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Cryptocurrency Market Reactions to Monetary Policy Announcements

Evidence Across Asset Classes

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ABSTRACT:

This thesis examines if scheduled U.S. Federal Open Market Committee (FOMC) interest rates decisions set through U.S. Federal Reserve are reflected in cryptocurrency returns and volatility based upon the daily level of data, and if reactions to FOMC decisions vary by type of cryptocurrency segment. The analysis covers four types of crypto asset functionally defined as major cryptocurrencies, stablecoins, meme coins, and privacy coins. The dataset spans from 31.8.2019 to 17.12.2025 and 49 FOMC decision dates which are categorized into three types - rate cuts, rate increases, and no change from previous decision. Event study estimates of abnormal returns used the CoinDesk Market Index as the benchmark and a baseline event window of [-1,+1]. To analyze the robustness of these findings, additional analyses included expanding the event window to [-2,+2] and performing distribution-free inference on event-specific cumulative abnormal returns through Wilcoxon signed-rank and sign tests. Also, the evaluation of the day-specific AAR results is conducted considering multiple comparisons.

Evidence of abnormal performance of crypto markets generally across all FOMC decisions at the daily frequency does not exist Most CAAR estimates are small and statistically insignificant across decision-category combinations. While some localized day-specific return patterns appear in individual category-day cells, these effects are not robust once multiple comparisons are taken into account. The findings therefore suggest that any return responses to FOMC decisions are limited and segment-specific rather than market-wide. Volatility is modeled using category-specific GARCH model with student-t innovations, and FOMC dummy variables are included in the variance equation. While the persistence of volatilities across all categories is high and heavy-tailed, the FOMC dummy variables did not demonstrate systematic and repeatable shifts in daily conditional variances. Therefore, the overall findings of this thesis indicate that scheduled FOMC decisions do not uniformly impact daily returns and volatility across cryptocurrency markets.

KEYWORDS: (monetary policy, central bank, cryptocurrency, event study, volatility, FOMC).

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TIIVISTELMÄ:

Tämä tutkimus tarkastelee, heijastuvatko Yhdysvaltain keskuspankin (Federal Reserve) rahapolitiikkakomitean (FOMC) ennalta aikataulutetut korkopäätökset kryptovaluuttojen tuottoihin ja volatiliteettiin päivätason aineistolla, sekä vaihtelevatko reaktiot kryptomarkkinasegmentin mukaan. Analyysissa käytetään neljää toiminnallisesti määriteltyä kryptovarallisuusluokkaa: suuret kryptovaluutat, stablecoinit, meemikolikot ja yksityisyyskolikot. Aineisto kattaa vuosien 31.8.2019-17.12.2025 ajanjakson sekä 49 FOMC-kokousten korkopäätöspäivää, jotka luokitellaan kolmeen ryhmään: koronlaskut, koronnostot ja päätökset, joissa korko pidettiin ennallaan. Epänormaalit tuotot estimoidaan tapahtumatutkimuksella, jossa vertailuindeksinä käytetään CoinDesk Market -indeksiä ja perusikkunana tapahtumaikkunaa [-1,+1]. Tulosten robustiutta arvioidaan laajentamalla tapahtumaikkuna [-2,+2]-muotoon sekä käyttämällä jakaumaoletuksista vapaita testejä tapahtumakohtaisille kumulatiivisille epänormaaleille tuotoille sekä tarkastelemalla päiväkohtaisia AAR-tuloksia useiden rinnakkaisten testien näkökulmasta.

Tulokset eivät anna näyttöä laaja-alaisista tai systemaattisista epänormaaleista tuottovaikutuksista kryptomarkkinoilla FOMC:n korkopäätösten ympärillä päivätason aineistolla. Suurin osa CAAR-estimaateista on pieniä eikä tilastollisesti merkitseviä eri päätös- ja kategoriayhdistelmissä. Vaikka yksittäisissä kategoria-päivä -soluissa havaitaan joitakin paikallisia päiväkohtaisia tuottokuvioita, nämä vaikutukset eivät osoittaudu robusteiksi, kun useat rinnakkaiset vertailut otetaan huomioon. Tulokset viittaavat siten siihen, että mahdolliset tuottoreaktiot FOMC:n päätöksiin ovat rajallisia ja segmenttikohtaisia, eivät koko markkinaa koskevia. Volatiliteettia mallinnetaan kategoriakohtaisilla Student-t -innovaatioita hyödyntävillä GARCH-malleilla, joissa varianssiyhtälöön sisällytetään FOMC:tä kuvaavat dummy-muuttujat. Vaikka kaikissa kategorioissa havaitaan voimakasta volatiliteetin kasautumista, korkeaa pysyvyyttä ja paksuhäntäisyyttä, FOMC-dummy-muuttujat eivät anna johdonmukaista näyttöä systemaattisista muutoksista päivittäisessä ehdollisessa volatiliteetissa. Kokonaisuutena tulokset osoittavat, etteivät ennalta aikataulutetut FOMC:n korkopäätökset johda yhdenmukaisiin päivätason tuotto- tai volatiliteettivaikutuksiin kryptomarkkinoilla.

AVAINSANAT: (monetary policy, central bank, cryptocurrency, event study, volatility, FOMC).

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Abbreviations

AAR	Average abnormal return
AR	Abnormal return
CAAR	Cumulative average abnormal return
CAPM	Capital asset pricing model
CAR	Cumulative abnormal return
CMI	CoinDesk Market Index
EMH	Efficient market hypothesis
Fed	Federal Reserve
FOMC	Federal Open Market Committee

1 Introduction

Crypto asset prices have shown an increasing sensitivity to global financial conditions, despite the fact that many crypto assets do not produce cash flows similar to those produced by typical securities. The purpose of this thesis is to investigate whether scheduled announcements of U.S. Federal Open Market Committee (FOMC) interest rate decisions are reflected in cryptocurrency returns and volatility at the daily level. In particular, the effects of scheduled FOMC decision announcements are examined, classified as a rate cut, a rate hike, or no change, and whether there are differences in how the various segments of the cryptocurrency market respond to scheduled FOMC decision announcements.

The chosen focus is on scheduled FOMC decision announcements due to informational efficiency. If public information is quickly incorporated into asset prices, then the anticipated portion of a policy decision will be reflected in prices prior to the announcement, and the only source of systematic price adjustments around the decision announcement would be related to the arrival of new information and the unanticipated component of the decision (Fama, 1970, pp. 387, 391, 410).

Another reason for focusing on scheduled FOMC decision announcements is that monetary policy decisions can affect asset prices through multiple channels and can affect the risk premium and the discount rate; thus, showing up in both the mean and the volatility of asset returns. Volatility is important when examining the behavior of cryptocurrency returns, since many exhibit volatility clustering and heavy-tailed distributions, indicating time-variation in the conditional variance and an increased probability of extreme values compared to normality assumptions. Therefore, models of conditional volatility that allow for time variation and potentially respond to information events is used (R. Engle, 2001).

It is worth noting that the cryptocurrency market is not homogeneous (Bengtsson & Gustafsson, 2023). Different crypto assets fulfill different economic functions and have user bases and trading objectives that may indicate different sensitivities to macroeconomic financial news. Stablecoins are intended to maintain price stability and are primarily used as liquidity tools, meme coins tend to be more speculative and driven by sentiment and privacy coins represent a unique segment of the market with unique market characteristics and possibly varying levels of regulatory sensitivity. Since there exist heterogeneity among the segments of the cryptocurrency market, effects that may be small or nonexistent in aggregated indices may continue to exist within individual segments of the market. Thus, this thesis compares reactions within four different asset classes: major cryptocurrencies, stablecoins, privacy coins, and meme coins, within a single empirical framework.

Empirically, an event-study approach is used to evaluate abnormal returns, and a conditional volatility model to determine if volatility reacts systemically to the announcements of scheduled FOMC decision announcements. Each scheduled FOMC decision announcement is treated as an event, and the abnormal returns over short announcement windows are evaluated to minimize the amount of unrelated news that contaminate the results, consistent with standard event-study methodology. Also, a GARCH-type framework is used to test if volatility reacts systemically to the scheduled FOMC decision announcements after accounting for volatility persistence and heavy tails. Together, these methodologies provide evidence regarding whether the announcements of scheduled FOMC decision announcements are associated with abnormal return performance and if the announcements of scheduled FOMC decision announcements alter the risk characteristics of the various segments of the cryptocurrency market.

1.1 Purpose of the study

The aim of this thesis is to analyze how FOMC scheduled announcements about interest rates influence cryptocurrency returns and their volatility by using daily data. Analysis is focused on short periods around the time of the FOMC's announcement decision dates and comparisons among major cryptocurrencies, stablecoins, meme coins and privacy coins, under one single research model.

An event study methodology is applied to determine the returns. An abnormal return is determined for each cryptocurrency for each trading day during the event window and then averaged together to create a cumulative average abnormal return (CAAR), where the CAAR represents the average abnormal return over all the trading days in the window. A baseline window of [−1,+1] is selected to include possible pre-announcement positioning and post-announcement adjustments in daily closing prices and keep the interpretation of the results tied to the announcement date. Conditional volatility is analyzed by incorporating an event dummies into a GARCH-type of conditional variance equation that captures the timing of the FOMC announcement.

If the cryptocurrency market includes some macro-financial information, then a scheduled monetary policy announcement should produce abnormal price movements in the cryptocurrency market in the vicinity of the announcement date rather than no abnormal price movement over a daily time frame. Therefore, hypothesis 1 is proposed to test if abnormal performance exists in the vicinity of the announcement date.

H1: In the FOMC announcement window [−1, +1], the mean cumulative average abnormal return (CAAR) differs from zero in at least one cryptocurrency category.

As previously stated, the cryptocurrency market is heterogeneous: stablecoins were designed to be a store of value, have low price volatility, provide liquidity and function as a money market instrument; meme coins have high price volatility due to speculation and investor sentiment; and privacy coins have unique characteristics that differentiate them from other cryptocurrency types. Therefore, if monetary policy news influences investor perceptions of risk and changes market conditions, then the magnitude and possibly even the direction of the abnormal return could vary depending on the type of cryptocurrency being examined. Hence, hypothesis 2 tests if the return reaction varies across different categories of cryptocurrencies in relation to FOMC decision dates.

H2: Abnormal return reactions differ across cryptocurrency categories (major cryptocurrencies, stablecoins, meme coins, and privacy coins) around FOMC decision dates.

In addition to influencing financial markets through risk premia and uncertainty, monetary policy decisions can also influence markets by increasing uncertainty about future outcomes and thereby shifting volatility rather than altering mean returns. Given that volatility is highly persistent and clustered in digital currency markets, an evaluation of event-induced changes in conditional volatility would require a control for the typical patterns of baseline volatility dynamics. Thus, hypothesis 3 investigates whether conditional volatility is increased following FOMC decision dates.

H3: FOMC decision dates are associated with higher conditional volatility on the event day or in the immediate surrounding days.

1.2 Structure of the study

The structure of this thesis includes 7 chapters. Chapter 1 will discuss a general overview of the subject matter including an explanation of the reason for conducting this study, as well as establishing the hypotheses. Chapter 2 will include an overview of the theories relative to monetary policy, financial market reactions, and volatility. The crypto currency market will be explained, along with the major asset classes that are being analyzed within this thesis in chapter 3. Chapter 4 will present an overview of previously published studies concerning monetary policy announcements and how they affect both traditional financial markets, and the crypto currencies. Chapter 5 will provide an overview of the data and methods utilized within the empirical portion of the study. Chapter 6 will present the empirical findings from the study, and the discussion of these findings. Lastly, chapter 7 will summarize the empirical findings of this thesis, as well as offer possible implications of those findings, and identify areas for potential future research.

2 Theoretical background

This thesis uses six interconnected theories to describe why FOMC announcements can impact cryptocurrency returns and volatility. Monetary policy and central banking theories will be used to illustrate how the actions of central banks and their communications shape financial conditions by changing interest rates, access to credit, investor expectations and the dissemination of information. The institutional roles of the Federal Open Market Committee will serve as the basis for understanding where the signals of monetary policy are created and disseminated to financial markets. Event studies will provide the underlying logical structure to identify short-term market reaction to FOMC announcements. The efficient market hypothesis and the theory of asset pricing will provide the structural context for the interpretation of such reactions as a response to the receipt of new information that leads investors to adjust their expectations of future cash flows, discount rates and risk premia. Volatility models will be used to examine how the variance of expected returns and the uncertainty surrounding those expected returns may also respond to monetary policy news, and not just the expected returns themselves. Finally, GARCH-type models will be employed to estimate the level of time-conditional volatility associated with the release of monetary policy news, and assess if FOMC announcements result in an increase or decrease in the uncertainty associated with investing in cryptocurrencies.

2.1 Monetary policy and central banking

The monetary policy encompasses all of the activities and strategies undertaken by central banks to affect the macroeconomic condition of the economy including inflation output and financial stability (Vredin & Sommar, 2023, p. 8). Central banks today primarily use monetary policy to accomplish this goal through manipulation of the level and direction of short-term interest rates in order to control the costs of borrowing, consumer spending, investments and ultimately the demand for goods and services (Mishkin, 1996, pp. 2-3; Vredin & Sommar, 2023). Ultimately, through this mechanism, monetary policy has a central position in determining the broad economic conditions and the overall financial market conditions.

One of the primary tools of monetary policy is the policy interest rate, which acts as a benchmark for short-term funding costs in the economy because central banks can steer overnight and other money-market rates closely around their operating target (Herrala & Tötterman, 2023). A central bank adjusts the policy rate to directly influence money-market rates and, through expectations about the future path of policy, to indirectly influence longer-term interest rates and broader asset prices (Strasser, 2018, p. 5). Beyond conventional interest-rate policy, central banks may employ non-traditional measures, such as large-scale asset purchases and other balance-sheet policies, particularly when the policy rate approaches the effective lower bound (Woodford, 2012). The ultimate goal of these policies is to affect longer-term yields and overall financial conditions (Eser et al., 2019).

There are several ways in which monetary policy influences the economy and those include the traditional interest rate channel, the credit channel and the expectations channel (Mohanty & Turner, 2008). The interest rate channel suggests that policy induced changes in the level of interest rates within the economy will have a direct effect upon the cost of capital and household borrowing behavior with the end result being the amount of spending and investing that occurs within the economy (Mishkin, 1996). The credit channel suggests that monetary policy will also influence the lending conditions within the economy by affecting the amount of credit available to borrowers and the quality of their balance sheet with the end result being the potential amplification of policy effects in the real economy (Bernanke & Gertler, 1995). Lastly, monetary policy works through the expectations channel by suggesting that financial decisions are made based upon expectations of future interest rates and future inflation and therefore central banks can influence current economic conditions by establishing expectations of the future course of policy (Woodford, 2002).

As part of contemporary monetary policy, the importance of central bank communications has grown significantly. Not only do statements issued by the central bank, press conferences and forward guidance provide information about the central bank's view of the state of the economy, they also serve to inform market participants of the central bank's reaction function and thus establish expectations of the central bank's future course of action. As financial markets are inherently forward looking, they react to not only the immediate policy action, but also to changes in expectations of future policy conditions (Gurkaynak et al., 2005). Accordingly, market reactions to monetary policy announcements reflect both surprises in the current policy decision and revisions in expectations about the future path of policy that are conveyed through the central bank’s communication (Gurkaynak et al., 2005, p. 56). In the forward-guidance literature, these expectation revisions are often interpreted as arising either from a change in expected future policy actions or from information revealed about the central bank’s outlook (Campbell et al., 2012, p. 1).

Therefore, monetary policy is best described as a combination of policy actions and expectations management. Through interest rates, credit conditions and expectations of investors, central banks create a macro-financial environment in which asset prices are created and economic decisions are made. Thus, monetary policy is a major factor in creating financial conditions and therefore a critical component of modern macro-financial analysis (Woodford, 2002, p. 17-18).

2.2 The Federal Open Market Committee

In the United States, the FOMC, which is the primary decision-making body of the Federal Reserve System, determines monetary policy decisions. The FOMC has total of twelve members of which seven members are of the Board of Governors of the Federal Reserve System, one president of the Federal Reserve Bank of New York and four members are the remaining Reserve Bank presidents, rotating on one-year terms. The FOMC implements monetary policy through open market operations and also sets the federal funds rate to help guide reserve levels and thus effect financial conditions in the broad economy (Board of Governors of the Federal Reserve System, 2026) The FOMC sets a target range for the federal funds rate, and communicates those decisions to the public at the end of each meeting of the committee (Board of Governors of the Federal Reserve System, 2026). The decisions made by the FOMC about interest rates directly affect short term interest rates, and through the financial markets, ultimately affect the overall economy (Board of Governors of the Federal Reserve System, 2026). After the financial crisis, the policy-making process was put into an explicit framework with the introduction of a near zero target for the federal funds rate in late 2008, which is an example of the operational use of the target (Board of Governors of the Federal Reserve System, 2026).

The FOMC's recurring and routine schedule for meetings creates a distinct place for its announcements within financial markets. The FOMC has eight regularly scheduled meetings each year and thus allows market participants to identify decision dates and continually revise their expectations before each meeting (Board of Governors of the Federal Reserve System, 2026). As most monetary policy actions contain elements of anticipated action, the market will be less likely to react to policy actions that have been anticipated and therefore, it is necessary to identify the elements of a decision that are expected versus those that are not (Bernanke & Kuttner, 2005, p. 1). In line with the notion of efficient markets as described by Fama (1970), price movement at the time of an announcement should be related to new information instead of what was previously expected. This is the reason why market based measures of expectations, specifically federal funds futures, are used as measures of the "surprise" from FOMC actions and to analyze how the market reacts to these actions (Kuttner, 2001, pp. 1-2).

According to Acosta et al., (2015, p. 6) the FOMC affects financial markets not only through the actual decision to implement monetary policy, but also through the communication and signaling aspects of the policy process. After each policy meeting, the FOMC communicates via several channels: the post-policy meeting announcement provides a synopsis of the Committee's views regarding the state of the economy, the outcome of the policy decision and the Committee's view of the near term and long run evolution of both the economy and monetary policy; in addition to the post-policy meeting announcement the FOMC may release other materials. Press conferences are another channel of communication which allows the Chair to provide further insight into the Committee's decision-making process and allows the public to ask questions from the Chair. These communications are important because longer-term interest rates and asset prices are greatly influenced by expectations of where the short-term interest rate will go in the future (Clarida et al., 1999, p. 1689; Woodford, 2002, p. 19). Similarly, Blinder et al. (2008, p. 12) argue that monetary policy is deficient if it ignores the communication of central bank. Quality of communication is also important aspect as poor communication can indeed do more harm than good.

One implication of this perspective is that monetary policy announcements can contain multiple dimensions of information. Jarociński & Karadi (2020, p. 1-2) emphasize that central bank announcement contains information about monetary policy decision as well as the central bank's assessment of the state of the economy which both can move asset prices. This is consistent with (Taylor, 1993) view that policy rules, understood as a reasonably well-defined contingency plan, have major advantages over pure discretion in improving economic performance. However, it also means that market responses to FOMC announcements can represent both policy and information effects, where the announcement alters investor views of future economic fundamentals (Nakamura & Steinsson, 2018, pp. 1286-1287).

The same logic also applies to the credibility theory of monetary policy. According to Barro and Gordon (1983, p. 1), under discretion, policymakers may try to boost the economy with unexpected inflation, but once people anticipate this behavior, inflation surprises stop working and cannot be repeated consistently. Therefore, discretionary policy may increase the average level of inflation over time, while policies that commit governments to rules or reputation and credibility-based mechanisms can improve outcomes (Barro & Gordon, 1983, pp. 1-3). Finally, given the U.S.'s status as the largest player in the global financial system, there are significant cross-border effects from U.S. monetary policy shocks and co-movements in asset prices across the world (Miranda-Agrippino & Rey, 2020, pp. 1-4).

2.3 Event study

Event study methodologies represent a systematic framework for determining how financial assets respond to the release of new information upon its public disclosure. The general idea behind event studies is fairly straightforward. If markets are informationally efficient then all of the price reaction to an announcement will occur within a brief time frame surrounding the announcement because investors will have updated their expectations and repriced risk associated with the announced news at the same time (Fama, 1970; Fama et al., 1969, p. 20). The use of event study has become a common methodology in analyzing firm- and economy-wide event data such as the announcement of an earnings announcement and announcements of macroeconomic variables (MacKinlay, 1997, p. 14).

The primary requirements of an event study are the identification of the exact date of the event (MacKinlay, 1997, p. 15). The event study methodology is commonly used with a variety of return types including daily returns and most methodologies are well-specified based upon standard methodology choices. However, valid inferences will always depend upon other methodology choices, for example, the expected return model and the definitions of the event window and estimation window (Brown & Warner, 1985, p. 25; MacKinlay, 1997). Furthermore, the prevalence of event study methodologies in the top academic finance journals also suggests that when these design choices are made appropriately event study methodologies are viewed as an acceptable means of quantifying announcement effects (Kothari & Warner, 2007, pp. 24-26).

2.4 Market efficiency and asset pricing

The Efficient Market Hypothesis (EMH) and asset pricing theory provide a key theoretical base to help understand how financial markets use information to create asset prices. The EMH states that financial asset prices include all publicly available information at a quick pace, so that price changes are based on arrival of new information as opposed to any predictable pattern of price movement that investors can use to gain an advantage (Fama, 1970, pp. 383, 387, 410). Therefore, the observed movement in prices can be viewed as primarily the incorporation of new information into the market's valuations. The EMH is clearly applicable to the methodological approach of an event study, which assesses whether specific events produce abnormal price movements after they release new information to the market.

A direct implication of EMH is that once relevant information has been released to the market, then investors will have no opportunity to consistently obtain abnormal returns through the reliance on publicly observable signals. A closely related concept to the EMH is that the market price represents the aggregation of the judgments of market participants, who continually evaluate available information and subsequently adjust their valuations accordingly. Thus, the EMH provides a theoretical foundation for focusing on short window periods around an event date, since any market reaction to new information should be confined to the time period immediately surrounding when that information is made available to the public. Thus, event studies assume that abnormal returns observed during a short window period around an announcement date, represent the market's response to that specific event.

Asset pricing theory extends the EMH by providing a reason why new information affects asset prices. The value of a financial asset can be defined as the present discounted value of the expected future cash flows from holding the asset, thereby indicating that the price of the asset depends on investor expectations concerning the future cash flows from owning the asset as well as the discount rate used to discount those future cash flows (Cochrane, 2005, pp. 2, 15; 2011, p. 1047). The discount rate captures the time value of money, as well as compensation for the risks assumed by the investor, and indicates that investors expect different returns on different investments due to varying levels of systematic risk. An event may affect an asset's price if the event causes an alteration in investor expectations concerning future cash flows, discount rates, or the perceived risk taken by the investor.

Traditional asset pricing models, including the capital asset pricing model (CAPM), formalize this idea by demonstrating that expected excess returns are positively correlated with an asset's beta, which measures its sensitivity to market wide risk (Lintner, 1965; Sharpe, 1964). Multifactor models later extended this framework by illustrating that expected returns may also reflect exposure to other systematic risk factors such as firm size, value characteristics, profitability, or investment behavior (Fama & French, 1993, p. 3; 2015, p. 1). Although there are differences in the specifications among traditional and multifactor models, they share the same underlying idea: asset prices react when new information changes investor expectations concerning future cash flows, discount rates, or perceived risk.

2.5 Volatility

The majority of the research on volatility forecasting is being done in financial markets since volatility is a major factor in determining investment decisions, valuations, and risk management and even monetary policy decisions (Poon & Granger, 2003, p. 478). Volatility is often used as a synonym for standard deviation or variance of returns calculated from actual data (Poon & Granger, 2003, p. 480). However, volatility and risk are not synonymous as there should be caution when viewing volatility as a representation of uncertainty due to the assumed distribution of returns and the state of the pricing environment (Poon & Granger, 2003, p. 480). Since option markets generally express and deal in "volatility units," measuring and predicting volatility is directly related to how derivatives are priced and hedged (Poon & Granger, 2003, p. 478).

An important empirical motivation for building volatility models is that the size of returns varies throughout time, with "riskier" times clustering together, but not in a random manner (Engle, 2001, p. 158). Engle (2001, p. 158) calls this "volatility clustering" and uses this to motivate the development of ARCH and GARCH models, which are specifically designed to model time varying conditional heteroskedasticity. Cryptocurrency markets have been found to exhibit similar characteristics to stock markets, including volatility clustering and ARCH effects, suggesting that a conditional variance model could be useful in modeling the variability of cryptocurrency market returns (Katsiampa, 2019). Further comparative analysis of volatility in cryptocurrencies has also demonstrated unique volatility behaviors and persistent characteristics compared to other financial assets, further supporting the need to model volatility as time variant versus constant (Klein et al., 2018).

Given that only daily closing price data are typically available, one of the easiest ways to estimate volatility is by calculating close-to-close volatility from daily returns, which is specifically mentioned as a historical volatility measurement method in addition to range-based methods (Sinclair, 2013, p. 38). Daily data events use return variability as proxy for return variability around the event (e.g., squared returns or absolute returns) in the absence of intraday data. The volatility literature also indicates that absolute returns could serve as a viable alternative to squared returns as a volatility metric (Poon & Granger, 2003). The theoretical advantages of using realized volatility for intraday time series with high frequency data to estimate ex post return volatility are substantial since it is derived from intraday returns by means of quadratic variation (Andersen et al., 2003, p. 581). Nevertheless, forecasting daily volatility in many cases continues to be conducted using the returns at the daily level when the relevant data are available with a higher frequency than daily, and practitioners have very often used ad-hoc methods such as simple exponential smoothing for estimating future volatility since they are fast, simple and easy to implement, especially in a multi-asset context (Andersen et al., 2003, pp. 579-580).

In this study, the time variation in volatility is estimated by using a GARCH(1,1) model, as it provides a simple and widely used framework for modeling conditional variance that reacts to new shocks while capturing persistence in volatility dynamics (Engle, 2001, pp. 161-162). The exact model specification, estimation approach, and the way FOMC dates are incorporated into the volatility dynamics are described in detail in the methodology section.

2.6 GARCH(1,1)

Empirical characteristics of financial asset returns have included time-varying volatilities, volatile clustering and fat-tailed distributions of shocks (Cont, 2001, p. 223-226). Similarly, cryptocurrency returns have exhibited these same characteristics such as fat-tails in logarithmic returns and some evidence that suggests volatility clustering and conditional heteroskedasticity (Abdullaev & Ibragimov, 2026, pp. 16-17). These stylized facts represent the basis for the use of conditional heteroskedasticity models where volatility is treated as an evolving latent process versus as a fixed parameter (Bollerslev, 1986; R. F. Engle, 1982).

In ARCH-type models, returns are specified in terms of a mean component plus an innovation with the principal departure from homoskedasticity being that the conditional variance of the innovation is permitted to vary through time. The evolution of the conditional variance through time in the original ARCH framework developed by Engle (1982) was based upon past squared shocks, but the addition of lagged conditional variances in the variance equation in the GARCH extension allowed for the specification of both short-term responses and long-term volatility patterns in a relatively parsimonious manner (Bollerslev, 1986). The persistence of such volatility patterns has been shown to be important in understanding the behavior of cryptocurrencies whose price volatility appears to exhibit clustering into high- and low-volatility regimes, rather than reverting rapidly to a stable level of volatility (Bruzgė et al., 2023).

Volatility has been found to respond to the arrival of new information and therefore it is common to incorporate event related information into the variance equation in order to permit the conditional variance to respond specifically to events that may result in changes to the perceived uncertainty or the risk environment associated with an asset, on days when announcements are made (Andritzky et al., 2007). Variance effects have been found to occur even when the mean effect of the announcement is either weak or statistically insignificant (Andritzky et al., 2007). Financial and crypto returns are frequently found to exhibit fat tails, therefore, the assumption of normally distributed innovations in GARCH-type models may underestimate the probability of extreme events (Abdullaev & Ibragimov, 2026; Cont, 2001). Hence, many empirical studies employ heavy-tailed distributions, such as Student-t in their GARCH-type models to provide a better fit for extreme values (Ardia & Hoogerheide, 2010).

3 Cryptocurrencies

Cryptocurrencies can be viewed relative to Nakamoto’s (2008) goal of a peer-to-peer electronic cash system which facilitates settlement of transactions with no intermediate trusted party and discourages double spending using an economic incentive. The various levels of maturity within the cryptocurrency ecosystem have allowed many of these projects to deviate from this baseline as they have sought to optimize different trade-offs: payment stability, transactional anonymity or community driven adoption. Each of these trade-off optimizations has created categories of cryptocurrencies where the economic purposes of those categories and their user bases suggest different pricing mechanisms and sensitivities to news events. Therefore, the structure of discussion on the functional categories of stablecoins, privacy coins and meme coins to provide a framework for the comparison of how the flow of policy day information affects different segments of the crypto currency market.

While the structure of the ledger itself differs between blockchain systems, how each system determines what blocks will be added to the chain is quite different. For example, in proof-of-work systems like Bitcoin, the creation of new blocks is dependent upon nodes solving computational problems related to hashes in order to produce new blocks, and it is this process of producing blocks that regulates the rate at which new blocks are produced, and thus secures the integrity of the chain (Gervais et al., 2016). On the other hand, proof-of-stake protocols determine who will be able to produce new blocks based on the amount of “stake” that a node holds, rather than the amount of computational power they utilize (Tripathi et al., 2023). For example, (Kiayias et al., 2017), provide an example of this design in the Ouroboros protocol, in which block validators are selected based on the amount of stake they have invested in the system, creating a stake weighted randomization method of block validation, rather than utilizing the high amounts of energy utilized in traditional mining methods. Although these systems may utilize different methodologies for determining what blocks are included in the chain, the ultimate goal of each methodology is to provide a reliable and auditable ledger that all participants in the system can independently audit, thereby preventing competing histories of transactions such as double spending.

The versatility of blockchain technology has allowed for the emergence of multiple categories of cryptocurrencies. As noted by Tripathi et al. (2023), the openness and programmability of public blockchain networks enable developers to create tokens with very different uses. Dionysopoulos and Urquhart (2024) identified different types of categories that currently represent the major part of the cryptocurrency market. Dionysopoulos & Urquhart (2024) mention stablecoins, which seek to maintain a fixed price, privacy coins, which are used to conceal transaction information and meme coins, whose popularity is based primarily on online communities and viral culture. Each category serves a unique purpose within the larger cryptocurrency ecosystem, and therefore the following sections describe each category in greater detail, outlining its primary characteristics, functionality, and importance in the overall cryptocurrency marketplace.

3.1 Blockchain

The concept of blockchain refers to a distributed ledger system, in which transaction records are collectively maintained by a network of nodes as opposed to being managed by a single central database owner. The primary goal of blockchain is to provide a tamper-evident ledger and to have the ability to be tamper-resistant in normal operation, due to the history of transactions being replicated across many participants and secured by cryptography and protocol rules. According to National Institute of Standards and Technology, blockchains are distributed digital ledgers where transaction records are stored within a shared ledger, such that in normal operation, previously published transactions cannot be changed (Yaga et al., 2018, p. 4)

From a data structure perspective, a blockchain stores information in blocks. According to (Yaga et al., 2018, p. 7) generally, a block will contain two parts, a block header that contains metadata and block data that contains transactions (and possibly other types of ledger events). A key element of the blockchain structure is that each block's header will include a cryptographic link to the prior block's header. This provides a chronological chain in which each new block commits to the prior history. If an earlier block's contents were modified, the corresponding cryptographic digest would no longer match the content that later blocks reference, thereby making the inconsistency detectable throughout the chain.

Yaga et al. (2018) states that at the network level, a blockchain must also define how new blocks are added and accepted. Users submit candidate transactions to nodes. The transactions are then propagated through the network. There is a designated role (which is often called a publishing node or miner depending on the system) that packages validated transactions into a new block. Importantly, broadcasting alone does not make a transaction part of the ledger, rather, it becomes part of the chain when it is included in a published block that the network accepts under its rules. These rules fall under consensus, which determines which proposed block and which chain, if there are competing histories is treated as the valid ledger state.

An example of a canonical implementation of blockchain is the bitcoin design, where the network timestamps transactions by placing them into an ongoing chain built with proof-of-work. This produces a record that becomes difficult to change retroactively without redoing the required work (Nakamoto, 2008). Regardless of the specific consensus model used, the practical meaning of blockchain is the combination of cryptographic linking of blocks, replication of the ledger across nodes, and a protocol for agreeing on which blocks will be appended to the shared history (Yaga et al., 2018, p. 4).

3.2 Stablecoins

Since the introduction of the first stablecoin on July 21, 2014, there are now over 150 stablecoins available, however the quality of these coins has dramatically differed. As of (CoinMarketCap, 2026), the total market capitalization of stablecoins has exceeded $270 billion USD and the leading stablecoin, Tether, has a market capitalization exceeding $180 billion USD.

According to Lyons and Viswanath-Natraj (2023), the main difference in the behavior of stablecoins compared to "normal" cryptocurrencies lies in the fact that stablecoins are linked to a national currency, primarily the United States Dollar. Similar to many other cryptocurrencies, stablecoins utilize a blockchain to allow for decentralized financial transactions and therefore may require fewer intermediary institutions (such as banks) than the traditional financial system. Stablecoins also tend to demonstrate less volatility than traditional cryptocurrencies, due to their collateralized pegs. Baur and Dimpfl, (2021) indicate that the volatility of Bitcoin relative to the U.S. dollar is approximately ten times larger than the volatility of major national currencies.

According to Klages-Mundt et al. (2020), stablecoins are generally categorized into two types: custodial and non-custodial. Custodial stablecoins are defined by Klages-Mundt et al. (2020) as being backed by off-chain reserves, including items such as bank deposits, short-term government securities and money market funds, that are owned by a stablecoin issuer, which allows users to redeem stablecoin for its equivalent value. Non-custodial stablecoins, on the other hand, rely on on-chain collateral, and smart contract rules (or algorithmic adjustments to the supply) to maintain the peg, but do not include a centralized reserve custodian. This research will focus on custodial stablecoins, particularly Tether (USDT) and USD Coin (USDC), since their reserve-backed redemption based design is central to analyzing both the stability and risks associated with these stablecoins (Catalini et al., 2022; Klages-Mundt et al., 2020).

Catalini et al. (2022) describe custodial, reserve-backed stablecoins as having a simple mint-and-redeem process, where the stablecoin is tied to a reference asset, i.e. the U.S. dollar. The issuer receives eligible assets (typically cash and very short term U.S. government securities), creates the same number of tokens and later burns those tokens when a user redeems for the underlying assets (Catalini et al., 2022). The price peg is maintained through convertibility and arbitrage: when the token price falls below one dollar, users purchase the tokens and redeem them at par and when the price rises above one, users deliver assets to create new tokens and then sell them, which pulls the price down to the peg (Lyons & Viswanath-Natraj, 2023). Stability depends on three basic conditions: liquid and low-risk reserves; enforceable and timely redemption; and reliable daily operations and disclosures (Echelpoel et al., 2020).

3.3 Privacy coins

Even though many believe that Bitcoin's complex blockchain technology will always keep users completely anonymous, several studies have shown this to be false in both the technical and academic communities. For example Goldfeder et al.(2018), showed that third party web trackers were able to link a person's identity with their Bitcoin address using online behavioral data. Additionally, Harvey & Branco-Illodo (2020), argue that it could be possible to identify an individual by combining the information obtained from the transaction data with the inferred context from the blockchain. The vulnerability of these systems has caused concern regarding the limitations of anonymity in public distributed ledger systems and ultimately, has spurred the creation of what are referred to as privacy coins, which are cryptocurrencies specifically designed to provide users with anonymity and confidentiality during blockchain based transactions.

According to Sapkota and Grobys (2021), privacy coins utilize advanced cryptographic techniques to conceal the recipient and sender wallet addresses and the amount being transferred during each transaction. Using mechanisms like ring signatures, zero-knowledge proofs and stealth addresses, privacy coins attempt to obscure transaction metadata and make it difficult to follow the flow of funds (Harvey & Branco-Illodo, 2020; Sapkota & Grobys, 2021). Ultimately, privacy coins strive to restore the level of transactional privacy once provided by physical currency while maintaining the decentralized nature and lack of trust inherent in all blockchain systems.

While one of the major issues with cryptocurrency is its potential use in money laundering and the transfer of illicit funds, it is also true that approximately 25% of Bitcoin users engage in illicit activities (Foley et al., 2019). Although privacy coins are often marketed as tools to enhance user anonymity and financial confidentiality, the very same attributes that protect legitimate users can concurrently support illicit and harmful activities. As Scharnowski (2024, p.1), states, privacy coins “stand out for their enhanced anonymity features, obscuring transactions and thus making them preferred choices for illegal activity.” The ability of privacy coins to obscure transaction flows, conceal user identities and preclude tracking makes them an attractive option in a wide array of criminal contexts including dark web ecosystems and transnational illicit finance (Scharnowski, 2024). Criminal actors exploit these features to “clean” proceeds from cybercrime, drug trafficking, ransomware attacks, or fraud before converting them back into fiat currencies or non-privacy cryptocurrencies.

An ongoing theme throughout empirical research is the positive association between privacy coins and dark web markets. Due to the increased difficulty of surveillance, dark net marketplaces, which are sites in which illicit goods and services are traded, are increasingly relying on privacy coins (Scharnowski, 2024), demonstrates that there exists a positive correlation between the trading volume of privacy coins and dark web traffic, implying that increases in Tor-based anonymized internet usage correspond to increases in Monero, Zcash, and Dash trading.

3.4 Meme coins

According to Iloh (2021, p. 2), memes are "units of cultural information" that spread quickly over digital networks and function as broadly recognized symbols within everyday conversation. The success of memes stems from the fact that they are capable of being adapted, humorous, and able to reflect common feelings and experiences, therefore enabling rapid movement among social spaces. Similarly, the expansion of meme coins is based on similar aspects of meme culture (collective involvement, community interpretation, and rapid viral dissemination), rather than on standard measures of finance. Therefore, meme coins are a financial extension of memetic culture, since they convert the logic behind quickly produced, socially engaging, and emotionally stimulating digital content into speculative financial activities.

As opposed to other forms of cryptocurrency, meme coins are a type of cryptocurrency that emerged specifically out of digital culture. The primary factor distinguishing meme coins from traditional cryptocurrency types is the manner in which the former's values increase due to social media hype, viral trends and participation by an online community (Kalacheva et al., 2025).

Further evidence for the memetic nature of meme coins is found in the social dynamics present within meme coin communities. Brichta (2025) illustrates how meme coins expand through "attention economy spirals," in which users reproduce memes, assume symbolic roles, and assist in creating shared speculative stories about a token's envisioned future. The practices involved create what Brichta (2025) calls "speculative imaginaries," i.e., collectively envisioned possible wealth created through humor, imitation and digital storytelling rather than through financial fundamentals. These imaginaries provide insight into why many investors treat meme coin investment as both a means of participating in a community game/creating identity, rather than as a solely financial decision.

As identified by Iloh (2021), and aligned with Brichta (2025), the mechanisms of meme-coin development were previously described by Liu and Tsyvinski (2021), who analyzed how attention-driven trading, social contagion and increased investor activity influence asset prices in modern digital markets. Liu and Tsyvinski (2021) demonstrated that when market participants respond to rapidly spreading information, the combined actions of those participants can create sudden and extreme price movements that have no basis in the underlying fundamentals, but are instead generated by attention shocks and imitation-based responses.

3.5 CoinDesk Market Index

According to the CoinDesk Market Index (2025) The CoinDesk Market Index (CMI) is the leading indicator within the CoinDesk Indices product suite and was specifically developed as a means to measure overall returns in digital asset markets and to exclude stablecoin prices from those returns. Eligible assets for inclusion in the CMI are defined through the CoinDesk Digital Asset Classification Standard, which currently includes 250 assets. Additionally, to be eligible for inclusion, an asset must have a CoinDesk reference rate that is supported by at least two exchange contributors. The CMI is based on market capitalization weighting. All eligible constituents are included in the CMI and their respective weights are a function of their relative market capitalization. The CMI is updated approximately every five seconds using each constituent's settlement reference rate, which is produced using a volume-weighted average price-based methodology across multiple exchanges and is available over a sixty minute window. Rebalancing occurs on a quarterly basis and is implemented on the second business day of January, April, July and October. Since stablecoins are excluded from the CMI by definition, the utility of the CMI as a benchmark to measure stablecoin performance is limited in this study to the stablecoin category. Thus, specifying the market model would involve comparing near-zero stablecoin returns with a much more volatile benchmark, which does not adequately reflect the stablecoin segment. Therefore, when considering the results of the market model for stablecoins, they should be viewed with some degree of skepticism. In addition, an examination of raw returns may be a useful check to assess whether or not the results are robust to alternative specifications.

4 Literature review

Research on cryptocurrency markets has increased exponentially during the last ten years as digital assets have become increasingly important in the global financial environment. Initially, researchers viewed cryptocurrencies as separate from traditional financial markets, however, later studies show an increase in sensitivity to macroeconomic and monetary policy changes for these digital currencies. The literature review below identifies and discusses five main areas of research which relate to this thesis: monetary policy announcements and financial markets, the distinction between expected and unanticipated components of monetary policy, empirical evidence from a variety of asset markets, how cryptocurrencies react to both macroeconomic and monetary policy news, and variations among different types of cryptocurrencies.

4.1 Monetary policy surprises and asset price reactions

Monetary policy announcements are viewed as major events in the financial markets by virtue of their ability to create new expectations of future interest rates, levels of liquidity, the cost of borrowing and the general state of the economy. It is due to these potential impacts that the empirical literature has investigated how asset prices respond to monetary policy announcements. There is widespread consensus among researchers that the reaction of asset prices to monetary policy announcements is largely dependent upon the amount of new information that is contained within a given monetary policy announcement relative to what was previously expected by the public. For example, Bernanke and Kuttner, (2005); Kuttner, (2001) argues that the asset price response to a monetary policy announcement is generally driven by the “surprise” component of a monetary policy decision as opposed to the monetary policy decision itself, since the anticipated components of monetary policy decisions will generally be factored into asset prices prior to the official announcement of said decision.

The distinction between expected and unexpected policy changes has been a fundamental principle in the empirical study of monetary policy transmission. Prior to the announcement date, the public will have developed expectations of a particular monetary policy decision and will have thus included those expectations in their respective asset prices. Therefore, by simply measuring the observed policy action at the time of the announcement may be less than accurate or entirely misleading in terms of the actual influence that monetary policy news had on the financial markets. Surprise-based measures allow researchers to extract the new information contained within a monetary policy announcement and separate the new information contained in the announcement from pre-existing expectations. This logic is specifically pertinent to event-based studies, wherein the goal is to determine if there were new pieces of information contained in a specific announcement that prompted an immediate market reaction.

Empirical evidence from traditional financial markets has provided strong support for the importance of the distinction between expected and unexpected monetary policy changes. Bernanke and Kuttner, (2005) has shown that equity markets react positively to unanticipated monetary policy changes, and that expected policy changes are generally irrelevant to explaining returns, suggesting that the pricing effects of monetary policy announcements stem from the revised expectations of future economic conditions, discount rates, or risk premia generated by the announcement. Thus, stock market reactions to monetary policy announcements represent both the direct implications of changes in interest rates and the additional, broader informational content that such decisions may imply regarding the future course of economic activity and financial conditions.

Results similar to those derived in the equity markets have been found in the fixed income markets, in which the responses to monetary policy announcements are often particularly quick and easy to observe. Interest rates and money market instruments tend to adjust nearly instantly to monetary policy shocks in order to reflect the tight linkage between central bank decisions and short-run funding conditions (Kuttner, 2001). However, longer term bond yields may respond to the current monetary policy decision as well as to changes in expectations of the future path of monetary policy, inflation, and economic activity (Gurkaynak et al., 2005). This distinction is important as it implies that monetary policy announcements can include information that affects the entire yield curve and not just the current interest rate. Therefore, the impact of monetary policy news may vary across maturities based on whether the announcement is intended to either change expectations of current interest rates or expectations of the future path of monetary policy.

Foreign exchange markets provide additional evidence that monetary policy announcements have far-reaching cross-asset effects. Exchange rates tend to react rapidly to unanticipated monetary policy changes as such changes alter relative interest rate expectations and the expected returns on domestic vs. foreign assets. Empirical evidence has demonstrated that monetary tightening tends to lead to currency appreciation, while monetary ease leads to currency depreciation (Anderson et al., 2003; Manners & Kearns, 2006). These responses demonstrate that monetary policy transmission operates across borders, in addition to domestically in asset markets, through alterations in capital flows, relative yields, and expectations of exchange rates. When combined, evidence from equities, fixed-income markets and foreign exchange markets indicate that monetary policy announcements affect multiple asset classes, though the magnitude, speed, and longevity of the reaction may vary depending on the market, and the conduit through which policy news is transmitted (Rigobon & Sack, 2004).

In addition to the implications for asset prices that arise from a central bank's choice of monetary policy actions, the informational content of monetary policy announcements has recently been shown to extend beyond an immediate policy rate decision (Gurkaynak et al., 2005; Nakamura & Steinsson, 2018). According to Gurkaynak et al., (2005); Nakamura and Steinsson, (2018) central bank's communication regarding policy decisions, which includes its policy statements and forward guidance, can influence expectations concerning the future trajectory of monetary policy, regardless of whether or not the policy action announced by the central bank was anticipated at the time of the announcement. This will be particularly important given the increasing transparency of central banking communications, as well as the increased reliance by market participants upon the "tone" associated with policy decisions. Thus, it follows that the market response to a monetary policy announcement should capture both the surprise component of the central bank's contemporaneous policy decision, and the additional information contained within the central bank's statement regarding its likely future policy decisions. From an empirical standpoint, this implies that monetary policy announcements are best characterized as multidimensional information events, and not simply as singular changes in a particular policy instrument.

4.2 Cryptocurrencies and macroeconomic announcements

While cryptocurrencies are now a significant portion of the global financial markets, there is an increasing body of work examining the response of cryptocurrency prices to macroeconomic news and monetary policy announcements. However, given the fact that cryptocurrencies are not linked to cash flows, interest rates, or central bank liabilities like traditional assets, there are questions about the applicability of conventional macro-financial transmission mechanisms to these markets.

Initial empirical studies have provided mixed results regarding the sensitivity of cryptocurrencies to macroeconomic announcement events. Although, many studies have found that major cryptocurrencies, especially Bitcoin, exhibit similar reaction patterns to U.S. monetary policy announcements as do high-risk financial assets (Karau, 2023). Studies have documented increased volatility and short-term price changes around FOMC announcements and indicate that monetary policy news is informative for cryptocurrency markets (Corbet et al., 2020; Karau, 2023). However, additional studies have discovered that the effect of macroeconomic announcement events on cryptocurrency returns is weak or unstable. Using both event-study and regression-based methodologies, several researchers have reported that cryptocurrency price responses to monetary policy decisions are often inconsistent over time and under varying market conditions (Bouri et al., 2017; Liu & Tsyvinski, 2021). The instability has been attributed to the speculative nature of the cryptocurrency markets, diverse investor participation and the lack of a direct link between cryptocurrencies and the real economy.

The body of recent work regarding how cryptocurrencies react to macro-economic events has been inconsistent. Several studies have shown that large cryptocurrencies (especially Bitcoin) exhibit an increase in volatility as well as short-term price reactions in the vicinity of Federal Reserve announcements, similar to those experienced by high-risk assets (Corbet et al., 2020; Karau, 2023; Ma et al., 2022; Pyo & Lee, 2020). Conversely, several additional studies have reported either that there is little reaction or unstable reactions to such announcements at different times and under varying conditions, and also that cryptocurrency returns were largely influenced by cryptocurrency-specific factors, rather than standard macro-economic risk premia (Bouri et al., 2017; Liu & Tsyvinski, 2021).

Additionally, there exists significant heterogeneity within cryptocurrency market responses to macroeconomic news events. While the responses of larger cap cryptocurrencies to monetary policy announcements are typically clearer and more consistent (Corbet et al., 2020), smaller and more speculative assets usually have more noisy and unpredictable price responses (Kumar Kulbhaskar & Subramaniam, 2023). Stablecoins are a special case since their design seeks to maintain price stability relative to fiat currencies and therefore they may be more responsive to liquidity conditions and monetary policy expectations than to speculative demand (Karkkainen & Broussard, 2025).

There are also numerous limitations to existing studies focusing on this area of inquiry. Most analyses have focused on a single cryptocurrency and have treated the cryptocurrency market as a homogeneous asset class. Additionally, the disparate choices made in terms of data frequencies, event windows, and benchmarks have contributed to the lack of consensus among empirical findings. Consequently, it is unclear whether monetary policy announcements generate systematic abnormal returns across the entire universe of cryptocurrencies or if the previously cited effects are due to a small subset of assets or certain market conditions.

4.3 Differences across cryptocurrencies

Many of the past studies evaluating the relationship between cryptocurrencies and economic indicators treat all cryptocurrencies equally. However, Corbet et al., (2020) show that there are differences in the purpose, development and investor base of each cryptocurrency. This suggests that one should anticipate different responses from cryptocurrencies based on the type of news received. Understanding these differences is important to understanding how monetary policy news affects the entire cryptocurrency market.

Most empirical research focuses on the larger cap cryptocurrencies because of their larger market size, and they serve as a benchmark for the rest of the cryptocurrency market. As such, they are most likely to be held by institutional investors and have the greatest correlation to the overall financial market. These cryptocurrencies are expected to respond to international macroeconomic events including monetary policy announcements (Calissano et al., 2024). There is evidence to support the idea that the price movements of the largest cryptocurrencies follow the price movement patterns of other high risk assets during periods of maximum uncertainty (Calissano et al., 2024).

Unlike large-cap cryptocurrencies, stablecoins represent a distinct type of crypto-asset. Lyons and Viswanath-Natraj, (2023) states that specifically stablecoins are designed to stabilize in value relative to fiat currency and are primarily used as an exchange medium and a liquidity instrument in the cryptocurrency ecosystem. Research suggests that the way that stablecoins react to economic news may be different from that of other cryptocurrencies. Specifically, demand for stablecoins is directly related to liquidity in the system, the need for transactions, and changes in risk aversion rather than speculation regarding prices. Therefore, monetary policy announcements that impact liquidity or interest rate expectations are expected to effect the use and dynamics of stablecoins and the broader cryptocurrency market in different ways than other cryptocurrencies.

Another group of cryptocurrencies includes highly speculative cryptocurrencies, such as meme coins. These cryptocurrencies are often influenced by sentiment from retail investors, social media, and speculation as opposed to fundamentals or macroeconomic data. Studies have found that speculative cryptocurrencies experience higher volatility and demonstrate a weaker link to economic news, and therefore, it is difficult to predict the reaction of these types of cryptocurrencies to monetary policy announcements, and that any observed reaction to monetary policy announcements could be temporary or irregular depending on the event (Ante, 2023; Bouteska et al., 2023).

Privacy coins constitute a distinct segment of the crypto market rather than a homogeneous subset of “mainstream” coins. Existing evidence shows that privacy and non-privacy coins exhibit two distinct market equilibria, implying different pricing relations and investor behavior (Sapkota & Grobys, 2021). However, there is no direct evidence on how privacy coins respond specifically to FOMC announcements or other monetary policy communications. This study seeks to fill that gap by comparing policy-day reactions across privacy and non-privacy categories within a unified empirical framework.

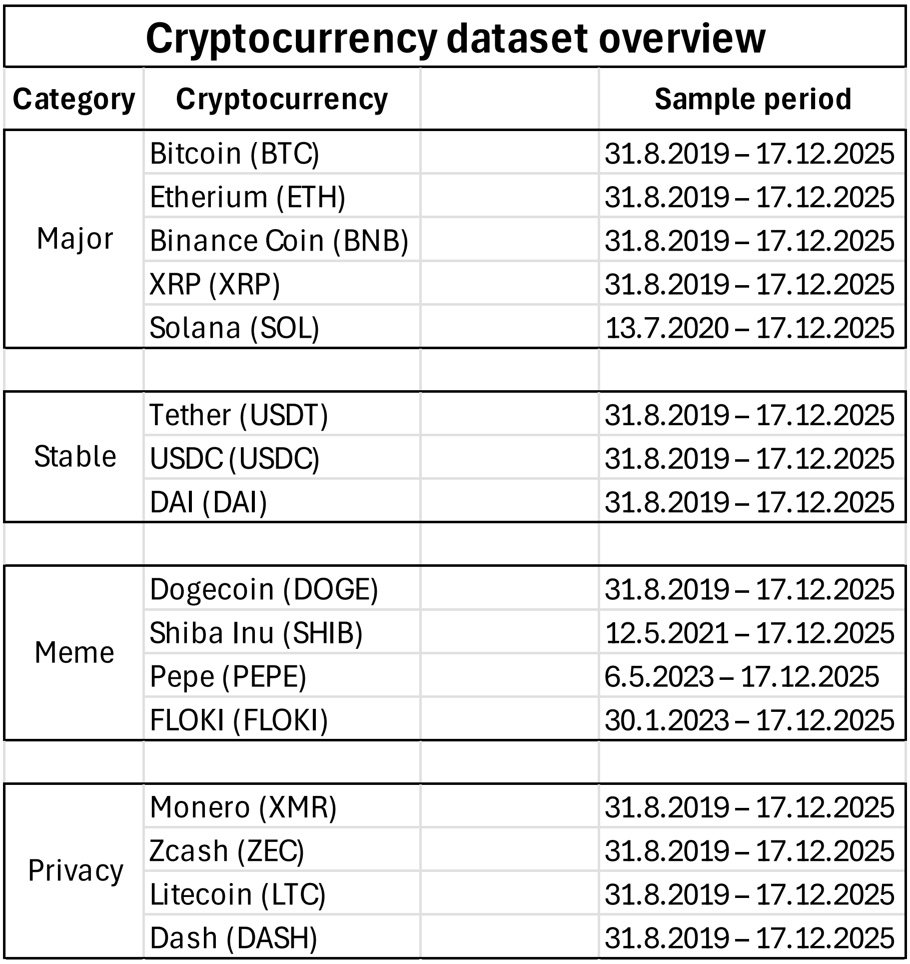
5 Data and methodology

The cryptocurrencies used in the dataset of this thesis are categorized into four categories as shown in table 1. The categories are major cryptocurrencies, stablecoins, privacy coins and meme coins, that consist total of 16 cryptocurrencies. A focus was placed on large, well-established assets within each category where the longest daily price histories could be obtained to allow the analysis of the daily cryptocurrency price around FOMC announcements, while also providing broad coverage across different types of cryptocurrencies. Daily closing prices of cryptocurrencies were obtained from Investing.com. The final data set consists of 33 280 daily observations.

The sample used in this thesis covers over six years of data, spanning from 31.08.2019 to 17.12.2025. The beginning date was selected to provide sufficient number of observations before the initial FOMC announcement in 2020 to allow for the formation of the estimation window around the event. The ending date was established at 17.12.2025 so that there would be sufficient subsequent event observations after the final FOMC announcement in 2025.

Since several of the cryptocurrency assets selected in this thesis were created after the beginning date of the sample, not all price series begin on 31.08.2019. This suggests that there is somewhat unbalanced panel where each cryptocurrency enters the sample when it becomes available. For example, Solana, Shiba Inu, Floki, and Pepe began to trade after 31.08.2019 and thus their price series begin later in the data as shown in table 1.

Table 1. Cryptocurrency dataset overview.



Cryptocurrency dataset overview

Category	Cryptocurrency		Sample period
Major	Bitcoin (BTC)		31.8.2019 – 17.12.2025
	Etherium (ETH)		31.8.2019 – 17.12.2025
	Binance Coin (BNB)		31.8.2019 – 17.12.2025
	XRP (XRP)		31.8.2019 – 17.12.2025
	Solana (SOL)		13.7.2020 – 17.12.2025
Stable	Tether (USDT)		31.8.2019 – 17.12.2025
	USDC (USDC)		31.8.2019 – 17.12.2025
	DAI (DAI)		31.8.2019 – 17.12.2025
Meme	Dogecoin (DOGE)		31.8.2019 – 17.12.2025
	Shiba Inu (SHIB)		12.5.2021 – 17.12.2025
	Pepe (PEPE)		6.5.2023 – 17.12.2025
	FLOKI (FLOKI)		30.1.2023 – 17.12.2025
Privacy	Monero (XMR)		31.8.2019 – 17.12.2025
	Zcash (ZEC)		31.8.2019 – 17.12.2025
	Litecoin (LTC)		31.8.2019 – 17.12.2025
	Dash (DASH)		31.8.2019 – 17.12.2025

Data regarding FOMC announcements were retrieved from Bloomberg. The event data set includes FOMC announcements from the first announcement made by the FOMC on 29.01.2020 through the announcement made on 10.12.2025. The meeting dates and time of the announcements were based upon the Federal Reserve's published FOMC calendar and included an unscheduled FOMC meeting held in March 2020. Information about the policy rate changes announced on each FOMC announcement day is also collected. Therefore, within the sample period there are 49 FOMC announcements of which the rates were increased 11 times, decreased 8 times and remained unchanged 30 times. These rate changes are used to estimate the size of the unexpected policy shock relative to expectations.

To establish a benchmark for market movements in the event study, this thesis uses the CoinDesk Market Index (CMI) as a proxy for the cryptocurrency market portfolio in the market model. The index data are obtained from Bloomberg. The benchmark is obtained at daily frequency and utilizes the daily close price. It is also aligned with the overall sample period of the cryptocurrency data (31.08.2019 – 17.12.2025).

Table 2. Descriptive statistics.

	No. Of Obs	Mean	Median	St.Dev	Min	Max
FOMC announcements	49					
Daily price obs (all coins total)	33280					
Unchanged	30					
Rate hike	11					
Rate cut	8					
Prior event day raw returns (t=-1)	700	-0,036	0	3,76	-14,2256	22,6995
Event day raw returns (t=0)	700	1,0161	0,0863	4,5871	-22,4997	26,8999
Post-event day raw returns (t=+1)	700	-0,0182	-0,01	7,3728	-14,9536	158,3848

Table 2 shows the summary statistics for the data set and event window returns. Daily returns during the event window were calculated as 100 x log returns. During a three-day event window (t = −1, 0, +1) there was a negative mean return prior to the announcement (−0,036), a clearly positive mean return on the day of the announcement (1,0161), and slightly negative mean return the day after (-0,0182). There were very little or no median returns prior to the announcement or the day after the announcement which may indicate that most daily price movements are relatively minor and that the mean return might have been impacted by some extreme events. This can be seen in the large difference in the lowest and highest values in the return distribution, especially at t = +1.

5.1 Methodology

This research employs an event study approach to investigate if there is a relationship between the periodically recurring FOMC meeting announcement days and the short-run changes in returns on cryptocurrencies. The event study model views every announcement day as an informational event and evaluates how returns behaved during a short event time frame relative to what would normally be expected during that time frame absent the event, where the normal return is determined by a benchmark model established prior to the event (MacKinlay, 1997, p. 15). Abnormal returns are calculated as the actual return on the event window minus the normal return. Statistically significant abnormal performance at the event will provide evidence that the event provided new information that was reflected in the price action during the event window (Kothari & Warner, 2007, pp. 24-25; MacKinlay, 1997, pp. 13-15). An event study design is especially well-suited to scheduled events such as monetary policy announcements because successful execution depends upon identifying when the event occurred and then limiting the horizon surrounding the event to minimize the impact of extraneous news (Kothari & Warner, 2007, pp. 24-25; MacKinlay, 1997, p. 37).

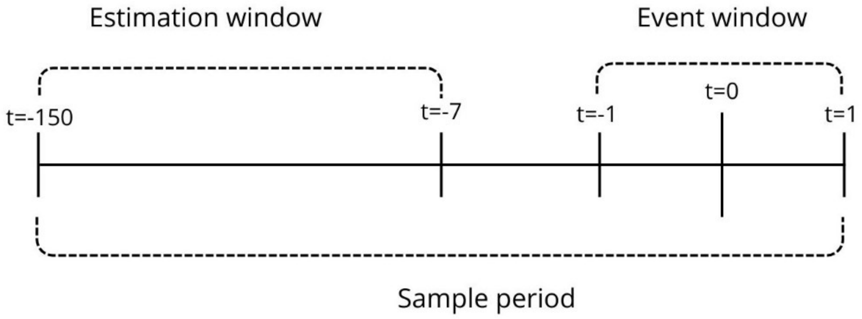


Figure 1. Illustration of sample period.

Each scheduled FOMC announcement date represents one event. In order to account for the fact that announcements occur on the intraday level and daily data is used in the analysis, the event window must also be set appropriately. Daily close prices may capture some of the reaction to an announcement that occurs on the announcement day itself and some that occurs after the announcement day, depending upon when the announcement was made and the trading activity that occurred around the release. As shown in figure 1, the baseline event window is defined as $t = -1, 0, +1$ to capture the pre-announcement day, the announcement day, and the day immediately following the announcement. The t = -1 day allows for any potential pre-positioning or information leakage prior to the announcement, and the t = +1 day allows for any delayed adjustment to the announcement at daily frequency (Peciulis & Vasiliauskaite, 2024, p. 79).

Expected returns were calculated using a pre-event estimation period prior to the event window. In the baseline model, the estimation window starts 150 days ($t = -150$) before the event and ends seven days ($t = -7$) prior to the event date, as illustrated in figure 1. Ending the estimation period seven days prior to the event decreases the probability that expectations about the event, leakage of information or announcement related trading will impact the parameter estimates used to calculate the expected returns (MacKinlay, 1997, pp. 15, 20).

In order analyze sensitivity to the size of the event window, an additional event window from $t = -2$ to $t = +2$ is included further on as a robustness check. This is added to provide a test for whether there are changes in the interpretation of the decision. The use of relatively short windows for events and the robustness tests based on longer windows is consistent with established practices in the area of event studies (Kothari & Warner, 2007, pp. 25-27; MacKinlay, 1997, p. 15).

For purposes of this research, each regularly scheduled FOMC announcement is treated as a separate source of new information about monetary policy and the crypto-markets' reaction to these announcements is analyzed via abnormal returns for each asset being examined. Abnormal returns for each asset is calculated as the actual returns to the asset less the return to the asset as predicted by the selected benchmark model estimated over a pre-announcement estimation period. The abnormal returns is then summed over the event window to produce the cumulative abnormal returns. The statistical significance of the abnormal returns is determined using t-tests that assess the difference between the average abnormal return around announcements and zero (Brown & Warner, 1985, pp. 9, 15; MacKinlay, 1997, pp. 28-29).

The selection of the length of the event window is a primary decision in the design of an event study analysis. As well as providing a better understanding of how prices respond to an event by having a focus on a short time frame when the exact timing of the event is known (MacKinlay, 1997, p. 15). According to (MacKinlay, 1997) Selecting a short window will enable a researcher to identify whether the effects of an event are reflected in stock prices during a relatively short time frame. Additionally, using shorter sample periods enables researchers to statistically measure the extent to which an event impacts stock prices. While researchers may extend their window further than one day in order to capture reactions after closing of the markets and to account for possible inclusion of information prior to or subsequent to the specific announcement date. A short multi-day window was selected for this study to permit capturing announcement related price adjustments while maintaining a sufficient narrowness of the window to minimize potential contamination from other news events (MacKinlay, 1997).

5.2 Return measurement

Daily cryptocurrency returns are computed as logarithmic returns. For each cryptocurrency i on day t,

$$R_{i,t} = 100 \cdot ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \quad (1)$$

where $P_{i,t}$ is the daily closing price. Scaling by 100 provides returns in percentage-like form, while retaining the additive nature of log returns on short time horizons.

The focus of interest in this analysis is the abnormal return defined as the actual return minus an estimated value for the normal return. Following the Dyckman et al. (1984) approach, estimation of expected returns is done with the use of the market model, which is widely employed in event studies, as it accounts for changes within the entire market and typically increases the statistical power of estimates when compared to a mean-constant benchmark (MacKinlay, 1997, pp. 15, 18). The market model used in this thesis is specifically based on CAPM as this type of approach was used in similar event study by Zhou (2025) where the risk-free rate was set to zero. Using a Cryptocurrency Market Index as a benchmark, for each cryptocurrency i, the expected returns can be estimated as:

$$E(R_{i,t}) = \alpha_i + \beta_i(R_{m,t} - r_{f,t}) + \varepsilon_{i,t}, \quad (2)$$

where $E(R_{i,t})$ is the estimated normal return, $R_{m,t}$ is the benchmark market return, $r_{f,t}$ is the risk-free rate set to 0, and $\varepsilon_{i,t}$ is the error term. Ordinary least squares (OLS) is used to estimate parameters α_i and β_i using data collected during the pre-event estimation window. Thus, abnormal returns are defined as

$$AR_{i,t} = R_{i,t} - \mathrm{E}(\mathrm{R}_{i,t}). \quad (3)$$

Using abnormal returns allows to isolate the deviations from normal market co-movements that occur in relation to the event announcement. To document the day-to-day announcement effects, this study documents average abnormal returns (AAR) for each relative day t in the event window for each event e. Since there are multiple cryptocurrencies that occur approximately at the same time as the FOMC event announcements and since the cryptocurrency returns may be highly correlated within an event, the aggregation process is conducted in a two-step procedure. In the first stage, the abnormal returns are averaged for each event e across cryptocurrencies within categories c to provide one event-category observation for each day for each category c:

$$\bar{A}R^{(c)}_{e,t} = \frac{1}{N_{c,e,t}} \sum_{i \in c} AR_{i,e,t}\,, \quad (4)$$

where $N_{c,e,t}$ is the number of cryptocurrencies in category c with available data for event e and for relative day t. In the second stage, AAR is calculated as the average of those event-category values for all events:

$$AAR_t^{(c)} = \frac{1}{N}\sum_{e=1}^{N} \bar{A}R_{e,t}^{(c)} . \qquad (5)$$

The AAR is intended to describe whether abnormal return performance occurs primarily on one specific day within an event window or over multiple days cumulatively.

To assess the total effect of the announcement window (T_1, T_2) for each cryptocurrency-event pair, cumulative abnormal returns (CAR) are calculated as the sum of abnormal returns for each pair over the entire window:

$$CAR_{i,e}(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{i,e,t} \, , (6)$$

Next, the category-level “fair averaging” process is applied at the event level, where the CAR for each cryptocurrency-event pair is averaged within each event for the cryptocurrencies in the same category.

$$CAR_e^{(c)}(T_1, T_2) = \frac{1}{N_{c,e}}\sum_{i \in c} CA\,R_{i,e}(T_1, T_2), \qquad (7)$$

where N is the number of cryptocurrencies in category c with sufficient data for event c . Finally, cumulative average abnormal returns (CAAR) for each category c are calculated by averaging the CARs from all events across events:

$$CAAR^{(c)}(T_1, T_2) = \frac{1}{N}\sum_{e=1}^{N} CA\,R_e^{(c)}(T_1, T_2). \qquad (8)$$

Results are provided at several levels of aggregation. First, abnormal return profiles and CAR for each coin and event are calculated. Then, the coins are grouped together by their predefined cryptocurrency classification categories (stablecoin, meme, major, and privacy), and then category results are determined by calculating an average CAR for all coins in the same category. Since cryptocurrency returns are heavy tailed, median abnormal return profiles by relative day are also reported as an additional measure to provide additional robustness check of the results to the sensitivity to extreme value outliers.

5.3 Statistical inference

To assess if abnormal performance during an announcement window varies from a value of zero, this study applies a test for cumulative average abnormal returns compared to a null hypothesis of no event-related effect. The null hypothesis for each category c, in terms of the interval [T1,T2] for event windows is as follows:

$$H_0: \text{CAAR}^{(c)}(T_1, T_2) = 0,$$

with a two-sided alternative:

$$H_1: \text{CAAR}^{(c)}(T_1, T_2) \neq 0.$$

Statistical significance is determined through the application of a one-sample t-test to the individual event data points. After forming the cumulative abnormal returns at the event level (i.e., one observation per event per category), the mean return (across all events) is tested for a difference from zero. The applicable test statistic is represented as follows:

$$t = \frac{C\bar{A}R^{(c)}}{s(CAR^{(c)})/\sqrt{N}}, \quad (9)$$

Where $C\bar{A}R^{(c)}$ is the mean value of the category-specific event-level CAR values, $s\left(CAR^{(c)}\right)$ represents the sample standard deviation of these category-specific CAR values, and N represents the number of usable event observations. This event-specific test methodology is employed due to the fact that returns across multiple cryptocurrencies observed at the time of the same FOMC announcement are likely contemporaneously correlated. If each of these observations were treated independently, it would result in overstating the number of observations available for use as part of the sample size. Additionally, shortening the length of the event window also reduces the likelihood that unrelated news affects the conclusions drawn and increases the ability to detect statistically significant effects.

5.4 Volatility modelling

According to Abdullaev and Ibragimov (2026), cryptocurrency returns have shown to exhibit volatility clustering and have heavy tails implying that the conditional variance is changing over time and that large return deviations occur more frequently than they would if the returns followed a normal distribution. In order to capture the time varying nature of volatility, this thesis will estimate conditional volatility via a GARCH(1,1) model with returns broken down into a mean component and a shock with time varying conditional variance (Bollerslev, 1986; R. F. Engle, 1982).

Let $r_{c,t}$ denote the daily (category) return at day t (the average return for all constituents of each category) constructed as a scaled logarithmic return:

$$r_{c,t} = 100 \cdot \ln\left(\frac{P_{c,t}}{P_{c,t-1}}\right). \quad (10)$$

In the mean equation, returns are specified with a constant:

$$r_{c,t} = \mu_c + \varepsilon_{c,t}, \qquad \varepsilon_{c,t} = \sigma_{c,t} z_{c,t}, \qquad (11)$$

where $z_{c,t}$ follows a standard Student-T distribution to accommodate the fat tails observed in the returns. The use of Student-T innovations is more robust to outliers than normal innovations (Li et al., 2009, p. 1). Thus, the conditional variance is modeled as a GARCH(1,1) process with announcement dummies added to the variance equation:

$$\sigma_{c,t}^2 = \omega_c + \alpha_c \varepsilon_{c,t-1}^2 + \beta_c \sigma_{c,t-1}^2 + \gamma_{Fed,c} Fed_t + \gamma_{Fed-1,c} Fed_{t-1} + \gamma_{Fed+1,c} Fed_{t+1} \quad (12)$$

where Fed_t is equal to 1 on a FOMC announcement date and 0 otherwise. The coefficients $\gamma_{Fed,c}$, $\gamma_{Fed-1,c}$ and $\gamma_{Fed+1,c}$ therefore measure increases in conditional volatility as a result of an FOMC announcement on the announcement date and the immediately surrounding days $(t = -1, 0, +1)$ relative to the usual GARCH persistence measured by $\alpha_c$and β_c. This model is based on the view that scheduled macroeconomic announcements may influence uncertainty and risk premia even if the average return effect is modest, and hence that volatility will react around the event window through adjustments in the perceived macro financial environment.

Returns are scaled by 100 (log-return × 100) and winsorized at the 1st and 99th percentiles to minimize the impact of extreme values on parameter stability. A Student-t distribution is used to estimate the innovations to capture fat tails in the return shock process. The model is estimated separately for each cryptocurrency category using maximum likelihood estimation.

6 Empirical results

This section examines the abnormal return responses of cryptocurrency categories around FOMC announcement dates via the market model event study process discussed in the methodology. Abnormal returns represent the difference between actual daily log return and the expected return per the benchmark market return. The base event window in this thesis is [−1,+1] of each FOMC announcement. Results will be provided at both the category level (major, stable, meme, privacy) and by decision type (rate cut, rate hike, unchanged) and the return values are all displayed as daily log returns.

To analyze how FOMC announcements impact typical market behavior over time, first the average abnormal return and its cumulative counterpart profiles are presented over the baseline event window [−1,+1] for each cryptocurrency category. As such, the following analysis is descriptive yet useful way to interpret the results presented later in the paper. The AR-profiles represent the timing of the reactions to the announcements, while the CAR-profiles represent whether abnormal returns accumulate or reverse over the days leading up to, immediately after, and possibly even beyond the announcements. Since event-time plots are primarily analyzed in terms of timing and shape, concentration of movements around t=0 would indicate that the announcement date serves as the primary focal point for market adjustments. Similarly, CAR-profiles that rise or fall in a steady fashion across the event window can be indicative of an accumulation of abnormal returns, while CAR-profiles that change directions may indicate short-lived spikes and partial reversals of abnormal returns. Importantly, since CAR is defined as the cumulative sum of abnormal returns over the event window, CAR(0) represents the cumulative abnormal returns from t=−1 through t=0 inclusive, i.e., CAR(0)=AR(−1)+AR(0).

Since cryptocurrency returns are often heavy-tailed and abnormal returns may be skewed (particularly in smaller and/or higher-beta segments), mean-based event-time profiles are supplemented with median-based event-time profiles. Mean-based profiles describe the average responses that contribute to the cumulative performance of abnormal returns over the event window, while median-based profiles serve as a robustness check to determine if there are any outlier returns that disproportionately influence the mean. Significant gaps between the mean and median event-time profiles show presence of extreme realizations that have a disproportionate effect on the mean.

6.1 Event-study overview and descriptive profiles

The magnitude of the abnormal returns on the announcement day (t=0) is examined across categories via an event-day summary table. All categories experience relatively small average abnormal returns on the announcement day (t=0), however, the central tendencies of the abnormal returns vary across the categories.

Table 3. Summary by category on the event day.

Category	Mean AR	Mean CAR	Median AR	Median CAR	Obs.
major	0.002	0.0026	-0.0001	-0.0018	236
meme	0.0021	-0.0007	-0.0021	-0.0041	121
privacy	0.0028	0.0011	0.0041	-0.0008	196
stable	0.0001	0.0	0.0	-0.0	144

As seen from table 3, privacy coins exhibited the highest mean positive abnormal return on the announcement day (mean AR(0) = 0,0028) with 196 observations. Major cryptocurrencies also exhibited a positive mean abnormal return (mean AR(0) = 0,002 and mean CAR(0) = 0,0026; 236 observations), indicating moderately positive abnormal returns on the announcement-day for large and highly liquid cryptocurrencies.

Meme coins showed the most asymmetric event-day abnormal returns. Although the mean abnormal return is marginally positive (mean AR(0) = 0,0021), the median abnormal return was negative (median AR(0) = −0,0021), and the median CAR was also negative (−0,0041). This mean – median divergence indicates that the mean abnormal return is influenced by a subset of large positive abnormal returns; whereas the normal reaction to the announcement day is slightly negative for meme coins. This is consistent with heavy-tailed distributions where extreme values have a greater effect on the mean than the median.

The mean and median abnormal returns of stablecoins were nearly zero for all statistics (mean AR(0) = 0,0001; mean CAR(0) = 0,0; median CAR(0) = −0,0) for the 144 observations. This result is consistent with the peg-oriented function of stablecoins as price-stabilizing instruments that minimize short-term price volatility compared to non-pegged cryptocurrencies.

The summary statistics for the event-day support the basis for the category separation utilized throughout the thesis. Stablecoins exhibit distinct behaviors from the other crypto-segments, while privacy and major categories exhibit positive average event-day abnormal returns. Meme coins exhibited the strongest distributional asymmetry, thus, the nature of the conclusions regarding the abnormal returns on the announcement-day depends on whether they are calculated using the mean or the median abnormal returns.

6.2 CAAR$[-1, +1]$ by decision type and category

This section tests hypotheses H1 and H2 through an assessment of the cumulative abnormal return around FOMC announcements. Hypothesis H1 tests whether there exists a deviation in the cumulative abnormal returns from zero and hypothesis H2 tests if the cumulative abnormal returns differ by category of cryptocurrency. For each announcement made during a FOMC meeting, the cumulative abnormal return over the window [−1,+1] is calculated at the coin level by summing the abnormal returns each day during the window. Each window CAR is then averaged at the event level, within category, to calculate a single observation for each category and decision type. The statistical inferences are based upon event-level data as for each category, and each decision type, an average [−1,+1] window CAR is calculated for each FOMC event (across all coins that fall into the category), and a one-sample t-test is performed to determine if the mean of those event-level CARs (CAAR) differ from zero.

The results are presented separately for the eight rate cut decisions, eleven rate hike decisions and thirty unchanged decisions. Due to the low number of rate cut and rate hike decisions, the statistical power for these two decision types is lower than that of the unchanged decisions. Therefore, it would be wise to consider the lower statistical power when evaluating any nonsignificant results.

Table 4. CAAR for full window [-1, +1].

Decision	Category	CAAR[-1,+1]	t_stat	p_value	n_events
Rate cut	**All**	-0,0035	-0,42	0,6869	8
	major	0,0003	0,04	0,9691	8
	stable	0,0007	0,572	0,5855	8
	meme	-0,0027	-0,136	0,8954	8
	privacy	-0,0038	-0,317	0,7608	8
Rate hike	**All**	0,006	0,759	0,4655	11
	major	0,0072	0,815	0,4341	11
	stable	-0,0001	-1,306	0,2209	11
	meme	0,0002	0,012	0,991	11
	privacy	0,0114	0,858	0,4109	11
Unchanged	**All**	0,0046	0,705	0,4867	30
	major	0,0025	0,409	0,6852	30
	stable	-0,0001	-0,28	0,7812	30
	meme	0,0394	0,775	0,4447	30
	privacy	0,0029	0,384	0,704	30

Table 4 shows that in all decision-category combinations, the null hypothesis that CAAR equals zero cannot be rejected at conventional significance levels. In the case of the eight rate cut decisions, the CAAR point estimates are small and imprecise across categories, with p-values far above 0,10. The "All" category average is -0,0035 (p = 0,6869), and estimates range from -0,0027 for meme coins to 0,0003 for major coins. Also, in the case of the thirty unchanged decisions as well as rate hikes, the CAAR estimates failed to reject the null of zero across categories. Some of the point estimates appear economically larger, such as the estimate for meme coins under unchanged decisions

(0,0340). However, the p-value indicates that the estimate is not reliably different from zero in the current sample.

Collectively, the results provide no evidence for significant, large-scale abnormal performance during FOMC announcement periods as seen in the CAAR analysis over the [-1, +1] window and daily frequency. Although all of the CAAR estimates were not found to be statistically different from zero in the base model, the findings need to be considered with respect to multiple testing across categories and decision types. The next section provides additional information to these window level results, as well as further investigation of abnormal returns at the individual day level (i.e., AAR), to see whether the effects are located in days t = -1, t = 0, or t = +1.

6.3 Day-by-day AAR (t= -1,0,+1) by decision type and category

While CAAR captures total abnormal performance throughout the entire [−1, +1] window, AAR capture the timing of the reactions relative to the event date. Specifically, AAR can help determine if there is a reaction prior to the event date (t = -1), at the time of the event date (t = 0), or after the event date (t = +1). Also, since AAR uses an event level, and not individual coin observations, AAR helps avoid inflated statistical inference due to treating each coin observation as independent. Therefore, to compute AARs, for each event date, and for each category, first the abnormal return averages for each coin in the category are computed to create a single event-date observation. Then one sample t-tests across all events is conducted to determine if the mean event-date AAR is different from zero.

Table 5. AAR with t-stat in parentheses by day.

Decision	Category	t=-1	t=0	t=+1
Rate cut	**All**	-0.008597(-1.34)	0.007175(0.81)	-0.002070(-0.37)
	major	-0.010230(-1.02)	0.009345(1.14)	0.001204(0.21)
	stable	0.000679(0.51)	0.000080(0.24)	-0.000073(-0.23)
	meme	-0.016297**(-2.80)	0.020367(1.24)	-0.006814(-0.52)
	privacy	-0.007770(-0.73)	0.003633(0.25)	0.000291(0.03)
Rate hike	**All**	0.004840(0.70)	0.005766(0.84)	-0.004653(-0.57)
	major	0.005085(0.61)	0.005812(0.65)	-0.003665(-0.33)
	stable	-0.000083(-1.17)	-0.000025(-0.31)	0.000003(0.04)
	meme	0.020033(1.67)	-0.006544(-0.43)	-0.013323(-1.55)
	privacy	-0.000337(-0.03)	0.016792*(2.10)	-0.005072(-0.46)
Unchanged	**All**	-0.000556(-0.15)	-0.001786(-0.39)	0.007014(1.16)
	major	0.000897(0.17)	-0.001535(-0.28)	0.003119(0.69)
	stable	-0.000157(-0.81)	0.000068(0.38)	0.000028(0.23)
	meme	-0.003382(-0.54)	-0.006434(-0.60)	0.049238(0.94)
	privacy	-0.000585(-0.12)	-0.002622(-0.46)	0.006115(1.16)
	** = statistically significant at 5%, *=statistically significant at 10%			

Generally, table 5 shows that across most decision types and categories, the AARs per day do not differ significantly from zero at conventional significance levels. For the "all" category, the AARs for rate cuts are negative on t = -1 (-0,008597) and positive on t = 0 (0,007175), however, neither is statistically significant (p = 0,2205 and p = 0,4439 respectively). The AARs for rate hikes are positive on both t = -1 (0,004840) and t = 0 (0,005766), but both p-values are greater than 0,10, and the AARs for unchanged decisions are close to zero on both t = -1 and t = 0, and also have a positive, but not statistically significant AAR on t = +1 (0,007014; p = 0,2561).

However, two categories were notable in terms of patterns. First, within the subsample of rate cuts, the AARs for meme coins exhibited a statistically significant negative AAR on t = -1. Thus, this suggests that meme coins exhibited negative abnormal returns on the day prior to the announcement of rate cuts. However, the AAR for meme coins on the announcement day was positive (0,020367), but not statistically significant, and the AAR for meme coins on the day after the announcement was again negative (-0,006814;

p = 0,6187). As such, this suggests that the reaction of meme coins around rate cuts is not simply a monotonic event-day response, but rather a more volatile, possibly reversal-prone adjustment around the announcement.

Second, within the subsample of rate hikes, the AARs for privacy coins displayed a statistically significant positive AAR on the announcement day (0,016792; t = 2,10). Additionally, the AARs for privacy coins were low and not statistically significant on t = -1 (-0,000337) and t = +1 (-0,005072). Thus, this pattern is consistent with a reaction that is focused on the announcement day, and not anticipated or delayed in the daily data.

The results in this report must nevertheless be viewed cautiously due to the nature of the AAR statistical analysis. Given that there are multiple parallel tests, across multiple decision types and categories, and event days within the AAR analysis, it is likely that some significant AAR test results will occur simply by chance. For this reason, the significance of the highlighted AAR patterns should not be taken as conclusive based solely on their raw p-value. To assess the robustness of the findings presented above, the robustness check section will apply a Bonferroni correction to account for the multiple comparisons.

Finally, the AARs for stablecoins remained near zero across decision types and days, and thus no AAR tests rejected the null hypothesis of zero. This is consistent with the descriptive event-day summaries and further supports the notion that stablecoins experience little to no abnormal price movements around FOMC announcements in daily data, even though the CAAR table indicated a statistically detectable, albeit very small, negative cumulative effect surrounding rate hikes.

6.4 Volatility results: GARCH(1,1)

This part of the thesis examines the hypothesis H3 through assessing whether the FOMC's announcement dates have an impact on conditional volatility in cryptocurrency markets. Conditional volatility is modeled using a GARCH(1,1) model estimated for category-level return indices (major, stable, meme, privacy). The mean equation is defined as a constant-mean process, and the conditional variance is defined as including the standard GARCH components as well as three event dummies that represent potential volatility impacts on the announcement date (Fed t), the day before (Fed t-1), and the day after (Fed t+1). The innovation component is defined using a Student-t distribution to allow for heavy tails. The returns are scaled (x 100) and winsorized at the 1% and 99% level prior to estimation to limit the influence of extreme values.

The GARCH term is strongly significant across categories, and the ARCH term is significant in major and privacy, and marginally significant in meme coins and the implied persistence ($\alpha + \beta$) is very high, suggesting substantial volatility clustering in crypto returns. For example in table 6, for the major cryptocurrencies, the ARCH term is 0,0795 ($p = 0{,}0147$) and the GARCH term is 0,9007 ($p < 0{,}001$), and therefore imply a persistence of about 0,98. Similar strong clustering was observed for the privacy coins, where the ARCH term is 0,0951 ($p < 0{,}001$) and the GARCH term is 0,9023 ($p < 0{,}001$), and therefore imply a persistence of almost 1. Similarly, high persistence was observed for the meme coins, with a large GARCH coefficient (0,7804; $p < 0{,}001$) and a marginally significant ARCH term (0,2186; $p = 0{,}0935$), and therefore suggest that shocks to volatility decay slowly in this segment as well.

Table 6. Category-level GARCH(1,1).

Major coins

Block	Variables	Coefficient	Std. Error	Z	P-value
Mean Equation	Constant	0,2143	0,0612	3,5008	0,0005
Variance Equation	Constant	0,2975	0,2442	1,2181	0,2232
Variance Equation	ARCH	0,0795	0,0326	2,4406	0,0147
Variance Equation	GARCH	0,9007	0,0486	18,5509	0,0000
Variance Equation	Fed	3,5955	4,5439	0,7913	0,4288
Variance Equation	Fed-1	-0,8171	2,7721	-0,2948	0,7682
Variance Equation	Fed+1	-2,0029	3,6880	-0,5431	0,5871
Distribution	nu	5,2787	0,5358	9,8522	0,0000
Stablecoins					
Mean Equation	Constant	0,0003	0,0003	0,8133	0,4161
Variance Equation	Constant	0,0002	0,0000	16,1871	0,0000
Variance Equation	ARCH	0,1000	0,0068	14,7908	0,0000
Variance Equation	GARCH	0,8500	0,0051	167,9090	0,0000
Variance Equation	Fed	0,0000	0,0014	0,0000	1,0000
Variance Equation	Fed-1	0,0000	0,0004	0,0000	1,0000
Variance Equation	Fed+1	0,0000	0,0012	0,0000	1,0000
Distribution	nu	4,9988	0,0944	52,9486	0,0000
Meme coins					
Mean Equation	Constant	-0,0711	0,0761	-0,9342	0,3502
Variance Equation	Constant	1,3580	2,8483	0,4768	0,6335
Variance Equation	ARCH	0,2186	0,1303	1,6773	0,0935
Variance Equation	GARCH	0,7804	0,1913	4,0800	0,0000
Variance Equation	Fed	8,9335	6,8702	1,3003	0,1935
Variance Equation	Fed-1	-4,5438	3,2198	-1,4112	0,1582
Variance Equation	Fed+1	2,3331	7,1020	0,3285	0,7425
Distribution	nu	3,6025	0,2587	13,9236	0,0000
Privacy coins					
Mean Equation	Constant	0,1930	0,0639	3,0215	0,0025
Variance Equation	Constant	0,2039	0,1164	1,7514	0,0799
Variance Equation	ARCH	0,0951	0,0204	4,6589	0,0000
Variance Equation	GARCH	0,9023	0,0218	41,4751	0,0000
Variance Equation	Fed	-1,8343	2,4881	-0,7372	0,4610
Variance Equation	Fed-1	-0,4488	2,1562	-0,2082	0,8351
Variance Equation	Fed+1	2,6656	2,0646	1,2911	0,1967
Distribution	nu	4,6224	0,4438	10,4150	0,0000

The estimated Student-t degrees of freedom parameter ν is strongly significant in every category, and ranges from approximately 3,6 to 5,3. These values represent significantly heavier tails than those represented under a normal assumption, which is consistent with the common occurrence of extreme return observations in crypto markets. As such, the Student-t specification is required to account for the frequent large daily moves in the meme and privacy segments.

The constant mean is statistically significant and positive for the major and privacy categories (major: 0,2143, $p < 0,001$; privacy: 0,1930, $p = 0,0025$), whereas it is not statistically different from zero for the meme coin category (-0,0711, $p = 0,3502$), and is economically and statistically negligible for the stablecoin category (0,00028, $p = 0,4161$). These estimates are consistent with the idea that stablecoin returns are centered near zero in daily data, while the other segments may have non-zero average returns over the sample period.

The critical parameters for testing hypothesis H3 are the coefficients on the Fed t, Fed t-1, and Fed t+1 dummies in the variance equation. With respect to the major, meme, and privacy categories, the coefficients on these dummies were not statistically significant at traditional confidence intervals, and had varying signs, and therefore do not represent a systematic increase in conditional volatility due to the FOMC announcements. For example, for the major cryptocurrencies, the Fed t coefficient was positive (3,5955), but not statistically significant ($p = 0,4288$), and the lead and lag terms were also not statistically significant. The meme coin coefficients were larger in magnitude (for example, the Fed t coefficient is 8,9335), but still not statistically significant ($p = 0,1935$), and are consistent with the high levels of baseline volatility and uncertainty surrounding the potential impact of FOMC announcements. The privacy coin category exhibited a negative Fed t coefficient (-1,8343; $p = 0,4610$) and did not have statistically significant lead or lag terms either.

The stablecoin category produced virtually zero event effect in the variance equation (the Fed t, Fed t-1, and Fed t+1 coefficients are all equal to 0 with p = 1,00). This result is consistent with the fact that the returns of stablecoins are so close to zero, and therefore the estimated model places virtually all of the conditional variance dynamics into the baseline GARCH structure, with little additional explanatory power provided by the event indicators.

In general, the GARCH estimates represent strong evidence for the existence of persistent and heavy-tailed volatility dynamics in all crypto categories, but do not produce conclusive evidence that the FOMC announcements (modeled as simple day indicators) have a systematic effect on conditional variance on the event-day or in the days immediately following the event.

6.5 Analysis of the results

The findings of both the event study of returns and volatility modeling provide a consistent description of the way in which cryptocurrency markets react to FOMC announcements through daily time-series data. The return-based event study was developed to identify short horizon price movements around the time of announcements, while the GARCH model was employed to determine if the announcement dates exhibited changes in systematic conditional variance relative to an assumed form of the unconditional variance function, including volatility clustering.

The primary finding from applying both of these methodologies jointly to this issue is that abnormal return effects are relatively selective and segment-specific, while the effects on volatility, as modeled here, are primarily absorbed by the persistence inherent in the volatility processes.

The main finding regarding abnormal returns is that no wide-scale abnormal return was observed in the cryptocurrency market overall, using both the [−1,+1] window and daily data for the full crypto market, in relation to FOMC announcements. Most of the CAAR estimates for every category of decisions and types were found to be statistically insignificant. Thus, the evidence indicates that the overall average cumulative abnormal performance of the cryptocurrency market cannot be reliably distinguished from zero, suggesting there was no large-scale abnormal return throughout the cryptocurrency market. However, some statistically significant return responses to the FOMC announcements were found to exist in certain time periods and market segments, specifically within the event window. For example, stablecoins in the CAAR table have shown to have an adverse impact as a result of interest-rate increase announcements. Although the [−1,+1] cumulative effect was negative and statistically significant, the magnitude of this effect is quite small. Two additional localized return response patterns have been found in the day-by-day AAR results. Meme coins have a significantly negative abnormal return the day before the announcement of a rate cut. Privacy coins, on the other hand, show a significantly positive abnormal return on the date of interest-rate increase announcements. However, because the analysis involves multiple parallel tests across categories, decision types, and event days, these isolated significant results should be interpreted cautiously and are further evaluated in the robustness check section of this thesis.

The GARCH estimates indicate that cryptocurrency markets have demonstrated extreme clustering of volatility and high levels of persistence across all categories, in addition to having heavy-tailed innovations captured by the Student-t distribution. However, when the variance equation was expanded to include event dummy variables (Fed t, Fed t−1, Fed t+1) the coefficients of the event dummy variables were found to be statistically insignificant in the majority, meme, and privacy categories and were effectively equal to zero in the case of stablecoins. From a practical perspective, it appears that the daily conditional variance dynamics are driven primarily by the two standard GARCH mechanisms, past shocks and past volatility, as opposed to the presence/absence of an FOMC date itself.

One possible explanation of these results is that, in daily data, FOMC communications are more likely to generate short-term price movement in specific segments rather than generate a systemic volatility “jump” which could be captured through the use of simple day-of-the-week indicator variables in a GARCH variance equation. This does not imply that macro-driven volatility responses do not exist. Rather, it implies that if any macro-driven effects exist, they are either occurring intraday, vary depending upon the event, or are being captured within the persistence in the volatility process. As a result, the total evidence supports a segmented response model of the cryptocurrency market. Thus, abnormal return responses surrounding FOMC communications are not uniformly distributed throughout the market, and volatility processes are persistent and heavily tailed, but are not systematically influenced by FOMC timing once the clustering of volatility has been controlled.

The main findings of this thesis support hypothesis H2 descriptively and by segment category conditionally as the data indicates diverse responses within each cryptocurrency segment, however the return-based evidence did not produce strong, nor robust evidence of abnormal performance systematically at the daily level. Regarding the hypothesis H1, the CAAR results do not present statistically significant evidence that cumulative abnormal returns differ from zero in the baseline window.

6.6 Robustness check

To test the sensitivity of conclusions to the length of the window, the base event window [−1,+1] is extended to [−2,+2]. For each FOMC event, abnormal returns are summed across t=−2, −1, 0, +1, +2 to create event-windows’ CARs at the coin level. CAAR is calculated as the mean of the event-level CAR series and tested against zero via a one-sample t-test to allow for comparison with the base results. Estimates derived from the [−2,+2] window do not provide additional support for the existence of systematic abnormal performance surrounding FOMC announcements. For each of the decision-category combinations, CAAR estimates tend to be imprecise and none of the estimates rejected the null hypothesis of zero at conventional levels of statistical significance. The result was true for rate cuts, as in most categories the point estimates were positive, although they were not statistically significant. The result was also true for rate hikes as the estimates were once again mostly positive, yet statistically insignificant. Finally, for unchanged decisions the CAAR estimates remained near zero. Collectively, extending the window did not change the qualitative conclusion that abnormal performance surrounding FOMC announcements is not pervasive in the daily data and does not systematically accrue over the course of a longer five-day window.

To eliminate reliance upon the assumption of normality, non-parametric tests are employed on the event-level [−1,+1] window CAR series utilized in the CAAR analysis. Specifically, the Wilcoxon signed-rank test is employed to test the null hypothesis that the median CAR equals zero, which provides inference that is less affected to heavy tails and outliers than mean-based t-tests (Barber & Lyon, 1997). Also, a sign test is reported, which evaluates whether the fraction of positive event-level CAR outcomes differs from one half. The use of nonparametric testing for abnormal returns has been applied in crypto event-studies, for example Diaconaşu et al. (2022) used them to test median significance of abnormal returns and CAR-type outcomes under non-normality concerns.

The non-parametric evidence corresponds with the parametric evidence in almost all decision-category cells. The p-values of each of the non-parametric tests are generally far greater than conventional threshold values which indicates that the median of the event-level CAR series is not significantly different from zero. As such, this pattern held true all rate-cut categories, all unchanged-decision categories, and most rate-hike categories. Although the stablecoin category among rate hikes produced the lowest p-value from non-parametrics (Wilcoxon p = 0,1475; sign test p = 0,2266), neither of these tests reject the null hypothesis at the conventionally accepted levels. Therefore, the non-parametric robustness tests have not provided affirmative evidence of a systemic median effect in any decision category. For the remaining categories and decision types, the lack of non-parametric significance further supports the notion that abnormal performance of stocks around FOMC announcements is not widespread market phenomenon.

In addition to the extended window and non-parametric test, day-to-day AAR results require an interpretation with respect to the multiple comparison problem. The AAR analysis is based on the same large number of parallel hypotheses tested over decision types, categories and event days; thus, it is likely that the increase in the number of tests will result in a larger likelihood of observing statistically significant coefficients by chance alone. Therefore, a Bonferroni correction is evaluated as a conservative robustness check. When the focus is placed on the 36 category-day comparisons (3 decision type x 4 categories x 3 event days) the adjusted 5% significance threshold is 0,05/36 = 0,0014. With this stricter threshold, there are no longer statistically significant AAR findings from the earlier conventional AAR estimates. Hence, these few conventionally significant AAR estimates can be viewed as indicative at best and not as conclusive stand-alone evidence of systematically different abnormal returns around the time of FOMC announcements. Therefore, the above conclusion of the thesis has been strengthened: at the daily level, the return-based evidence supports the view that there are no pervasively abnormal returns around the time of the FOMC announcements, and any significant abnormal return patterns observed are sensitive to the standard adjustments for multiple testing.

7 Conclusion

This thesis determined if the FOMC's scheduled interest rate decisions affected abnormal return behaviors, and volatility in the cryptocurrency markets, using a short announcement window and a daily dataset. The empirical design used an event-study approach with a market-model to estimate abnormal returns, along with a GARCH(1,1) specification with FOMC dummy variables in the variance equation, to estimate how the decision impacts volatility, and analyzed the data at both the aggregate level and across four categories of cryptocurrencies.

The primary conclusion of the thesis with respect to return-based evidence is that, using daily data, FOMC decision days have limited, systematic, abnormal performance across all of the cryptocurrency markets. More specifically, the CAAR estimates for the decision-date window were small and statistically insignificant across most decision-category combinations. At the same time, the findings are not purely zero effects. The few statistically detectable responses are typically found to be localized to some segments of the cryptocurrency markets, rather than representing the entire market. However, the isolated day-specific AAR findings should be interpreted cautiously, as they do not remain statistically significant once a Bonferroni adjustment is applied to account for the multiple category-day comparisons. Therefore, the return-based evidence supports the notion of heterogeneity as the primary characteristic of response to FOMC announcements, particularly when looking at differences between stablecoin and non-pegged asset responses, and when considering responses of higher-risk segments of the market. As such, aggregation of the responses across sub-segments of the market can mask the existence of smaller market effects.

The volatility-based evidence provides a complimentary perspective regarding the impact of FOMC announcements on the cryptocurrency markets. While all of the categories exhibit the typical characteristics that are considered to motivate the use of conditionally-heteroscedastic models in analyzing crypto-market volatility (i.e., strong volatility clustering, high persistence of volatility, and fat-tailed innovations), the inclusion of additional FOMC dummy variables in the variance equation did not provide consistent evidence of significant or systematic volatility shifts in the cryptocurrency markets at the daily-frequency.

The robustness checks provided further support for these interpretations. Specifically, expanding the length of the event-window to a longer symmetric window did not significantly enhance the evidence of abnormal-performance across the board, suggesting that the baseline conclusion is not an artifact of selecting a narrow [−1,+1] window. Additionally, non-parametric inference based on the event-level CARs supported the parametric results in virtually all instances, providing further evidence that the lack of widespread significance is not primarily due to the imposition of normality assumptions. In addition, after adjusting the day specific AAR analysis using a Bonferonni correction method, the AARs found to be statistically significant were no longer significant after taking multiple comparisons into consideration.

In total, the primary contribution of this thesis is not that cryptocurrency markets ignore monetary policy, but rather that scheduled FOMC rate-decisions do not uniformly translate into either a daily abnormal-return or volatility pattern across the universe of cryptocurrency markets. Rather, any detected responses to FOMC decisions tend to be highly selective, conditioned upon the category of crypto-assets, and dependent upon the type of decision made by the FOMC, which is consistent with the notion that crypto-assets represent multiple classes of assets in an economic sense. In terms of practical application, the findings suggest that the use of a single aggregated crypto-index to infer monetary policy sensitivity can be misleading, as it can obscure or mask offsetting or sparse effects of the decision across various sub-segments of the market that have different economic functions and investor bases.

7.1 Limitations and future research

The conclusions drawn from this study are contingent upon the use of daily-frequency data and the design choices made necessary by conducting daily-event studies. First, daily closing prices may be too coarse to capture intraday announcement dynamics as effects that occur within minutes or hours may be diminished or even reversed prior to closing. Second, the relatively small sample size of decisions of certain types limits the statistical power of the tests, therefore "no significance" should not be taken as definitive proof of no effect, especially for less frequent decision types. Third, the event classification of decisions based upon actual rate changes is a practical proxy for policy news and future research could strengthen the identification of the relationship between FOMC announcements and crypto-market activity through the use of more explicit measures of policy-surprise (e.g., futures-implied surprises) and by separately identifying "policy" vs. "information" components of FOMC communications. Fourthly, the stablecoin category has another benchmark specification limitation. Since CoinDesk Market Index does not include stablecoins by design, the market model for the stablecoin category links near zero returns to a far more volatile benchmark. Therefore, this reduces the interpretable ability of the estimated alpha and beta coefficients and therefore the reliability of the abnormal return estimates for stablecoins as compared to the normal pegged cryptocurrency categories.

Possible extensions to the current study follow directly from the limitations identified above. Intraday crypto-data around announcement-time stamps would enable more precise identification of timing and would also likely be the best method for testing whether the volatility-responses are concentrated within the day. A second extension could be to determine if responses are also state dependent using separate estimations of the models for each type of environment (e.g., high vs. low volatility or high vs. low liquidity) since the overall impact may obscure significant variations that occur only under certain circumstances. Finally, increasing the cross-section of the data, both within categories and across additional functional categories, would likely improve external validity and clarify which types of crypto assets are most sensitive to global financial conditions.

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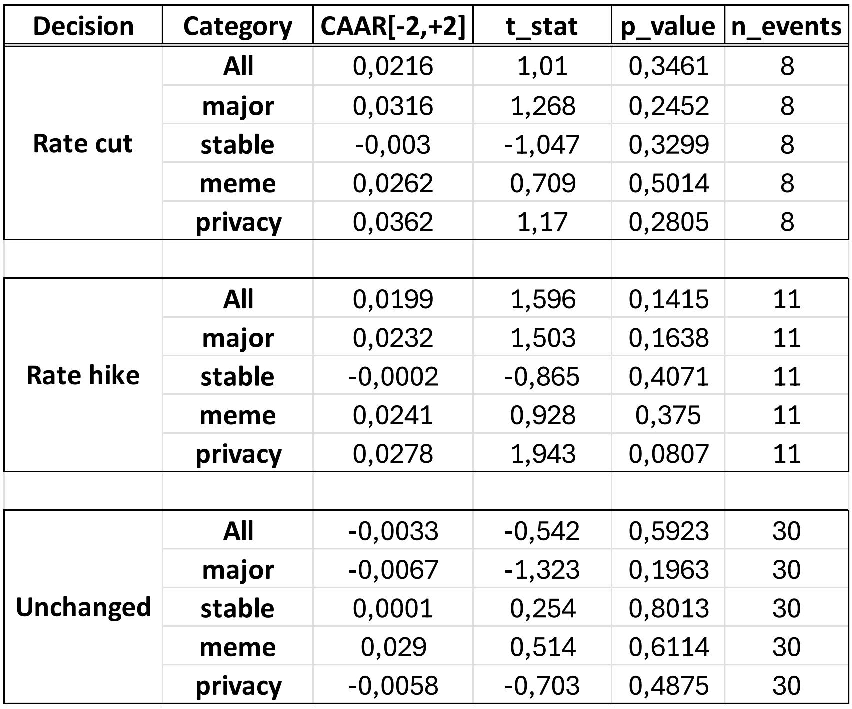
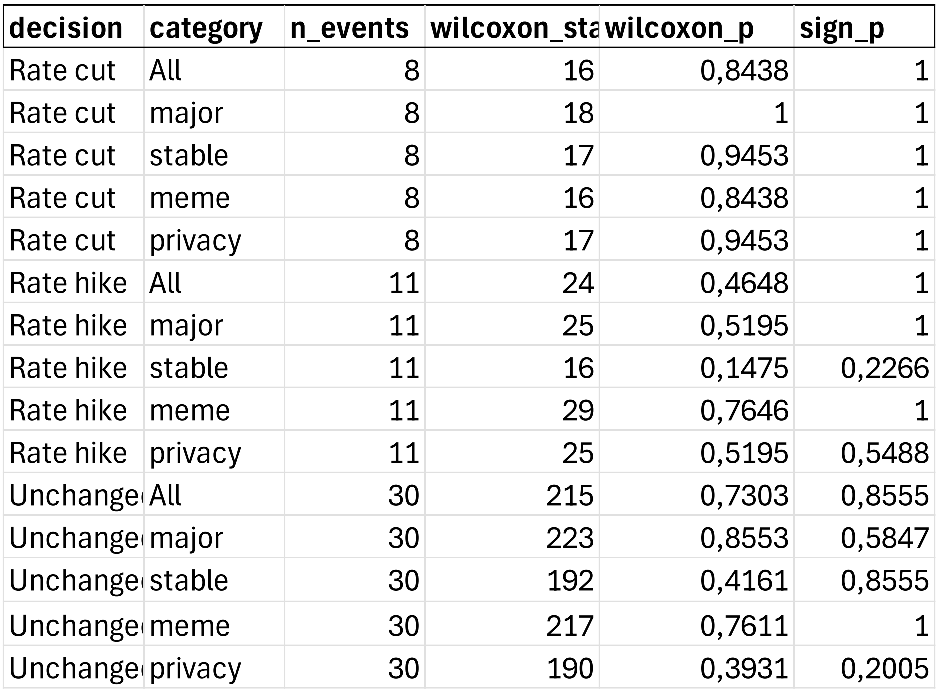
Appendices

Appendix 1. CAAR for window [-2, +2].



Decision	Category	CAAR[-2,+2]	t_stat	p_value	n_events
Rate cut	**All**	0,0216	1,01	0,3461	8
	major	0,0316	1,268	0,2452	8
	stable	-0,003	-1,047	0,3299	8
	meme	0,0262	0,709	0,5014	8
	privacy	0,0362	1,17	0,2805	8
Rate hike	**All**	0,0199	1,596	0,1415	11
	major	0,0232	1,503	0,1638	11
	stable	-0,0002	-0,865	0,4071	11
	meme	0,0241	0,928	0,375	11
	privacy	0,0278	1,943	0,0807	11
Unchanged	**All**	-0,0033	-0,542	0,5923	30
	major	-0,0067	-1,323	0,1963	30
	stable	0,0001	0,254	0,8013	30
	meme	0,029	0,514	0,6114	30
	privacy	-0,0058	-0,703	0,4875	30

Appendix 2. Nonparametric CAR tests [-1,+1]



decision	category	n_events	wilcoxon_sta	wilcoxon_p	sign_p
Rate cut	All	8	16	0,8438	1
Rate cut	major	8	18	1	1
Rate cut	stable	8	17	0,9453	1
Rate cut	meme	8	16	0,8438	1
Rate cut	privacy	8	17	0,9453	1
Rate hike	All	11	24	0,4648	1
Rate hike	major	11	25	0,5195	1
Rate hike	stable	11	16	0,1475	0,2266
Rate hike	meme	11	29	0,7646	1
Rate hike	privacy	11	25	0,5195	0,5488
Unchange	All	30	215	0,7303	0,8555
Unchange	major	30	223	0,8553	0,5847
Unchange	stable	30	192	0,4161	0,8555
Unchange	meme	30	217	0,7611	1
Unchange	privacy	30	190	0,3931	0,2005

Appendix 3. CAAR and AAR results with short estimation window (23 days)

Decision	Category	CAAR[-1,+1]	t_stat	p_value	n_events
Rate cut	**All**	0,0011	0,164	0,8746	8
	major	0,0043	0,618	0,5564	8
	stable	0,0005	0,491	0,6385	8
	meme	-0,0086	-0,435	0,6767	8
	privacy	0,0109	0,862	0,4173	8
Rate hike	**All**	0,011	1,037	0,3241	11
	major	0,012	0,968	0,3557	11
	stable	-0,0002	-3,148	0,0104**	11
	meme	0,0089	0,578	0,5759	11
	privacy	0,019	1,095	0,2991	11
Unchanged	**All**	0,0032	0,502	0,6193	30
	major	0,0017	0,233	0,8172	30
	stable	-0,0001	-0,432	0,6692	30
	meme	0,034	0,67	0,5082	30
	privacy	0,0011	0,147	0,8845	30

** = statistically significant at 5%

Decision	Category	t=-1	t=0	t=+1
Rate cut	**All**	-0.007081(-1.16)	0.008836(1.08)	-0.000666(-0.12)
	major	-0.009166(-0.96)	0.011004(1.33)	0.002423(0.40)
	stable	0.000775(0.60)	-0.000010(-0.03)	-0.000310(-0.87)
	meme	-0.013294**(-3.09)	0.017418(1.09)	-0.012774(-1.23)
	privacy	-0.004827(-0.41)	0.009293(0.78)	0.006445(0.65)
Rate hike	**All**	0.004355(0.60)	0.007213(1.00)	-0.000615(-0.08)
	major	0.004731(0.52)	0.006733(0.68)	0.000495(0.05)
	stable	-0.000085(-1.30)	-0.000014(-0.13)	-0.000061(-0.68)
	meme	0.017021(1.48)	-0.003300(-0.22)	-0.004795(-0.52)
	privacy	-0.000051(-0.01)	0.019144**(2.34)	-0.000098(-0.01)
Unchanged	**All**	-0.000077(-0.02)	-0.002872(-0.66)	0.006163(0.94)
	major	0.000842(0.16)	-0.003613(-0.68)	0.004495(0.78)
	stable	-0.000166(-0.88)	-0.000007(-0.06)	0.000061(0.46)
	meme	0.000823(0.09)	-0.011121(-0.99)	0.044267(0.84)
	privacy	-0.001214(-0.28)	-0.001918(-0.35)	0.004207(0.75)

** = statistically significant at 5%

Appendix 4. Use of artificial intelligence in the thesis

Language model used: OpenAI ChatGPT

AI tools were used as an assistance during some phases of the writing process. Especially for outlining section structures and improving language quality. All text improved using AI was reviewed critically by the authors. The authors also verified, revised and adapted any content enhanced with AI to fit the context of the thesis. The authors are responsible for the empirical analysis, statistical computations, interpretation and conclusions in the thesis. The authors did not use AI tools to create the dataset or run the models, nor did they determine the final results. The authors followed the guidelines of University of Vaasa on the responsible use of AI in thesis work.