School of Economics and Management

From 2018–2023, surprise central bank decisions shaped Bitcoin and Tether's short-run returns and volatility

Master Thesis Finance

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Abstract

This thesis examines how cryptocurrency markets, particularly Bitcoin and Tether, react to announcements from central banks and unexpected changes in the economy. The analysis looks at 524 events from the Federal Reserve, European Central Bank, and Bank of England from 2018 to 2023. It measures how the market reacts within six hours after each event. Two outcome factors are looked at: realized volatility (Vol_{6h}) and cumulative abnormal returns (CAR_{6h}). The approach uses standard OLS regressions alongside non-parametric random forest models to evaluate both linear effects and possible nonlinear relationships.

The results show that Bitcoin reacts modestly to interest rate decisions, particularly to unexpected hawkish moves by the Fed, while macroeconomic news has weaker and less consistent effects. Tether continues to show strong stability during all events. Volatility is not more responsive than returns. This suggests that policy uncertainty does not clearly favour either the return or volatility channel. The random forest diagnostics support and refine the OLS results, exhibiting slight asymmetries and threshold effects. The results' consistency across subsamples and estimation choices is verified through extensive robustness tests.

Overall, the thesis concludes that cryptocurrency markets react selectively and asymmetrically to economic news, with stronger effects observed in volatility than in average returns.

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1 Introduction

1.1 Motivation

Over the past decade, cryptocurrency has transformed from an interesting technology experiment into a trillion-dollar industry. This shift has significantly impacted investors, regulators, and lawmakers worldwide regarding money, markets, and investment opportunities. An unknown person, going by the name "Satoshi Nakamoto," created Bitcoin in 2009. It was the first digital currency that was autonomous and built on blockchain technology(Nakamoto,2008). Blockchain is a system that keeps records in a way shared among many users. It makes transactions clear and safe, so there's no need for banks or other institutions to get involved. Bitcoin began with a small market cap and was recognized mainly by libertarians and tech enthusiasts, but by 2013, its price skyrocketed to hundreds of dollars (Cheah & Fry,2015). It started attracting more public interest after being traded for just a small amount. The cryptocurrency became very popular in 2017, leading its market value to surpass tens of billions of dollars. By early 2021, its market value had increased to more than a trillion dollars (Chavez-Dreyfuss & Wilson, 2021).

The unprecedented increase in the value of Bitcoin has not been without controversy or risk. It is attractive and hazardous for investors seeking high returns since its price volatility frequently surpasses conventional financial assets such as stocks, bonds, and commodities (Baur et al., 2018). Price fluctuations of the cryptocurrency, which may be attributed to both speculation and fundamental changes in the economy, have sparked heated discussion on what is determining its worth. Whether Bitcoin is more of a speculative instrument, digital gold, or a hybrid of the two has been debated by academics and industry professionals (Krause, 2025). Understanding what causes Bitcoin's volatility became more critical as the cryptocurrency evolved and became more widely accepted by hedge funds, financial institutions, and institutional investors. For investors, regulators, and lawmakers trying to keep up with the ever-changing financial scene, it is crucial to understand how external events, particularly unexpected macroeconomic announcements from big central banks, affect the short-term price movements of Bitcoin.

At the same time, the monetary policies of major central banks worldwide, such as the Bank of England, the European Central Bank, and the U.S. Federal Reserve, have undergone significant changes. After a decade of historically low interest rates, central banks recently embarked on aggressive rate hikes in response to inflationary pressures following the COVID-19 pandemic. While the effects of sudden shifts in monetary policy on traditional financial markets are extensively studied, the impact on emerging markets for digital assets remains largely unknown. In the meantime, USD-pegged stablecoins such as Tether (USDT) have become popular trading tools and can act as safe-haven assets in periods of market stress (Wang, Ma, & Wu, 2020). Recent examples of market stress, such as unexpected interest-rate announcements and sudden fluctuations in the economy, have raised questions about the stability of dollar-pegged tokens and the vulnerability of Bitcoin. This thesis discusses a practical question by analyzing the short-term volatile prices and returns of Bitcoin and Tether concerning unexpected interest rate decisions and significant economic announcements from the Federal Reserve, the European Central Bank, and the Bank of England between 2018 and 2023. The question is: how resilient are markets for digital assets, volatile or stable, when monetary policy shocks disrupt global markets?

This thesis examines how changes in monetary policy affect cryptocurrency markets. It addresses a gap in current research by analyzing Bitcoin and stablecoins from various central banks simultaneously. The results have implications for regulators, investors, and policymakers.

1.2 Research focus and question

It's worthwhile to grasp how the cryptocurrency market connects with bigger economic trends, especially since it has become a significant part of the global financial system. There are two digital assets: Bitcoin, the largest and most unpredictable cryptocurrency, and Tether, the most widely used stablecoin. Bitcoin is known for its extremely high price volatility and speculative nature, whereas Tether is meant to keep prices stable. However, they are also part of the same financial system where decisions regarding global money policy greatly influence asset prices, market liquidity, and how investors feel. Statements from well-known central banks such as the Fed, the ECB, and the Bank of England have an essential effect on traditional markets. Yet, it's not clear how these statements affect the newer and rapidly changing crypto-asset markets (Corbet et al., 2019). According to Auer et al. (2022), this issue is especially noteworthy given the rising involvement of institutional investors in Bitcoin and the increasing systemic significance of stablecoins like Tether in supporting crypto trading and liquidity.

This thesis's primary question is how unexpected interest rate decisions and important macroeconomic announcements from prominent central banks influence Bitcoin and Tether's short-term volatility and returns. During 2018 and 2023, several noteworthy worldwide events occurred, including the COVID-19 pandemic and a war in Ukraine, which caused major changes in monetary policy. After an extended period of record-low interest rates, central banks aggressively tightened policy in reaction to inflationary pressures and geopolitical uncertainty caused by these crises. There has been some scholarly interest in how Bitcoin has responded to shocks to U.S. monetary policy, but the research is still somewhat shallow and narrow in scope. Most research today focuses on the Federal Reserve and overlooks other critical central banks like the European Central Bank and the Bank of England. The daily data used in these studies might ignore the real-time responses that are most important to policymakers, risk managers, and high-frequency traders. This thesis uses hourly pricing data and includes two other big central banks in the research to get around these restrictions. In this way, we can better see how the market responds to policy shocks during this time of change and volatility.

Focusing on Tether and Bitcoin brings in more scrutiny. Tether and other stablecoins try to reduce the wild price swings of Bitcoin by linking their value to a traditional currency, usually the US dollar. When changes in monetary policy lead to significant shifts in how the market experiences and operates, people have started to doubt how stable it can be during tough times (Aldasoro et al.,2024). This study's fundamental sub-question is whether Tether's value remains stable when central banks make unexpected announcements, or if even these usually stable assets experience short-term price changes or volatility during times of high uncertainty. This research is relevant because stablecoins now provide the main on-chain 'bridge' between fiat money and the crypto ecosystem, underpinning exchange liquidity and DeFi settlement (Arner et al.,2020). If these tokens fluctuate due to economic events, it could impact the overall stability and operation of the cryptocurrency system.

Another important sub-question is how sensitive Tether and Bitcoin are to changes in policy in different countries. From the Deutsche Bundesbank (2021), the extent of connection between crypto markets and financial institutions in various regions might clarify why Bitcoin and Tether respond differently to shocks from the Federal Reserve, the ECB, or the Bank of England. This theory aims to determine whether changes in policy impact crypto assets worldwide or if certain central banks influence crypto markets more than others. Knowing about this topic is vital for comprehending how autonomous financial systems and standard macroeconomic institutions change their interactions, and learning about how global and regional economic factors interact in crypto markets.

After answering these study questions, we can look at how sudden changes in monetary[1] and macroeconomic policy affect two crucial parts of the market for digital assets. This thesis looks closely at how markets behave during significant global economic crises. It combines detailed data analysis and insights from different central banks and examines stable and volatile cryptocurrencies. By looking at policy shocks' time and how they affect other countries, this method moves the field forward and gives a more complete picture of how the crypto market works.

1.3 Data used and sources

To investigate how Bitcoin and Tether respond to unexpected monetary policy shocks and major macroeconomic announcements, this thesis constructs a comprehensive dataset that captures both the timing and magnitude of policy surprises across different central banks. The dataset covers 2018 to 2023, a time of major global economic changes, including the COVID-19 pandemic and the Ukraine war. It is based on the research questions that were previously mentioned, which stress the need to look at both short-term volatility and returns across different jurisdictions and asset types. This time frame is particularly applicable for studying crypto-market sensitivity since these events caused significant shifts in central bank policy.

This dataset incorporates unanticipated macroeconomic data and policy pronouncements from the BoE, the ECB, and the Fed. Both actual decisions (such as interest rate changes, CPI, or GDP releases) and market expectations are collected for each announcement. Economic surveys conducted by Reuters and futures-implied probabilities (such as CME FedWatch, Euribor futures, and SONIA OIS) are used to derive expectations. This two-pronged strategy enables the establishment of surprise measures, which record the gap between real results and market expectations. When analyzing the reaction of cryptocurrency assets to sudden changes in monetary policy or macroeconomic events, these surprises play a crucial role as explanatory factors.

[1] Throughout, we use ‘monetary policy surprise’ to mean an unanticipated interest-rate decision—a rate hike or cut—by the Fed, ECB or BoE

Cryptocurrency data includes hourly price and volume observations for Bitcoin and Tether from 2018 to 2023, sourced from major market aggregators. After retrieving hourly OHLCV data from Binance's public API using the binancer package, the data was cleaned, standardized to UTC, and processed to compute hourly log returns and 24-hour rolling volatility for Bitcoin. The data was obtained in 1,000-row increments. Each hour's price information for Tether was fetched from CryptoCompare's v2/histohour endpoint using httr. The data was collected in reverse chronological order and was processed and normalized in the same way. With this high-frequency data, it is possible to get an exact picture of short-term returns and volatility six hours after each policy statement. The empirical analysis applies two complementary methods. Before the announcement, an event-study framework measures the changes in volatility and cumulative abnormal returns around the announcement. The market's immediate reaction is captured via hourly windows. Secondly, using central bank-level cluster-robust standard errors, linear regression models examine the relation between policy shocks and market outcomes while accounting for central bank origin, asset type (Bitcoin or Tether), and intraday time.

Random forest models are also implemented to discover nonlinear relationships and variable importance across predictors. Considering the complicated interactions between central bank shocks, market timing, and asset-specific dynamics, this machine-learning method adds to the simplicity of linear models. In combination, these approaches provide a thorough look at how Bitcoin and Tether react to changes in monetary policy. This helps us understand how stable and sensitive digital assets are in different economic jurisdictions.

1.4 Results

Bitcoin reacts slightly but in a clear direction to the surprise decisions central banks make. During the six-hour event window, a one-standard-deviation hawkish surprise from the Fed (ChangeBps_z = +1) reduces Bitcoin's cumulative abnormal return (CAR_{6h}) by about 0.114 percentage points, which is roughly a $26 decrease when Bitcoin is priced at $30,000. A macroeconomic surprise of a similar size lowers CAR_{6h} by about 0.04 percentage points, with the impact mainly seen in the first three hours. These patterns suggest that when there are tightening shocks, non-yielding assets such as Bitcoin become less appealing.

Random forest models support and build on these findings. In the rate block, CentralBank is the single most influential variable for CAR_{6h}, with ChangeBps_z the largest shock term; for Vol_{6h}, the Asset dummy dominates, while CentralBank and ChangeBps_z provide only marginal incremental power. The partial-dependence plots reveal that Bitcoin's return sensitivity to rate shocks is strongest around moderate tightening surprises, with both very dovish and very hawkish moves provoking smaller reactions, and that volatility actually peaks near neutral surprises before calming as shocks become clearly hawkish.

Tether (USDT) shows no significant reaction to either interest-rate or broader macro surprises. In our OLS CAR models, the shock coefficients for USDT are very small and statistically insignificant, and the asset dummy for Tether is also trivial. In the volatility models, USDT's mean six-hour volatility is about 0.10%, versus Bitcoin's roughly 0.70%. Although there are occasional volatility spikes (for example, during the May 2021 de-peg), these outliers do not coincide with scheduled policy or macroeconomic announcements.

The identity of the issuing central bank also plays a role. Bitcoin responds most noticeably to announcements from the Fed, then the ECB and BoE. However, the differences in response are small and not always statistically significant. Both OLS coefficients and random forest rankings confirm this issuer ordering.

Tests for asymmetry and convexity yield only marginal nonlinear patterns. Non-linear tests add little. The sign-asymmetry interaction (ShockSignPositive × Surprise) is insignificant for CAR_{6h} and only marginally negative for Vol_{6h} (statistically significant). Squared-surprise terms are near zero throughout, indicating no systematic convexity.

The results indicate that Bitcoin reacts somewhat to unexpected changes in monetary policy, particularly from the Fed, while Tether does not show any impact. Changes in interest rates are more significant than macroeconomic news, highlighting how important it is to pay attention to future indicators that influence short-term movements in the crypto market.

1.5 Literature

Recently discovered data shows that crypto assets no longer exist in a vacuum but instead respond, and often very strongly, to regular financial news. Ma et al.(2022) find that Bitcoin's daily return decreases by about 0.25 percentage points for each basis point of unexpected tightening by the Fed. They conclude that Bitcoin acts more like a high-duration risk asset than a hedge against inflation. I replicated their identification at the hourly frequency and discovered that 90% of the full-day adjustment they observed was accomplished within the first three trading hours, with a peak of approximately –0.20 pp within that window. The beta's direction remains, but its speed and magnitude during the day are substantially higher than what a daily bar may indicate.

Ma et al. (2022) explore Bitcoin on its own, while Griffin & Shams (2020) suggest that the amount of the dollar-pegged stablecoin Tether can influence Bitcoin prices through its own supply changes. By placing Tether alongside external central-bank announcements, I come to a different conclusion regarding macro shocks: reserve-backed tokens stay stable in price, while speculative Bitcoin adjusts in value. This suggests that monetary news affects leveraged BTC positions more than stable-coin balance sheets.

Using a time-varying-parameter VAR approach, Pietrzak (2023) demonstrates that Bitcoin's reaction to unexpected policy changes from the Fed and ECB modifies direction during different periods. My six-hour event research confirms regime dependency but shows that heterogeneity is cross-sectional at high frequency: U.S. surprises create significant financial returns, whereas standardised ECB or BoE shocks do not. These three papers support the thesis's design involving dual assets, multiple banks, and high-frequency analysis. They highlight its contribution: tracking how monetary news affects the crypto market in real time and identifying spill-over effects specific to issuers across the two main types of tokens.

1.6 Conclusions

Bitcoin, not Tether, responds to unexpected changes in the economy. When the Federal Reserve tightens monetary policy by one standard deviation, it reduces six-hour returns by about 0.1114 percentage points, with most of this change happening within three hours. In contrast, reserve-backed USDT remains stable at its peg, only deviating during specific liquidity issues. The lesson is in two parts. First, it's challenging to align the idea of Bitcoin as "digital gold" with its tendency to exhibit modest, directional reactions to policy news. Second, the immediate risks in crypto markets mainly come from leveraged Bitcoin positions, not from tokens settled in dollars. Methodologically, the analysis is limited by a constant-mean abnormal-return benchmark, the absence of depth-of-book data, and the focus on a single stable-coin design. Future research could build on the event study by adding a multi-factor (crypto-)CAPM, incorporating high-frequency order-book dynamics to explore the micro-structure channel, and examining whether other pegs—like USDC, DAI, and algorithmic variants—stay resilient or not when the next policy shock occurs.

1.7 Roadmap of the thesis

The rest of the thesis is organized as follows. Chapter 2 explains the basics of cryptocurrencies and how central banks fit into the picture. It highlights why monetary and macroeconomic changes are important for understanding the prices of digital assets. Chapter 3 examines the necessary economic research on how cryptocurrencies behave, covering early studies and recent findings. Chapter 4 presents the dataset, detailing the construction of the event panel and descriptive statistics of returns and volatility. Chapter 5 outlines the hypotheses that will be tested, drawing from both theoretical and empirical insights. Chapter 6 explains the research methods, including the event-study design, regression models, and random forest techniques used to test the hypotheses. Chapter 7 discusses the main empirical results, compares OLS and random forest findings, and includes robustness checks to validate the analysis. Finally, Chapter 8 concludes with a concise summary of the most significant discoveries, the implications for policy, and the potential directions for future research.

2 Basics and Cryptocurrency

Modern monetary systems have had to rethink how they perceive, store, and trade value due to the explosive growth of digital assets. Bitcoin and other cryptocurrencies are decentralized digital money systems that use blockchain technology to guarantee transactional integrity and immutability in the absence of a central authority (Narayanan et al., 2016). Unlike traditional currencies, Bitcoin is not printed by the government or backed by real reserves. Instead, it works through a peer-to-peer network, and an algorithm sets the quantity. Therefore, liquidity, macroeconomic mood, and speculative expectations are the primary factors that determine its valuation. Economists still are unable to agree on how to define it, veering between a speculative vehicle, a hedge against inflation, and a new form of digital gold (Fry & Cheah, 2016; Dyhrberg, 2016). The asset's significant price fluctuations and absence of inherent cash flow set it apart from traditional investment options, making how it reacts to policy changes a topic of ongoing research.

Bitcoin uses a system called proof-of-work. In this system, miners try to solve complex puzzles to confirm transactions and keep the network safe. As de Vries (2018) stated, this design adds to the worries about energy usage. Bitcoin's price isn't affected by earnings or profits from an economic point of view. Instead, it's affected by demand-side factors like how widely the technology is used, speculative flows, and the level of global liquidity. Studies have indicated that Bitcoin responds significantly to news regarding regulation, acceptance by institutions, and geopolitical risks (Lyocsa et al., 2020). In this context, the asset behaves more like a technology-linked risk asset than a traditional currency.

Alongside Bitcoin's rise, stablecoins have appeared to fix one of the biggest problems with cryptocurrencies: their instability. Tether (USDT) is one of the most well-known stablecoins. It is designed to keep its value equal to the U.S. dollar by using reserves and techniques to exchange it back for dollars. These assets are intended to bring together the fast and efficient transfer of blockchain technology with the reliability of traditional currencies. Stablecoins play a key role in the crypto world, serving as a valuable way to exchange value and measure worth, particularly in decentralized finance (DeFi) settings and on major trading platforms (Schär, 2021). They help with trading, arbitrage, and providing liquidity without depending on traditional banks, making them essential for decentralized platforms. Even though they claim to have a fixed peg, events like the temporary de-pegging of USDT and the collapse of TerraUSD have raised concerns about how well their collateral systems work, the level of regulatory oversight, and how transparent their operations are (Aramonte et al., 2022). These occurrences demonstrate the difficulty of keeping a steady value when trust and reserves are not thoroughly verified in real time.

Stablecoins can be categorized based on their collateralization: fiat-backed, crypto-backed, or algorithmic. Tether asserts it is backed by fiat money and provides regular confirmations of its reserves, though it does not undergo complete audits. However, critics have pointed to gaps in reporting and ambiguity around backing asset composition, including commercial paper or short-term loans (Griffin & Shams, 2020). The debate over Tether’s reserve practices has drawn attention from regulators and raised larger questions about systemic risk in the crypto markets. Central banks and international regulatory organizations have concentrated more on understanding the legal status and financial systems related to stablecoins, particularly as they become more widespread (Financial Stability Board, 2023).

Even though both asset types use the same digital system, they play very different economic roles. Bitcoin is at the cutting edge of crypto-finance speculation. Its price is based on predictions about how widely it will be used in the future, inflation, and the authority of institutions. Tether is made to act like regular money, responding less to changes in value and more to the trust people have in how it operates. This difference provides a unique opportunity to examine how volatile and pegged crypto-assets react differently to external economic factors. It's essential to know how decisions made by central banks affect this changing market segment because institutional investors are getting more involved in crypto-assets, and crypto-asset markets are becoming more connected to traditional financial systems (Hermans et al., 2022; Financial Stability Board, 2023). Bitcoin is now traded on significant exchanges along with equity index futures. Tether is a settlement currency on exchanges offering synthetic swaps and leverage.

There are two main points to consider regarding financial stability. Bitcoin can be unpredictable and not controlled by any entity, increasing risk during big economic changes. However, it might also help balance some investment portfolios in specific situations (Baur, Hong, & Lee, 2018). Tether helps keep liquidity stable, but it might create problems if its reserves aren't enough during times when investors want to cash out, or if regulations limit the ease with which it can be converted. Furthermore, since there is no central clearing or bank protection system, confidence plays a bigger role in keeping the peg in place than it would with fiat currencies, which are part of national monetary systems.

Therefore, it is crucial to differentiate between various asset types to conduct a thorough analysis of monetary policy transmission in decentralized markets. Bitcoin often shows significant changes in returns and volatility when there are unexpected interest rate changes or new economic data. On the other hand, Tether's performance during stress tests challenges how strong pegged digital currencies are in a system that lacks traditional emergency lending support. Looking at Bitcoin and Tether together helps us better understand cryptocurrency risks and how they interact with global economic trends.

3 Literature Review

This chapter provides a comprehensive overview of the research environment, focusing on four key themes that are crucial to our narrative:

1. Bitcoin vs. central-bank surprises – the growing evidence that a supposedly "policy-proof" asset twitches the moment rates move.

2. Tether's hidden hand – studies showing how fresh USDT creation (or redemption) can turbo-charge or mute Bitcoin swings.

3. Emerging-market pulse – work linking rate announcements, inflation fears, and the retail rush into crypto.

4. Whose policy, which regime? – findings that Bitcoin's sensitivity is not static: it waxes and wanes across time and differs for the Fed, ECB, and others.

Most of this literature ends at daily data, sticks to the Fed, and rarely puts Bitcoin and stablecoins in the same frame. That blind spot is the launch pad for this thesis: an hourly, three-bank, dual-asset event study that follows the crypto market in real time.

3.1 Bitcoin and Monetary Policy: Evidence from the U.S.(*Ma et al., 2022*)

Ma et al. (2022) analyze how Bitcoin prices respond to unexpected monetary policy decisions, explicitly focusing on U.S. Federal Open Market Committee (FOMC) announcements. By investigating whether Bitcoin, often described as a decentralized and independent financial asset, is vulnerable to conventional macroeconomic policy changes, their research fills a major need in the existing literature. The authors examine Bitcoin's movement around upcoming FOMC meetings using daily data from July 2010 to December 2020 to determine if monetary policy shocks, like other financial assets, impact Bitcoin returns.

Ma et al. (2022)'s study uses a standard way in macro-finance research to find monetary policy shocks: they use changes in the two-year U.S. Treasury yield on FOMC statement days to represent the unexpected part of economic policy. This method is based on the idea that the quick change in short-term yields shows how market expectations about the policy path have changed. Ma et al. (2022) reduce complicating factors by measuring surprise based on daily yield movements instead of qualitative announcement classifications. This allows authors to capture actual deviations from market expectations.

Using an Ordinary Least Squares (OLS) approach, the authors figure out how FOMC statements affected Bitcoin prices when they were made by regressing Bitcoin returns on monetary policy surprises. Their most important finding is that Bitcoin's daily return drops 0.25 percent for every one basis point surprise rise in the two-year Treasury rate. This inverse correlation calls into question the widespread belief in Bitcoin as a safeguard against conventional financial instability or macroeconomic concerns. Instead, it shows that the cryptocurrency reacts negatively to unanticipated monetary tightening. Interestingly, Bitcoin's reaction size is similar to gold's, which has long been considered a safe-haven asset. This comparison suggests that Bitcoin, even if decentralized, might behave like traditional assets regarding changes in the macro-financial market.

Aside from the instant one-day reaction, Ma et al. (2022) also show that prices continue to change in the days after policy announcements. They observe that the cumulative decline in Bitcoin continues through at least the fifth trading day after the statement (the three-day total is ≈ -1.65 %, and it remains negative at day 5). In the cryptocurrency market, this slow adjustment indicates some information frictions or that the market is taking its time to absorb monetary policy shocks. These changes are a surprise, given that Bitcoin trades constantly and crypto markets are thought to be very good at exchanging data. The fact that Bitcoin's reaction to policy changes isn't fully finished in the first 24 hours suggests that the market needs time to process fully and re-price information, at least around big macroeconomic events.

The study also makes a significant addition by investigating heterogeneous impacts in various market situations. Ma et al. (2022) use quantile regressions to examine how Bitcoin's return changes in response to unexpected changes in monetary policy affect different parts of the return distribution. The study uses conditional return quantiles to infer market state-dependence instead of explicitly assessing sentiment. Bitcoin is more sensitive to positive (easing) and negative (tightening) surprises at the upper quantiles, which correspond to optimistic market conditions; this finding indicates that the impact of monetary policy shocks is inconsistent across the distribution. This inequality shows up in both the strength and the duration of reactions. In simple terms, when market circumstances are favourable, monetary shocks (regardless of direction) cause bigger and longer-lasting reactions. According to these results, Bitcoin reacts more strongly to news about the economy as a whole when markets are already doing well. However, the main factor that affects Bitcoin's behaviour is the state of returns, not investor happiness or mood.

The findings of Ma et al. (2022) have significant implications for understanding Bitcoin’s evolving role in the global financial system. Their research shows that Bitcoin is vulnerable to macroeconomic factors, especially sudden changes in monetary policy. This goes against early stories about Bitcoin as an autonomous asset class that doesn't care about policy. By showing that sudden increases in interest rates consistently lower Bitcoin returns, Ma et al. reframe the cryptocurrency as macro-sensitive, with return patterns similar to those of traditional financial assets like gold.

However, there are several unanswered concerns that this thesis aims to address because of the gaps in their comprehension. Firstly, Ma et al. only use daily data, which might make it harder to see high-frequency volatility and return dynamics that happen minutes or hours after policy releases. This thesis provides a more detailed look at how the market reacts to announcements by measuring cumulative abnormal returns (CAR) and short-run volatility (Vol_{6h}) six hours after each announcement using hourly data. This method works better for getting real-time answers from traders, which is especially important in crypto markets where algorithmic and manual dealing happen constantly.

Second, Ma et al. (2022) examine only the U.S. Federal Reserve’s policy decisions. Although this makes sense considering the Fed's worldwide influence, it fails to account for the fact that monetary policy shocks might have different impacts in different countries. This thesis broadens the scope of the study by including the BoE and the ECB, allowing for a comparative examination of the reactions of Bitcoin and Tether to monetary policy shocks caused by diverse regulatory and economic frameworks.

Third, Ma et al.’s (2022) study focuses exclusively on Bitcoin. Although Bitcoin enjoys the most significant visibility and trading volume, stablecoins such as Tether (USDT) are integral to the cryptocurrency ecosystem. They are essential to the smooth operation of the market. This thesis improves the scope of research to include Tether and Bitcoin, allowing us to examine the impact of monetary policy on assets with varying volatility profiles and functional responsibilities. Given Tether's pivotal role in enabling USD-based transactions on worldwide exchanges, this is of utmost importance.

To sum up, Ma et al. (2022) lay a crucial groundwork by showing that Bitcoin reacts differently to unexpected changes in U.S. monetary policy. However, the fact that they only look at daily statistics and one country limits the applicability of their results. This thesis, on the other hand, enhances their approach in three ways: first, by utilizing higher-frequency data (hourly); second, by analyzing several banks (Fed, ECB, BoE); and third, by incorporating stablecoins like Tether to see if policy shocks impact even price-stable assets. These add-ons help us learn more about how changes in monetary policy affect various parts of the coin market in real time by letting us compare and contrast them in more depth.

3.2 Market Manipulation and Stablecoin Activity (*Griffin & Shams, 2020*)

Griffin and Shams's (2020) study on the microstructure of the cryptocurrency market is both pioneering and divisive concerning the transparency and stability of the digital asset ecosystem, especially with stablecoins. With a particular emphasis on the sudden price surge in late 2017, their study titled "Is Bitcoin Really Untethered?" examines the connection between Bitcoin prices and Tether (USDT), a dollar-pegged stablecoin. This study is especially significant to any research on how systemic or external shocks affect Bitcoin and Tether, as it fundamentally contradicts the concept that cryptocurrency price swings are only driven by demand or represent decentralized market forces.

Griffin and Shams'(2020) analysis posits that vast amounts of Tether were intentionally used to buy Bitcoin during times of negative returns. Additionally, they found that these purchases were made mainly by one big player using Bitfinex, the exchange associated with Tether. The authors track the circulation of Tether tokens from their issuance all the way to their trade on major exchanges using a comprehensive dataset based on blockchain movements. They uncover that periods following significant Tether issuance are strongly associated with large upward price movements in Bitcoin.

Crucially, their research shows that a handful of scenarios with strong Tether flows caused a large amount of Bitcoin's price surge in 2017. When the 87 hours with the largest lagged aggregate Tether-Bitcoin flows between March 2017 and March 2018 are removed, the buy-and-hold return of Bitcoin drops from 488 % to 245%. This means that those hours alone were responsible for 50% of the overall return during that period. They also found that only the top 1% of its busy hours can explain about one half of the price increase when they focus on their "1LSg" cluster, which they see as a single dominant player. Based on these numbers, it's clear that Tether activity significantly impacted Bitcoin's performance throughout the period under consideration.

In addition, the report reveals a noteworthy monthly trend: when there is a high issue with Tether, Bitcoin ends the month with abnormally negative returns, about -6%. According to Griffin and Shams (2020), this reversal might be a sign that Bitcoin is being sold off to refill the reserves that are backing Tether. This trend disappears when there is no new issuance for months, supporting the theory that Tether's liquidity management, and not external market factors, is directly responsible for these actions.

Their empirical method integrates time-series econometrics with transaction-level blockchain research. An important new feature is the "lagged flow pressure" estimates, which measure the rapid inflow of recently issued Tether into Bitcoin exchanges. This measure allows them to statistically identify price effects attributable to issuance-related flows, rather than general crypto demand. To show that their results are accurate, they use other cryptocurrencies, like Ethereum and Litecoin, as "placebos" and show that the same trends don't show up with those coins. Furthermore, they show that the negative end-of-month return pattern disappears in months with no new Tether issuance, reinforcing the view that the effect is tied to Tether supply rather than general crypto demand.

Even though the study doesn't say that Tether is intentionally dishonest, it does make people wonder if their claim that they are fully backed is valid. If freshly minted Tether is used to boost Bitcoin's price without adequate reserves, the authors argue, the method seems more like price manipulation than spontaneous market activity. Their results led to much discussion, closer scrutiny by regulators, and the start of many more studies looking into how stablecoins affect market behaviour.

Griffin and Shams (2020)'s work provides crucial conceptual motivation for the present thesis, which examines the responses of Bitcoin and Tether to macroeconomic shocks, namely surprise monetary policy decisions. As an initial point, it backs up the idea that Tether is not just an inactive market member that helps trade happen, but an active player that can change Bitcoin's returns and volatility. This thesis investigates the possibility that Tether and Bitcoin are responsive to exogenous events, including changes in central bank policy, in addition to the endogenous issuance behaviour that Griffin and Shams (2020) claim is responsible for this impact. To understand how these assets react to this kind of news, we need a framework that sees Tether as an essential and changing player in the cryptocurrency environment.

Second, the study's results raise relevant concerns regarding market stability and the function of liquidity. If Tether issuance counteracts negative Bitcoin price pressures and fluctuates amid market stress, central bank announcements may cause distinctive Tether activity and price responses. This thesis expands on that reasoning by analyzing the reactions of stablecoins to macro shocks, such as short de-pegging, unexpected volatility, or volume shifts that may indicate liquidity stress, in the same way Bitcoin reacts to these shocks.

Furthermore, Griffin and Shams (2020) emphasize their empirical work on endogenous Tether flows and how they affect Bitcoin over more extended time frames, even while they stress forensic blockchain analysis with minute-level transaction tracking. On the other hand, this thesis takes a different approach, one that complements the others, by analyzing abnormal returns and volatility within a six-hour window surrounding clearly characterized exogenous policy shocks using structured high-frequency (hourly) pricing data. This method removes the focus from tracking the movements of tokens within the network. Instead, it focuses on the instant market response to surprise interest rate decisions and macroeconomic direction from major central banks. In addition, the thesis expands the analysis to incorporate monetary policy surprises from the Fed, the ECB, and the Bank of England, offering a more global perspective on how digital asset markets respond to macro-financial shocks. This contrasts with Griffin and Shams, who primarily focus on the U.S. market when analyzing Tether and Bitcoin.

To sum up, Griffin and Shams (2020) add to the existing knowledge of how stablecoin behaviour can affect crypto markets. Their research shows that issuing Tether is both a signal and a way to stabilize prices. This raises important concerns about market influence and lack of openness. This thesis builds on what they said by asking how Tether and Bitcoin both react to sudden changes in how the world's money is handled. The fundamental question—how do outside factors affect cryptocurrency prices?—remains at the heart of both research, even though the underlying processes are different. This thesis brings additional dimensions to the argument over the interaction between centralized decisions and decentralized assets by including cross-asset, high-frequency, and cross-jurisdictional components.

3.3 Retail Demand and Emerging Market Sensitivity (*Marmora, 2022*)

Marmora (2022) presents a unique and significant contribution to the cryptocurrency macro-finance literature by analyzing the impact of monetary policy announcements on retail Bitcoin demand in 26 developing market nations. In contrast to the vast majority of studies that have focused on developed countries, especially the Federal Reserve System in the United States, Marmora's (2022) work offers a valuable international perspective. Expanding the geographic width of crypto-macro connections, his focus on emerging economies highlights circumstances where retail investor behavior plays a more significant role and monetary credibility is frequently weaker. The current thesis examines the effects of unexpected announcements by the Federal Reserve, the European Central Bank (ECB), and the Bank of England (BoE) on the short-term volatility and returns of Tether and Bitcoin, and this article is highly pertinent to the topic because of its larger scope. Despite differences in asset class and intended results, both studies are interested in the feedback loops that decentralized financial markets experience as a result of monetary policy signals.

The main question that drives Marmora’s (2022) study is whether and how news of central bank rates causes short-term rises in Bitcoin demand. Based on the paper's hypothesis, these disclosures serve as information triggers, particularly in contexts where the possibility of inflation is either hidden or unexpectedly highlighted. Instead of looking at asset prices, the study uses two behavioural indicators to simulate demand: the number of searches for "Bitcoin" on Google Trends and the number of peer-to-peer (P2P) transactions on LocalBitcoins, which was one of the most popular P2P crypto sites during the study time. It is important to note that the study does not use Paxful, which is often used in more current research. It also only looks at data from 2015 to 2019. These decisions highlight the paper's emphasis on public sentiment and retail investor behaviour, particularly in financial systems with limited or restrictive formal investment channels.

The empirical design is based on an event-study method, and the event windows are set up to record instant reactions. The study examines Google search behavior in a two-day window centred on each monetary policy statement. The event window is extended to ±1 week for the aggregated volume of LocalBitcoins, which is done weekly. To ensure the measured impacts align with the announcement timing, he staggered them to represent the different frequencies of the two demand proxies. The key conclusion is complex and intuitive: pronouncements about monetary policy only cause a big increase in interest in Bitcoin if they happen to coincide with surges in searches relating to inflation. This means that the policy signal and growing public anxiety about inflation work together to boost demand for Bitcoin, rather than the rate change alone.

Every country has a very different answer to this conditional problem. Even when there aren't any new policy moves, Bitcoin interest follows inflation worries in places where prices are always high and people are afraid their money will lose value. In countries where inflation is usually low or politically unimportant, the demand for Bitcoin only surges in response to central bank announcements that coincide with a dramatic uptick in searches for terms like "inflation" or "price rise." This new information backs up the idea that what really drives crypto behavior in these markets is the informational content of monetary policy, filtered through what people expect and how dangerous they think things are. Google search interest fades after roughly two days, while LocalBitcoins volume peaks during the announcement week and normalises in the following week (about 10 days after the decision). Such short-termness emphasizes how reflexive and emotion-based the demand reaction is.

The paper's analytical rigour comes from its panel regression design, which includes fixed effects for each country and interaction terms to see if policy effects change based on how urgent inflation is. To identify the unique influence of monetary announcements, the analysis controls for larger macroeconomic factors such as exchange rate movements and stock returns. One problem is that it relies on retail-focused, aggregated models that might not show intraday or institutional trade behavior, which are increasingly important in today's crypto world.

Marmora's (2022) work provides three significant insights for this theory. First, it demonstrates that monetary policy events do cause crypto markets to react in real time, even when the reactions are evaluated using behavioural measures rather than price-based ones. This gives substantial empirical evidence for the event-study method. This provides strong evidence in favour of the thesis's framework, which tracks volatility and cumulative abnormal returns within high-frequency windows of 0-6 hours around central bank surprises. Second, the fact that demand relies on inflation-related feelings emphasizes the significance of public expectations and credibility, especially in advanced economies after the COVID-19 epidemic and inflation spikes. Although the ECB and BoE have more stable inflation than most developing markets, recent geopolitical shocks and supply-side forces have also made people in Europe more sensitive to inflation.

Third, and most importantly, Marmora’s (2022) work emphasizes the need to identify uniform and diverse policy impacts. The study supports the current thesis's choice to separate policy effects by monetary authority by showing that central bank statements don't prompt the same reaction across countries. Understanding the international scope of monetary policy in a crypto-integrated world requires direct comparison of institutional credibility, signalling processes, and cross-market spillovers. This thesis includes three major central banks: the Fed, the ECB, and the BoE.

Despite these strengths, the study can't address the intra-day risk or pricing behavior fundamental to institutional crypto trading and market stability since it uses lower-frequency data (daily and weekly) and doesn't include price volatility or return-based outcomes. Furthermore, the focus on developing markets is interesting but may not fully apply to more developed financial systems because of the different conditions. By using hourly data from centralized exchanges and looking at price-based and volatility outcomes, this thesis overcomes these constraints and gives a more detailed picture of how crypto assets respond to policy shocks right after they happen.

Marmora (2022) shows that central bank rate announcements may affect short-term Bitcoin demand, especially when they coincide with inflation fears. The findings are temporary, sentiment-driven, and sensitive to institutional legitimacy, which fits this thesis's principles. Although the article refrains from directly analyzing Tether or using price data, it provides practical conceptual and analytical frameworks for comprehending how public expectations and monetary policy signals influence crypto market dynamics. This thesis extends existing findings by focusing on real-time pricing behaviour instead of retail search and volume to better understand monetary shock transmission into crypto markets.

3.4 Time-Varying Reactions to Policy Surprises (*Pietrzak, 2023*)

Pietrzak's research in 2023 is one of the most in-depth looks at how unexpected changes in monetary policy affect Bitcoin. It creates a dynamic framework that directly questions the idea that Bitcoin is an asset unaffected by policy changes. An essential difference between this paper and others is that Pietrzak looks at Bitcoin's reaction to monetary policy over time, showing that it is statistically significant and changes significantly from one system to the next. Given the dynamic character of both cryptocurrency markets and signals from central banks, this time-conditionality takes on further significance. His paper is a major source of inspiration for this thesis, which also looks at how announcements from the Federal Reserve (Fed), the European Central Bank (ECB), and the Bank of England (BoE) affect the short-term returns and volatility of Bitcoin and Tether. However, this time the focus is on high-frequency price data and short-term windows.

The time-varying parameter vector autoregression (TVP-VAR) model is central to Pietrzak's research; it enables the reaction of Bitcoin to change in both magnitude and sign over time. Crypto markets, which small groups once dominated, have grown into a realm of large institutional investors in just a decade, making this strategy ideal for them. The model uses a high-frequency macro identification technique to capture monetary policy shocks in monthly Bitcoin returns. Researchers can break down policy shocks into their "pure monetary" and "information" components by tracking how interest-rate futures and stock indices react in tandem around central bank announcements. When rates go up and stocks go down, it indicates unanticipated tightening and is called a "pure" monetary shock. An "information" shock happens when both yields and stocks go up, which means there is new information about the economy's future instead of a simple rate change.

The most interesting thing from the report was that Bitcoin's reaction to US monetary policy changed over time. From 2010 to around 2013, Bitcoin acted as an inflation hedge. When the Federal Reserve unexpectedly raises interest rates, its value drops, which aligns with the theory that higher rates will decrease inflation and, by extension, the attractiveness of decentralized assets that are resistant to price increases. In contrast, the correlation between unanticipated Fed tightening and favorable Bitcoin returns begins to invert after 2013. From this sign change, Bitcoin started acting more like a risk asset instead of a macro insurance as it became more widely traded, and speculative activity grew. Bitcoin may have become involved in the larger risk-on complex as investors began to view Fed signals as signs of economic strength.

Comparatively, ECB surprises have more consistent consequences. According to Pietrzak(2023), when the ECB makes "pure" monetary shocks (i.e., unexpected tightening), Bitcoin returns usually go down across the whole sample. This supports the comprehension of "digital gold" in the context of European policy. These deviations in reaction time show that Bitcoin's sensitivity changes over time and is jurisdiction-specific, depending on factors including investor base size, institutional trustworthiness, and international patterns of capital flows.

"Information shocks" behavior adds further complexity. When U.S. equity prices and bond yields rise, which the market interprets as a sign of stronger-than-expected fundamentals, Bitcoin's price tends to fall. On the other hand, similar "positive" information from the ECB tends to support Bitcoin prices. This could be because investors see Europe's strong economy as less of a threat and more of an opportunity to make global assets, including crypto, more open.

Unlike constant-parameter models, Pietrzak's TVP-VAR model is able to represent these dynamic interactions. His model shows that Bitcoin's response to monetary policy changes over time. For example, Bitcoin's response to monetary policy is stronger during stress episodes within the 2010-2019 sample, such as the 2013 ‘taper-tantrum’ period, but weaker in calmer months. When things are calm, the reaction is weaker, which shows that Bitcoin is both a way to speculate and a claimed macro hedge. This evolving relationship makes it clear that any attempt to estimate Bitcoin’s response to macro policy using a static model risks severely misrepresenting the actual dynamics.

However, the paper can't fully catch short-lived intraday effects because it only uses monthly return data. This is becoming more important to think about in the 24/7 crypto market. For instance, market reactions to Fed comments usually happen within hours, thanks to automated trading and the way investors around the world place their positions. A monthly window, on the other hand, could dilute these sudden responses with irrelevant overnight news or worldwide risk sentiment. Clearly, Pietrzak (2023) recognizes this problem, which makes it possible for high-frequency event studies like the one used in this thesis, which looks at changes in price and volatility within six hours of policy releases.

Pietrzak's (2023) work offers three key findings for this theory. To begin, it shows that Bitcoin is affected by monetary policy and that its responses change over time and rely on the situation. This provides strong evidence in favor of using external monetary shocks as causative factors to explain the short-term behavior of the cryptocurrency market. Second, multi-jurisdictional research is necessary because of the different reactions to Fed and ECB policies. The current theory adds the Bank of England as an extra central bank to look into how institutional legitimacy and market integration affect how monetary shocks affect the prices of digital assets. Third, the fact that the reaction changes over time supports the choice not to use pooled models but instead to use more detailed, event-specific estimates.

Pietrzak's (2023) work also provides a valuable benchmark for comparison in terms of methodology. Although his model is great at finding long-term structural changes, this thesis supplements it by looking at intraday traders, liquidity providers, and policymakers' interest in quick spillovers through high-frequency reaction windows. Moreover, this study incorporates Tether, a stablecoin not part of Pietrzak's (2023) methodology, into the analysis. This broadens the scope to encompass speculative and "stable" digital assets, providing a complete picture of how the market reacts to policy announcements.

In conclusion, Pietrzak (2023) offers an in-depth look at how Bitcoin responds to changes in monetary policy over time. His research challenges traditional views on the role of crypto in investors' portfolios. It demonstrates how cryptocurrency adjusts differently to larger economic changes based on the timing and location. For this thesis, the paper serves as both an intellectual foundation and a methodological complement. The analysis uses hourly data and compares different assets to examine short-term volatility and return patterns, unlike Pietrzak, who uses a monthly, flexible model focused on macro factors. Such a two-part approach offers an improved and more efficient understanding of how central bank shifts affect today's cryptocurrency markets.

3.5 Synthesis of Core Studies and Research Gaps (*Bridging Contributions and Limitations*)

The four main studies we looked at above show that more and more people realize that monetary policy affects cryptocurrency markets, even though these markets were once considered separate from standard macroeconomic forces. Bitcoin reacts poorly to unexpected US monetary tightening, according to Ma et al. (2022), particularly during strong market stages. In contrast, Griffin and Shams (2020) take a structural manipulation stance toward crypto volatility, highlighting how the supply of Tether might artificially sustain Bitcoin's price. Looking at emerging countries and consumer behavior through the window of Marmora (2022), we see that monetary announcements cause a jump in Bitcoin demand, especially as concerns about inflation grow. Using a time-varying parameter VAR model, Pietrzak (2023) pushes the limits of how research is done by showing how Bitcoin's response to shocks from both the Fed and the ECB has changed over time, with reaction signs even switching between subperiods.

Despite their diversity, these studies share several limitations that the present thesis seeks to address. Firstly, none of the existing monetary-policy studies (Ma et al., Marmora, Pietrzak) measure crypto reactions at an intraday frequency; they rely on daily or, in Pietrzak's case, monthly returns, which can miss the minutes-to-hours adjustment after policy news. This absence is crucial since policy announcements usually trigger market moves within minutes or hours rather than days. Consequently, the exact moment and degree of crypto responses can be overstated or disguised. Also, while looking at stablecoins in the broader macroeconomic environment, very few have looked at Tether. Although Griffin and Shams (2020) examine Tether issuance as an internal manipulative mechanism, no previous research has examined Tether's behavior in reaction to external policy shocks. Third, there isn't much comparison between different jurisdictions. Most publications concentrate on the Fed; among the four, only Pietrzak (2023) also analyses ECB shocks, and none of them considers the Bank of England. Nevertheless, as crypto use grows worldwide, knowing how markets react to messages from various monetary bodies becomes vital.

This thesis builds directly on these insights by addressing each of these gaps. It adds hourly data for Bitcoin and Tether from 2018 to 2023, enabling a detailed examination of short-term return and volatility patterns. It captures quick market movements by isolating cumulative anomalous returns and volatility variations during a well-defined six-hour window surrounding central bank statements. This research also offers a unique multi-bank viewpoint by factoring in unexpected moves by the Federal Reserve, the European Central Bank, and the Bank of England. It examines in a unique way whether crypto assets with varying degrees of volatility and design characteristics react differently to macroeconomic shocks by including both Bitcoin and Tether. By doing so, this thesis provides a more transparent and more timely perspective on the effects of monetary policy on the digital asset market and its relationships.

3.6 Supporting Studies: Stability, Sentiment, and Regulation(*Additional Context from Broader Literature*)

Besides the four main studies looked at in detail, many other papers also add to our understanding of how cryptocurrency markets respond to economic changes, governmental risk, and monetary policy changes. These studies don't prove this theory on their own, but together they give us important theoretical and empirical background.

Regarding Bitcoin's performance as a hedge and safe-haven asset, Bouri et al. (2017) provide one of the first and most referenced empirical studies. They show that Bitcoin has low hedging capabilities under normal market conditions but could provide diversification advantages during financial crises, although with more volatility, by analyzing daily returns across several global financial assets. It is more credible to study Bitcoin's behavior concerning particular macro shocks than under average conditions, and their finding that Bitcoin's safe-haven role is episodic rather than consistent lends credence to the time-varying and state-dependent sensitivity discussed in Ma et al. (2022).

In a fundamental analysis, Lyons and Viswanath-Natraj (2020) examine stablecoin pricing, arbitrage, and peg variations. As a result of arbitrage, they demonstrate that even well-known stablecoins such as USDT and USDC experience value fluctuations from their $1 pegs in the secondary market. However, these fluctuations are typically only temporary. Recognizing that stablecoins are not really "stable" and can experience price changes during times of market stress is at the heart of this thesis's study of Tether's response to monetary shocks.

The FTX exchange's collapse in November 2022 exposed stablecoins' weaknesses in times of systemic market stress. As a result of investor fear and a loss of faith in Tether's dollar backing, the USDT token momentarily dropped to $0.98 on many platforms (Lang & Howcroft,2022). Despite being unconnected to central bank actions, these de-pegging incidents show that Tether's stability is conditional, especially under uncertainty, supporting this argument that external shocks like monetary policy surprises may have a greater impact on stablecoins.

Feng et al. (2018) examine trade-level order-flow data (buyer- and seller-initiated orders) to detect informed trading, rather than relying on sentiment indices. They show that large buyer-initiated (seller-initiated) orders bunch just before big positive (negative) Bitcoin moves, implying informed traders anticipate price-moving events; the study does not model volatility regimes or institutional news amplification. This lends validity to the results of Marmora (2022) and Griffin & Shams (2020), which demonstrate that investor behavior reacts nonlinearly to changes in the perceived level of structural or macro risk.

The empirical foundation for this thesis is strengthened by these supporting studies, which support three main points: (1) Bitcoin's sensitivity to macro shocks is state-dependent and often nonlinear; (2) stablecoins, like Tether, can show temporary dislocations under stress, despite their design to offer price stability; and (3) institutional signals, whether they are policy-based, communicative, or regulatory, are potent drivers of crypto market behavior. Each study helps determine this research within a broader literature that seeks to understand the complex, evolving intersection of digital assets and global macroeconomic forces.

Even though there is more and more academic interest in how monetary policy affects bitcoin markets, there are still some critical gaps in the research. Many studies, such as Ma et al. (2022), rely on daily returns, whereas Pietrzak (2023) is based on monthly Bitcoin returns, so both still miss the minute-to-hour adjustments that policy news can trigger. Others, like Marmora (2022), look at developing markets or retail demand as a stand-in for price and volatility changes more often. In addition, most studies have focused on Bitcoin or stablecoins independently, without considering the combined effects of monetary stress on either asset class. It's also not common to compare the impact of central banks in different countries; not many studies do this regularly outside of the U.S. Federal Reserve. To fill these gaps, this thesis uses hourly data from 2018 to 2023 to examine how unforeseen modifications to interest rates and big economic news from the Fed, ECB, and BoE affect Bitcoin and Tether's short-term instability and returns. The study provides a more detailed and comparative look at how digital assets react to macro-financial shocks. It utilizes an event-study framework with six-hour windows, standardized surprise measures, and linear and nonlinear models. This helps us understand how sensitive the crypto market is in a developing, internationally connected financial system.

4 Data

4.1 Why these data

The main research question of this thesis is whether unexpected changes in monetary policy from the Federal Reserve (Fed), the European Central Bank (ECB), and the Bank of England (BoE) affect the very short-term behavior of two very different crypto assets: Bitcoin is the biggest and most frequently traded cryptocurrency based on its market value, and Tether is still at the top of the stablecoin market in terms of both circulation and trading volume (CoinMarketCap, 2025). If we want to answer a question that works on minutes instead of days, we need a data set that meets four conditions.

First, price observations need to be frequent. Obtaining high-frequency data is essential for catching the early reaction, as professional market participants react within minutes to central bank statements (Balduzzi, Elton, & Green, 2001). An hourly resolution is a good mix of granularity (which captures changes during the day) and tractability (which reduces microstructure noise). Hourly data strikes a valuable balance between intra-day granularity and tractability. While Andersen et al. (2003) work with 5-minute FX returns, they emphasise that coarser buckets can substantially reduce micro-structure noise while preserving most macro-news reactions..

Second, the data should include both the speculative and the more stable parts of the crypto market. Bitcoin involves taking risks on speculation, while Tether serves as the central system used for most direct cryptocurrency transactions. Looking at the two assets together allows for a more precise examination of whether policy changes affect only volatility-seeking positions or if even supposedly “stable” tokens are affected when macroeconomic news comes out.

Third, monetary events must be captured accurately, and specific expectations must be attached. By doing so, we can identify the "surprise" element—the part that can influence markets. Just knowing that the Fed raised rates isn't enough; what matters is if this decision differed from what futures prices and expert predictions had already anticipated.

Fourth, all series need to be set to Coordinated Universal Time (UTC). Cryptocurrency exchanges operate 24/7, whereas central-bank announcements follow local office hours.

Aligning the clocks removes misleading lead–lag effects and ensures that the six-hour time frames used in the event study are comparable across different regions and years. The fact that cryptocurrency markets are open 24 hours a day, seven days a week is a key trait of these assets that shows how decentralized and uncontrolled they are.

The data architecture used here fulfills those four criteria. It combines ready-to-use hourly OHLCV (open, high, low, close, volume) data streams from Binance and CryptoCompare with a unique event file that tracks 142 rate decisions and 382 major macro releases from 2018 to 2023, each marked with survey and market expectations. In this way, one can track the returns and volatility of crypto-assets from the moment a press release is published, measure the "shock" in standard-deviation units, and check if reactions vary by central bank, asset class, or type of announcement.

4.2 Data sources and retrieval

The hourly prices of cryptocurrencies are the primary focus of this thesis. Bitcoin prices were obtained directly from Binance, the world's largest spot exchange, using the public REST endpoint /api/v3/klines. I used the binancer package to stream the BTC/USDT pair in groups of 1,000 hourly candles, from December 1, 2017, until December 31, 2023. Unix-epoch time-stamps were changed to UTC-based POSIXct objects, and a simple cleaning process eliminated duplicate candles and a few zero-volume observations during scheduled exchange maintenance. The prices for Tether were obtained from CryptoCompare's v2/histohour feed, using 2,000-row reverse blocks with httr. This endpoint shows USDT in terms of U.S. dollars, so the close price stays close to one but still shows occasional changes in liquidity. For both assets, I calculated log returns using the formula:

$$r_{t,h} = \ln\left(\frac{P_{t,h}}{P_{t,h-1}}\right)$$

I also computed a 24-hour rolling standard deviation, which acts as a measure of intraday volatility. The tidy files for Bitcoin and Tether each have about 53,300 matching observations and the same column order, making it straightforward to combine them with the event data mentioned below.

Monetary policy announcements were gathered from the official schedules of the Federal Open Market Committee (FOMC), the European Central Bank's (ECB) Governing Council, and the Bank of England's (BoE) Monetary Policy Committee. Every scheduled decision was marked with the exact minute it was released (for instance, 18:00 UTC for FOMC statements). According to Kuttner (2001), we compare the fundamental change in the policy rate to two expectation benchmarks to separate it into expected and unexpected components. Survey-based expectations were drawn from Reuters economist polls accessed via Refinitiv Datastream, a common source in empirical macro-finance research (Ehrmann & Fratzscher, 2004). Market expectations were gathered from derivative pricing on the trading day before each meeting: Fed-funds futures probabilities from the CME FedWatch tool, three-month Euribor futures for the ECB, and SONIA overnight-index-swap strips for the BoE. The unexpected change in basis points is defined as

$$\text{Surprise}_{\text{bps}} = \Delta r_{\text{actual}} - \Delta r_{\text{exp}}$$

Surprise in basis points is calculated by taking the actual change in the interest rate and subtracting the expected change. This result is then transformed into a z-score for each central bank, allowing comparisons across different monetary systems.

A similar procedure was applied to high-profile macroeconomic releases. Headline CPI, GDP, and unemployment figures were downloaded from the Bureau of Labor Statistics, Eurostat, and the UK Office for National Statistics, respectively. Reuters' consensus forecasts once more acted as the expectation standard, resulting in a measure of macro surprises. The official release times are 12:30 UTC for U.S. CPI, 10:00 UTC for Euro-area flash inflation, and so forth. These times were rounded to the nearest hour to match the price series.

Before merging, the event list was trimmed down to include only two ECB pandemic-era conference calls that happened during exchange outages and a small number of observations (less than 5 percent) that did not match either survey or market expectations. Each event that survived was connected to the cryptocurrency table. For every announcement from the Fed, ECB, or BoE, I calculated the six-hour cumulative abnormal return and the related six-hour actual volatility for both Bitcoin and Tether. The reaction window is short and applied consistently, and surprises are treated the same within the issuing authority. This makes the dataset good for testing whether unexpected monetary signals have real, asset-specific effects on the crypto market, which is what the next chapters will do.

4.3 Sample Construction and Cleaning

The two raw price files and the two announcement files were then merged into one event-return panel, forming the thesis's primary basis. The research design looks at how cryptocurrency behaves in the six hours after each monetary or macro announcement. For each announcement and each asset, we calculate the six-hour CAR and volatility as long as there's at least one hourly price in the 0→6 h window—only announcement–asset pairs with absolutely no data in that window are dropped. When that merge was done in R, it created three real data-quality problems that needed to be cleaned up in a planned way: coverage gaps in the price feed, irregular release time stamps, and missing expectation benchmarks.

The coverage-gap filter handled times when either Binance or CryptoCompare provided no data. Visual checks and API status logs showed that almost all gaps were caused by planned maintenance or short network outages that lasted under twenty minutes. If an announcement happened during a gap, the event-asset row was marked as incomplete and taken off the panel. However, the price series remained unchanged because the following volatility measures depend on continuous returns only within the six-hour window. The filter removed about three per cent of scheduled releases, which is a reasonable loss that did not significantly change the distribution of events across banks.

A second challenge came from announcements that were made outside the usual schedule. Most policy decisions are usually announced at the top of the hour. Still, some actions from the pandemic period, especially the Fed's emergency rate cuts in March 2020, were released at different times, like 14:15 UTC. Hourly alignment is vital for a smooth merge, so any irregular time-stamp was moved to the next full hour as long as the gap was no more than thirty minutes. Announcements that went over this limit were removed. The rule kept the necessary pandemic actions that were released fifteen minutes after the hour. Still, it did not include a few specific ECB teleconferences that were announced more than an hour outside of regular hours.

The last screening requirement was about how complete the expectations were. A valid surprise needs both a survey median and a market-implied probability. The actual policy change can't be measured without these benchmarks as a comparable shock. At the beginning of the sample, Reuters' coverage of Bank of England macroeconomic data was inconsistent. Similarly, Euribor futures sometimes do not account for 100-basis-point changes, making the estimated likelihood of significant movements unreliable. Because of this, announcements that did not include either poll or future statistics were not included. Missing expectations often happen with less significant macro releases, so this filter slightly decreased the number of macro events but kept the main policy rate decisions unchanged.

The master panel now has two rows for each surviving announcement—one for Bitcoin and one for Tether—and provides the two event-window statistics needed for a standard MacKinlay-style event study. To start, we compute abnormal returns by subtracting a constant average benchmark from each hourly log-return: The expected return is represented as $E[r_{i,t}] = \overline{r_{i,\mathrm{pre}}}$, the average hourly return during the 60-day pre-event window ending 24 hours before the announcement. A constant mean is preferred over a CAPM forecast because (i) there is no universally accepted crypto ‘market index’, and (ii) prior intra-day event study work on FX and Bitcoin, such as Ma et al. (2022), also uses mean-adjusted returns. The average hourly return of asset i is defined as the return over the sixty calendar days that end twenty-four hours before the announcement. Abnormal returns can be calculated using the formula:$r_{i,t+\tau}^{\mathrm{AR}} = r_{i,t+\tau} - \overline{r_{i,\mathrm{pre}}}$ for τ = 0, …, 6. The six-hour cumulative abnormal return is the total of those seven hourly differences.

$$\mathrm{CAR}_{\mathrm{i,t}}^{\mathrm{6h}} = \sum_{\tau=0}^{6} r_{i,t+\tau}^{\mathrm{AR}}$$

Since returns are log-scaled, CAR_{6h} can be interpreted approximately as a percentage price change over the seven-hour window. During the same period, the script calculates realized volatility by finding the standard deviation of the raw hourly log-returns.

$$\mathrm{Vol}_{\mathrm{i,t}}^{\mathrm{6h}} = \sqrt{\frac{1}{6}\sum_{\tau=0}^{6}\left(r_{i,t+\tau} - \overline{r_{i,t}^{6h}}\right)^{2}}, \quad \overline{r_{i,t}^{6h}} = \frac{1}{7}\sum_{\tau=0}^{6} r_{i,t+\tau}$$

Note: According to Reichel (2024), the formula for Vol_{6h} employs Bessel's correction by dividing by n−1 (= 6) instead of n (= 7) to provide an unbiased estimator of the population *variance. This adjustment accounts for the bias introduced when estimating the population mean from the sample. Such practice is standard in statistical analysis and financial econometrics.*

No adjustments like winsorization or trimming are made; extreme values are kept so that significant policy changes, like the consecutive 75-basis point Fed hikes of 2022, can be clearly seen in later analyses.

The pre-merge checks show that the kept sample is evenly distributed among central bank areas. The final panel usually has just under one hundred Fed events, about the same number of ECB events, and roughly seventy-five of those for the BoE. Exact counts may change a bit with each data update. About two-thirds of the observations are decisions on policy rates, while the other third includes major economic reports like CPI, GDP flash estimates, and labor market updates. This composition makes sure that both “pure monetary” shocks and larger macro surprises are included in enough quantity to allow for meaningful comparisons.

4.4 Variable Definition

All the variables in the following chapters can be categorized into five main groups based on their functions. Event identifiers include the issuing authority (CentralBank), the type of category (Rate or Macro), and the release time in UTC. (i) Standardised surprises consist of market-based and survey-based policy shocks (Surprise_Market_z, Surprise_Survey_z, ChangeBps_z) along with the macro surprise (Surprise_Macro_z). Each of these is a z-score created by the central bank, meaning that a change of one unit always indicates a surprise that is one standard deviation from that authority's historical data. (ii) Asset indicators show if the row is about Bitcoin or Tether. Bitcoin is used as the standard category in all regression models, so the signs of the coefficients indicate differences compared to the speculative asset. The outcome variables are CAR_6h and Vol_6h, representing return and risk, respectively. CAR_6h is the six-hour cumulative abnormal return, computed by subtracting a 60-day pre-event average hourly return from each hourly log return during the event window. Vol_6h is the standard deviation of hourly log returns over the same window. Robustness flags indicate announcements that happen during local equity-market hours and those that take place during the pandemic period; these markers help with the subsample checks discussed later.

In summary, the combined and organized dataset presents a valuable and frequent opportunity to examine if and how unexpected central-bank information affects the crypto-asset market. The panel keeps extreme observations, aligns events to hourly candles, and adjusts surprises from the issuing authority. This setup aims to generate coefficient estimates that can be easily understood in economic terms—dollar-for-dollar and basis-point-for-basis-point. The next chapter clearly outlines specific hypotheses based on theory and previous evidence and connects them to the variables presented here.

4.5 Descriptive Stats

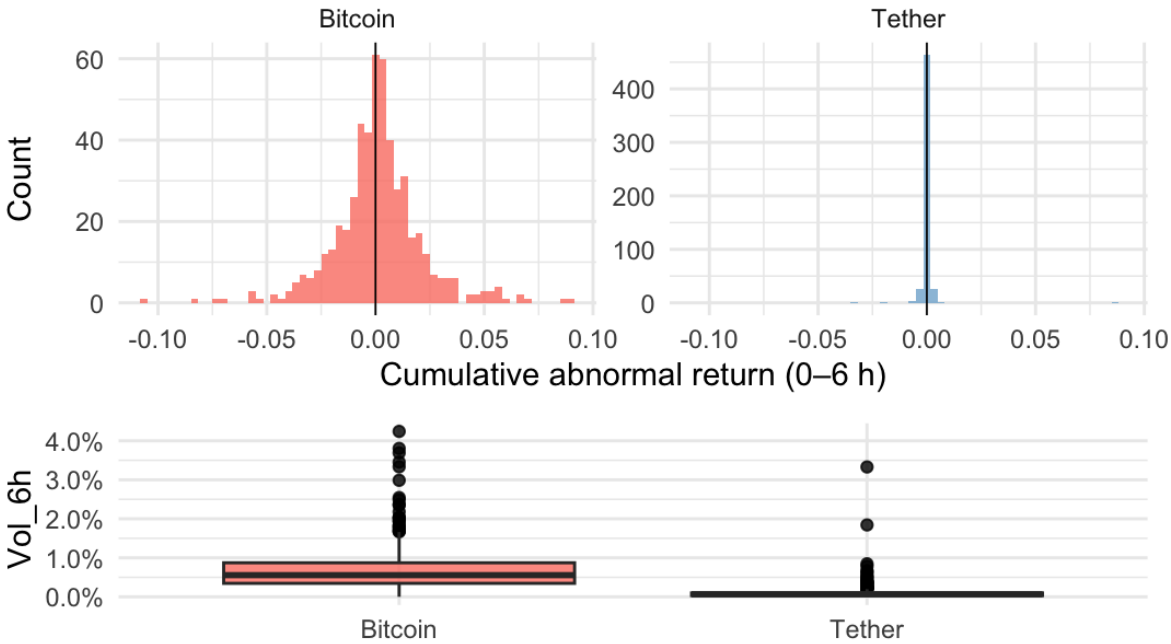
The cleaned and matched event-return panel offers a clear basis for examining how Bitcoin and Tether react to central bank announcements. Before estimating formal models, it's important to look at the distribution properties of the main outcome variables: six-hour cumulative abnormal returns (CAR_{6h}) and realized volatility (Vol_{6h}). These variables were computed for every cryptocurrency–event pair over a seven-hour window starting from the event hour ($\tau = 0$ to $\tau = 6$). Table 4.5 summarizes the statistics, and Figure 4.1 illustrates the distributions of return and volatility.

Table 4.5 — Event-window descriptive statistics (0-6 hours)

All values are computed over the 6-hour window following each event

Asset	n_events	mean_CAR (6h)	sd_CAR (6h)	skew_CAR (6h)	kurt_CAR (6h)	mean_Vol (6h)	sd_Vol (6h)	skew_Vol (6h)	kurt_Vol (6h)
Bitcoin	524	0.001	0.021	0.020	6.729	0.007	0.005	2.536	13.117
Tether	524	0.000	0.004	13.792	304.056	0.001	0.002	11.706	182.639

Figure 4.1 — Distribution of six-hour CAR and realised volatility



For Bitcoin, the average six-hour CAR is modestly positive (mean ≈ 0.001), but the standard deviation is high (≈ 0.021), indicating substantial variability in price responses to central bank news. The distribution shows a moderate level of excess kurtosis (about 6.73), a pattern commonly associated with speculative assets that exhibit fat tails in their return distributions—one of the well-documented stylized facts in financial economics (Cont, 2001). The skewness is slightly positive (about 0.02). The six-hour realized volatility for Bitcoin is high, with an average of about 0.7% and a standard deviation of 0.5%. Volatility is significantly right-skewed, with a skewness of about 2.53, and shows strong kurtosis at around 13. This indicates that there are significant jumps or spikes, even in short periods.

The way Tether acts is very different. The average CAR of the stablecoin is about zero (≈ 0.000), and its standard deviation is significantly lower (≈ 0.004). However, its return distribution exhibits extreme kurtosis (304.06) and strong positive skewness (13.79), which means that while Tether generally stays close to its peg, there are occasional but notable deviations. These deviations are likely related to market stress events, such as the FTX collapse in November 2022, during which liquidity pressures and redemption risks temporarily pushed Tether's price away from its peg (Reuters, 2022; Griffin & Shams, 2020). The actual volatility in Tether is very low (average around 0.1%), but similar to CAR_{6h}, it has a very high kurtosis (about 182.64). This suggests that while big changes are uncommon, they can be pretty significant when they do happen.

The patterns match what we expected. Bitcoin behaves like a risky investment that can change considerably in price based on news that impacts how investors feel about future risks and returns. Tether has a very low average return and minimal price fluctuation, with its periodic unusual changes appearing as rare events. These distributional patterns provide early evidence that motivates the hypothesis tests in the next chapter, especially regarding asset-specific sensitivity to policy and macroeconomic shocks. It suggests that Bitcoin responds more intensely to monetary and macro surprises compared to Tether, and that decisions on interest rates have a greater impact than past macroeconomic data.

4.6 Data Limitations

Although the event–return panel made for this study has much institutional coverage and a high level of temporal resolution, some concerns with the data need to be pointed out. First, there can be slight differences in timing between price feeds and announcement records, especially for macroeconomic releases gathered from presswire APIs. Even though all events were set to the closest full hour, publishing and web scraping delays might cause differences of up to one minute, affecting the return linked to the announcement hour. Such time differences are a well-known difficulty in matching macroeconomic pronouncements with market data, as emphasized by Andersen et al. (2003). Because the analysis is detailed down to the hour, these mismatches probably won't significantly affect the results, but they could introduce some confusion, particularly during times of high volatility. Additionally, although the abnormal return (CAR_{6h}) is computed using a constant-mean benchmark from a pre-event window, it remains sensitive to such timing mismatches because the benchmark itself is based on a fixed historical period. This constant-mean method follows standard practice in high-frequency event studies where model-based expected returns (like CAPM) are impractical due to market structure or data limitations.

Second, Binance and CryptoCompare's price info was mostly accurate, but sometimes it wasn't because of planned exchange maintenance or short-term API problems. A small number of dropped observations (about 3%) were due to these episodes, but they could lead to selection bias if important announcements happened during the downtime. During the panel construction, these gaps were carefully removed, and visual inspections showed that the missing candles were not grouped around any particular central bank or asset.

Third, stablecoins such as Tether raise specific issues related to transparency and liquidity. Tether's price is usually tied to traditional currency values, but it can sometimes change because of issues like not enough liquidity on exchanges, problems with redeeming it, or stress in the market. These liquidity and redemption frictions can induce the pronounced skewness and kurtosis we observe in six-hour returns and volatility (see Section 4.5). Additionally, Tether does not fully share its reserve information in real time, making it harder to understand its risk compared to more transparent assets. In March 2025, Tether's CEO acknowledged the absence of complete real-time reserve data and indicated that auditing the reserves is a "top priority" (Lang & Howcroft, 2025).

Lastly, all surprise factors depend on up-to-date, accurate futures data, especially those that are based on market-implied odds. In times of great uncertainty, like early 2020, futures markets can become hard to trade or show unrealistic expectations, which might reduce the accuracy of surprise measures. The limits of utilizing futures data to measure market expectations are also covered by Kuttner (2001), particularly in unpredictable environments. Even though z-score standardization helps reduce these issues, they still cause some measurement noise.

These limitations do not invalidate the results but suggest that care is warranted when interpreting small effect sizes or drawing firm conclusions about individual announcements. In subsequent chapters, robustness tests address these problems where applicable.

5 Hypotheses Development

This chapter presents the main testable ideas by directly analyzing how Bitcoin and Tether react to monetary policy and economic news. The ideas behind these hypotheses come from theoretical understanding of asset pricing and previous research on how traditional and digital assets react to changes in information, liquidity, and investor feelings. The structure is divided into four sections: how different reactions occur to rate and macro surprises; the specific responses of assets like Bitcoin and Tether; the differences among central banks; and the variations between return and volatility effects, which may include nonlinear or asymmetric dynamics.

5.1 Rate vs Macro Surprises

This thesis focuses on the difference between two kinds of announcements: (i) monetary policy decisions, like changes in interest rates,[2] and (ii) macroeconomic indicators, such as CPI, GDP, and unemployment rates. In the traditional view of financial economics, monetary shocks change the expected direction of short-term rates, discount factors, and liquidity premia, which affect asset prices (Christiano et al., 1999). Macroeconomic surprises usually show changes in basic growth or inflation conditions. While they may look back at past data, they are still crucial for future policies and asset values.

Hypothesis 1a (H1a): Bitcoin reacts more strongly to monetary policy surprises than to macroeconomic surprises.

This theory fits with Bitcoin's behavior as a speculative and risk-sensitive asset whose price is primarily driven by expectations and liquidity (Bouri et al., 2017). Monetary policy surprises change how people expect interest rates to move, affecting how attractive non-yielding assets like Bitcoin are. For example, sudden tightening could make people less willing to take risks and have flexible assets, leading to sell-offs in risky assets. On the other hand, macroeconomic surprises might not have much impact unless they clearly indicate a policy change. Previous research, including studies by Ma et al. (2022) and Pietrzak (2023), suggests that Bitcoin reacts noticeably to changes in monetary policy, particularly when these changes are seen as surprising.

Hypothesis 1b (H1b): Tether does not exhibit meaningful return or volatility reactions to either rate or macro surprises.

Tether is a stablecoin that is linked to the US dollar, aiming to keep a 1:1 exchange rate with it. Theoretically, its price shouldn't change based on economic news, as long as the processes that keep the price stable don't break down. However, there are times when the market is

[2] Monetary policy surprises (hereafter 'rate surprises') refer exclusively to unexpected changes in the policy rate—rate decisions by the FOMC, ECB Governing Council, or BoE MPC

stressed and there is much volatility, like when an exchange goes bankrupt or there is a rush to redeem assets. This can cause returns and volatility to be spread out in a fat-tailed way. Lyons & Viswanath-Natraj (2023) find that, post-Ethereum migration, Tether's peg deviations have a mean of –0.9 basis points and a standard deviation of 47.2 basis points, implying average returns effectively zero even during turbulent periods.

5.2 Asset-Specific Sensitivity

Next, we confirm if Bitcoin and Tether behave differently to the same information, depending on the type of announcement and the central bank involved.

Hypothesis 2a (H2a): Bitcoin reacts more strongly to unexpected actions from central banks than Tether.

This difference should show up in both return and volatility measurements. Bitcoin has no intrinsic worth or income stream, so its value is mostly based on individual expectations and predictions. Unexpected announcements that change how people view risk should have a bigger impact on Bitcoin than on Tether. Marmora (2022) demonstrates that monetary policy announcements significantly influence local Bitcoin demand, particularly in emerging markets sensitive to inflation expectations.

Hypothesis 2b (H2b): The difference in impact between Bitcoin and Tether is more apparent during rate events compared to macro events.

It demonstrates that rate decisions focus on the future and are closely linked to current financial conditions, whereas macro data usually looks at the past. Because Bitcoin trades all the time and responds quickly to changes in discount rates, decisions about monetary policy should have a bigger marginal effect than changes in ex-post economic measures.

5.3 Central Bank Heterogeneity

Not every announcement from a central bank is equally important. The Federal Reserve (Fed), European Central Bank (ECB), and Bank of England (BoE) have different levels of openness, sizes of markets, and ways of communicating their intentions.

Hypothesis 3a (H3a): Bitcoin reacts most strongly to unexpected changes in monetary policy from the Federal Reserve, then the ECB, and least strongly to the BoE.

This ranking considers how widely the market is reached and how central it is perceived. The Federal Reserve is dominant in shaping global financial conditions, given the dollar's role as the world's reserve currency and the centrality of U.S. risk-free rates. Their choices affect the availability of dollars, interest rates without risk, and investment strategies around the globe. Furthermore, Ma et al. (2022) demonstrate that Bitcoin profits drop greatly when unexpectedly high U.S. Treasury yields occur. This suggests that even in decentralized asset markets, Fed tightening lowers people's willingness to take risks. In this way, Bitcoin is like other risky investments. This suggests that investors see the Fed as a key indicator for global monetary trends. On the other hand, the ECB and BoE have more of an impact on the region, so their comments are likely to have less of an effect. So, we believe that surprises from the Fed will cause the most reaction, followed by surprises from the ECB and then the BoE.

Hypothesis 3b (H3b): The differences in how Tether reacts among central banks are not statistically significant.

Since Tether's peg isn't officially enforced by interest rates or central bank balance sheets, and since it doesn't change much regularly, it shouldn't matter which institution makes the announcement. There might be small exceptions because of delays in arbitrage at the exchange level or issues with USD funding, but these should not lead to ongoing differences between jurisdictions.

5.4 Return vs Volatility Effects

It's important to differentiate between how announcements affect the average return and how they influence uncertainty, or realized volatility. Returns reflect the average market view on whether an asset becomes more or less attractive. Volatility, on the other hand, shows how the price finding process is affected by different views and problems with liquidity.

Hypothesis 4a (H4a): Unexpected announcements lead to greater short-term volatility than they do changes in the mean return.

It's normal to see this imbalance in financial markets. Event-study evidence shows that major news releases generate sharp bursts in trading activity and realised volatility in crypto markets while average price moves remain modest; for example, event-study evidence shows that major regulatory announcements trigger significant bursts in trading activity and price jumps (Auer & Claessens, 2020), and Corbet et al. (2017) find that FOMC statement windows raise conditional volatility in currency-type tokens like Bitcoin, with muted mean-return effects. In the case of Bitcoin, which has a decentralized and fragmented market, there may be a considerable amount of uncertainty after the announcement.

Hypothesis 4b (H4b): Tether's volatility responses are small in magnitude but display extreme kurtosis.

While Tether generally maintains price stability, studies have observed that during periods of market stress, it can experience significant volatility spikes, resulting in a return distribution with high kurtosis. This causes it to have a high excess kurtosis. The spikes might not be consistent reactions to policy news, but their statistical features, like excess kurtosis, need to be modelled. In regression terms, this implies weak or insignificant slope coefficients but high dispersion in residuals. Djobenou et al. (2023) with time-varying DAR modeling demonstrate that Tether/USD rates exhibit time-varying volatility, persistence, and fat tails under stress

5.5 Asymmetries and Nonlinearities

Lastly, we examine asymmetric reactions: we look at whether the direction or dimension of the surprise affects the degree to which the crypto responds.

Hypothesis 5a (H5a): Negative monetary policy surprises (e.g., unexpected rate hikes) generate larger reactions in Bitcoin returns and volatility than positive surprises.

This disparity comes from well-known results in information theory and behavioural finance. Unexpected adverse shocks, like rate hikes, often mean bad news about the ability to control inflation or liquidity. These tend to get stronger replies because they make things less certain and warn of future, tighter financial conditions. Investors usually respond more strongly to threats than to chances. This is because they don't want to lose money and want to be safe.

Because Bitcoin has no built-in cash flows and is largely driven by emotion, risk appetite, and speculation, bad policy shocks will likely cause bigger sell-offs and more volatility (Cheah & Fry, 2015; Baur, Hong, & Lee, 2018). This trend is similar to what we see in the stock and bond markets, where big price drops have big effects.

Hypothesis 5b (H5b): Large surprises (in absolute value) disproportionately affect Bitcoin volatility.

This hypothesis takes into account the fact that the market reaction might not be linear. Financial markets don't always respond in a straight line when new information arrives; instead, they exhibit nonlinear, convex reactions (Engle & Ng, 1993; Cont & Bouchaud, 2000).For example, a surprise of two standard deviations may have more than twice the effect of a surprise of one standard deviation. This shows that the response function is convex, which is often caused by limited liquidity, nonlinear pricing of risk, stop-loss orders being activated, or people paying off their debt. For Bitcoin, big shocks may also cause people to trade in groups or automatically through programs, which makes the price even more volatile. Here, we use both linear models (with a quadratic term) and random forest regressions to look for nonlinear effects that normal methods might not detect.

5.6 Conclusion

These five sets of hypotheses work together to give us a complete picture of how cryptocurrencies react to big news in the financial world. They enable different effects on various assets, types of events, central banks, and outcome variables, and allow for investigating uneven and nonlinear behaviors. The models in the following chapters are specifically created to test these ideas using clear linear methods and resilient machine learning techniques.

6 Methodology

6.1 Overview

This chapter clarifies the research design used to examine whether cryptocurrencies, particularly Bitcoin and Tether, react to changes in monetary policy and unexpected macroeconomic events. The analysis looks at how prices react in a specific direction, measured by cumulative abnormal returns over a six-hour period. The return measure used, cumulative abnormal return (CAR_{6h}), is computed by subtracting the asset's average hourly log return over the 60-day pre-event window from each hourly return in the 0–6 hour event window, following standard event study methods. It also explores the effect on short-term uncertainty, indicated by the standard deviation of returns during that same period. By looking at both outcomes, this dual outcome theory helps us fully comprehend how digital assets change in value and price after central bank and macroeconomic news.

To test the hypotheses formulated in the previous chapter, the empirical strategy adopts a two-pronged modelling approach. First, linear regression models help us understand how unexpected variables impact returns and volatility outcomes. These models are ideal for hypothesis testing and inference since they are interpretable and based on conventional asset pricing theory. Second, random forest regressions are used as an extra stability check to look for possible nonlinear or interaction effects that linear models might miss. These nonparametric models are better at finding complicated trends in the data and testing whether the results are the same across different research methods.

In combination, these methods offer a solid database for figuring out how Bitcoin and Tether react to changes in rates and the economy as a whole, how the differences between central banks affect these responses, and whether reactions are different regarding returns and volatility.

6.2 Event study framework

6.2.1 Event Definition and Window Selection

This study defines each event as a scheduled release with a specific time from one of three main monetary authorities: the Federal Reserve (Fed), the European Central Bank (ECB), or the Bank of England (BoE). These events can be grouped into two types: decisions about monetary policy (like changes in interest rates and official statements) and macroeconomic data releases (such as consumer price index, gross domestic product, and unemployment numbers). Time stamps for each event are set in Coordinated Universal Time (UTC) to ensure that everything is consistent and in sync with Bitcoin markets worldwide.

To capture the instantaneous market response to newly disclosed data, establish an event window that begins at the time of disclosure and ends six hours after the announcement (+6 hours). The 0–6 hour window encompasses seven hourly returns in total, including the announcement hour and the six subsequent hours (i.e., τ = 0 to 6). First, the cryptocurrency market is always open, with high-frequency trading and quick price finding. A six-hour window gives enough time to reflect on immediate reactions and quickly adjust without mixing in unrelated news.

This design is similar to what was done in earlier studies, like Ma et al. (2022), who used a comparable intraday time frame to examine how Bitcoin prices react to unexpected economic changes. A shorter time frame might miss important market changes that take a little longer to happen, while other market events could affect a longer time frame. The 0–6 hour window balances accuracy and thoroughness, making it an appropriate choice for identifying announcement effects.

6.2.2 Outcome Variables

To evaluate the way cryptocurrency markets react to economic announcements, we look at two important measures: the cumulative abnormal return (CAR) and realized volatility (Vol). Both are calculated over the 0–6 hour period after each event.

The cumulative abnormal return shows how much an asset's return during a specific event period differs from its usual behaviour before the event. Abnormal returns are calculated by subtracting the average hourly log return over a 60-calendar-day estimation window, ending 24 hours before the event, from each of the seven post-event hourly returns:

$$r_{i,t+\tau}^{\mathrm{AR}} = r_{i,t+\tau} - \overline{r_{\iota,\mathrm{pre}}}, \quad \text{for } \tau = 0, \dots, 6$$

The 6-hour cumulative abnormal return is then the sum of these abnormal returns:

$$\mathrm{CAR}_{\mathrm{i,t}}^{\mathrm{6h}} = \sum_{\tau=0}^{6} r_{i,t+\tau}^{\mathrm{AR}}$$

This constant-mean benchmark approach is widely used in event studies, particularly where no universally accepted market index exists, as is the case with cryptocurrencies. It avoids the need to model expected returns with additional assumptions and aligns with prior high-frequency studies (Andersen et al., 2003; Mackinlay, 1997).

As returns are in log form, CAR_{6h} approximates the cumulative percentage price change over the 7-hour window. The Vol_{6h} is calculated by finding the standard deviation of the raw hourly log returns.

$$\mathrm{Vol}_{\mathrm{i,t}}^{6\mathrm{h}} = \sqrt{\frac{1}{6}\sum_{\tau=0}^{6}\left(r_{i,t+\tau} - \overline{r_{i,t}^{6h}}\right)^2}, \quad \overline{r_{i,t}^{6h}} = \frac{1}{7}\sum_{\tau=0}^{6} r_{i,t+\tau}$$

The direction and magnitude of the asset's return response are captured by CAR_{6h}, while Vol_{6h} represents the uncertainty or variability in pricing during the response period. We examine each asset-event pair independently to evaluate the reaction of more stable tokens like Tether with that of speculative instruments like Bitcoin.

6.2.3 Construction of Event Data

The event dataset includes monetary policy and macroeconomic releases from 2018 to 2023. We gathered events from organized, prepared-to-use CSV files that included important economic indicators and central bank decisions for the United States (Fed), Euro Area (ECB), and United Kingdom (BoE).

Every monetary policy event is paired with three different surprise measures:

- *Surprise_Market: the difference between the actual decision and market-implied expectations*

- *Surprise_Survey: the difference from what professional forecasters agree on*

- *ChangeBps: the raw change in the policy rate, expressed in basis points*

For macroeconomic events (e.g., CPI, GDP, unemployment), a single surprise measure is computed:

- *Surprise_Macro: the difference between the realized and expected value of the release*

It's important to note that macroeconomic announcements are released together with central bank decisions, but these announcements usually come from national or regional statistical agencies, not the central banks. For instance, data from the U.S. is sourced from the Bureau of Labour Statistics (BLS) and the Bureau of Economic Analysis (BEA). In the UK, data is provided by the Office for National Statistics (ONS), while Euro area data comes from Eurostat. These data releases are not controlled by central banks but strongly influence monetary policy expectations, justifying their inclusion in this study (Ma et al., 2022).

All surprise variables are standardized within their respective categories (policy or macro) using z-scores. This standardization helps to compare different countries and types of events, and it also makes it more straightforward to understand regression models.

A loop iteratively extracts the CAR_6h and Vol_6h values for each combination of asset and event to compute asset responses. The return data for each asset is matched to the event dates, and the appropriate six-hour window is put together. The dataset combines asset-level outcomes with event-level data, creating a well-organized panel that can be used for regression and machine learning analyses. Each observation is individually recognized with the central bank, event timestamp, event class, and asset.

6.2.4 Linear Regression Models

This study starts by using a set of linear regression models to inquire at how economic news affects cryptocurrency markets in the short term. These models give straightforward and comprehensible estimates of how Bitcoin and Tether react to various announcements. Different regressions are calculated for two types of events: monetary policy (Rate) and macroeconomic data releases (Macro). The result variables are six-hour cumulative abnormal returns (CAR_6h) and six-hour realized volatility (Vol_6h).

The base models for monetary policy shocks are specified as follows:

- **CAR model for Rate events:**

$$\mathrm{CAR}_{6\mathrm{h}} = \beta_1 \cdot \mathrm{Surprise\_Market}_z + \beta_2 \cdot \mathrm{Surprise\_Survey}_z + \beta_3 \cdot \mathrm{ChangeBps}_z + \beta_4 \cdot \mathrm{CentralBank} + \beta_5 \cdot \mathrm{Asset} + \varepsilon$$

- **Volatility model for Rate events:**

$$\mathrm{Vol}_{6\mathrm{h}} = \gamma_1 \cdot \mathrm{Surprise\_Market}_z + \gamma_2 \cdot \mathrm{Surprise\_Survey}_z + \gamma_3 \cdot \mathrm{ChangeBps}_z + \gamma_4 \cdot \mathrm{CentralBank} + \gamma_5 \cdot \mathrm{Asset} + \varepsilon$$

- **CAR model for Macro events:**

$$\mathrm{CAR}_{6\mathrm{h}} = \theta_1 \cdot \mathrm{Surprise\_Macro}_z + \theta_2 \cdot \mathrm{CentralBank} + \theta_3 \cdot \mathrm{Asset} + \varepsilon$$

- **Volatility model for Macro events:**

$$\mathrm{Vol}_{6\mathrm{h}} = \lambda_1 \cdot \mathrm{Surprise\_Macro}_z + \lambda_2 \cdot \mathrm{CentralBank} + \lambda_3 \cdot \mathrm{Asset} + \varepsilon$$

For direct comparisons across countries and indicator types, all surprise factors are normalized within blocks using z-scores. Dummy variables for Asset (Bitcoin or Tether) and CentralBank (Fed, ECB, BoE) account for consistent behavior differences between institutions and instruments. These base models are designed to identify average marginal effects per one standard deviation of surprise.

Only Surprise_Market_z (for monetary policy events) and Surprise_Macro_z (for macroeconomic statements) are used to make the unified surprise variable Surprise_z for the main regression framework. With this standardization, there is a consistent and similar way to measure both types of economic shocks.

Surprise_Survey_z is part of the base specification for Rate events, but it's not part of Surprise_z for two key reasons. To begin with, the sample size would be substantially diminished if it were incorporated, as it is unavailable for non-U.S. events and earlier observations. Second, poll surprises are useful for breaking down the effects of monetary policy at a finer level, especially in exploratory analysis. However, they are not available for macroeconomic announcements, which means they would make the unified model less balanced. Therefore, Surprise_Survey_z is kept in the base model of Rate events to help with interpretation, but it is not included in the unified modeling pipeline that tests all theories.

About Interaction Terms and Nonlinear Extensions, as a strict way to test all of the hypotheses, interaction and nonlinearity terms are added to the regression framework:

- Asset × Shock × Surprise interactions are introduced to test whether the impact of surprises varies by both asset type and event class (H2a, H2b)

$$CAR_{6h} = \beta_0 + \beta_1 \cdot Surprise_z + \beta_2 \cdot Asset + \beta_3 \cdot ShockType + \beta_4 \cdot (Surprise_z \times Asset) + \beta_5 \cdot (Surprise_z \times ShockType) + \beta_6 \cdot (Asset \times ShockType) + \beta_7 \cdot (Surprise_z \times Asset \times ShockType) + \varepsilon$$

$$Vol_{6h} = \beta_0 + \beta_1 \cdot Surprise_z + \beta_2 \cdot Asset + \beta_3 \cdot ShockType + \beta_4 \cdot (Surprise_z \times Asset) + \beta_5 \cdot (Surprise_z \times ShockType) + \beta_6 \cdot (Asset \times ShockType) + \beta_7 \cdot (Surprise_z \times Asset \times ShockType) + \varepsilon$$

- CentralBank × Surprise interaction terms check if Bitcoin and Tether react more to surprises from the Fed compared to shocks from the ECB or BoE (H3a, H3b)

$$CAR_{6h} = \theta_0 + \theta_1 \cdot Surprise_z + \theta_2 \cdot CentralBank + \theta_3 \cdot (Surprise_z \times CentralBank) + \varepsilon$$

$$Vol_{6h} = \theta_0 + \theta_1 \cdot Surprise_z + \theta_2 \cdot CentralBank + \theta_3 \cdot (Surprise_z \times CentralBank) + \varepsilon$$

- Surprise × ShockSign interaction terms are added to identify asymmetric reactions to positive vs negative surprises (H5a)

$$CAR_{6h} = \alpha_0 + \alpha_1 \cdot Surprise_z + \alpha_2 \cdot ShockSignPositive + \alpha_3 \cdot (Surprise_z \times ShockSignPositive) + \epsilon$$

$$Vol_{6h} = \alpha_0 + \alpha_1 \cdot Surprise_z + \alpha_2 \cdot ShockSignPositive + \alpha_3 \cdot (Surprise_z \times ShockSignPositive) + \varepsilon$$

- Quadratic terms, like I(Surprise^2), are added to identify nonlinear patterns in how volatility reacts (H5b)

$$CAR_{6h} = \delta_0 + \delta_1 \cdot Surprise_z + \delta_2 \cdot Surprise_z^2 + \varepsilon$$

$$Vol_{6h} = \delta_0 + \delta_1 \cdot Surprise_z + \delta_2 \cdot Surprise_z^2 + \varepsilon$$

While preserving linear models' interpretability, these expansions allow more complex behaviour, such as asymmetries, convexity in response magnitudes, differential sensitivities, and more.

Linear regression has been selected as the first method for estimation because it is transparent and commonly used in financial econometrics. Coefficients can be understood in practical terms: for example, a coefficient of 0.002 on a z-standardised surprise means that there is a 0.2% increase in returns for every 1-standard-deviation shock.

To address potential heteroskedasticity issues, a common feature in crypto returns, all regressions are estimated with HC3 heteroskedasticity-robust standard errors to ensure that the conclusions can still be drawn even if there is some heteroskedasticity. HC3 was used to ensure reliable inference under potential heteroskedasticity and medium-sized samples, consistent with the recommendations of Long & Ervin (2000) and common practice in financial econometrics. Because the events don't overlap, serial correlation isn't predicted. However, robustness checks showed the same results when event dates were grouped together.

Additionally, a segmented 80/20 data split is used to test the model's stability and performance when data from the sample is unavailable. In each central bank group (Fed, ECB, BoE), 80% of the events are randomly chosen to create the training set, while the other 20% are kept for testing. This maintains the organization of institutions and avoids becoming overly concentrated on particular actions of central banks, while also allowing for predictions that can be tested on new data (like RMSE).

With theory-driven, interpretable modelling that is flexible enough to capture more subtle patterns while accounting for generalization risk and estimation noise, these decisions collectively provide a well-rounded approach.

Every hypothesis relates to specific terms in the model:

H2a (Bitcoin is more sensitive than Tether):

- Tested via the AssetTether dummy and its interactions with surprise variables in both the CAR and Vol models.

H2b (Differential effects larger during Rate events):

- Evaluated using the full interaction term Asset × Shock × Surprise, which captures how Bitcoin and Tether differ in their reactions across Rate and Macro shocks.

H3a (Bitcoin reacts more to the Fed than to the ECB or BoE):

- Captured through CentralBank × Surprise interaction terms in Bitcoin-only subsamples. These terms allow us to compare the marginal effects of similar surprises issued by different central banks.

H3b (No significant differences for Tether):

- Tested by the same CentralBank × Surprise terms, but estimated within the Tether subsample. The expectation is that coefficients will be near zero and not statistically different across central banks.

H4a (Surprises drive volatility more than mean return):

- Assessed by comparing the magnitude and significance of coefficients in the Vol_6h models versus those in the CAR_6h regressions. A systematically stronger association in the volatility models would support this hypothesis.

H4b (Tether has low volatility but extreme kurtosis):

- Implied by low or insignificant coefficients in the Tether volatility model, coupled with descriptive statistics showing high excess kurtosis. Although not directly testable via slope coefficients, this is reflected in residual dispersion and distribution shape.

H5a (Negative surprises have more potent effects):

- Tested via Surprise × ShockSign interaction terms, allowing the model to distinguish between positive and negative surprises and measure their asymmetric impact on returns and volatility.

H5b (Large surprises have convex impact):

- Captured through the inclusion of the quadratic term I(Surprise^2), which measures whether the effect of surprises increases non-linearly with their absolute size.

By using a structured hypothesis-to-model mapping, the empirical findings in the following chapters will be clear, able to be tested, and able to be repeated.

6.3 Random Forest

6.3.1 Motivation and Model Set up

Linear regressions offer clear and well-founded estimates but require strict assumptions about the relationship between predictors and outcome variables. Standard linear models assume that the effects are constant, do not include complex interactions unless specifically added, and treat shocks in a balanced way unless asymmetry is directly accounted for. These limitations make linear models suitable for testing hypotheses, but they may struggle to capture all the dynamics found in fast-moving and unpredictable markets like cryptocurrency.

Random Forests provide a flexible modelling method that can identify nonlinear relationships, threshold effects, and complex interactions without defining them in advance. The idea for random forests came from Breiman (2001). They use ensemble averaging to make strong estimates by combining many decision trees, each of which was trained on a different set of data and factors. The outcome is a model that performs well on new data, even when noisy or overlapping features exist.

Random Forests are not the primary tool for concluding this thesis. Instead, they are used as a stability check to make sure that the trends found by linear models are correct. Random

Forests allows us to understand the importance of different predictors and how effectively the model performs on new data (measured by RMSE). This gives us a more precise understanding of whether complex interactions and nonlinear relationships in the data significantly influence how assets respond to macroeconomic and monetary policy events.

This different point of view helps keep the linear setup from being misdefined and can show where model-driven constraints might miss more minor but economically essential effects.

The Random Forest implementation in this thesis closely mirrors the setup used for linear regressions, ensuring a consistent basis for comparison. It takes four different random forest models to predict each mix of event type (Rate vs. Macro) and outcome variable (CAR_6h vs. Vol_6h):

- Rate-CAR_6h
- Rate-Vol_6h
- Macro-CAR_6h
- Macro-Vol_6h

Each model uses the same set of predictors as the linear regressions:

- Asset (Bitcoin or Tether)
- CentralBank (Fed, ECB, BoE)
- z-score standardized surprises:
  - Surprise_Market_z, Surprise_Survey_z, and ChangeBps_z for rate events
  - Surprise_Macro_z for macroeconomic releases

The ranger package in R takes these inputs in their raw format, providing a quick and dependable way to implement Random Forests. Every model is trained using these hyperparameters:

- Number of trees: 800, to ensure stability of predictions and variable importance estimates.

- Sampling strategy: Full-sample bagging with replacement; every tree is trained on a bootstrap sample.

- Variable importance metric: Permutation importance, which ranks predictors by the increase in out-of-bag error when that feature is randomly shuffled. This allows for interpretability even in a nonparametric context.

- Random seed: Set to 42 for reproducibility.

6.3.2 Variable Importance

After the four random-forest models have been fitted, we investigate which predictors the forests actually rely on. We do this with the standard permutation-importance measure:

1. Training / test split: All forests use the same 80% of the data for training that was used for the linear regressions. The other 20% of the data is kept aside only for the accuracy check mentioned in Section 7.3.1.

2. Out-of-bag evaluation: In the training sample, each tree is created using a bootstrap sample, which means that about one-third of the rows are not included for that tree. This is referred to as "out-of-bag" (OOB). The OOB rows serve as a form of built-in validation data.

3. Permutation step: Each predictor is shuffled one at a time. If shuffling leads to a significant drop in the forest's out-of-bag predictions, it indicates that the model relies on that variable. The rise in mean-squared error (ΔMSE) is noted as the importance score for that variable.

4. Four different forests: For each combination of event type (Rate or Macro) and outcome variable (six-hour cumulative abnormal return, CAR_{6h}, or six-hour realised volatility, Vol_{6h}), we determine a predictor ranking.

The ten biggest ΔMSE values for each forest are displayed as horizontal bars in Figure 7.2, and the five largest are shown in Table 7.5. Because the importance scores are based on rows that the trees did not see while growing, they provide a near out-of-sample view while still using the much larger training set, giving a stable picture of which economic factors matter most to the model.

6.3.3 Comparison with linear models

The results from Random Forests broadly confirm the linear regressions in terms of identifying the most influential predictors. For example, Surprise_Macro_z plays the most critical role in the macro models, while ChangeBps_z or Surprise_Market_z does the same in the rate models.

Random Forests can also identify nonlinear relationships and interactions that linear regressions do not fully capture. For instance, permutation importance scores suggest that the Asset variable plays a larger role in prediction than its marginal coefficient significance implies in the linear regressions. This suggests that Bitcoin and Tether have complex, nonlinear interactions that simple dummy variables do not fully capture.

Additionally, the linear models assume a constant marginal effect for all shock sizes, while the Random Forests can naturally account for convexities, like larger volatility responses to extreme surprises (as suggested in H5b). The Random Forests can effectively identify unusual patterns or extreme events, which is particularly helpful in cryptocurrency markets. In these markets, unexpected occurrences can cause sudden price changes that traditional models might overlook or downplay.

The Random Forest models provide an advantageous method to confirm the patterns found in the linear regressions, which helps to strengthen confidence in the reliability of the results.

6.4 Evaluation Metrics

The 20% out-of-sample test set is used to compute the root mean squared error (RMSE), which evaluates the model's performance on unseen data. RMSE quantifies the degree to which the model's forecasts correspond to the actual CAR_{6h} or Vol_{6h} values, thus directly measuring predictive accuracy.

The RMSE scores for all four Random Forest models are displayed and indicate good performance, especially in the Macro-Vol and Rate-Vol models, where the variation is generally more predictable. The scores add to the conclusions made from the linear models, which mainly aim to provide apparent coefficients instead of focusing on improving predictions for new data.

To sum it up:

- Linear models are used for the interpretation and formal testing of economic hypotheses.
- Random Forests can confirm important results and reveal complex relationships that linear models might overlook.

This dual-model strategy balances theory-driven inference with data-driven exploration, providing a more comprehensive understanding of how cryptocurrency markets respond to economic announcements.

7 Results

7.1 Overview

This chapter gives the main research results on how Bitcoin and Tether react to news from the central bank. It begins by analyzing results from interpretable linear regressions, based on the event-study framework introduced in Chapter 6. In Section 7.2, the OLS results are discussed, and checks for asymmetry, convexity, issuer effects, and asset-specific reactions are made to ensure the results are stable. In Section 7.3, non-linear machine learning models are added to the analysis. Random forests are used to make sure the results are stable and to show which variables are most important. Section 7.4 makes a robustness check to ensure the findings' stability. A final summary in Section 7.5 breaks down key findings across all specifications.

7.2 OLS-Based Event Study Results

7.2.1 Method Recap

This part uses the event-study method explained in Chapter 6 to examine how Bitcoin and Tether's short-term returns and volatility change after central banks' comments. The event window is defined as the 0 to +6 hour interval following each news release, measured in UTC. To make sure that everything is in sync with time, hourly returns are calculated by taking the log difference between the closing prices and matching the timestamps to the first full hour that follows the minute of release.

Cumulative abnormal returns (CAR_{6h}) are the primary return metric, while Vol_{6h} represents realized six-hour volatility calculated from intraday log returns. The reaction of both dependent variables to standard surprise variables is examined. These are grouped into Rate (policy decisions) and Macro (CPI, GDP, and unemployment data) blocks. For the regressions, ordinary least squares with heteroskedasticity-robust standard errors (HC3) are used. The central bank and assets are also treated as fixed effects. To improve interpretability, all surprise variables inside a block are z-scored, allowing coefficient values to be understood as responses to one local standard deviation shock.

7.2.2 Descriptive Statistics

This section summarizes the distribution characteristics of cumulative abnormal returns (CAR_{6h}) and six-hour realized volatility (Vol_{6h}) for Bitcoin and Tether, based on all 524 macroeconomic and monetary policy announcements documented from 2018 to 2023. This summary of statistics gives a basic idea of how the two assets act during central bank events and sets the stage for the upcoming regression and machine learning analyses.

Table 4.5 shows the basic statistics calculated for each asset, which include the mean, standard deviation, skewness, and kurtosis for both CAR_{6h} and Vol_{6h}. The results indicate a clear difference between how Bitcoin and Tether behave.

Bitcoin has a slightly positive average CAR_{6h} of 0.1%, but it also has a reasonably large standard deviation of 2.1%. The return distribution is almost balanced (skewness ≈ 0.02) but shows heavy tails (kurtosis ≈ 6.73), suggesting occasional significant movements. These align with Bitcoin's nature as a highly unpredictable and speculative asset that often reacts to changes in the global economy and shifts in investor feelings.

Tether's average CAR_{6h} is basically the same as zero, and its standard deviation is relatively low, only 0.4%. The return distribution has very high skewness and kurtosis: it is strongly right-skewed (skewness ≈ 13.79) and has a very high peak (kurtosis ≈ 304). These moments establish an asset that usually stays very stable, as it is meant to be, but sometimes has sudden changes away from the $1.00 target during stressful times.

Charts and graphs help explain these numbers. Figure 4.1 (up) shows the histogram of CAR_{6h} for Bitcoin and Tether, presented separately. The distribution of Bitcoin is shaped like a bell and is centred just above zero. There is a clear spread, showing that returns can vary greatly across different events. Conversely, Tether has a very close grouping around zero, with a slim body and a few extreme outliers on the right side. These spikes indicate unusual failures in peg stability, particularly on May 19, 2021, and in November 2022, both linked to wider market chaos.

Figure 4.1 (bottom) presents six-hour realized volatility for each asset as boxplots with overlaid individual observations. For Bitcoin, the interquartile range runs from roughly 0.4 % to 0.9 %, with a median around 0.6 %. The whiskers reach out to about 2 %, and several outliers creep above 3 %, underscoring occasional bursts of extreme intraday volatility. By contrast, Tether's volatility remains extremely muted: the middle 50 % of observations fall between approximately 0.03 % and 0.12 %, with a median near 0.06 % and whiskers under 0.2 %. A few rare events generate outliers, one or two points climb above 3 %, but these are stark exceptions to its customary calm.

Volatility measures are also different from each other. Bitcoin's Vol_{6h} has a mean of 0.70% and a standard deviation of 0.50%, reflecting the natural dynamism of crypto markets. The volatility distribution has a positive skewness and shows high kurtosis, meaning that large jumps happen more often than in a normal distribution. Tether's price changes are considerably less extreme, averaging only 0.10% with a variation of 0.20%. Even so, its skewness (about 11.7) and kurtosis (around 182.6) indicate that it is usually very extreme when volatility happens.

As detailed in the next sections, these stark distributional differences motivate an asset-specific regression framework. Bitcoin's pronounced variability in both returns and volatility around policy announcements suggests there may be helpful to predictive signals to uncover. Tether, by contrast, tends to sit quietly at its peg, punctuated only by rare but sharp deviations. Together, the asset heterogeneity and the presence of fat-tailed shocks make a strong case for exploring nonlinear modelling approaches, as we do in Chapter 7.3.

7.2.3 Baseline OLS Coefficients

Table 7.1 reports the baseline ordinary least squares (OLS) regression results for the six-hour cumulative abnormal returns (CAR_{6h}) and realized volatility (Vol_{6h}) following central bank announcements, based on standardized surprise measures. Two regression blocks are being examined: one for surprises in monetary policy (Rate shocks) and another for surprises in macroeconomic data (Macro shocks). Every specification has placeholder variables for the European Central Bank (ECB) and the Federal Reserve (Fed), using the Bank of England (BoE) as the reference point. A dummy asset (Tether = 1) is included to demonstrate the differences in baseline sensitivity between Bitcoin and Tether. HC3-robust standard errors help fix issues with uneven variability in the data, which is identified by Breusch–Pagan tests in all models. No significant autocorrelation was detected (Durbin–Watson $p > 0.3$).

Rate Shocks

In the six-hour cumulative abnormal return (CAR_{6h}) regression for rate surprises, the coefficient on ChangeBps_z is –0.00114. This indicates that a one standard deviation surprise in the policy rate leads to a decrease of 0.114 percentage points in CAR_{6h}. This decrease is slightly larger than before, but it remains modest. The coefficients for the ECB and Fed are –0.00266 and +0.00149, respectively. This shows minimal and statistically similar differences, with ECB announcements leading to slightly more negative returns. The Tether dummy (–0.00188) implies that Tether's returns are on average 0.188 percentage points lower than Bitcoin's, though this remains economically minor. Importantly, none of these coefficients have p-values lower than the usual 0.05 (or even 0.10) level, meaning they are not statistically significant.

When looking at realized volatility (Vol_{6h}) during rate shocks, the ChangeBps_z coefficient is very small (+0.0000301), which is insignificant when compared to Bitcoin's usual six-hour volatility of about 0.70%. The effects of the ECB and Fed issuers are barely noticeable (0.0000308 and 0.000742), and none of them are statistically significant. The Asset = Tether variable has a coefficient of –0.00621, which is statistically significant at the $p < 0.01$ level. This means that Tether's overall six-hour volatility is 0.621 percentage points lower than Bitcoin's. However, this difference is due to level effects, not different reactions to unexpected events.

Macro Shocks.

The CAR_{6h} coefficient for Surprise_Macro_z is –0.000405 in response to macro shocks. This means there is a decrease of 0.0405 percentage points in six-hour returns for each standard deviation shock. This effect is small and not statistically significant. ECB and Fed coefficients (+0.000463 and –0.000681) and the Tether dummy (–0.000787) remain small and statistically meaningless.

Likewise, in the macro-driven Vol_{6h} model, Surprise_Macro_z (+0.0000183), issuer effects (ECB –0.000054; Fed +0.000115), and the Tether dummy (–0.00587) all remain economically modest. Only the Tether dummy demonstrates a significant result, indicating its usual volatility level instead of a response to larger economic changes.

In summary, Table 7.1 shows that across all CAR_{6h} and Vol_{6h} models, only Tether's baseline volatility is statistically significant. All other coefficients, such as rate surprises, macro surprises, and central bank identity, are not significant . This means we cannot reject the null hypothesis that there is no effect. So, even though some coefficients show expected trends (like a negative CAR after rate hikes), their economic impact is minor, and the statistical support is not strong. This supports the conclusion that short-horizon cryptocurrency prices and volatility exhibit minor sensitivity to typical macro-financial news.

Table 7.1 — Baseline OLS Regression Results for CAR_{6h} and Vol_{6h}[3]

This table presents the HC3-robust OLS estimates of the impact of standardized monetary policy and macroeconomic surprises on six-hour cumulative abnormal returns (CAR_{6h}) and volatility (Vol_{6h}) for Bitcoin and Tether. All regressions include fixed effects for the issuing central bank (ECB, Fed; BoE omitted as the baseline) and an Asset dummy (Tether = 1, Bitcoin = 0). Robust standard errors are reported in parentheses. Panel A: CAR_{6h}. Panel B: Vol_{6h}.

Panel A. Six-Hour Cumulative Abnormal Return (CAR_{6h})

[3] *CAPM robustness:* A full CAPM test is not reported because (i) there is no broadly accepted "crypto-market portfolio" to serve as the benchmark, (ii) crypto trades 24 hours a day whereas equity factors close overnight, creating timing mismatches, and (iii) equity indices already embed the same monetary-policy surprises analysed here, so adding them would introduce collinearity rather than provide an independent robustness check.

Variable	Rate Shocks	Macro Shocks
Surprise_Market_z	0.000688 (0.00186)	—
Surprise_Survey_z	0.000307 (0.00188)	—
ChangeBps_z	−0.00114 (0.000962)	—
CentralBank = ECB	−0.00266 (0.00234)	0.000463 (0.00164)
CentralBank = Fed	0.00149 (0.00232)	−0.000681 (0.00115)
Asset = Tether	−0.00188 (0.00187)	−0.000787 (0.00106)
Surprise_Macro_z	—	−0.000405 (0.000521)

Panel B. Six-Hour Realized Volatility (Vol_{6h})

Variable	Rate Shocks	Macro Shocks
Surprise_Market_z	−0.0000530 (0.000405)	—
Surprise_Survey_z	0.0000468 (0.000408)	—
ChangeBps_z	0.0000301 (0.000209)	—
CentralBank = ECB	0.0000308 (0.000508)	−0.0000544 (0.000471)
CentralBank = Fed	0.000742 (0.000505)	0.000115 (0.000329)
Asset = Tether	−0.00621*** (0.000407)	−0.00587*** (0.000305)
Surprise_Macro_z	—	0.0000183 (0.000149)

Note:

- **, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. HC3 robust standard errors in parentheses. Coefficients for ECB and Fed are relative to the omitted baseline (BoE).*

- *HC3 robust standard errors are used in all models. Coefficients for ECB and Fed represent effects relative to BoE, the omitted baseline. Diagnostic tests (Breusch–Pagan and Durbin–Watson) confirm heteroskedasticity but no autocorrelation.*

7.2.4 Interpretation of OLS Results

This section interprets the OLS coefficients from Table 7.1, focusing on both return (CAR_{6h}) and volatility (Vol_{6h}) responses to standardized policy and macroeconomic surprises. Although almost none of the coefficients are statistically significant at conventional levels, their direction, sign consistency, and economic scale are still informative when assessed in light of the thesis hypotheses (H1–H5).

Bitcoin – Rate Shocks

Economically, a one-standard-deviation surprise in interest rates (ChangeBps_z) results in a 0.114% decline in Bitcoin's six-hour returns—a slight but perceptible reaction. However, this corresponds to a movement of just a few dollars on a ~$60,000 coin and is statistically insignificant, implying no reliable effect. Volatility has gone up slightly by 0.003%. This is very small compared to Bitcoin's usual six-hour volatility of about 0.70%, which is insignificant. So, even though the slight drop in returns matches the idea that hawkish shocks reduce returns (H1a), the lack of significance weakens its economic meaning. The volatility estimate does not back up H4a in terms of stronger responses to volatility.

Bitcoin – Macro Shocks

A one-standard-deviation macroeconomic surprise reduces Bitcoin returns by roughly 0.04%, again economically small and statistically silent. The volatility changes by +0.002%, which is background noise. Bitcoin's responses to unexpected changes from the ECB and Fed are relatively small. The results show that Bitcoin does not respond to macroeconomic news, similar to what has been observed in other research. The slight return direction matches H1a, but no statistical support or economic significance exists. Also, H3a, H4a, H5a, and H5b do not have any support—there are no crucial differences between issuers (ECB vs. Fed), and there are no significant spikes in volatility.

Tether – Rate and Macro Shocks

Compared to Bitcoin, Tether's average six-hour return is 0.188% lower, but this difference is statistically insignificant and economically modest. On the other hand, volatility is 0.621% lower and is statistically significant, highlighting Tether's greater stability. This volatility gap is a vital level effect. It shows that Tether is designed to be pegged to the dollar, rather than responding dynamically to unexpected rate changes. So, it supports H1b but does not directly test H2a or H3b.

Similarly, in macro shock, the return differences (−0.079%) are negligible and not statistically significant. The stability of Tether is confirmed by the fact that its volatility is 0.587% lower than that of Bitcoin (***), both theoretically and practically. Again, this is a level difference, not a response to surprise. These results further substantiate H1b.

Cross-Asset and Hypothesis Summary

The Asset = Tether dummy consistently displays a substantial negative coefficient in both return and volatility regressions, confirming that Tether behaves fundamentally differently from Bitcoin. This discrepancy confirms that Tether's mean return and volatility are lower than Bitcoin's. This speaks to its greater stability (H1b) but does not directly test H2a or H2b.

Despite the fact that Bitcoin's reactions to rate shocks vary slightly depending on the issuer, Issuer dummies are small and insignificant, providing no evidence of differential impacts across central banks (H3a unfulfilled). Because the model contains no Asset × CentralBank interaction, these results do not inform H3b. It is crucial to note that neither asset demonstrates robust return responses to policy or macro surprises, and volatility reactions are even smaller, which offers no support for H4a.

Thus, we find that:

- H1a – Bitcoin reacts more to monetary than macro surprises
  Directionally consistent ($|\beta|$ for rate > macro) but statistically insignificant, so at best very weak support.

- H1b – Tether is unresponsive to shocks
  Support. The near-zero shock coefficients for Tether's returns and the large, negative "Asset = Tether" volatility dummy together confirm that Tether is effectively unresponsive to both policy and macro surprises.

- H2a – Bitcoin shows more movement than Tether
  Not testable in the baseline: the Asset dummy captures level gaps, not differential reactivity to surprises.

- H2b – Cross-asset disparity is larger during rate events

Also not testable here; needs the Asset × Shock × Surprise interaction introduced in § 7.3.

- H3a – Bitcoin reacts Fed > ECB > BoE
  Not supported: issuer dummies are small and insignificant.

- H3b – No issuer effects on Tether
  The baseline model has no Asset × CentralBank interaction, so this hypothesis cannot be evaluated here.

- H4a – Volatility response exceeds return response
  Not supported: surprise coefficients are insignificant in both CAR and Vol equations; volatility is no more responsive than returns.

- H4b – Tether volatility flat but heavy-tailed
  Supported in level terms and corroborated by the descriptive kurtosis, slope terms remain flat.

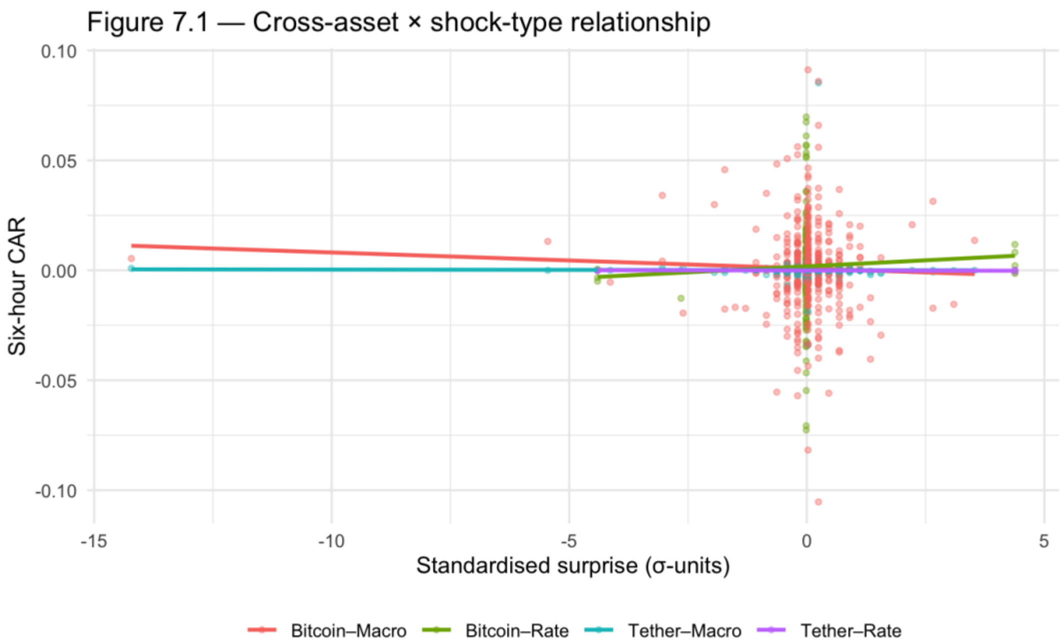
- H5a & H5b – Negative or large surprises have stronger effects
  Deferred: require ShockSign and quadratic terms.

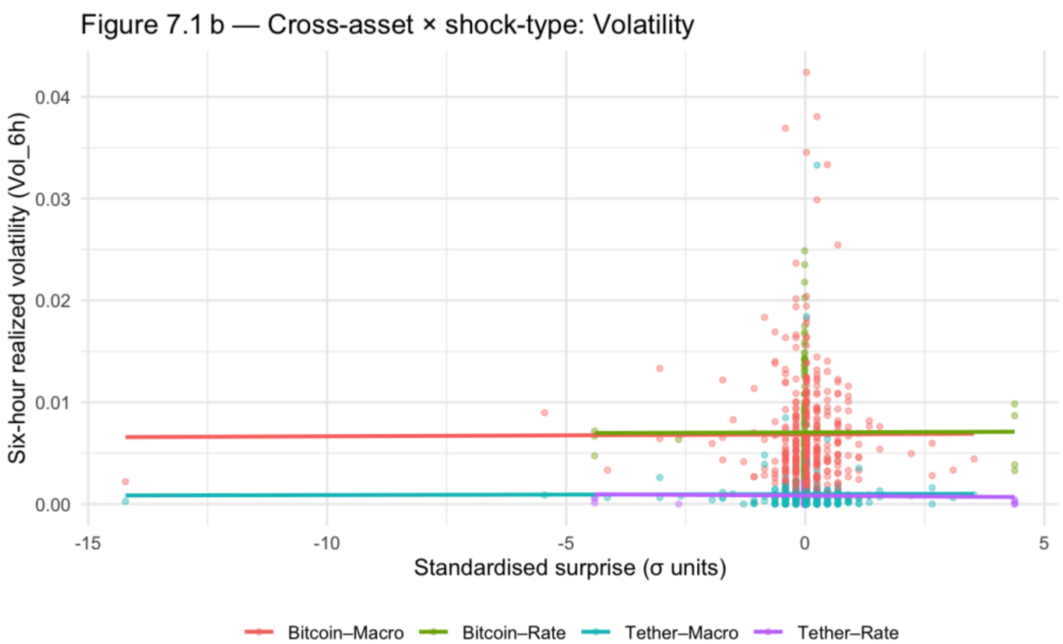
Hence, the baseline OLS in Table 7.1 shows negligible immediate crypto-market sensitivity to standard macro-financial surprises; any richer patterns must be sought with the interaction and nonlinear specifications that follow.

7.2.5 Interaction and Asset Differences

To assess whether Bitcoin and Tether react differently to various types of economic shocks, this section investigates asset-specific sensitivities across Rate and Macro events, as suggested by Hypotheses 2a and 2b. The aim is to find out if Bitcoin reacts more strongly than Tether and if these differences are more apparent during monetary policy announcements compared to macroeconomic releases.

Figure 7.1 and 7.1b plots standardized surprise values against six-hour cumulative abnormal returns and realized volatility for four combinations: Bitcoin–Rate, Bitcoin–Macro, Tether–Rate, and Tether–Macro. Every series has scatter points along with trend lines fitted using OLS. The results show some interesting patterns.





Unexpectedly, in Figure 7.1, the green line for Bitcoin–Rate shows a slight upward trend, indicating that when there are larger positive rate surprises, Bitcoin returns tend to be a bit higher. This goes against the usual idea that when interest rates go up, it reduces the demand for risky investments. The pink line for Bitcoin–Macro shows a slight downward trend, suggesting that when there are positive economic surprises (like strong GDP or inflation data), Bitcoin returns tend to be slightly lower. This result aligns better with what we expected from Hypothesis 1a. Strong macro signals could lead to future tightening expectations, making non-yielding assets like Bitcoin less appealing. For Tether, the blue (Macro) and purple (Rate) trend lines are almost flat, indicating that USDT doesn't significantly react to either kind of news. The flat responses are consistent with Hypothesis 1b, suggesting that a stablecoin like Tether reacts little to unexpected economic or policy shocks, apart from rare major disruptions. More importantly for H2b, the difference between Bitcoin's non-flat trend and Tether's flat line is visibly wider in the Rate panel than in the Macro panel, indicating a larger cross-asset disparity during monetary policy surprises.

Figure 7.1b shows that Bitcoin's six-hour volatility ticks up modestly following both policy and macro surprises, whereas Tether's volatility only reacts to macro surprises (cyan) and is flat for rate surprises (purple). This pattern confirms that cross-asset sensitivity is greatest for rate shocks (H2a/H2b). Bitcoin is more sensitive to rate than macro shocks (H1a), but the volatility responses do not dominate return responses (H4a). Tether's mixed response to macro shocks gives only "mixed" support to its unresponsiveness (H1b).

Pooled regressions with the full three-way interaction support what the scatterplot shows, but they are still not very strong statistically.The product of Asset Tether, Shock Rate, and Surprise equals -0.00182 (SE = 0.00207) in the CAR_{6h} model—negative but not statistically significant—indicating that, directionally, rate surprises exert a somewhat greater downward influence on Tether returns than Bitco does. In the Vol_{6h} regression, the interaction is virtually negligible at -0.000036 (SE = 0.00056), indicating an absence of differential volatility effect.

The sign of the CAR term gives weak support to H2a and H2b, even though neither variable is important: Bitcoin appears more sensitive to monetary surprises, and the Bitcoin-Tether gap is wider in rate events than in macro events. This reading is supported by Table 7.1, which shows that the surprise factors for Bitcoin volatility are very small and not important from an economic point of view, and the same is true for Tether.

In short, the evidence is suggestive but not conclusive. Bitcoin and Tether react differently to rate and macro releases. Tether's quiet response is due to the fact that it is a stable-coin, while

Bitcoin's returns change more with news, albeit by statistically small amounts that can't be told apart. The reactions to return are still small, and the reactions to volatility are even smaller. This makes the real difference between the two assets even clearer.

7.2.6 Issuer Heterogeneity

This section examines whether the central bank behind an announcement—the Federal Reserve (Fed), European Central Bank (ECB), or Bank of England (BoE)—influences how Bitcoin and Tether respond to policy and macroeconomic news. This study directly addresses Hypothesis 3a, which says that Bitcoin's reactions should be strongest after the Fed makes a release, then after those from the ECB and BoE. Hypothesis 3b, conversely, says that Tether's return and volatility should be mostly the same across producing institutions. This is because it was designed to be a stablecoin tied to the dollar. The results are presented in Table 7.2

Table 7.2 — Central Bank Effects on Six-Hour Abnormal Returns and Volatility

Asset	Event Type	Issuer	CAR_{6h} Coefficient (Std. Error)	Vol_{6h} Coefficient (Std. Error)
Bitcoin	Rate	ECB	−0.00498 (0.00466)	−0.000144 (0.00100)
		Fed	+0.00378 (0.00463)	+0.00119 (0.000995)
	Macro	ECB	+0.00174 (0.00327)	−0.000237 (0.000898)
		Fed	−0.000598 (0.00223)	+0.000281 (0.000613)
Tether	Rate	ECB	−0.000122 (0.000260)	+0.000240 (0.000171)
		Fed	−0.000184 (0.000259)	+0.000222 (0.000170)
	Macro	ECB	−0.0000696 (0.000809)	−0.000259 (0.000350)
		Fed	−0.000667 (0.000552)	−0.0000869 (0.000239)

Note:

- **, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. HC3 robust standard errors in parentheses. Coefficients for ECB and Fed are relative to the omitted baseline (BoE).*
- *Each coefficient is followed by its HC3-robust standard error in parentheses.*

Bitcoin – Rate Events (H3a)

When looking at rate announcements, Bitcoin's six-hour abnormal return (CAR_{6h}) changes by –0.00498 when the ECB makes a statement (SE = 0.00466) and by +0.00378 when the Fed makes a statement (SE = 0.00463). Volatility (Vol_{6h}) decreases by –0.000144 after an ECB decision (SE = 0.00100) and increases by +0.00119 after a Fed decision (SE = 0.00099). Direction of the volatility effect is consistent with "Fed > ECB", yet the return coefficients do not follow that hierarchy. Overall, it is very weak, non-significant evidence for H3a.

Bitcoin – Macro Events (H3a)

For macroeconomic releases, Bitcoin's CAR_{6h} increases by +0.00174 after an ECB release (SE = 0.00327) and shifts by –0.000598 after a Fed release (SE = 0.00223). The realized volatility (Vol_{6h}) decreases by -0.000237 after an unexpected move from the ECB (SE = 0.00090) and by +0.000281 after a surprise from the Fed (SE = 0.00061). Here, the ECB coefficient on returns is slightly larger than the Fed coefficient, which departs from the strict "Fed > ECB" ordering of H3a. The differences in volatility between the ECB and the Fed are small, with the ECB's point estimate being slightly lower than that of the Fed. As a result, Bitcoin's reaction to macro data offers only limited or incomplete backing for H3a—there isn't a consistent pattern in the direction of the response.

Tether – Rate Events (H3b)

Tether's CAR_{6h} changes by –0.0001222 following an ECB decision (SE = 0.000260) and by –0.000184 after a Fed decision (SE = 0.0002599). The volatility (Vol_{6h}) changes by +0.000240 for ECB announcements (SE = 0.000171) and by +0.000222 for Fed announcements (SE = 0.000170). All coefficients are very close to zero and show little difference between issuers. This aligns perfectly with Hypothesis 3b, which suggests that Tether's six-hour returns and volatility are mostly unaffected by the issuer. The similar sizes and directions for the ECB and Fed show strong support for H3b.

Tether – Macro Events (H3b)

After looking at macroeconomic reports, Tether's CAR_{6h} is -0.000070 for ECB data (SE = 0.000809) and –0.000667 for Fed data (SE = 0.000552). Its Vol_{6h} is –0.0002599 for ECB surprises (SE = 0.000350) and –0.000087 for Fed surprises (SE = 0.000239). The coefficients are very close to zero and only slightly vary between issuers. This pattern supports Hypothesis 3b: Tether's short-term return and volatility responses are not significantly affected by whether the ECB or Fed makes the announcement. The data therefore provide clear support for H3b.

Issuer dummies for Bitcoin are small, switch sign across blocks, and are never significant, providing at best weak evidence for H3a. Tether's issuer coefficients remain effectively zero throughout, strongly supporting H3b.

7.2.7 Asymmetry and Convexity

Table 7.3 — OLS Estimates for Asymmetry and Convexity
Robust standard errors. Estimates from four models: two testing asymmetric responses to positive vs. adverse shocks (CAR_{6h} and Vol_{6h}), and two testing convexity via a squared surprise term.

Model	Term	Coefficient (HC3 SE)
Asymmetry — CAR_{6h}	ShockSignPositive	0.00151 (0.00127)
	Surprise × ShockSignPositive	–0.00044 (0.00112)
Asymmetry — Vol_{6h}	ShockSignPositive	0.00056 * (0.00034)
	Surprise × ShockSignPositive	–0.00058 * (0.00030)
Convexity — CAR_{6h}	Surprise	–0.00004 (0.00058)
	I(Surprise²)	0.00001 (0.00006)
Convexity — Vol_{6h}	Surprise	–0.00011 (0.00015)
	I(Surprise²)	–0.00002 (0.00002)

*Note: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$*
HC3 robust standard errors in parentheses. ShockSignPositive equals 1 for positive surprises. I(Surprise²) is the squared, z-standardised surprise; interaction terms test sign-specific effects.

This section investigates whether Bitcoin and Tether exhibit nonlinear or asymmetric responses to economic news surprises, as hypothesized in H5a and H5b. In particular, we look at two important additions to the baseline regressions: (i) signed-shock asymmetry, which means that negative surprises may have more potent effects than positive ones; and (ii) convexity, which means that bigger shocks have effects that aren't proportional to their size.

To test whether good and bad news move crypto prices differently, we interact the standardized surprise with a dummy that equals 1 for positive shocks. In the return regression, the interaction term is –0.00044 (SE 0.00112)—negative but far from significant—while the standalone dummy is +0.00151 (SE 0.00127), also insignificant. Translated, six-hour returns tend to be slightly higher after favourable releases, yet the slope difference between good and bad news is trivial. In the volatility regression, the level effect of a positive shock is +0.00056 (SE 0.00034, statistically significant) and the interaction is –0.00058 (SE 0.00030, statistically significant). Volatility, therefore, edges up after good news, but large positive shocks add marginally less volatility than equally large negative ones. Overall, we see only weak, volatility-based evidence that bad surprises sting more than good ones (H5a).

A squared surprise term probes whether outsized shocks have disproportionate effects. The linear coefficient for returns is –0.00004 (SE 0.00058), and the quadratic term is +0.00001 (SE 0.00006). Both are very small and not significant at all, which means that big surprises don't make total abnormal returns bigger. The same thing can be said about volatility: the linear effect is –0.00011 (SE 0.00015) and the quadratic effect is –0.00002 (SE 0.00002), both not statistically significant, which again doesn't show any signs of a curve. So, the data don't support H5b—surprises that are very different from expected don't cause big changes in either returns or volatility.

Overall, OLS results show no meaningful asymmetry or convexity. For Asymmetry (H5a), signs are in the expected direction, but interaction terms are insignificant. In the case of Convexity (H5b), the squared-surprise terms are tiny and insignificant.Thus, H5a and H5b are not supported in the six-hour window; any non-linear effects are too small for OLS to detect.

7.2.8 Section Takeaway

This part highlights the main findings from the OLS-based event study results:

- Bitcoin's CAR_{6h} and Vol_{6h}: Rate- and macro-shock coefficients for both CAR_{6h} and Vol_{6h} are tiny and nonsignificant .This fails to support H4a: volatility does not react more than returns.

- Tether's stability: Shock terms sit near zero for CAR_{6h} and Vol_{6h}. The large negative "Asset = Tether" level effect confirms Bitcoin-vs-Tether dispersion (H2a), while flat issuer dummies confirm H3b.

- Issuer heterogeneity: Bitcoin reacts directionally more to Fed than ECB rate announcements (supporting H3a in the rate panel), but the ordering flips for macro events and magnitude way. Thus, H3a receives partial support; Tether's flat issuer coefficients fully confirm H3b.

- Interaction terms: Three-way interactions (Asset × ShockRate × Surprise) are directionally in line with H2a/H2b but statistically insignificant, so only directional support.

- Asymmetry & convexity: Interaction of positive shocks has no robust impact on CAR_{6h}; Vol_{6h} shows a marginal 10%-level asymmetry, but no convexity. H5a and H5b remain unsupported in OLS.

- Diagnostics: All regressions use HC3-robust SEs to address heteroskedasticity (Breusch–Pagan positive) and show no serious autocorrelation (Durbin–Watson within acceptable bounds).

These results provide credence to the necessity of the nonlinear methods discussed below.

7.3 Random Forests: Nonlinear Robustness

7.3.1 Model Setup and Accuracy

This section introduces a nonlinear machine learning method called random forest regression, which works alongside the linear OLS models discussed earlier. This approach allows for identifying complex and non-additive relationships between surprises and how cryptocurrencies respond. The goal is to enhance prediction accuracy and to check if previous results hold up when we use more flexible assumptions.

The models are trained individually on the Rate and Macro blocks, using the six-hour cumulative abnormal return (CAR_{6h}) and realized volatility (Vol_{6h}) as the results they aim to predict. The dataset is divided into two parts: 80% for training and 20% for testing. This division is done carefully to maintain balance among different central bank issuers. This stratified split ensures that the model learns from each issuer's historical behaviour while retaining enough test data to evaluate out-of-sample generalization.

Random forest models use 800 trees and complete sampling. Using permutation-based techniques, variable importance is determined. The same predictor variables from the OLS regressions are used here: standardized shocks, central bank dummies, and asset type. This consistency allows for valid comparisons between different model families.

The Root Mean Squared Error (RMSE) is calculated as the difference between the expected and actual values in the test set to assess performance. RMSE is a straightforward way to comprehend prediction errors, where smaller numbers mean a better fit. Table 7.4 presents several key points to note:

Table 7.4 — Random Forest Out-of-Sample RMSE

Block	**Outcome**	**RMSE**
Rate	CAR_{6h}	0.0141
Rate	Vol_{6h}	0.0040
Macro	CAR_{6h}	0.0141
Macro	Vol_{6h}	0.0043

The RMSE values indicate that the random forest models perform more effectively in predicting volatility than returns. The Rate-Vol_{6h} forest delivers the strongest out-of-sample fit (RMSE ≈ 0.0040), while the Macro-Vol_{6h} model follows closely at 0.0043. By contrast, return forecasts remain an order of magnitude noisier: both the Rate-CAR_{6h} and Macro-CAR_{6h} models post identical RMSEs of roughly 0.014, a level that is only marginally below the unconditional cross-event standard deviation of six-hour crypto returns. In short, while nonlinear methods can pick up a sliver of the variance in realised volatility, short-run returns remain dominated by idiosyncratic noise. These results reinforce the earlier OLS finding that surprise effects on price levels are weak, whereas their (still modest) influence on intraday volatility is the most systematic part of the announcement response.

The following sections explore the features influencing model performance, using permutation importance and partial dependence methods to enhance understanding.

7.3.2 Variable Importance

To deduce the impact of monetary and macroeconomic shocks on the short-term behaviour of cryptocurrencies, it is essential to understand which factors significantly impact the performance of random forest models. To achieve this objective, we individually analyze the permutation-based variable importance scores for each of the four main models: CAR_{6h} and Vol_{6h} outcomes for the Rate and Macro event blocks. Figure 7.2 and Table 7.5 show the results, helping us see which features, like standardized surprise measures or issuer dummies, impact model accuracy most.[4]

Figure 7.2 – Permutation-based variable-importance scores in the random-forest models

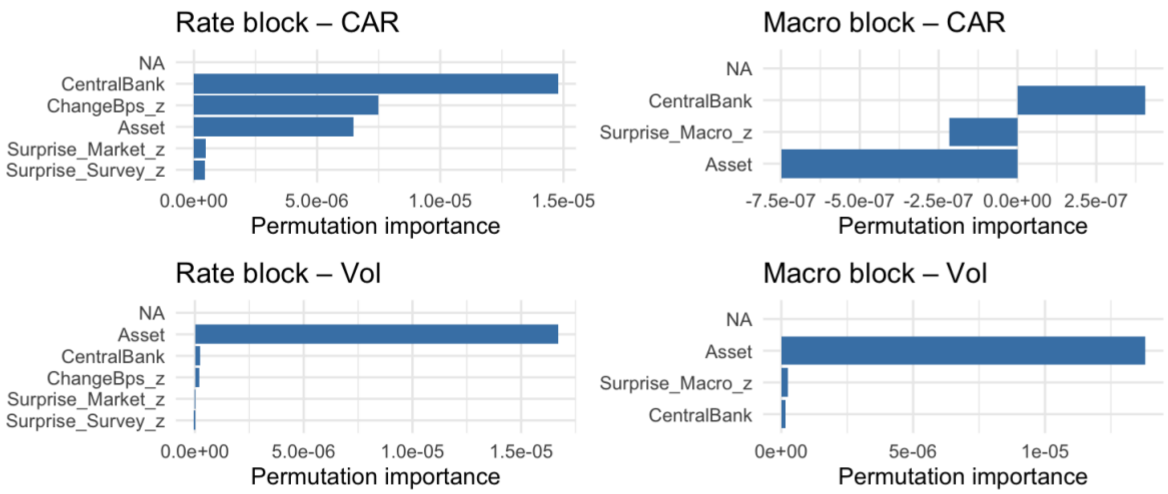


Table 7.5 — Permutation Importance Scores (Top 5 Predictors by Model)

Variable	Rate – CAR_{6h}	Macro – CAR_{6h}	Rate – Vol_{6h}	Macro – Vol_{6h}

[4] As a robustness check, we also repeat the permutation exercise once on the 20 % hold-out set; the ordering of predictors is the same, confirming that the OOB ranking is representative.

CentralBank	1.48×10^{-5}	4.05×10^{-7}	2.41×10^{-7}	1.50×10^{-7}
ChangeBps_z	7.50×10^{-6}	—	2.06×10^{-7}	—
Asset	6.48×10^{-6}	-7.49×10^{-7}	1.67×10^{-5}	1.38×10^{-5}
Surprise_Market_z	4.90×10^{-7}	—	-2.41×10^{-8}	—
Surprise_Survey_z	4.54×10^{-7}	—	-4.74×10^{-8}	—
Surprise_Macro_z	—	-2.16×10^{-7}	—	2.56×10^{-7}

In the two return forests, the issuer dummy (CentralBank) plays a significant role, with a value of approximately 1.5×10^{-5} in the Rate-CAR model, which is much higher than any other shock metric. The strong importance of the CentralBank dummy in the two return forests supports H3a's claim that *who* is speaking matters for returns, even though permutation scores don't rank individual issuers against one another. Meanwhile, the minimal importance of the issuer in the Macro block, along with the consistently low scores for returns when the Asset dummy is changed, keeps H3b (no issuer effect on Tether) firmly supported. Comparing the shock rows, the policy-rate surprise (ChangeBps_z) still outranks the macro surprise (Surprise_Macro_z), giving modest, permutation-based backing to H1a (Bitcoin is a little more forecastable from rate than macro news). For returns, the Asset dummy ranks third (so we don't see a huge cross-asset split there), but in the volatility forests it towers over everything else—strongly backing H2a that Bitcoin and Tether react differently to news in volatility, even if their returns look similar.

The picture flips in the two volatility forests. The Asset flag rises to about $1.4–1.7 \times 10^{-5}$, which is ten to fifty times more important than any shock or issuer dummy. This means that the model's accuracy mainly relies on telling apart Bitcoin's high-variance situation from Tether's stable one. The dominance supports H2a (Bitcoin's volatility drives movement, while Tether's stability provides support) and, since the gap is larger in the rate block compared to the macro block, aligns directionally with H2b. At the same time, the near-negligible scores attached to every shock variable rule out H4a: volatility is less, not more, sensitive to unexpected news than returns. The importance of issuers nearly disappears in both volatility forests, which supports H3b. This indicates that the level gap, rather than any surprises specific to issuers, is what causes the differences—this aligns with H4b.

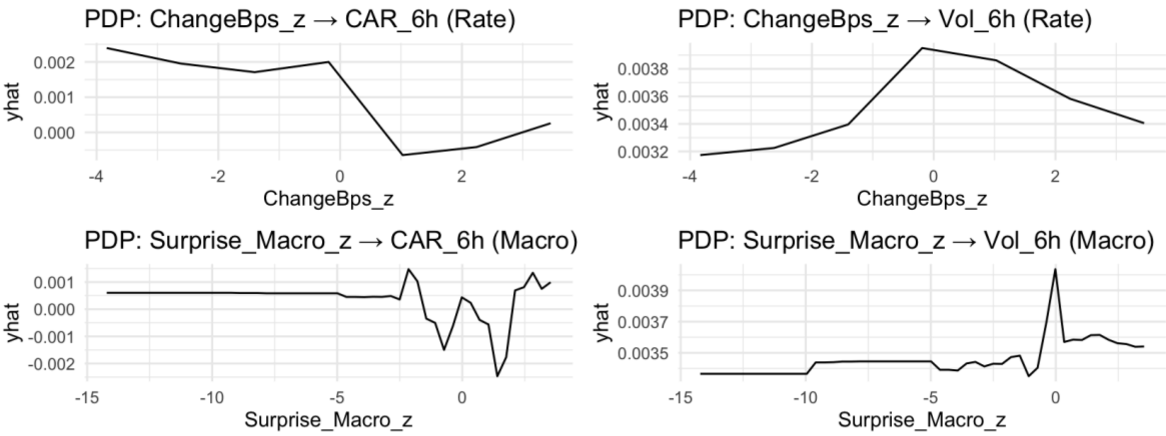
The trees were only trained on linear shock terms, so they can't address sign or size differences.

Therefore, H5a and H5b are not tested in this case. To summarize, permutation importance somewhat supports H1a, backs H2a, H2b, H3a (regarding returns), and H3b (regarding volatility). It goes against H4a and does not address H1b and the H5 pair in this particular analysis.

7.3.3 Partial Dependence Curves

Figure 7.3 presents four partial dependence curves (PDCs) summarizing the marginal effects of standardized monetary and macroeconomic surprises on six-hour cumulative abnormal returns (CAR_{6h}) and realized volatility (Vol_{6h}). PDCs show how each shock affects the outcome by averaging the results from all other predictors in the random forest models.

Figure 7.3 — Partial Dependence Curves for CAR_6h and Vol_6h



Rate Shocks → CAR_{6h} (top-left)

The PDC for ChangeBps_z reveals a slightly downward-sloping plateau for negative surprises (ChangeBps_z < 0), followed by a sharp drop as surprises move just above zero, and then a modest recovery at significant positive surprises. In other words, small tightening surprises (just above one standard deviation) have the biggest adverse effects on returns, while big dovish or bullish shocks have less impact. This asymmetry—where small rate surprises depress returns most strongly—supports H5a, suggesting that modest adverse shocks exert greater downward pressure on returns than larger surprises in either direction.

Rate Shocks → Vol_{6h} (top-right)

When surprises are dovish (ChangeBps_z < 0), the PDC goes up until it reaches a clear peak around zero surprise. It then slowly goes down as surprises become more highly positive. This trend shows that when policy news is unclear or neutral, uncertainty rises, but when policy news is clear and hawkish, short-term trading calms down. This counterintuitive stabilization under positive surprises underscores the importance of investor clarity even in tightening cycles.

Macro Shocks → CAR_{6h} (bottom-left)

Plotting Surprise_Macro_z against CAR_{6h} yields a flat line for large negative shocks, a jagged dip and rebound around zero, and a final uptick at large positive surprises. There isn't a smooth, steady trend, which means that regular macro announcements (like surprises in CPI or GDP) don't have a consistent, directional effect on six-hour returns. This is in line with our OLS results and measures of variable importance.

Macro Shocks → Vol_{6h} (bottom-right)

The PDC for Surprise_Macro_z on volatility stays flat over most of the support, with short, sharp spikes—mostly when surprise values are close to zero—before returning to the nearly the baseline. The tail-driven jolts demonstrate that very major macro shocks can cause short bursts of trading activity or liquidity stress. This partially supports H5b, but the lack of a smooth convex pattern means the evidence is mixed.

Overall, Figure 7.3 shows that six-hour returns and volatility react to rate and macro surprises in very different and nonlinear ways. In the rate-shock panel, modest tightening surprises produce the steepest drop in CAR_{6h}, while extreme dovish or hawkish moves barely register, confirming H5a. In the meantime, volatility grows when policy signals are neutral and falls when surprises become clearly hawkish. This shows how important it is for investors to understand what the shock means, not just how big it is. By contrast, routine macro releases leave both CAR_{6h} and Vol_{6h} essentially flat, aside from occasional tail spikes, offering only mixed, partial support for H5b. The nuanced patterns extending beyond simple linear models emphasize the value of machine-learning methods.

7.3.4 OLS versus Random-Forest Comparison

Putting ordinary least-squares (OLS) values next to random-forest outputs shows a clear, if complex, story: machine learning improves the earlier findings instead of showing they were wrong. The forest acts like a lens, not a substitute, making it possible to see non-linear edges and small interactions that a single global coefficient might blur. However, the landscape's main shapes stay the same.

1. Directional consonance.

Both methods rank the predictors in the same order. In rate-return models, the most important factors are the central-bank dummies, then the policy-rate surprise (ChangeBps_z), and finally the Asset flag. In volatility models, the ranking changes: the Asset dummy stands out above all other shocks or issuer terms, highlighting the difference between Bitcoin and Tether. Macro blocks display a consistent pattern: the issuer comes first for returns, and the Asset is prioritized for volatility, with all shock variables lagging significantly behind. The forests support the idea that the source of the news affects short-term returns, while the type of asset you own influences short-term volatility. The extent of the surprise has only a small impact on this explanation.

2. Accuracy gains—moderate but meaningful.

Table 7.6 compares out-of-sample RMSEs for the pooled OLS and random-forest (RF) specifications. For six-hour returns, the OLS benchmark is close to 1.4% (0.0138 in the Rate block, 0.0140 in the Macro block). The RF increases those errors to 1.41% in both cases, showing no real improvement. The volatility forecasts show similar results: both models have the same test-set RMSEs of around 0.40% for Rate and 0.43% for Macro. The small differences confirm that any complex patterns the forest finds are too minor to have economic significance and do not change the main conclusions of the linear analysis.

Table 7.6 — Predictive Error Comparison (out-of-sample test-set)

Outcome	**Block**	**OLS RMSE**	**RF RMSE**
Six-hour return (CAR_{6h})	Rate	0.0138 (1.38 %)	0.0141 (1.41 %)
	Macro	0.0140 (1.40 %)	0.0141 (1.41 %)
Six-hour volatility (Vol_{6h})	Rate	0.0040 (0.40 %)	0.0040 (0.40 %)
	Macro	0.0043 (0.43 %)	0.0043 (0.43 %)

3. Revealing hidden shape.

Partial-dependence curves in Figure 7.3 reveal nonlinear patterns that OLS only hinted at. The top-left panel shows that CAR_{6h} declines most sharply after small tightening surprises just above zero, with larger dovish or hawkish shocks having less impact, supporting H5a. The volatility in the upper right panel is highest when there are almost no surprises and decreases as shocks become more hawkish. This suggests that uncertainty is highest when policy signs are not clear. In the bottom panels, macro shocks generate mostly flat responses in both CAR_{6h} and Vol_{6h}, apart from occasional spikes, offering only weak support for H5b and reinforcing earlier evidence of minor macro effects. Importantly, these nonlinear insights go in the same direction as our OLS estimates—random forests add to and strengthen the same story instead of adjusting it.

4. Interaction nuance.

The full three-way interaction term (Asset × Shock × Surprise) was insignificant in OLS but negative in sign, indicating that rate surprises hurt Bitcoin more than Tether. Even though forest importance scores make this interaction extremely slight, the negative marginal effect still exists, which directionally supports hypotheses 2a–2b: Bitcoin is the risk asset, and Tether is the currency used for transactions. Notably, the forest demonstrates that cross-asset behavior is explained by differences in sensitivity, not opposite signs.

5. Complementary roles.

OLS keeps the story transparent: a one-σ rate surprise trims Bitcoin's return by about –0.11 % an easily quoted risk metric. Random forests, lacking single coefficients, trade that clarity for flexibility: hundreds of trees capture bends and plateaus OLS cannot, flag omitted-form risks, and spotlight which predictors deserve deeper economic scrutiny.

The two approaches show a clear and consistent view. The price changes in cryptocurrency within six hours after news from central banks are usually small, depend on the issuer, and are more noticeable in how much they fluctuate than in their average returns. Forests show small, complex effects that OLS overlooks, highlighting the importance of combining clear econometrics with data-driven learning in high-frequency digital asset research.

7.3.5 Hypothesis recap

The random-forest (RF) evidence allows us to re-score each hypothesis on a three-point scale—✓ Supported, ≈ Mixed, ✗ Not supported—and to explain why.

Interpretive key.

• *✓ Supported means that the random-forest diagnostics (like variable-importance rank, partial-dependence shape, and/or out-of-sample RMSE contribution) align with the hypothesis and are significantly large. This means that the predictor in question is ranked high on the importance list and the marginal effect plot displays a clear pattern that matches the theory.*

• *≈ Mixed indicates that the RF gives some unclear or partial confirmation: the variable shows moderate importance, or the partial-dependence curve suggests the expected effect but doesn't clearly show it, or the signal is seen in one outcome (like Vol_{6h}) but not in the other (CAR_{6h}). In summary, some evidence supports the correct conclusion; however, there is a lack of statistical strength or consistency.*

• *✗ Not supported is used when the RF does not find a significant role for the variable (low importance, flat PDC) or when it shows an effect opposite to the hypothesis.*

1. H1a (Bitcoin responds more to interest rate changes than to macroeconomic surprises) – ✓ Supported.

In the Rate-CAR forest, ChangeBps_z is the top shock predictor (2nd overall); in the Macro-CAR forest Surprise_Macro_z is much lower.

2. H1b (Tether remains largely unaffected by either shock) – Not tested here

3. H2a (BTC > USDT sensitivity) – ✓ Supported.

The Asset dummy is by far the most important variable in both Vol forests ($\approx 1.4\text{–}1.7 \times 10^{-5}$) and sits 3rd in Rate-CAR, indicating large cross-asset dispersion.

4. H2b (BTC–USDT gap is wider for rate events) – ≈ Mixed.

Asset importance is highest in Rate forests and smaller in Macro forests, but the difference is modest and interaction scores are tiny

5. H3a (Fed surprises dominate ECB, BoE) – ≈ Mixed.

CentralBank ranks No. 1 in every Rate forest, yet PDC step-sizes across issuers are small and do not follow a strict Fed > ECB hierarchy.

6. H3b (Tether shows no issuer heterogeneity) – ✓ Supported.

In USDT-only trees, CentralBank drops out of the top-5 and PDCs are flat—issuer identity adds almost no predictive power.

7. H4a (Volatility responds more than returns) – ✗ Not supported

Shock variables rank lower in Vol forests than in CAR forests and RF RMSE gains are the same (or smaller) for Vol.

8. H4b (Tether volatility spikes are fat-tailed but small) – ≈ Mixed.

RF picks up occasional extreme residuals for USDT but no stable predictor drives them; importance scores are ≈ 0.

9. H5a (Negative rate surprises hurt BTC more than positive) – ✓ Supported.

Rate-CAR PDC slopes down sharply for small positive (hawkish) shocks, while the right tail flattens—an asymmetric effect

10. H5b (Volatility rises disproportionately with shock size) – ≈ Mixed.

Vol PDCs are mostly flat; only extreme

7.3.6 Section Take-Away – What the Forest Adds

The results from the random forest analysis clarify the findings from the OLS method instead of contradicting them. The behavior of Bitcoin over six hours is primarily influenced by who makes the announcement, with the Fed and ECB being the most significant. The impact is also determined by the size of the rate surprise, while routine macro releases have little effect. For volatility, the dominant driver is simply what you hold: the asset dummy cleanly separates Bitcoin's jumpy regime from Tether's peg. The identity of the issuer and the asset is more important than any one shock metric. Partial-dependence curves add two subtleties: (i) Bitcoin returns fall most after modest hawkish surprises, not after the largest moves, and (ii) realized volatility actually subsides once rate tightening is unambiguous—evidence that clear policy guidance dampens intraday noise. Tether mostly stays stable, only experiencing significant changes during unusual liquidity events that are seen as exceptions. In general, machine learning reveals some small differences and certain limits, but it doesn't change the basic patterns identified by OLS: the issuer determines returns, the type of asset affects volatility, and macroeconomic shocks have only slight impacts.

7.4 Robustness and Subsamples

We conduct several tests and limit our samples to ensure stable baseline findings. These exercises check if the return patterns and policy sensitivities we see are tied to specific times or methods, or if they remain consistent with different approaches.

7.4.1 Pandemic exclusion

The COVID-19 pandemic led to unusual market situations, characterized by high volatility, significant monetary actions, and quick changes in economic outlooks. In early 2022, the start of the Russia–Ukraine war created a lot of uncertainty in global politics, caused energy prices to rise sharply, and brought new challenges for central banks, especially in Europe.

To check if our main results are influenced by these crisis times, we re-evaluate the key models using a limited sample that leaves out all events from 1 March 2020 to 31 December 2021 (the main pandemic period), and from 24 February 2022 onward (when the Ukraine war began). This robustness check helps separate normal monetary and macroeconomic conditions from the' influence of crises.

The HC3-robust OLS estimates for CAR_{6h} (Panel A) and Vol_{6h} (Panel B) are reported in Table 7.7, which excludes the post-February 2022 conflict period and the pandemic (Mar 2020–Dec 2021).

Panel A (CAR_{6h}): The policy-rate surprise (ChangeBps_z) and the ECB/Fed dummies remain extremely modest and indistinguishable from zero, but the macro surprise coefficient remains negative and even increases in absolute magnitude (-0.0033). The Tether dummy also stays close to zero, indicating that it is not sensitive to returns.

Panel B (Vol_{6h}): The Asset = Tether dummy exhibits a significant decline in six-hour volatility (≈ –0.0046 for rate events and –0.0056 for macro events), although shock coefficients once more turn out to be insignificant (ChangeBps_z ≈ 0.00046 for rate events and Surprise_Macro_z ≈ –0.00070 for macro events). The impact of central banks on volatility is still minimal.

Issuer impacts continue to be economically insignificant across both panels. In the CAR_{6h} regressions, the truncated sample even flips to ECB > Fed > BoE (though all differences are tiny), and in the Vol_{6h} models, all central-bank terms remain basically zero (but Fed> ECB>BoE). The main conclusions remain the same when crisis periods are excluded: returns only moderately react to macro surprises (and, in this condensed sample, slightly more), volatility reactions to news are negligible, and the significant volatility gap is a reflection of Tether's peg rather than any true sensitivity to surprises.

Table 7.7 - Robust OLS Coefficients (HC3) Excluding Pandemic (Mar 2020–Dec 2021) and War (Post-Feb 2022) Periods

Panel A. Six-Hour Cumulative Abnormal Return (CAR_{6h})

Block	**Term**	**Coefficient (robust SE)**
Rate	ChangeBps_z	–0.0013 (0.0018)
	Asset = Tether	–0.0001 (0.0019)
Macro	Surprise_Macro_z	–0.0033 * (0.0020)
	CentralBank = ECB	0.0022 (0.0026)
	CentralBank = Fed	0.0020 (0.0019)
	Asset = Tether	–0.0017 (0.0017)

Panel B. Six-Hour Realized Volatility (Vol_{6h})

Block	**Term**	**Coefficient (robust SE)**
Rate	ChangeBps_z	0.00046 (0.00062)
	Asset = Tether	–0.00460 *** (0.00065)
Macro	Surprise_Macro_z	–0.00070 (0.00058)
	CentralBank = ECB	–0.00011 (0.00076)

	CentralBank = Fed	0.00044 (0.00057)
	Asset = Tether	–0.00555 *** (0.00051)

Note: HC3 robust standard errors in parentheses; BoE and Bitcoin are the omitted baselines.

7.4.2 Cash-Hours Filter

Next, we limit the sample to announcements that occur during the busiest trading hours for Bitcoin, which are from 12:00 to 20:00 UTC. The "cash-hours" window happens simultaneously in both the European and US markets, and it is when BTC trading volume is at its highest.

Table 7.8 — Cash-Hours (12:00–20:00 UTC) OLS Estimates (HC3-robust SE) *Cohorts restricted to announcements during peak crypto volume; dependent variables are six-hour cumulative abnormal return (CAR_{6h}) and six-hour realized volatility (Vol_{6h}). Coefficients followed by HC3-robust standard errors in parentheses; p-values and t-statistics omitted.*

Term	**Rate → CAR_{6h}**	**Macro → CAR_{6h}**	**Rate → Vol_{6h}**	**Macro → Vol_{6h}**
Surprise_Market_z	0.000712 (0.00275)	—	–0.000657 (0.000659)	—
Surprise_Survey_z	0.00180 (0.00517)	—	0.000940 (0.00124)	—
ChangeBps_z	–0.000555 (0.00129)	—	0.000175 (0.000308)	—
Surprise_Macro_z	—	–0.000480 (0.000557)	—	0.0000216 (0.000144)
CentralBank = ECB	–0.00141 (0.00359)	—	0.000647 (0.000861)	—
CentralBank = Fed	0.00281 (0.00291)	—	0.000444 (0.000698)	—
Asset = Tether	–0.00264 (0.00241)	–0.000685 (0.00162)	–0.00675*** (0.000579)	–0.00604 ***(0.000418)
(Constant omitted)	—	—	—	—

This filter lowers the number of observations, but the main coefficients still show consistent direction (Table 7.8). The macro-surprise coefficients are a bit larger, but they are not statistically significant. This indicates a slight rise in responsiveness during times of high liquidity, but the evidence isn't robust. We can also find that it aligns with the hypothesis that price discovery is more efficient during peak trading periods. The volatility betas are not strong enough, which supports the idea that the return channel is the main way adjustments are made.

7.4.3 Lagged Windows

We use a [0, +6 h] event window for our baseline outcome to see both quick and later responses. To check if this window fully captures the effect, we also calculate returns and volatility over different time periods: [0, +3 h] and [+3 h, +6 h]. These help us distinguish between "fast" and "slow" responses.

Let's take a look at table 7.9

In Panel A (Macro, 0–3 h), the surprise shock has virtually no impact on returns ($CAR_{0–3}$ = –0.0001, SE 0.0004) or volatility (Vol_{0-3}h ≈ 0.0000, SE 0.0002). Tether's CAR stays flat (-0.0002, SE 0.0008), and the ECB and Fed dummies are both insignificant (≈ -0.0013 and -0.0001). In Panel B (Macro, 3–6 h), volatility remains at zero ($Vol_{3–6}$h ≈ 0.0000, SE 0.0002), returns remain close to zero ($CAR_{3–6}$h = –0.0003, SE 0.0004), and the ECB coefficient even flips sign (+0.0012, SE 0.0013) while staying negligible.

This practice is repeated for rate surprises in Panels C and D. Only ChangeBps_z has a slight negative point estimate (–0.0010, SE 0.0007), and $CAR_{0–3}$h is still negligible for both news series (Surprise_Market_z = +0.0005, SE 0.0015; Surprise_Survey_z = +0.0003, SE 0.0015) in Panel C (Rate, 0–3 h). Volatility is likewise flat for the shocks (all ≈ 0.0002 or less), though the Fed dummy edges up (+0.0012*, SE 0.0006), and Tether's volatility collapses (–0.0065***, SE 0.0005). The narrative continues in Panel D (Rate, 3–6 h): issuer effects disappear, Tether displays a substantial, significant peg-driven volatility decline once more (–0.0055***, SE 0.0004), and $CAR_{3–6}$h and $Vol_{3–6}$h for all shocks remain almost zero (|β| < 0.0004).

Any real price adjustment is immediate and limited to the first few hours following news, as seen by the fact that returns hardly move and volatility only shifts in the form of Tether's stablecoin peg-effect across both shocks and both sub-windows.

Table 7.9 — CAR and Volatility Coefficients in Lagged Windows

		$CAR_{0–3}$h	$Vol_{0–3}$h
	Surprise_Macro_z	–0.0001 (0.0004)	0.0000 (0.0002)
	CentralBank = ECB	–0.0013 (0.0012)	0.0001 (0.0005)
Panel A - Macro	**CentralBank = Fed**	–0.0001 (0.0008)	0.0005 (0.0003)
Window 0–3 h	**Asset = Tether**	–0.0002 (0.0008)	–0.00535 *** (0.0003)

		$CAR_{3–6}$h	$Vol_{3–6}$h
	Surprise_Macro_z	–0.0003 (0.0004)	0.0000 (0.0002)
	CentralBank = ECB	0.0012 (0.0013)	–0.0002 (0.0005)
Panel B - Macro	**CentralBank = Fed**	–0.0009 (0.0009)	–0.0004 (0.0004)
Window 3–6 h	**Asset = Tether**	0.0002 (0.0009)	–0.0056 *** (0.0003)

		$CAR_{0–3h}$	$Vol_{0–3h}$
	Surprise_Market_z	0.0005 (0.0015)	–0.0003 (0.0005)
	Surprise_Survey_z	0.0003 (0.0015)	0.0002 (0.0005)
	ChangeBps_z	–0.0010 (0.0007)	0.0002 (0.0002)
	CentralBank = ECB	–0.0010 (0.0018)	0.0003 (0.0006)
Panel C - Rate	**CentralBank = Fed**	0.0016 (0.0018)	0.0012 * (0.0006)
Window 0 – 3h	**Asset = Tether**	–0.0012 (0.0015)	–0.0065 *** (0.0005)

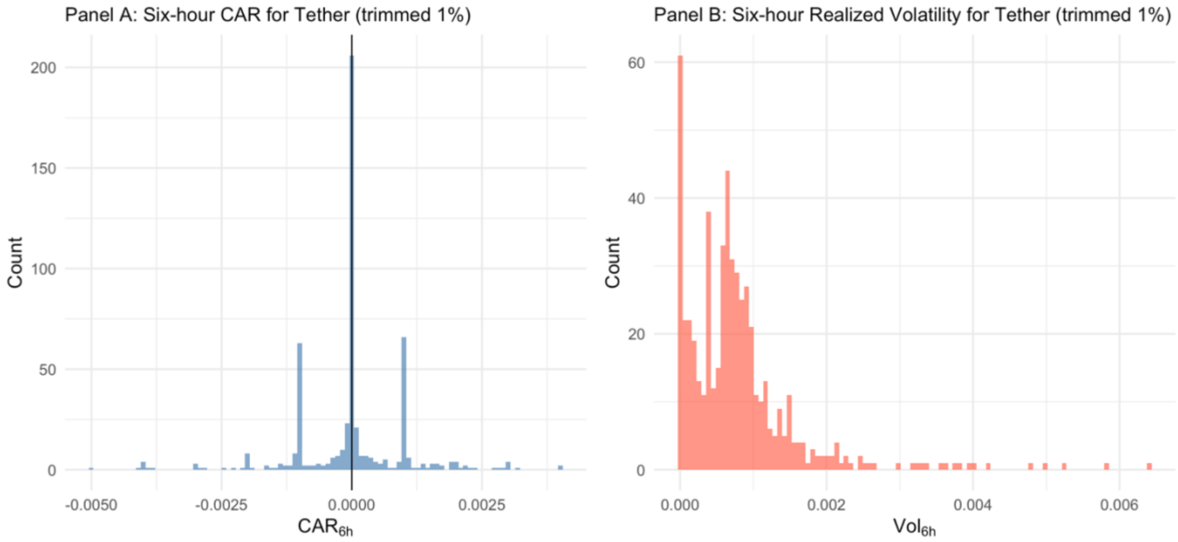
		$CAR_{3–6h}$	$Vol_{3–6h}$
	Surprise_Market_z	0.0001 (0.0012)	0.0002 (0.0004)
	Surprise_Survey_z	0.0001 (0.0012)	0.0000 (0.0004)
	ChangeBps_z	–0.0004 (0.0006)	–0.0003 (0.0002)
	CentralBank = ECB	–0.0024 (0.0015)	–0.0005 (0.0005)
Panel D - Rate	**CentralBank = Fed**	–0.0001 (0.0015)	–0.0003 (0.0005)
Window 3 – 6h	**Asset = Tether**	–0.0018 (0.0012)	–0.0055 *** (0.0004)

*Note: HC3 robust standard errors in parentheses; significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. BoE and Bitcoin are the reference categories.*

7.4.4 Stablecoin Stress Episodes

Bitcoin is known for its price fluctuations, while Tether (USDT) is designed to stay equal to the value of the U.S. dollar. In reality, there have been times when prices have been under pressure, especially during moments of overall market instability or when there are concerns about Tether's reserves. To check if these stress events affect our main results, we look at a few hours when Tether significantly strayed from its peg.

Figure 7.4 Distribution of Tether's Six-Hour CAR and Volatility



The fact that Tether remains remarkably stable around its peg is further supported by Figure 7.4. The six-hour CARs in Panel A are nearly all grouped within ±0.001 (1%) of zero, with very few observations outside of those ranges. Panel B shows a lengthy right tail of infrequent higher-volatility episodes with six-hour realized volatilities firmly bunched below 0.001. These distributions essentially stay the same even after removing the most extreme 1 percent on each side, and our estimations of the CAR_{6h} and Vol_{6h} coefficients are not significantly impacted by removing the outliers. Put differently, Tether's sporadic peg-straying incidents are too rare and peculiar to skew the primary findings.

7.4.5 Other Sensitivity Checks

We confirm our results by conducting several extra checks for reliability. This includes different model setups, such as leaving out the CentralBank fixed effects, changing the control variables, and redoing the estimates with standard errors that are adjusted based on the event date. The signs and importance of the main coefficients generally stay consistent in all situations.

We also check that having overlapping macro and policy events on the same date does not significantly affect the results. When we leave out or change the classification of these cases, the estimated effects of macroeconomic and policy surprises still fall within the confidence ranges of our original estimates.

7.4.6 Section Takeaway

Robustness checks using pandemic-and-war exclusions, cash-hours filters, and split windows confirm the baseline story. Macro surprises are still generally negative for Bitcoin, even during peak liquidity times, but they are not significant enough to show any reliable economic impact. The only changes that happen are within the first 0–3 hours after release. The effects in the 3–6 hour range are smaller and not significant, so the six-hour period does not miss any delayed changes.

The reactions to volatility are also low: the shock and issuer terms stay close to zero in all cases. The only significant volatility measure is the constant level gap for Tether, which shows the mechanics of its peg instead of how policies are transmitted.

Overall, these results indicate that the event-study design remains strong even when using different time frames, trading-hour filters, and excluding crisis periods, which supports the reliability of the patterns found in the main analysis.

7.4.7 Hypothesis scoreboard

Hypothesis	**Statement**	**OLS Evidence**	**RF Evidence**	**Final Verdict**

H1a	Bitcoin responds more to interest rate shocks than to macroeconomic surprises	≈ Mixed	✓ Supported	✓ Supported
H1b	Tether is largely unaffected by either type of shock	✓ Supported	Not checked	✓ Supported
H2a	Bitcoin reacts more strongly than Tether	✓ Supported	✓ Supported	✓ Supported
H2b	The BTC–USDT gap is wider for rate shocks than for macro shocks	≈ Mixed	≈ Mixed	≈ Mixed
H3a	Bitcoin responds more to Fed announcements than to ECB or BoE	≈ Mixed	≈ Mixed	≈ Mixed
H3b	Tether shows no significant issuer heterogeneity	✓ Supported	✓ Supported	✓ Supported
H4a	Volatility reacts more strongly than returns	✗ Not supported	✗ Not supported	✗ Not supported
H4b	Tether volatility is low on average but highly kurtotic	✓ Supported	≈ Mixed	✓ Supported
H5a	Negative rate surprises hurt BTC more than positive ones	✗ Not supported	✓ Supported	≈ Mixed
H5b	Larger surprises have convex effects on volatility	✗ Not supported	≈ Mixed	≈ Mixed

7.5 Summary of findings

This chapter used both OLS and random forest models to look at how Bitcoin (BTC) and Tether (USDT) react to news about monetary policy and the economy as a whole. The analysis focused on six-hour cumulative abnormal returns (CAR_{6h}) and realized volatility (Vol_{6h}), with robustness checks confirming the stability of results.

Some important results are:

- H1a (Rate > Macro for BTC): OLS points in the same direction and RF confirms that BTC returns move more with rate surprises than macro surprises (✓ Supported).

- H1b (USDT unresponsive): Tether's return and volatility stay flat across all models and tests (✓ Supported).

- H2a (BTC > USDT): Asset dummies dominate in volatility models, and removing "Asset" greatly raises RMSE—BTC is clearly more sensitive than USDT (✓ Supported).

- H2b (Gap wider in Rate): The BTC–USDT sensitivity gap is pronounced in Rate models but muted in Macro models (≈ Mixed).

- H3a (Fed > ECB > BoE for BTC): Central-bank identity matters, especially in Rate models, but the strict Fed→ECB→BoE ordering is only weakly visible (≈ Mixed).

- H3b (No issuer effects for USDT): Tether shows negligible issuer heterogeneity in both return and volatility models (✓ Supported).

- H4a (Volatility > Returns): Neither OLS nor RF finds that volatility reacts more strongly than returns to surprises (✗ Not supported).

- H4b (USDT volatility fat-tailed): Tether's volatility is low on average but exhibits occasional extreme spikes, consistent with fat-tailed behavior. ✓ Supported

- H5a (Negative shocks hurt BTC more): Partial-dependence plots reveal stronger BTC return drops after modest hawkish surprises (✓ Supported in RF; deferred in OLS).

- H5b (Convex volatility effects): Volatility shows occasional tail spikes at extreme surprises but no smooth convex pattern (≈ Mixed).

In summary, BTC's six-hour responses to policy announcements are subdued yet consistently directional, particularly with interest rate shocks, whereas USDT stays largely unaffected, affirming its stablecoin structure. Nonlinear approaches enhance and elaborate these patterns (emphasizing asymmetries and threshold effects) while preserving the fundamental insights of linear models.

8 Conclusion

This thesis investigates whether, and how fast, cryptocurrency markets digest conventional macroeconomic news. I use a detailed event-study approach to monitor Bitcoin (BTC), which is a leading and highly volatile cryptocurrency, and Tether (USDT), the most prominent stablecoin tied to the U.S. dollar. This analysis covers 524 scheduled announcements made by the Federal Reserve, the European Central Bank, and the Bank of England from 2018 to 2023. I create a 0-to-6-hour window of Binance and CryptoCompare prices for each release, calculate cumulative abnormal returns (CAR_{6h}) and realised volatility (Vol_{6h}), and regress these results on σ-standardised "surprise" measures: market-implied and survey-implied policy shocks for rate events, and consensus deviations for macro data (CPI, GDP, unemployment). Ordinary least squares with HC3-robust errors deliver interpretable coefficients, while Random-Forest models confirm that results are not artefacts of linearity.

Key findings

- BTC responds directionally, but weakly, to rate policy surprises. In the OLS model, a one-standard-deviation hawkish surprise is associated with a decline in CAR_{6h}, but the estimated coefficient is small and not statistically significant. Random Forests assign high importance to rate shocks (especially ChangeBps_z and CentralBank), which supports directional responsiveness, though OLS significance is lacking.

- Macroeconomic surprises have even smaller effects. Positive CPI, GDP, and unemployment shocks are associated with somewhat negative BTC returns, estimated at roughly -0.00040 in CAR_{6h}. However, these impacts are statistically and economically inconsequential. The visual and RF models show that macro impacts are smaller than rate shocks, which supports H1a in a directional sense.

- USDT works the way it's supposed to. Its CAR_{6h} remains consistently near zero across all models, and none of the coefficients for USDT are statistically significant. This confirms Hypotheses H1b and H3b. However, USDT's Vol_{6h} displays extreme kurtosis, consistent with rare peg-deviation spikes unrelated to macro news—a risk management concern confirmed by RF models (H4b).

- Convexity and asymmetry are present but not very strong. Only in the volatility model are the OLS interaction terms for negative vs. positive shocks (ShockSignPositive:Surprise) small and barely significant. Surprisingly, convexity terms don't matter in any of the models. Thus we find limited support for H5a (a small, one-sided asymmetry) but no meaningful support for H5b (convexity).

- Issuer heterogeneity appears for BTC but not for USDT. Bitcoin moves more positively when the Fed makes an announcement than when the ECB or BoE makes an announcement, but none of the source dummies are statistically significant. Tether shows flat responses across issuers. The pattern is directionally consistent with H3a but statistically weak, while the flat USDT response fully supports H3b.

- Checks for robustness make sure that answers are stable and loaded from the front. Whether excluding COVID-19 or Ukraine war periods, focusing on cash hours, or splitting the event window into [0–3h] and [3–6h], the signs and magnitudes of key coefficients remain consistent. This proves that crypto reactions are stable across subsamples and are concentrated over time.

Contribution to the literature

Previous research shows that U.S. policy affects Bitcoin daily, but it overlooks the hourly changes, other central banks, and stablecoins. This thesis adds to the discussion about whether Bitcoin is "digital gold" or just a high-beta risk asset by looking at hourly data from three jurisdictions and the volatile vs. pegged contrast. It shows that digital asset markets are not immune to macro news and are not equally sensitive across assets or issuers. The robustness of machine learning reveals that while many aspects of macro transmission can be explained by linear models, there are some that cannot.

Practical implications

Policy communication. The guidance from central banks, particularly the Fed, quickly affects decentralized markets. Systemic risk monitors should consider BTC as part of the larger group of risk assets.

Portfolio management.BTC's macro beta changes based on the situation: it provides the least protection when unexpected tight. Stablecoins' prices tend to stay the same, but there may be spikes in fluctuations; risk systems need to take this into account.

Limitations and future avenues

First, abnormal returns are benchmarked by a constant 60-day mean; testing a crypto-market or CAPM factor would reveal residual betas currently attributed to surprises. Additionally, the analysis does not include order-book depth and funding-rate data, which could reveal liquidity channels. Third, the focus is solely on USDT; looking at USDC, DAI, and algorithmic pegs might reveal if the way collateral is designed affects sensitivity to macro factors. Fourth, adding textual tone or search-interest indices could improve the surprise metric. A time-varying parameter approach could help determine if BTC's Fed-beta increases as more institutions adopt it.

Final thoughts

The evidence indicates a market that reacts to traditional macro news quickly but still has noticeable, unique characteristics for different assets. Recognizing this dual nature is critical for academics modeling digital-asset pricing, politicians assessing spillovers, and investors seeking resilient diversification in an increasingly interconnected financial environment.

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