offer a comprehensive perspective on market-level effects.

Keywords: Event Study; Monetary policy announcement; Market Reactions; Cryptocurrency

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## 1. Introduction

Cryptocurrencies represent a relatively new asset class that emerged with the creation of Bitcoin in 2009 and are recognized as one of the fastest-growing financial markets (Almeida and Goncalves 2023). Between 2009 and 2018, cryptocurrencies were largely considered uncorrelated with traditional asset classes, and it was believed that macroeconomic conditions and policies had no significant influence on their prices and returns (Kyriazis et al. 2023). The increasing role of cryptocurrencies in financial markets, coupled with growing institutional investor participation – particularly during 2020 and 2021 – has attracted significant interest from investors and hedge funds (Fletcher 2021). Since late 2021, cryptocurrencies have mirrored the downward trends of the U.S. stock market, a development attributed to the Federal Reserve's (Fed) higher interest rate announcements aimed at combating inflation (Hammouda 2024). While the effects of Federal Open Market Committee (FOMC) announcements on traditional asset prices and returns are well-studied, their impact on cryptocurrency markets remains largely unclear. This notable gap presents an opportunity to analyze the relationship between U.S. monetary policy and the cryptocurrency market, assessing how these asset prices and returns react.

This study aims to address two research questions. First, it determines how cryptocurrency market returns are influenced by the Fed´s monetary policy announcements. To answer this, I calculate the average market reaction by separating anticipated and unanticipated monetary policy actions across a sample of 57 observations, comprising days when the Federal funds rate (FFR) was changed and days of FOMC meetings. The analysis focuses on short-term windows surrounding policy announcements from 31 January 2018 to 18 September 2024, a period that captures the emergence and expansion of cryptocurrencies while providing sufficient data to evaluate the market's response. Second, this study examines the heterogeneity in market responses, particularly asymmetries in price reactions, by incorporating interaction terms that combine the surprise component with dummy variables into the regression analysis.

For the first research question, I determine that, over the complete period, changes in the raw FFR are expected to have no effect on the cryptocurrency market. However, when isolating the market's reaction to surprise changes, cryptocurrency returns are expected to exhibit a weak response to the expected component and a stronger response to the unexpected component. My findings show that the raw change in the FFR did not have a significant impact on cryptocurrency market returns. When distinguishing between the expected and unexpected components, the results remain statistically insignificant, showing a weak positive reaction to the expected change in the FFR and a moderate negative reaction to the unexpected change.

Regarding the second research question, I find no strong empirical evidence that any of the three tested asymmetries significantly affect the broad cryptocurrency market. However, two of these asymmetries – the sign of the surprise and the direction of the FFR change – are close to statistical significance, with t-statistic values nearing the threshold required for significance. The results suggest that positive surprises (rate hikes) lead to negative returns, while during monetary tightening cryptocurrency returns unexpectedly results in an increase in the FFR. The third asymmetry shows that returns respond positively to surprises on days when the FFR remains unchanged, in contrast to the negative reaction observed on days with rate changes.

This study contributes to two broad strands of literature. The first examines the impact of monetary policy announcements on financial markets and asset prices. In this context, my study seeks to extend the existing literature on traditional financial markets to a new asset class of cryptocurrencies. To ensure the comparability of my results, I follow the methodology of Bernanke and Kuttner (2005), which is appropriate for high-frequency analysis. The second strand of empirical research to which this study contributes examines the price behavior of cryptocurrencies. Here, this paper aims to confirm findings from previous research on price behavior (Baur et al. 2018; Bouri et al. 2018; Alam et al. 2024) and the effect of policy announcements on cryptocurrency prices and returns (Shaikh et al. 2020; Karau 2021; Ma et al. 2022; Kyriazis et al. 2023). Given the lack of consensus, my study further extends the Bitcoin-centric literature by analyzing the broader cryptocurrency market.

The rest of the paper is organized as follows. Section 2 gives an overview of existing literature of the related research. Section 3 introduces cryptocurrencies and outlines monetary policy and its transmission mechanisms. Section 4 introduces the analyzed data. Section 5 explains the methodology used for the event study and regression analyses, while Section 6 presents results. Section 7 concludes.

## 2. Contribution to Literature

With this study, I contribute to the strand of empirical literature studying the impact of monetary policy on financial markets, particularly asset prices, as well as to the strand that investigates the price behavior of cryptocurrencies. The following two sections introduce both strands of literature and explain this study's contribution to each.

### 2.1. Literature on the Effects of Monetary Policy on Financial Markets

This paper contributes to the strand of literature examining the effects of unexpected monetary policy announcements on asset prices, such as those by Kuttner (2001), Demiralp and Jorda (2004), Bernanke and Kuttner (2005), and Gürkaynak et al. (2005). While this area of research is extensive and well-established, the primary focus has been on traditional asset classes. My paper differs from these studies as it examines how unexpected changes in monetary policy influence returns of cryptocurrencies, extending the literature on a new asset class. Furthermore, unlike Gürkaynak et al. (2005), who distinguish between target component (short-term effects) and path component (long-term effects) of monetary policy, I focus on the target component to capture the immediate impact of policy announcements on cryptocurrency returns.

Different approaches exist in the literature for measuring monetary policy shocks, including innovations in the FFR within VAR models (Bernanke and Mihov 1998), the narrative approach (Romer and Romer 2004), and the extraction of surprises from bond or futures market data at daily or intraday frequencies (Kuttner 2001). Each method has its challenges: for instance, the VAR approach struggles with causality identification, and the narrative approach encounters difficulties in measuring unconventional monetary policy shocks when rates are near zero. In such cases, shadow interest rates can provide an alternative measure of monetary policy (Wu and Xia 2016; Marfatia 2021). Among these methods, extracting surprises from bond or futures market data has become a widely adopted practice due to its success in high-frequency identification. Kuttner (2001) argues that the approach for isolating the unexpected element of a target rate change generally "delivers a nearly pure measure of the one-day surprise target change." Moreover, it reduces potential bias from the so-called Fed information effect or Fed forward guidance, which is relevant as the analysis includes a period of strong forward guidance during the

COVID-19 pandemic (Paul 2020). Therefore, this paper implements an “event-study” style of analysis following the approach of Bernanke and Kuttner (2005). I seek to produce results that can be more easily compared with the existing literature.

Empirical studies consistently find a negative short-run relationship between monetary policy shocks and stock market returns (Laeven and Tong 2010). This relationship is explained by the discounting of cash flows and adjustments in expectations regarding future cash flows (Campbell and Ammer 1993; Lobo 2000). Bernanke and Kuttner (2005) further attribute the negative impact of unexpected shocks on stock prices to adjustments in expected excess returns. In contrast, studies of the bond market generally find that monetary policy shocks are positively associated with bond yields due to the inverse relationship between bond prices and yields. Kuttner (2001) demonstrates that unexpected changes in the FFR positively affect both short- and long-term Treasury yields. Building on this, Gürkaynak, Sack, and Swanson (2005) analyze intraday market reactions to FOMC announcements and find a significant positive reaction in bond yields to unexpected changes, particularly for short-term Treasury yields.

Beyond stocks and bonds, policy announcements also significantly impact other financial markets, such as commodities and currencies, including exchange rates. Commodities, particularly gold, are primarily driven by interest rates, inflation expectations, and safe-haven demand. Empirical evidence from Scrimgeour (2015) shows that monetary policy surprises, especially during tightening cycles, lead to declines in commodity prices, including gold. This negative response to tighter monetary policy is further supported by Blose (2010), which argues that the opportunity cost of holding gold increases under such conditions, thereby depressing its value. Studies on currencies, including exchange rates, identify a positive relationship between monetary policy shocks and exchange rate movements, with unexpected monetary tightening typically leading to currency appreciation and unexpected easing resulting in depreciation. The U.S. dollar frequently appreciates during periods of unanticipated monetary tightening, driven by higher interest rate differentials, its perceived stability and lower associated risk (Fatum and Scholnick 2005). Supporting this, Gürkaynak et al. (2005) and Eichenbaum and Evans (1995) confirm that monetary policy surprises result in immediate and significant exchange rate movements.

## 2.2. Literature on Cryptocurrencies

Several studies have investigated the relationship between monetary policy and cryptocurrency markets. The literature generally suggests that the price behavior of cryptocurrencies is largely independent of traditional financial assets (Baur et al. 2018; Ji et al. 2018). Baur et al. (2018) argue that cryptocurrencies offer diversification benefits due to their low correlation with traditional assets. Ji et al. (2018) further note that this distinct behavior persists even in high-stress market conditions, implying that cryptocurrencies may respond to monetary policy differently from traditional assets. While Bouri et al. (2018) propose that cryptocurrencies display safe-haven properties during periods of market turbulence, earning the label of "digital gold," Alam et al. (2024) contend that their behavior aligns more closely with speculative assets than traditional safe-haven assets like gold.

Many studies examine cryptocurrency prices and returns in relation to monetary policy, focusing primarily on Bitcoin, but the findings remain inconsistent. Some studies suggest that cryptocurrency prices are unresponsive to Fed policy announcements (Vidal-Tomas and Ibanez 2018; Nguyen et al. 2019). Vidal-Tomas and Ibanez (2018) observe that Bitcoin prices remain unaffected on days when major central banks carry out open market operations. Similarly, Nguyen et al. (2019) conclude that Bitcoin returns are unaffected by U.S. monetary policy but observe that tightening monetary policy in China positively affects returns. They also explore policy regime asymmetries, concluding that cryptocurrencies respond more strongly to monetary policy tightening than easing, with rate hikes having a greater impact on returns than rate cuts. In contrast, other studies identify noticeable reactions. Pyo and Lee (2020) demonstrate that Bitcoin returns differ significantly on FOMC announcement days, aligning with equity market patterns during specific announcements. Shaikh (2020) and Ma et al. (2022) focus on the immediate effects of Fed announcements on cryptocurrency returns. Shaikh (2020) finds that unexpected changes significantly impact cryptocurrency markets, with stronger negative reactions observed during periods of monetary tightening, attributed to the increased cost of capital and reduced liquidity. Ma et al. (2022) also observes a negative response but suggests that the direction depends on market regimes. Adding further complexity, Karau (2021), by analyzing intraday price movements, identifies differing effects: ECB tightening lowered Bitcoin valuations, while Fed tightening increased them, potentially due to emerging market demand. This finding contrasts with the conclusions of Ma et al. (2022) and Shaikh (2020), who report negative responses to tightening policies. None of these studies explicitly apply the approach of isolating unexpected components and measuring immediate reactions in the style of Bernanke and Kuttner (2005).

This paper aims to make two key contributions to the literature. First, the lack of agreement regarding the response of cryptocurrencies, particularly Bitcoin, to monetary policy makes further investigation imperative. I seek to address this gap and shed light on the connection between cryptocurrency markets and monetary policies. Second, to the best of the author's knowledge, the existing literature analyzing the reaction of cryptocurrency returns to unexpected changes, particularly across the broader market, remains limited. The most relevant study is Kyriazis et al. (2023), which focuses on the broad cryptocurrency market and isolates the unexpected component in the style of Bernanke and Kuttner (2005). Their findings indicate a negative response to monetary policy surprises. However, Kyriazis et al. (2023) is limited by a short observation period (2018–2022), which is attributed to the nascent nature of the cryptocurrency market. Therefore, this paper extends the observation period to provide a more comprehensive analysis of how the cryptocurrency market reacts to monetary policy changes.

## 3. Background

### 3.1. Cryptocurrencies

This section introduces cryptocurrencies, describing their characteristics and presenting structural data on the cryptocurrency market development to provide context for later analyses. Cryptocurrencies are digital representations of value that operate on decentralized networks without central bank or governmental control. Designed as mediums of exchange, stores of value, and units of account – core monetary functions – cryptocurrencies enable users to transfer, store, and trade value electronically without intermediaries (European Banking Authority 2014). Most cryptocurrencies are built on blockchain technology, which functions as a decentralized ledger that records transactions across a network of computers (Nakamoto 2008). This decentralized structure eliminates the need for a central authority, as transactions are validated by a distributed network of participants, known as "nodes", ensuring the system is more transparent, secure, and resistant to manipulation (Bonneau et al. 2015).

Cryptocurrencies serve a dual role, functioning both as alternative currencies and as speculative investment assets. Initially designed to function as a medium of exchange, they aim to facilitate peer-to-peer transactions without intermediaries, offering an alternative to fiat currencies like the US dollar (Hacioglu 2019). However, high volatility, limited acceptance, and low user confidence limits their adoption for everyday transactions (Baur et al. 2015). Cryptocurrencies are increasingly viewed as stores of value, often compared to gold for their finite supply and decentralized nature. Like gold, cryptocurrencies are often perceived as hedges against inflation and currency devaluation. Yet, the evidence is mixed – Rodriguez and Colombo (2024) suggest that cryptocurrencies are a useful hedge during inflationary periods, others argue that their extreme price volatility undermines their reliability as inflation hedges (Pinchuk 2023). Nevertheless, without tangible value and historical precedent, cryptocurrencies are influenced by market capitalization and demand-side factors, driven by trading activity that is determined by short-term profit-seeking rather than long-term value preservation (Pogudin et al. 2020).

For these reasons, cryptocurrencies are increasingly recognized as alternative asset rather than alternative currencies. However, cryptocurrencies exhibit fundamental differences that distinguish them. Unlike equities, which represent ownership stakes in companies, or bonds, which provide fixed-income returns, cryptocurrencies lack intrinsic value as they do not confer ownership rights or generate predictable cash flows (Bianchi 2020). Instead, their prices are driven primarily by speculative demand, resulting in unpredictable price movements, defined by high-risk, high-reward opportunities. This speculative nature contrasts sharply with the stability of traditional assets. Government bonds, for instance, provide stability and are regarded as safe-haven investments, while equities offer long-term growth potential. This distinction is further reflected in low correlation with traditional assets, that potentially offer diversification benefits (Ankenbrand and Bieri 2018).

Since its inception with Bitcoin in 2009, the cryptocurrency market has grown significantly, reaching a total market capitalization of $3.6 trillion in December 2024 (Coinmarketcap 2024). The growth was accompanied by a nearly 190% increase in the global user base between 2018 and 2020. Approximately 9,000 active cryptocurrencies are currently listed across global exchanges, with most market activity concentrated in a few major assets like Bitcoin and Ether (Statista 2024). The top ten cryptocurrencies account for 89% of total market value (S&P Global 2024). Figure 1 illustrates the development of the S&P Broad Digital Market Index (SPCBDM) over the period of 2018 through 2024.

**Figure 1 (Market Index Performance) about here**

From Figure 1 it becomes clear that the cryptocurrency market experienced rapid growth, with the SPCBDM recording an annualized return of 65.25% over the last five years. In early 2018, total market capitalization stood at approximately $800 billion but fell sharply to $200 billion by the end of the year. A dramatic rebound followed, fueled by pandemic-era stimulus in late 2020 that pumped up speculative investments, pushing market capitalization to a peak of $3 trillion in late 2021 (Reuters 2024). This was followed by the “crypto winter” of June 2022, during which the market lost over two-thirds of its value, dropping to $800 billion. The decline coincided with a general reduction in risk appetite and the collapse of the FTX exchange in November 2022. A recovery can be observed from 2023 onwards, further accelerated in 2024 by optimism surrounding the U.S. election. Therefore, the cryptocurrency market´s value fluctuations appear closely tied to the macroeconomic conditions, mainly shifts in monetary and fiscal policy. Interest rates, which had been constrained by the zero lower bound since 2019, rose incrementally as the global economy entered a recovery trajectory, affecting liquidity conditions and investor sentiment in the market.

## 3.2. Monetary Policy

This section provides an overview over the topics of monetary policy and the transmission mechanisms. Monetary policy refers to the actions and communications measures undertaken by a central bank to manage a nation's money supply, credit conditions, and interest rates to achieve specific macroeconomic goals (Mishkin 2011). The objectives of U.S. monetary policy include price stability, maximum employment, and sustainable economic growth. In the United States, these goals are implemented by the Fed. The Fed is responsible for setting and executing monetary policy for which it employs a range of monetary policy tools that can be broadly categorized as conventional and unconventional measures. Among these tools, the FFR – a conventional monetary policy instrument – is the main mechanism through which the Fed influences the economy. The FFR represents the interest rate at which depository institutions lend reserves to one another overnight. By setting a target range for this rate, the Fed indirectly affects borrowing costs for consumers and businesses, guiding economic activity.[2] Conventional tools, such as open market operations and the interest on reserve balances, are typically used during normal economic conditions to achieve the target FFR. In contrast, when interest rates approach the zero lower bound, the Fed employs unconventional tools like quantitative easing or forward guidance to provide additional economic stimulus (Fed Website 2024).

The monetary transmission mechanism describes the processes through which macroeconomic variables are influenced via various channels. These channels—interest rate, exchange rate, credit, and asset price channels—serve as levers for the effects of monetary policy to affect the economy. For instance, the interest rate channel operates by altering borrowing costs, which directly impacts consumer spending and business investment. Similarly, the exchange rate channel influences the value of the domestic currency, affecting inflation. The credit channel affects the availability of loans, while the asset price channel alters wealth and consumption patterns through changes in asset valuations (Mishkin 2011).

In traditional financial markets, changes in the FFR influence stock price valuations primarily through the interest rate channel. Lower rates reduce the discount rate applied to future cash flows, increasing the present value of stocks and driving up their prices (Mishkin 1996). Additionally, the liquidity channel supports equity markets during monetary easing by providing greater access to funds, encouraging investment in higher-risk assets. The risk sentiment channel further amplifies these effects, as monetary easing typically increases investor confidence and willingness to take on risk, increasing equity prices. Conversely, monetary tightening increases the discount rate, suppresses liquidity, and dampens risk sentiment, often resulting in equity market declines. For bonds, lower FFR levels typically lead to declining yields, as bond prices move inversely to interest rates. This effect is driven by the interest rate channel, which makes existing bonds with higher coupon rates more attractive during periods of monetary easing. Furthermore, the exchange rate channel affects both equities and bonds. A weaker U.S. dollar during monetary easing increases the competitiveness of export-driven companies,

[2] FOMC announces FFR decisions through a written statement issued immediately after each scheduled meeting.

benefiting equities in these sectors. Simultaneously, foreign demand for U.S. bonds may rise due to favorable exchange rate movements (Mishkin 1996).

While traditional financial assets are influenced by well-established monetary transmission channels, cryptocurrencies, as an emerging asset class, show different dynamics. These differences stem from the speculative nature and decentralized structure and thus require a focus on alternative channels such as liquidity and risk sentiment. As stated in 3.2., cryptocurrencies lack intrinsic value tied to future cash flows or dividends, making the interest rate channel less relevant in influencing their valuations. Moreover, the exchange rate channel exhibits a more nuanced influence on cryptocurrency markets. As cryptocurrencies are largely denominated in fiat currencies like the U.S. dollar, changes in exchange rates can influence their attractiveness for international investors. However, this effect is more indirect and less pronounced compared to its influence on equities and bonds. Instead, the cryptocurrency market is mainly driven through liquidity and risk sentiment channels. Monetary easing encourages investors to seek higher-risk, higher-reward assets. The risk sentiment channel further accentuates these effects, as monetary easing often fosters a “risk-on” environment, that lead to increased demand for cryptocurrencies, as investors seek higher returns. Monetary tightening diminishes liquidity and reduces risk appetite, shifting investor sentiment towards safer asset, fostering a “risk-off” environment.

# 4. Data

The dataset for this study contains Federal funds futures contracts and cryptocurrency market return data for 57 monetary policy events for the years 2018 through 2024. These events include (1) days when the Fed adjusted the FFR and (2) FOMC meeting days. Within the dataset, I match Fed policy events with corresponding cryptocurrency market daily returns. Section 4.1 outlines the dataset and sources, Section 4.2 explains sample construction, and Section 4.3 evaluates the dataset.

## 4.1. Dataset and Source Description

I construct the dataset by merging two separate datasets. The first contains daily Federal funds futures data, capturing market expectations of Fed policy decisions and used to construct a measure of “surprise” rate changes. The second dataset is constructed by downloading and consolidating daily cryptocurrency market index data.

The data for this study come from two sources: The data for the first dataset were sourced from the Chicago Mercantile Exchange (CME Group Inc.), a global derivatives marketplace and largest options and futures contracts exchange globally. The second dataset is downloaded from S&P Global Market Intelligence, a financial institutions-focused commercial database operated by Standard & Poor's. Two separate datasets are used because this study requires Federal funds futures data as well as daily market return data, which can only be obtained separately.

Using two different sources as the main source for this study has two reasons. First, CME Group Inc. is commonly used for studies requiring 30-day Federal funds futures data due to its comprehensive coverage of U.S. interest rate futures markets. These contracts serve as a widely accepted benchmark measure of market expectations, ensuring comparability with other studies on asset classes. Additionally, CME Group Inc. data is transparent and accessible, offering consistent historical records and daily pricing information. However, the CME does not provide a cryptocurrency market index suitable for this analysis, specifically a broad-based index covering the entire digital asset market. Therefore, the second dataset is sourced from S&P Global, which, in contrast, provides broad market indices with historical data coverage, allowing for a more thorough analysis going back to 2018.

## 4.2. Dataset and Sample Construction

The sample is constructed using a three-step process. This process consists out of A) defining the regional focus, B) defining scope and period to be analyzed and C) cleaning the data.

**A) Defining the regional focus:** The dataset focuses on monetary policy actions of the Fed, focusing on the FFR as the primary policy tool under analysis. The focus is justified by the central role of U.S. monetary policy in global financial markets, particularly for assets predominantly traded and denominated in U.S. dollars. Cryptocurrencies, largely priced and traded in U.S. dollars across international exchanges, are likely to be more directly influenced by Fed decisions than by monetary actions of other central banks. As of November 2024, approximately 60% of all cryptocurrency transactions are conducted in USD or USD-pegged stablecoins (Coin gecko 2024). Other major central banks, such as the European Central Bank, the Bank of England, and the People's Bank of China, also engage in significant monetary policy actions, including interest rate adjustments. However, their influence on the cryptocurrency market is primarily indirect, impacting global markets through secondary effects rather than direct interactions (ECB 2022). Including these central banks in the analysis would expand the sample size but excessively broaden the geographic focus, introducing indirect effects that could dilute the interpretability of results. Favouring depth over width, this study exclusively examines the monetary policy actions of the Fed.

**B) Defining the type of monetary policy action:** The dataset covers the period from 2018 to 2024, beginning when the cryptocurrency market gained significant traction through surging Bitcoin prices (Narayanan et al. 2016), market expansion (Catalini 2020), and growing institutional interest (Yermack 2017). The scarcity of data for the broader cryptocurrency market before 2018 makes this timeframe essential to ensure data availability and consistency. To be included in the sample, monetary policy actions must fall within the defined period. The sample consists of two types of events: (1) days when the FFR was adjusted and (2) all FOMC meetings. These events are categorized into scheduled and unscheduled types. Scheduled events include regular FOMC meetings, during which economic conditions are assessed, and policy directions are determined. Unscheduled, or intermeeting, events involve policy adjustments made outside of scheduled meetings, typically in response to urgent economic developments (Fed 2019).[3]

**C) Defining the Data cleaning process:** The data cleaning process mainly comprises the identification of relevant event dates and monetary policy actions that meet the criteria outlined earlier. The data for the sample retrieved from CME Group Inc. includes daily data for the FFR during the specified period. The dataset does not contain any missing values and therefore can be filtered to include only days, at which an FOMC monetary policy announcement or intermeeting event took place. Outliers are retained due to the limited sample size for market reactions compared to prior studies.[4] Moreover, there is no economic reason to exclude outliers. Considering the volatile nature of the cryptocurrency market, extreme values likely represent meaningful market reactions rather than anomalies. Therefore,

[3] In contrast to Bernanke and Kuttner (2005), who exclude FOMC dates without rate changes, this study follows Laeven and Tong (2010) by including them to capture baseline market responses and isolate the specific effects of rate changes through comparison with non-action events.
[4] Kuttner (2001) analyzes 42 target rate changes (1989–2000), Bernanke and Kuttner (2005) examine 131 observations (1989–2002), Rigobon and Sack (2003) study 63 rate changes (1994–200, and Gürkaynak, Sack, and Swanson (2005) analyze FOMC announcements (1990–2004), including scheduled and unscheduled meetings.

excluding these observations can risk omitting critical events important to the analysis. As such, no additional removal steps are required.

### 4.3. Dataset Evaluation

Table 1 provides an overview of size and relevance of the sample. The sample includes 57 observations, 23 of which involve changes in the FFR. Most announcements occurred during scheduled FOMC meetings, except for three intermeeting cases. The October 4, 2019, intermeeting addressed repo market disruptions that temporarily raised the FFR above its target (New York Fed 2019). The subsequent two intermeetings were emergency rate cuts during the COVID-19 pandemic, with the Fed reducing the target rate by 50 basis points on March 3 and 100 basis points on March 15.

**Table 1 (Sample Overview) about here**

The sample is constrained by the small number of FOMC announcements and rate adjustments observed within a relatively short timeframe. Limitations here are twofold. First, the scarcity of cryptocurrency market data prior to 2018 reduces the sample size and the number of observable announcement days. Broad cryptocurrency market indices were introduced only in late 2017 or later, which reflects the limited market breadth at the time. In early 2017, there were approximately 600 cryptocurrencies, which expanded to over 1,800 by 2018 due to the Initial Coin Offering (ICO) boom. Therefore, extending the timeframe prior to 2018 adds little analytical value, as it relies on Bitcoin-centric data. Second, the fact that FOMC announcements are infrequent and occur approximately eight times a year for scheduled meetings, with additional intermeeting changes being rare, inherently limits the sample size.

Despite these limitations, the included observations are systematically important. The Fed is the most closely watched central bank, and its announcements represent the most influential monetary policy decisions globally. Therefore, the sample comprises announcements, which have significant impact on both the U.S. and globally. This representation of key event days ensures that the sample is representative for analyzing the cryptocurrency market.

# 5. Methodology

This paper uses an event-study style of analysis to evaluate the effect of monetary policy in short-term windows around policy announcements. I generally follow the methodology of Bernanke and Kuttner (2005) with my analysis. The analysis entails the calculation of the market reaction to FFR changes by decomposing the changes into anticipated and unanticipated changes, as well as a regression analysis in the aggregate that quantifies the impact on cryptocurrency returns.

## 5.1. Measuring the Surprise Element of Policy Actions

In the approach of Bernanke and Kuttner (2005), the immediate response of the stock market to a monetary policy action is determined by distinguishing between reactions to expected and unexpected policy actions. Markets typically do not react to anticipated policy changes, as markets are forward-looking and incorporate any information about anticipated policy changes in advance. One approach to isolate the unexpected component, is the method outlined by Bernanke and Kuttner (2005), which use Federal funds futures data to construct a measure of "surprise" rate changes. While asset prices also respond to revisions in future policy expectations influenced by changing economic conditions, the focus on surprises allows to circumvent the issues of endogeneity and simultaneity, allowing for a clearer analysis of how the market reacts to monetary policy. In this paper, I adopt the approach of Bernanke and Kuttner, employing a market-based method to gauge the response of cryptocurrency returns to unanticipated changes in the FFR. This involves a two-step process to measure and prepare the surprise and expected components for the analysis.

With the first step the surprise element of any specific change in the FFR is calculated, based on the change in the futures contract's price relative to the day prior to the policy action. For an event taking place on day $d$ of month $m$ , the unexpected, or "surprise," target funds rate change can be derived from the rate implied by the current-month futures contract. Since the contract's settlement price is based on the monthly average FFR, the change in the implied futures rate must be scaled by a factor related to the number of days in the month affected by the change,[5]

[5] The contracts, officially referred to as "30 Day Federal Funds Futures," are traded on the Chicago Board of Trade. The implied futures rate is 100 minus the contract price.

$$\Delta i^u = \frac{D}{D-d}\left(f^0_{m,d} - f^0_{m,d-1}\right) \tag{1}$$

where $\Delta i^u$ is the unexpected target rate change, $f^0_{m,d}$ is the current-month futures rate, and $D$ is the number of days in the month. This method effectively gauges the surprise change in the FFR, as the monthly average effective rate on which the contract is based closely aligns with the average target rate. To minimize month-end noise, unscaled changes in the 1-month futures rate are used to calculate the funds rate surprise on the last three days of the month. For rate changes on the first day, $f^1_{\{m-1,D\}}$ is used instead of $f^0_{\{m,d-1\}}$.

Once the unexpected component is calculated, in a second step the expected component of the rate change is defined as the difference between the actual change and the surprise, or

$$\Delta i^e = \Delta i - \Delta i^u \tag{2}$$

## 5.2. Computing Daily Returns

Daily cryptocurrency market returns are used as the dependent variable to analyze the immediate market reaction to changes in the FFR. In preparation for the regression analysis the returns are proxied by daily percentage changes in the SPCBDM. Specifically, the daily return $R_t$ for day $t$ is calculated as,

$$R_{t,i} = \frac{P_{t,i} - P_{t-1,i}}{P_{t-1,i}} \times 100 \tag{3}$$

where, $P_t$ denotes the closing price of the SPCBDM on day $t$, and $P_{t-1}$ represents the closing price on the previous day.

The SPCBDM is a value-weighted index, weighted by the equivalent of market capitalization for cryptocurrencies, comprising 291 constituents. It provides a more realistic reflection of the overall market and reduces single-asset bias common in more narrowly focused indices like the Bloomberg Galaxy Crypto Index (BGCI) or Nasdaq Crypto Index (NCI). The daily calculation frequency effectively captures short-term market reactions to monetary policy changes, thereby ensuring an accurate analysis of the immediate impact on cryptocurrency returns.

## 5.3. Key event dates

The observation period focuses on the timeframe from January 2018 to September 2024, during which key monetary policy events were identified. The first event in the sample is the FOMC meeting on January 31, 2018, and the last corresponds to the FOMC meeting on September 18, 2024. The event window is defined as a 1-day period centered around each key event.

Despite other studies using different durations, such as intraday (Gürkaynak, Sack, and Swanson 2005) or multi-day windows (Rigobon and Sack 2003), the 1-day event window is most appropriate for this paper for three reasons. First, it effectively captures the immediate market reaction to monetary policy announcements, ensuring that cryptocurrency returns are directly linked to the surprise without the influence of longer-term market adjustments. Second, by narrowing the window to a single day, it minimizes external noise, such as macroeconomic data releases, geopolitical events, and corporate earnings, which could obscure the observed effects. Alternative approaches that also address external noise, such as using intraday data or employing heteroskedasticity-based estimators, obtain results very similar to studies using 1-day event windows. Third, it is consistent with existing literature and ensures that the results are comparable to previous studies. Bernanke and Kuttner (2005) have demonstrated the validity of this approach for traditional financial markets, while recent cryptocurrency-focused studies, such as Ma et al. (2022) or Kyriazis et al. (2023), have applied similar event windows.

## 5.4. Hypotheses

For this study three hypotheses are formulated (H1, H2, and H3). The first two hypotheses focus on the immediate market response for the first research question: H1 evaluates the effect of raw FFR changes, while H2 distinguishes between expected and unexpected rate changes. For the second research question H3 explores heterogeneity in market responses, particularly asymmetries in price reactions.

First, I expect that changes in the FFR influence cryptocurrency returns, with the magnitude of the effect depending on whether the change was anticipated or unanticipated. However, baseline estimates in H1 exhibit no significant response to raw rate changes. This is consistent with the efficient market hypothesis (Urquhart 2016), which suggests that cryptocurrencies like Bitcoin exhibit semi-strong market efficiency, implying that prices incorporate publicly available information and fully price in expected changes before they are announced. In contrast, unanticipated policy changes introduce new information that markets have not accounted for, leading to stronger price adjustments. This supports H2 in line with the theoretical role of surprises in financial markets, where unexpected events cause immediate repricing due to the introduction of unanticipated risks. For cryptocurrencies, which lack intrinsic value tied to cash flows or dividends, it can be expected that they are particularly sensitive to unanticipated macroeconomic announcements.

Second, for H3, I do not anticipate significant asymmetries regarding the sign of the surprise or whether the FFR changes on the event day, but I expect asymmetry based on the direction of the policy change. This asymmetric response is driven by differing market dynamics under tightening and easing monetary conditions. Cryptocurrencies often behave more like speculative assets than safe-haven assets, which makes them prone to asymmetrical reactions (Bouri et al. 2018). Specifically, I predict that the magnitude of the cryptocurrency market's reaction will be stronger to monetary tightening, leading to sharper declines compared to the gains observed during monetary easing. Rate hikes reduce liquidity by increasing borrowing costs and signaling a stricter monetary stance, fostering a "risk-off" sentiment that drives investors toward safer investments, such as bonds, which offer higher yields (Nguyen et al. 2019). Monetary easing improves liquidity but signals economic weakness that dampens the positive impact.

***H1:*** *Over the complete period changes in the raw FFR are expected to have no effect on the cryptocurrency market.*

***H2:*** *When isolating the market's reaction to surprise changes, cryptocurrency returns are expected to exhibit a weak response to the expected component and a strong response to the unexpected component.*

***H3:*** *Cryptocurrency returns exhibit asymmetric responses to monetary policy announcements. Monetary tightening leads to stronger market reactions, while monetary easing result in weaker or muted reactions.*

## 5.5. Regression Analysis

With a multiple regression analysis, I seek to determine the effect of the expected and unexpected component of FOMC announcements on cryptocurrency market return in the period between 2018-

2024, using a 1-day event window around each policy. Therefore, daily cryptocurrency returns serve as dependent variable and the measure of expected and unexpected components as independent variables. To prepare for the main regression, I first conduct a baseline regression to estimate the general reaction of cryptocurrency prices to monetary policy. In the second step, I analyze the specific effects of the expected and unexpected components on cryptocurrency returns.

Baseline estimates serve as a starting point to examine the relationship between the FFR and cryptocurrency returns. They assess whether changes in the FFR have immediate, general effects on the cryptocurrency market, using a regression of the SPCBDM value-weighted index return on the raw change in the FFR,

$$H_t = \alpha + b\Delta i_t + \epsilon_t \tag{4}$$

making no distinction between surprise and expected changes. $H_t$ represents the cryptocurrency return and $i_t$is the funds rate target. The raw change is the difference between the actual rate and the previous rate, without any adjustments for market expectations.

The main regression distinguishes between expected and unexpected rate changes, where $\Delta i_t^e$ is the expected component and $\Delta i_t^u$ the unexpected component outlined in Equation (5),

$$H_t = \alpha + b^e\Delta i_t^e + b^u\Delta i_t^u + \epsilon_t \tag{5}$$

In equation (5), $\alpha$ denotes the intercept and $b$ represents the coefficients of the corresponding variables with $b^e$ for the expected component and $b^u$ for the unexpected component. In both specifications, the error term $\epsilon_t$ accounts for non-monetary policy factors that affect returns on event days, assumed to be orthogonal to the changes in the FFR.[6]

## 5.6. Summary Statistics

Table 2 presents summary statistics for the main variables in the analysis. It contains statistics for the average return on the cryptocurrency market index and the monetary policy decisions.

**Table 2 (Descriptive Statistics) about here**

[6] Bernanke and Kuttner (2005) do not incorporate control variables in their regression models. Instead, their results are based on a set of assumptions of orthogonality and heteroskedasticity, both of which were tested and confirmed to hold in this analysis.

The average return of the cryptocurrency market index is 1.10%, with a standard deviation of 3.58%. These values are significantly higher than those of traditional financial markets like the S&P 500, which exhibit average daily returns of 0.03% to 0.04% and typical daily standard deviations of 0.5% to 2%. The wide range of returns (-7.76% to 12.20%) and substantial daily volatility in the index can be attributed to a robust bull market during the COVID-19 pandemic, marked by significant growth in the cryptocurrency market, followed by a bear market driven by rising interest rates.

For monetary policy decisions, the average FFR change is approximately 6 basis points, with a standard deviation of 29 basis points. The largest increases occurred during four consecutive 75 basis point hikes between June 15, 2022, and November 2, 2022. The largest decrease took place on March 23, 2020, with a 100 basis point cut. Expected changes closely follow actual changes in all categories, suggesting the observation period was largely predictable by the market.

**Figure 2 (Time Series Plot) about here**

Figure 2 plots actual changes in the FFR alongside the surprise change. The most substantial positive target surprise was observed on March 3, 2020, with a 30 basis point rate shock, significantly exceeding market expectations. In contrast, the most pronounced negative target surprise occurred on February 1, 2023, reflecting an unexpected rate shock of 24 basis points.

# 6. Results

## 6.1. Event Study Results

To answer the first research question, which inquires how the cryptocurrency market returns were affected by the Fed monetary policy announcements, I conduct several regressions. Table 3 shows the results from regression (1) that I run as a benchmark to analyze the response of returns to the raw change in the FFR and regression (2) in which I distinguish between expected and unexpected changes.

**Table 3 (Regression Results) about here**

Table 3, column (1) reports a positive regression coefficient (3.10) for the raw change in the FFR across the total sample. This suggests that a 1% increase in the FFR is associated with an expected increase of 3.10% in cryptocurrency returns. However, the result is not statistically significant at the 10% level, and the regression exhibits low explanatory power, as indicated by the low R-squared value. As expected, there is no empirical evidence to support a systematic response of cryptocurrency returns to raw changes in the FFR.

The raw change coefficient in my analysis is comparable in magnitude and direction to that reported by Kyriazis et al. (2023), who find a positive return of 3.23%. Both results indicate a weak positive relationship between raw changes in the FFR and cryptocurrency returns, though neither is statistically significant. This aligns with the general expectation that anticipated changes in monetary policy do not produce a measurable impact. In contrast, Bernanke and Kuttner (2005) report a negative return of -0.61% for stock markets, indicating that raw changes in the FFR are associated with negative returns for equities. While their findings also lack statistical significance, the negative direction aligns with financial theory for equities, contrasting with the theory and results for cryptocurrencies.

Table 3 column (2) shows a negative relationship between cryptocurrency market returns and unexpected changes in the FFR. When comparing the two components in terms of magnitude and direction, the unexpected rate change demonstrates a stronger effect on returns relative to the expected component. A 1% unexpected increase in the FFR is associated with a decrease in the return of the broad market index by 4.20%. In contrast, the coefficient for the expected rate change is positive (2.51), implying a potential positive relationship to an expected increase in the FFR. However, neither result is statistically significant at the 10% level. This suggests that while the unexpected actions of the Fed may influence the volatility of returns on these assets, their impact on cryptocurrency returns lacks strong empirical support. Additionally, these factors appear far from being the most critical determinant of cryptocurrency returns, as reflected by the low R-squared value of 7.35%.

The findings[7] are generally in line with existing literature, as Ma et al. (2022) observes a similar negative relationship between an unexpected change and cryptocurrency prices, with a hypothetical 25 basis point increase in the FFR leading to a 6.25% decline in Bitcoin prices. My analysis, however, documents a

[7] To ensure comparability, the results are standardized to reflect the impact of a 1% unexpected change in the FFR, following Bernanke and Kuttner (2005). Other studies, including Ma et al. (2022) and Kuttner (2001), present findings scaled to 1 basis point or 25 basis point changes, respectively. For precise findings in these contexts, see the referenced papers.

1.05% decrease in the broad cryptocurrency market index in response to a 25 basis point unexpected FFR increase, indicating a somewhat weaker sensitivity compared to Bitcoin. This reduced sensitivity can be explained with the index comprising cryptocurrencies with varying degrees of responsiveness to macroeconomic conditions, with this heterogeneity diluting the aggregate response of the index. Moreover, Nguyen et al. (2019) find no significant relationship between interest rates and cryptocurrency prices for the U.S., which aligns with the statistical insignificance of the expected and unexpected components in my analysis. Kyriazis et al. (2023) similarly finds that a 25 basis point unexpected increase in the FFR leads to a 4.80% decline in returns for the cryptocurrency market, focusing on a shorter period from 2018–2022. My findings align qualitatively with Kyriazis et al. (2023), showing a negative return in response to unexpected FFR changes. However, the magnitude of the effect is less pronounced. This difference in performance can be attributed to the extended period of my analysis, during which the cryptocurrency market exhibited reduced volatility, lower speculative trading, and increased institutional participation, reflecting the market's gradual maturation.

When compared to traditional assets, the cryptocurrency market demonstrates a response to unexpected increases in the FFR that mirrors the negative pattern observed in the stock market, while the bond market exhibits an inverse relationship. For instance, Kuttner (2001) finds that a 25 basis point surprise increase in the FFR leads to a 1% decline in stock prices, while Bernanke and Kuttner (2005) report a slightly larger 1.30% decline in the broad equity market. My findings, although statistically not significant, align closely with these results, suggesting that cryptocurrencies, like equities, are sensitive to shifts in monetary policy as they have become more institutionalized. This sensitivity also extends to gold, as Blose (2010) observes that an increase of the same magnitude can lead to a 1.00% decline in gold prices. Similarly, Rigobon and Sack (2003), Gürkaynak et al. (2005), and Wang et al. (2011) attribute gold price declines to the increased opportunity cost of holding non-yielding assets during periods of tighter monetary policy. In contrast, Cochrane and Piazzesi (2002) observe a 0.5% rise in bond prices in response to a 25 basis point increase.

In summary, the results regarding the impact of monetary policy announcements on the cryptocurrency market are partially aligned with expectations. The raw change in the FFR does not significantly affect cryptocurrency returns. However, when distinguishing between the expected and unexpected components, the expected component exhibits a weak reaction, while the unexpected component shows a moderate reaction. Consequently, my predictions regarding the immediate market response are not fully realized. As a result, I can verify Hypothesis H1, but Hypothesis H2 is only partially supported.

## 6.2. Asymmetries

To answer the second research question, examining the heterogeneity in market responses, particularly asymmetries in price reactions, this section presents results for three potential asymmetries: (i) whether responses of cryptocurrency return differ based on the sign of the surprise, (ii) whether the response depends on if the FFR increases, and (iii) whether the response depends on if the FFR changes or not. To test these scenarios, three dummy variables are defined: one for positive surprises in the FFR change, one for positive rate changes in the FFR, and one for no rate changes. Interaction terms are created by combining the surprise with each dummy variable, including these individually in the regressions.

**Table 4 (Asymmetries Regression Results) about here**

For the first asymmetry tested, column (3) of Table 4 shows that the addition of the interaction term for positive surprises renders the results for SPCBDM statistically insignificant. The baseline coefficient for unexpected changes in the FFR (6.47) indicates a positive relationship between unexpected changes and cryptocurrency returns. In contrast, the negative coefficient (-18.28) for the interaction term suggests an inverse relationship between unexpected rate hikes and cryptocurrency returns. These results imply an asymmetry: positive surprises (rate hikes) are associated with a stronger negative reaction, while negative surprises (rate cuts) correspond to a positive reaction in cryptocurrency returns. However, as both coefficients are statistically insignificant, the findings do not provide robust evidence.

These results align with Kyriazis et al. (2023), who also finds that unexpected positive surprises result in larger negative cryptocurrency returns compared to the positive reactions to negative surprises, though these responses are inconsistent and lack statistical robustness. This stronger reaction to positive surprises can be attributed to liquidity constraints and a “risk-off” behavior triggered by unexpected rate hikes, which aligns with the behavior observed in risk-sensitive assets like cryptocurrencies, as noted by Bouri et al. (2018). Similarly, Bernanke and Kuttner (2005) identify significant asymmetries in equity market responses to the sign of surprises, showing that unexpected rate hikes generally cause larger negative reactions in equity prices than the positive effects of rate cuts. This pattern parallels the behavior of cryptocurrencies, suggesting that cryptocurrencies increasingly mirror the reactions observed in equity markets for unexpected rate cuts or hikes (Hammouda 2024).

The results presented in Column (4) of Table 4 correspond to the asymmetry test for the direction of the actual FFR change. When the interaction term for an increase in the FFR is included, the coefficient for unexpected changes in the SPCBDM return (-11.10) increases in absolute magnitude compared to the corresponding value in the main regression (-4.20) indicating a strong negative reaction to monetary policy surprises when there is no tightening. In contrast, the coefficient for the interaction term is positive (23.34), suggesting a link between monetary tightening and positive cryptocurrency returns. These findings imply an asymmetry: Monetary tightening appears to induce a stronger positive reaction, whereas monetary easing is associated with weaker or negative returns, depending on the actual policy stance. However, the results are not significant enough to support firm conclusions.

Surprisingly, the results indicate that monetary tightening may not always be perceived negatively within cryptocurrency markets. These findings suggest that cryptocurrency investors tend to be more responsive to monetary policy when there is an increase in the FFR. During the observed period, this can largely be attributed to anticipated rate hikes, which removed2 uncertainty. This insight helps interpret some unconventional observations about cryptocurrency behaviors documented in recent literature. The positive reaction to monetary tightening aligns with a strand of literature that identifies positive returns in response to such policies (Nguyen 2019; Karau 2021). The observed positive relationship between monetary policy rates and cryptocurrency returns may reflect capital flight from stock markets, as tightening monetary policies negatively affect stock returns (Lobo 2000). Evidence further suggests that higher costs of capital, indicated by rising FFR, are associated with higher cryptocurrency returns (Dyhrberg, 2016). These results also diverge from Bernanke and Kuttner (2005), who found that monetary tightening negatively impacts equity markets. Nonetheless, this aligns with the broader view that cryptocurrencies do not always behave like traditional assets and can serve as assets for portfolio diversification (Baur et al. 2018). Karau (2021) further proposes that this may be driven by a signaling effect, where rate hikes are interpreted as indicators of a stable market environment and supporting cryptocurrencies role as a hedge against inflation (Rodriguez and Colombo 2024).

The third asymmetry test presented in Column (5) of Table 4 reports a positive coefficient (9.40) for the interaction term, suggesting that cryptocurrency returns exhibit a positive response when the FFR remains unchanged. For SPCBDM, the findings indicate a marginally stronger return of -4.53% compared to -4.20% observed in the main regression. Nevertheless, both coefficients are statistically insignificant. These findings imply an asymmetry: cryptocurrency returns reacts positively to surprises when the Fed leaves rates unchanged compared to the negative response when rate changes occur.

Kyriazis et al. (2023) similarly reports a positive coefficient for the case where no changes in the FFR occurred, and that it might be associated with a positive reaction, but their findings also show no statistically significant impacts on cryptocurrency returns. The direction of the response aligns with my results, though the magnitude of my coefficient (9.39) is notably smaller compared to their result (65.51). When the FFR remains unchanged and it is associated with positive returns, it signals that the Fed is aligned with market expectations, reducing uncertainty and fostering a "risk-on" sentiment, as liquidity conditions remain favorable benefiting speculative assets. This aligns with Bernanke and Kuttner (2005) which findings highlight that the absence of a FFR has a coefficient (10.42), suggesting that "no change" decisions are associated with a positive and significant impact on equity returns.

Table 5 summarizes the findings of the results section and the evaluation of my hypotheses.

**Table 5 (Evaluation of Hypotheses) about here**

## 6.3. Robustness Tests

In this section, I assess the robustness of my results by incorporating alternative data.

**Robustness Test (Ia):** The robustness test examines the consistency of results across market segments using alternative indices (results shown in table 6). The S&P Cryptocurrency MegaCap Index (SPCMC) tracks the performance of Bitcoin and Ethereum, while the S&P Cryptocurrency LargeCap Index (SPCBLC) focuses on highly liquid crypto assets. To assess mid- and small-cap patterns, the S&P Cryptocurrency BDM Ex-MegaCap Index (SPCBXM) excludes Bitcoin and Ethereum, and the S&P Cryptocurrency BDM Ex-LargeCap Index (SPCBXL) excludes all large-cap assets. The findings for

SPCMC, SPCBLC, and SPCBXL confirm the robustness of the regressions. In contrast to my results, the SPCBXM shows a statistically significant response of 3.83% to raw FFR changes.

**Robustness Test (Ib):** The results regarding the asymmetries remain robust in magnitude and direction when alternative indices are used (results shown in table 7). Across all three asymmetry tests, the SPCBXM demonstrates slightly weaker reactions compared to other market indices. This suggests that mid- and small-cap cryptocurrencies, which constitute the majority of SPCBXM, are less responsive to FFR changes and related monetary policy asymmetries. These findings imply that the reactions observed in broader indices are likely driven by the significant influence of large-cap assets such as Bitcoin and Ethereum, which are excluded from SPCBXM.

## 7. Conclusion

This paper set out to understand how cryptocurrency market returns are influenced by the Fed's monetary policy announcements and whether there is heterogeneity in market responses. Replicating the methodology of Bernanke and Kuttner (2005), an event study is conducted for a sample of 57 monetary policy announcements. I find that the raw change in the FFR does not significantly affect cryptocurrency returns. However, when distinguishing between the expected and unexpected components, the expected component exhibits a weak positive reaction, while the unexpected component shows a moderate negative response. This reflects a reduced risk appetite among investors, creating a "risk-off" environment due to fears of economic slowdown and increased borrowing costs, which dampen trading activity and liquidity. These findings, although not statistically significant, confirm the results of Bernanke and Kuttner (2005) for equities, showing cryptocurrencies increasingly mirror equity market reactions during surprise changes.

For the second part of the analysis, I conduct regressions to examine asymmetries in market responses, particularly price reactions. While no statistically significant asymmetry is identified, the t-statistics for the asymmetries regarding the sign of the surprise and the direction of the FFR change are near the threshold. Positive surprises lead to negative returns, confirming the findings of Kyriazis et al. (2023), while during monetary tightening cryptocurrency returns unexpectedly results in an increase in the FFR. This second result helps interpret unconventional observations about cryptocurrency behaviors documented in recent literature (Nguyen et al. 2019; Karau 2021), setting them apart from traditional assets due to potential capital flight from stock markets and signaling effects, supporting cryptocurrencies role as a hedge against inflation and their diversification potential.

My findings have potential implications for investors, policymakers, and regulators. For investors, the negative reactions to unexpected FFR changes shows the importance of incorporating macroeconomic variables into cryptocurrency trading and portfolio allocation strategies. The observed parallels between cryptocurrency and equity market reactions suggest that cryptocurrencies may not provide the same diversification benefits during monetary tightening as previously assumed, requiring investors to reassess their risk management frameworks. For policymakers, the asymmetry observed in responses to monetary tightening versus easing underscores the need to understand how signaling effects and capital flight dynamics influence cryptocurrency markets. Regulators may use these insights to design policies addressing the potential spillovers of monetary policy into speculative asset markets, as cryptocurrencies become more integrated into the financial system.

The validity of my paper is limited by estimates of the unexpected component being close to zero during the effective lower bound (ELB) period, where estimates of monetary transmission may be quite small or imprecise. This could lead to conclude that monetary policy has no effect on the economy. However, this can be problematic, as monetary policy can still have an impact at the ELB, even though through longer horizons than those used to calculate the unexpected component. Furthermore, my analysis is constrained by a limited sample of events due to the nascent nature of cryptocurrencies, resulting in no statistical significance for the variables analyzed, which further limits the validity of the findings.

Future research could entail several avenues to address the limitations of this study. First, the analysis could be expanded by incorporating data from other central banks, such as the ECB or the Bank of England to see if regional differences offer robust insights. Second, future studies could focus on subcategories of cryptocurrencies, such as stablecoins, utility tokens, or payment tokens, to determine whether different use cases exhibit varying sensitivities to monetary policy. Third, researchers could extend the event window to capture longer-term effects of monetary policy changes, particularly during periods of ELB constraints.

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The S&P Cryptocurrency LargeCap Index (SPCBLC): SPCBLC is a daily price return index and a subset of the S&P Cryptocurrency Broad Digital Market (BDM) Index designed to track the constituents of the S&P Cryptocurrency BDM Index with the largest market capitalization publicly available on the S&P Global website.
Retrieved from: https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-largecap-index/#data

The S&P Cryptocurrency BDM Ex-MegaCap Index (SPCBXM): SPCBXM is a daily price return index designed to track the constituents of the S&P Cryptocurrency BDM Index, excluding the constituents of the S&P Crytocurrency MegaCap publicly available on the S&P Global website.
Retrieved from: https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-bdm-ex-megacap-index/#data

The S&P Cryptocurrency BDM Ex-LargeCap Index (SPCBXL); SPCBXL is a daily price return index designed to track the constituents of the S&P Cryptocurrency BDM Index, excluding constituents of the S&P Cryptocurrency LargeCap Index publicly available on the S&P Global website.
Retrievd from: https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-bdm-ex-largecap-index/#data

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## List of Abbreviations

| | |
|---|---|
| BGCI | Bloomberg Galaxy Crypto Index |
| CME | Chicago Mercantile Exchange |
| ECB | European Central bank |
| ELB | Effective lower bound |
| Fed | Federal Reserve |
| FFR | Federal funds rate |
| FOMC | Federal Open Market Committee |
| ICO | Initial Coin Offering |
| NCI | Nasdaq Crypto Index |
| SPCBDM | S&P Cryptocurrency Broad Digital Market Index |
| SPCBLC | S&P Cryptocurrency LargeCap Index |
| SPCBXL | S&P Cryptocurrency BDM Ex-LargeCap Index |
| SPCBXM | S&P Cryptocurrency BDM Ex-MegaCap Index |
| SPCMC | S&P Cryptocurrency MegaCap Index |
| USD | United States Dollar |
| VAR | Vector autogression |

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## Appendix

**Table 1: Sample Overview**

The table summarizes the number of FOMC meeting days and intermeeting days, along with the corresponding actual changes, expected changes, and unexpected changes. The full sample consists of 57 observations over the period from January 2018 to September 2024. Data for the event days is sourced from the Fed website, with all statistics expressed in basis points (bp).

| Date | | Actual (bp) | Expected (bp) | Unexpected (bp) |
|---|---|---|---|---|
| 2018 | 01/31 | 0 | 0 | 0 |
| | 03/21 | 25 | 25 | 0 |
| | 05/02 | 0 | 0 | 0 |
| | 06/13 | 25 | 25 | 0 |
| | 08/01 | 0 | -1 | 1 |
| | 09/26 | 25 | 25 | 0 |
| | 11/08 | 0 | 1 | -1 |
| | 12/19 | 25 | 28 | -3 |
| 2019 | 01/30 | 0 | 0 | 0 |
| | 03/20 | 0 | 3 | -3 |
| | 05/01 | 0 | -3 | 3 |
| | 06/19 | 0 | 3 | -3 |
| | 07/31 | -25 | -25 | 0 |
| | 09/18 | -25 | -30 | 5 |
| | 10/04 | 0 | 1 | 1 |
| | 10/30 | -25 | -25 | 0 |
| | 12/11 | 0 | 0 | 0 |
| 2020 | 01/29 | 0 | 0 | 0 |
| | 03/03 | -50 | -80 | 30 |
| | 03/15 | -100 | -112 | 12 |
| | 03/23 | 0 | -4 | 4 |
| | 04/29 | 0 | 0 | 0 |
| | 06/10 | 0 | 0 | 0 |
| | 07/29 | 0 | 0 | 0 |
| | 09/16 | 0 | 0 | 0 |
| | 11/05 | 0 | 0 | 0 |
| | 12/16 | 0 | 0 | 0 |
| 2021 | 01/27 | 0 | 0 | 0 |
| | 03/17 | 0 | 0 | 0 |
| | 04/28 | 0 | 0 | 0 |

| | | | | |
|---|---|---|---|---|
| | 06/16 | 0 | 2 | -2 |
| | 07/28 | 0 | 0 | 0 |
| | 09/22 | 0 | 0 | 0 |
| | 11/03 | 0 | 0 | 0 |
| | 12/15 | 0 | 0 | 0 |
| 2022 | 01/26 | 0 | 0 | 0 |
| | 03/16 | 25 | 21 | 4 |
| | 05/04 | 50 | 49 | 1 |
| | 06/15 | 75 | 79 | -4 |
| | 07/27 | 75 | 75 | 0 |
| | 09/21 | 75 | 72 | 3 |
| | 11/02 | 75 | 74 | 1 |
| | 12/14 | 50 | 50 | 0 |
| 2023 | 02/01 | 25 | 49 | -24 |
| | 03/22 | 25 | 28 | -3 |
| | 05/03 | 25 | 28 | -3 |
| | 06/14 | 0 | -2 | 2 |
| | 07/26 | 25 | 25 | 0 |
| | 09/20 | 0 | 0 | 0 |
| | 11/01 | 0 | 0 | 0 |
| | 12/13 | 0 | 0 | 0 |
| 2024 | 01/31 | 0 | 0 | 0 |
| | 03/20 | 0 | 0 | 0 |
| | 05/01 | 0 | 0 | 0 |
| | 06/12 | 0 | 0 | 0 |
| | 07/31 | 0 | 0 | 0 |
| | 09/18 | 50 | -60 | 10 |

**Table 2: Descriptive Statistics**

The table represents the descriptive statistics of the main variables used in the regression analysis. SPCBDM return is the percentage change in the closing price of the cryptocurrency market over the period t and t-1, where t is the FOMC meeting date. The actual change is the change in the Federal funds rate (FFR) announced at FOMC meetings. The expected change is the change between the actual change and the unexpected change. The surprise change is the shock in the FFR implied by the current month futures contract. The full sample consists of 57 observations over the period from January 2018 to September 2024. All variables are expressed in percentage terms.

| | **#Obs** | **Mean** | **SD** | **Min** | **Max** |
|---|---|---|---|---|---|
| **Variable** | | | | | |
| SPCBDM Return (%) | 57 | 1.10 | 3.58 | -7.76 | 12.20 |
| Actual Change (%) | 57 | 0.06 | 0.29 | -1.00 | 0.75 |
| Expected change (%) | 57 | 0.05 | 0.32 | -1.12 | 0.79 |
| Surprise change (%) | 57 | 0.01 | 0.06 | -0.24 | 0.29 |

**Table 3: Regression Results**

The table presents the results of the regressions using the following regression models:

$$H_t = \alpha + b\Delta i_t + \epsilon_t$$

$$H_t = \alpha + b^e \Delta i_t^e + b^u \Delta i_t^u + \epsilon_t$$

Regression (1) uses the 1-day SPCBDM value-weighted cryptocurrency return on changes in the raw Federal funds rate of the full period. Regression (2) reports the results from the regression of the 1-day SPCBDM value-weighted cryptocurrency return on the surprise and expected components of the funds rate change over the full period. The full sample consists of the 57 observations over the period from January 2018 to September 2024. All variables are expressed in percentage terms. Parentheses contain t-statistics, calculated using heteroskedasticity-consistent estimates of the standard errors. Stars, *, ** and *** indicate the statistical significance at the 10%, 5% and 1% level, respectively. The data are retrieved from S&P Global Market Intelligence.

| Regressor | (1)<br>*SPCBDM* | (2)<br>*SPCBDM* |
|---|---|---|
| Constant | 0.01** | 0.01** |
| | (1.99) | (2.14) |
| Actual Change | 3.10 | - |
| | (1.43) | - |
| Expected Change | - | 2.51 |
| | | (1.04) |
| Surprise Change | - | -4.20 |
| | | (-0.59) |
| Obs. | 57 | 57 |
| $R^2$ | 0.06 | 0.07 |

**Table 4: Asymmetries Regression Results**

The table reports the results from regressions of the 1-day SPCBDM value-weighted cryptocurrency return on the surprise and expected components of the change in the Federal funds rate, all expressed in percentage terms. Regression (3) includes the positive surprise dummy that is set to 1 when the surprise change in the Federal funds rate (FFR) is greater than 0. Regression (4) includes the positive actual rate change dummy equal 1 when the FFR is increased, and regression (5) includes the no rate change dummy equal 1 when the FFR is unchanged. The full sample consists of the 57 observations over the period from January 2018 to September 2024. Parentheses contain t-statistics, calculated using heteroskedasticity-consistent estimates of the standard errors. Stars, *, ** and *** indicate the statistical significance at the 10%, 5% and 1% level, respectively. The data are retrieved from S&P Global Market Intelligence.

| Regressor | (3)<br>*SPCBDM* | (4)<br>*SPCBDM* | (5)<br>*SPCBDM* |
|---|---|---|---|
| Constant | 0.02** | 0.01** | 0.01** |
| | (2.39) | (2.36) | (2.12) |
| Surprise Change | 6.47 | -11.10 | -4.54 |
| | (0.68) | (-1.10) | (-0.62) |
| $1_{\{\Delta i^u > 0\}}$ | -18.27 | | |
| | (-1.57) | | |
| $1_{\{\Delta i > 0\}}$ | | 23.34 | |
| | | (1.48) | |
| $1_{\{\Delta i = 0\}}$ | | | 9.40 |
| | | | (0.66) |
| Obs. | 57 | 57 | 57 |
| $R^2$ | 0.08 | 0.09 | 0.07 |

**Table 5: Evaluation of Hypotheses**

The table presents a summary of the hypotheses proposed in the paper, along with my findings and an assessment of each hypothesis.

| Name | Hypothesis | Findings | Evaluation |
|---|---|---|---|
| Hypothesis H1 | Over the complete period changes in the raw FFR are expected to have no effect on the cryptocurrency market. | I report an insignificant positive reaction on the cryptocurrency market through changes in the raw FFR. | H1 verified |
| Hypothesis H2 | When isolating the market's reaction to surprise changes, cryptocurrency returns are expected to exhibit a weak response to the expected component and a strong response to the unexpected component. | I find a positive weak reaction for the expected component and a negative moderate reaction for the unexpected component. Both are statistically insignificant. | H2 Partly verified |
| Hypothesis H3 | Cryptocurrency returns exhibit asymmetric responses to monetary policy announcements. Monetary tightening leads to stronger market reactions, while monetary easing result in weaker reactions. | For the sign of the surprise, positive surprises (rate hikes) are linked to stronger negative reactions, while negative surprises (rate cuts) correspond to positive reactions. For the direction of the change, monetary tightening induces stronger positive reactions, whereas monetary easing is associated with weaker or negative reactions. For the third asymmetry, cryptocurrency returns react positively to surprises when the Fed leaves rates unchanged, in contrast to the negative reaction observed on days with rate changes. Although, these are not statistically significant the t-statistics are close to the threshold. | H3 falsified |

**Table 6: Robustness Test Event-Study: Alternative Indices**

The table presents the results of robustness regressions, comparing the responses of different market segments using alternative indices, as defined by the following equations:

$$H_t = \alpha + b\Delta i_t + \epsilon_t$$

$$H_t = \alpha + b^e \Delta i_t^e + b^u \Delta i_t^u + \epsilon_t$$

Regressions (6), (8), (10), and (12) use the 1-day value-weighted cryptocurrency return on changes in the raw Federal funds rate (FFR) over the full period. Regression (6) uses the S&P Cryptocurrency MegaCap Index (SPCMC), (8) uses the S&P Cryptocurrency LargeCap Index (SPCBLC), (10) uses the S&P Cryptocurrency BDM Ex-MegaCap Index (SPCBXM), and (12) uses the S&P Cryptocurrency BDM Ex-LargeCap Index (SPCBXL). Regressions (7), (9), (11), and (13) report the results from the regression of the 1-day value-weighted cryptocurrency return on the surprise and expected components of the FFR change over the full period.

The full sample consists of the 57 observations over the period from January 2018 to September 2024. All variables are expressed in percentage terms. Parentheses contain t-statistics, calculated using heteroskedasticity-consistent estimates of the standard errors. Stars, *, ** and *** indicate the statistical significance at the 10%, 5% and 1% level, respectively. The data are retrieved from S&P Global Market Intelligence.

| Regressor | (6) *SPCMC* | (7) *SPCMC* | (8) *SPCBLC* | (9) *SPCBLC* | (10) *SPCBXM* | (11) *SPCBXM* | (12) *SPCBXL* | (13) *SPCBXL* |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.01* | 0.02* | 0.01** | 0.02** | 0.01* | 0.03** | 0.01 | 0.02* |
| | (1.78) | (1.94) | (2.02) | (2.16) | (1.87) | (2.07) | (1.61) | (1.73) |
| Actual Change | 2.91 | - | 3.11 | - | 3.83** | - | 3.20 | - |
| | (1.30) | | (1.44) | | (2.12) | | (1.33) | |
| Expected Change | - | 2.30 | - | 2.53 | - | 3.43 | - | 2.70 |
| | | (0.92) | | (1.04) | | (1.46) | | (1.07) |
| Surprise Change | - | -4.80 | - | -4.20 | - | -5.17 | - | -3.16 |
| | | (-0.68) | | (-0.58) | | (-0.16) | | (-0.49) |
| Obs. | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
| $R^2$ | 0.06 | 0.07 | 0.06 | 0.07 | 0.08 | 0.08 | 0.06 | 0.07 |

**Table 7: Robustness Test Asymmetries: Alternative Indices**

The table reports the results from regressions of the 1-day value-weighted cryptocurrency return on the surprise and expected components of the change in the Federal funds rate (FFR), all expressed in percentage terms. For regressions (14), (17), (20) and (23) the positive surprise dummy is set to 1 when the surprise change in the FFR is greater than 0. For the regressions (15), (18), (21) and (24) the positive actual rate change dummy equal 1 when the FFR is increased and for (16), (19), (22) and (25) the no rate change dummy equal 1 when the FFR is unchanged.

The full sample consists of the 57 observations over the period from January 2018 to September 2024. All variables are expressed in percentage terms. Parentheses contain t-statistics, calculated using heteroskedasticity-consistent estimates of the standard errors. Stars, *, ** and *** indicate the statistical significance at the 10%, 5% and 1% level, respectively. The data are retrieved from S&P Global Market Intelligence.

| Regressor | (14) *SPCMC* | (15) *SPCMC* | (16) *SPCMC* | (17) *SPCBLC* | (18) *SPCBLC* | (19) *SPCBLC* | (20) *SPCBXM* | (21) *SPCBXM* | (22) *SPCBXM* | (23) *SPCBXL* | (24) *SPCBXL* | (25) *SPCBXL* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Constant | $0.01^{**}$ | $0.02^{***}$ | $0.03^{*}$ | $0.02^{**}$ | $0.01^{**}$ | $0.01^{**}$ | $0.02^{**}$ | $0.01^{**}$ | $0.02^{**}$ | $0.01^{*}$ | $0.01^{*}$ | $0.01^{*}$ |
| | (2.21) | (2.56) | (1.02) | (2.41) | (2.37) | (2.14) | (2.17) | (2.15) | (2.05) | (1.96) | (1.95) | (1.72) |
| Surprise C. | 6.00 | -12.00 | -5.16 | 6.70 | -11.10 | -4.55 | 6.78 | -5.52 | -0.97 | 4.60 | -8.65 | -2.76 |
| | (0.61) | (-1.14) | | (0.69) | (-1.10) | (-0.62) | (0.78) | (-0.60) | (-0.13) | (0.55) | (-0.88) | (-0.42) |
| $1_{\{\Delta i^u > 0\}}$ | -18.42 | | | -18.58 | | | -13.62 | | | -13.30 | | |
| | (-1.49) | | | (-1.59) | | | (-1.39) | | | (-1.15) | | |
| $1_{\{\Delta i > 0\}}$ | | 16.10 | | | 15.44 | | | 9.71 | | | 12.29 | |
| | | (1.42) | | | (1.49) | | | (1.16) | | | (1.13) | |
| $1_{\{\Delta i = 0\}}$ | | | 9.82 | | | 11.00 | | | 5.56 | | | 11.27 |
| | | | (0.65) | | | (0.75) | | | (0.32) | | | (0.70) |
| Obs. | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
| $R^2$ | 0.08 | 0.08 | 0.07 | 0.07 | 0.09 | 0.07 | 0.09 | 0.08 | 0.08 | 0.08 | 0.08 | 0.07 |

**Figure 1: Market Index Performance**

The figure displays the performance of the S&P Cryptocurrency Broad Digital Market Index (SPCBDM) over the complete period of January 2018 to September 2024 in USD. The SPCBDM is a daily price return index designed to track the performance of digital assets listed on recognized open digital exchanges. The index launch date is Jul 13, 2021. All information for an index prior to its launch date is hypothetical back-tested, not actual performance, based on the index methodology in effect on the Launch Date. The data are retrieved from S&P Global Market Intelligence.

**Figure 2: Time Series Plot Actual Change vs. Surprise Change**

Figure 2 shows the monetary policy surprises along the actual policy changes in the FFR. The bars indicate the target surprises, while the solid line indicates actual policy changes. The full sample consists of the 57 observations over the period from January 2018 to September 2024.