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Monetary Policy and Financial Markets: A Causal Analysis of the Fed's Interest Rate Effect on the U.S. Stock Market and Major Cryptocurrencies

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Abstract: ***This study investigates the causal relationship between the Federal Reserve's interest rate policy and financial markets, with emphasis on asset-specific responses across major U.S. stock indices and leading cryptocurrencies. The Fed's interest rate decisions significantly influence various economic facets, including the stock market's behavior, making it crucial to understand these liaisons for investors, banks, and policymakers. This study contrasts the reactions of the Nasdaq, DOW, and S&P500 indices with those of Bitcoin and Ethereum, while controlling for inflation, long-term interest rates, supply chain disruptions, and energy prices to provide a thorough analysis. The intervention centres around the Fed's rate cuts prompted by the COVID-19 pandemic, a period marked by unprecedented economic turmoil. The study aspires to offer insights into monetary policy's role and value. Findings reveal distinct heterogeneity in market reactions: while the Nasdaq index experienced robust and sustained positive effects following the policy intervention, the DOW exhibited significant adverse impacts and the SP500 responded in more nuanced fashion. Cryptocurrencies display comparatively weaker and less consistent responses, indicating reduced sensitivity to conventional monetary policy transmission. The findings aim to shed light on how Fed interest rate adjustments can drive financial institutional policies. This study's results indicate that the Federal Reserve's rate cut initiated during the COVID-19 pandemic illuminates the complex transmission mechanisms of monetary policy, and that there is a differential effect of interest rates on crypto vs. stock markets. This study aims to enhance understanding of market dynamics in response to monetary interventions, providing valuable insights for investors, financial institutions, and policymakers navigating periods of crisis.***

Keywords: Stock Market, Cryptocurrency, Bitcoin, Monetary Policy, Financial Markets, COVID-19, Nasdaq

1. Introduction

The Federal Reserve, often called "the Fed," plays a vital role in the United States economy through its interest rate policy, which is crucial in steering economic growth and stability (Bernanke, 2013). The Effective Federal Funds Rate (EFFR) is a tool of the Fed's monetary policy, capturing its interest rate decisions. Often perceived as a barometer of economic health, the stock market reacts to the Fed's interest rate policy. The linkage between Fed rate changes and U.S. stock market performance remains a keen interest to economists, investors, and policymakers. Ehrmann and Fratzscher (2004) highlight that individual stocks react in a highly heterogeneous fashion to U.S. monetary policy shocks. These stock reactions create ripples in market volatility and influence the broader economic outlook, underlining the critical role of monetary policy in shaping market dynamics (Ehrmann & Fratzscher, 2004). Therefore, monetary policy shocks influence market volatility and overall economic outlook. The EFFR is a benchmark for many interest rates applicable to savings, loans, and mortgages. Understanding the causal relationship between EFFR and stock market performance is pivotal for anticipating changes in economic trends. This study seeks to explore and establish a causal relationship between EFFR and stock market performance by examining the National Association of Securities Dealers Automated Quotations(NASDAQ) Composite Index, Dow Jones Industrial Average(DOW), and Standard & Poor's 500 Index(SP500).

Events that affect the economy impose adaptive shifts to monetary strategies employed by the Federal Reserve; one such event is the COVID-19 pandemic. The COVID-19 pandemic ushered in an unparalleled economic disruption and led to significant volatility in global stock markets (Aggarwal, Nawn, & Dugar, 2021). The COVID-19 pandemic prompted rapid monetary interventions by central banks globally (Deng, Xu, & Lee, 2022). Central banks worldwide, including the Federal Reserve, implemented emergency measures. These included slashing interest rates to near-zero levels and engaging in quantitative easing to foster liquidity and to support economic recovery. Various policy measures, such as lockdowns and interest rate cuts, were implemented worldwide to mitigate the pandemic's health, political, and economic effects (Deng et al., 2022; Narayan, Phan, & Liu, 2021). Through this study, we seek to explain the causal links underpinning the Fed's interest rate policy and US stock market performance. This study explores whether the Fed's interest rate policy impacts US stock market performance using a Difference-in-Differences (DiD) approach, particularly during critical periods like the COVID-19 pandemic. For instance, there is uncertainty about the economy's revival in response to policy interventions in the wake of events such as COVID-19 (Altig et al., 2020). This study's approach extends beyond conventional analysis by incorporating Bitcoin (BTC) and Ethereum (ETH) as an untreated control group to isolate the effects of rate changes on the stock market. The emerging field of cryptocurrency provides an intriguing comparison to traditional markets. This study attempts to untangle the distinctive effects of interest rate policies on the stock market, juxtaposed with cryptocurrencies by employing BTC and ETH. To strengthen the findings, controls for inflation, long-term interest rates, supply chain disruptions, and energy prices are integrated into the analysis. This study explores two core hypotheses:

Hypothesis 1: *The Fed's interest rate impacts the stock market, and the rate cuts introduced during the COVID-19 pandemic produced distinct effects across the stock market.*

Hypothesis 2: *There is a differential effect of interest rates on the stock market vs the crypto market; cryptocurrencies are less sensitive to conventional monetary policy.*

The premise of hypothesis 1 is grounded in the traditional understanding of monetary policy's influence on financial markets. Changing the effective federal funds rate impacts borrowing costs, investment returns, and liquidity within the economy, influencing investor actions and market dynamics (Bernanke & Blinder, 1992). The Fed enacted a significant rate cut in March 2020 to mitigate economic disruption in response to the COVID-19 pandemic. This study utilizes the Fed's rate cut on March 16, 2020, as the critical intervention point. The Fed's action presents a unique context for understanding stock market responses to monetary policy measures. This study aims to enrich the understanding of monetary policy's efficacy. Understanding the interplay between Fed rate changes and stock market performance is crucial for those involved directly in financial markets and for policymakers. The second hypothesis delves into the contrasting responses between traditional financial markets and the emergent cryptocurrency market to monetary policy actions. Schär (2021) highlights that cryptocurrencies like Bitcoin(BTC) operate within a decentralized framework using blockchain. The Bitcoin(BTC) is largely independent of traditional banking systems and central bank interventions (Berentsen, Frey, & Schaltegger, 2019). During the COVID-19 pandemic, cryptocurrencies displayed significant volatility; however, many argue that this market's fluctuations are driven more by technological, speculative, and macroeconomic factors rather than direct impacts of interest rate changes (Corbet, Larkin, & Lucey, 2020). Evaluating hypothesis 2 provides insights into the evolving dynamics of financial systems, highlighting the unique characteristics and resilience of decentralized cryptocurrencies in contrast to traditional assets.

To explore the differential effect of interest rate policy on stock indices and digital currencies, we first review relevant literature on the relationship between monetary policy and financial markets, with a focus on the Covid-19 pandemic context and highlight gaps in the comparative responses of cryptocurrencies and equities. Second, we outline the data sources and describe the methodological framework, notably the use of a difference-in-differences (DiD) approach. The analysis encompasses tests for the parallel trends assumption and implements various robustness checks. Third, we present the results and discuss their implications. Finally, we propose avenues for future research and conclude with a summary.

2. Literature Review

A) Existing Literature

Studies have examined the interplay between monetary policy and stock market dynamics (Phan & Narayan,2020; Ashraf, 2021; Bernanke & Kuttner, 2005; Corredor et al., 2013; Ehrmann & Fratzscher, 2004; Bernanke & Blinder, 1992; Rigobon & Sack, 2003). Studies have explored linkage between macroeconomic factors and stock performance (Lettau & Ludvigson, 2001; Fama, 1981; Chen, Roll, & Ross, 1986; Campbell & Shiller, 1988; Ferson, & Harvey, 1991; Schwert, 1989).

Interest rate sensitivity of stock market: Bernanke and Kuttner (2005) explored the impact of monetary policy announcements on equity prices, demonstrating that unexpected rate changes can lead to significant market reactions. Rigobon and Sack (2004) examined monetary policy's role in influencing asset prices, illustrating that the anticipation of interest rate changes, and not just the actual changes, can lead to noteworthy adjustments in stock values. Campbell and Yogo (2006) have delved into the performance of equity markets under varying interest rate regimes. Estrella and Mishkin (1998) evaluated the threshold effects of the 10-year Treasury yield, establishing that the 10-year Treasury yield surpassing critical levels, like 5% impacts stock market performance. Collectively, these studies highlight the sensitivity of stock market performance to interest rates.

COVID-19 responses and stock markets: Studies show that interest rate changes in response to COVID-19 impacted stock markets (Zhang, Hu, & Ji,2020; Scherf, Matschke, & Rieger,2021; Deng et al.,2022; Aggarwal et al., 2021). Ashraf (2021) contributed a contemporary view of how monetary policies during the COVID-19 pandemic affected global stock markets. Phan and Narayan (2020) emphasized that while monetary policies typically aim to stabilize markets, their effectiveness can differ greatly during crises such as pandemics. The Fed’s near-zero rates and asset purchases were critical to the post-March 2020 equity rebound. Andrade et al. (2016) found that short-term and medium-term yields affected by Federal Reserve actions play a crucial role in stabilizing stock prices during economic crises. Kiley (2018) discussed the preventive measures of monetary policy in supporting equity markets, emphasizing that accommodative policies often shield the market from detrimental effects during economic shocks. These studies collectively highlight that Fed policies during COVID-19 impacted stock prices.

Existing studies highlight the intricate relationship between interest rates and stock market performance. They emphasize that understanding interest rate dynamics is essential for anticipating stock market performance, particularly in response to monetary policy changes. However, gaps remain, which this study aims to address through its approach using BTC and ETH as a control group, and focusing on COVID-19-era monetary interventions.

B) Gaps addressed

Monetary policy effects: Despite advancements in understanding the relationship between monetary policy and equity markets, significant gaps persist in the literature in isolating the explicit impacts of the Fed's monetary policy from other confounding variables such as inflation, supply chain disruptions, and energy prices. Typical studies on factors influencing stock valuations focus solely on short-term rates (Fama, 1981). Energy costs influence market dynamics: this perspective is thin in the literature, with a focus primarily on financial indicators (Hamilton, 2009). Guido et al. (2024) highlight the importance of Global supply chain pressure and its implications on monetary policy. Existing studies have often included just one or two of the factors, obscuring the direct effects of interest rate changes. This study aims to provide a more nuanced assessment of how interest rate changes are associated with stock market performance during a crisis, while accounting for the role of multiple macroeconomic variables. Existing studies do not integrate a wide range of economic indicators. This study offers a thorough analysis of market dynamics by including the Effective Federal Funds Rate (EFFR), the Market Yield on U.S. Treasury Securities at 10-year Constant Maturity, the Consumer Price Index (CPI), the West Texas Intermediate (WTI) Oil Prices, and the Global Supply Chain Pressure Index (GSCPI). These control factors create a framework that adds depth to the exploration of monetary policy effects. By controlling for these influences, the analysis seeks to clarify asset-class sensitivities around key policy interventions, while acknowledging the potential confounding effects, particularly during the COVID-19 pandemic.

Cryptocurrency role: Cryptocurrencies, especially Bitcoin (BTC), operate outside central banks' purview, making them less directly influenced by monetary policy decisions (Baur, Hong, & Lee, 2018). However, the interactions and implications of cryptocurrencies relative to conventional monetary policy present various gaps that warrant further exploration. Bitcoin initially showed independence from traditional markets, but recent events have highlighted that while Bitcoin initially served as a diversification asset, it began exhibiting increased sensitivity to U.S. Federal Reserve policy shifts starting in late 2020, often mirroring the behavior of other risky assets amid central bank announcements (Karau, 2023). At the same time, it served as a hedge in some emerging markets during COVID-19, and its effectiveness as a protective asset varied significantly across regions (Ji et al., 2019; Marmora, 2022). There is a growing sensitivity of cryptocurrencies to conventional market drivers, potentially driven by increasing institutional investments and Bitcoin's integration into broader financial strategies (Corbet et al., 2020). There is emerging evidence that monetary policy measures and liquidity provision also transmit effects to cryptocurrency returns (Ma et al., 2022; Nguyen et al., 2019). The extent to which cryptocurrencies react to monetary policy shifts is not entirely understood. Further research is needed to comprehensively identify specific triggers linking monetary policy and Bitcoin's volatility (Aalborg et al., 2019). Institutional actions and asset allocation strategies significantly shape Bitcoin's market dynamics and its correlation with traditional financial markets (Makarov & Schoar, 2020). Therefore, gaps persist in understanding the differential influence of interest rates on cryptocurrencies compared to conventional stock markets. This study aims to address these gaps and advance the knowledge of how cryptocurrencies fit within the broader monetary landscape using Hypothesis 2.

Focus on US market specific dynamics: Ashraf (2021) demonstrated that stock markets reaction to COVID-19 were not uniform across countries, emphasizing that economic structures and policy responses contributed to differing levels of market resilience. Rajan and Zingales (2003) emphasize that political interests can influence financial innovation. Thus, the U.S. market dynamics may differ from markets that are shaped by political interests. Therefore, it is critical to focus narrowly, to capture nuances of country-specific dynamics, and to contribute to original insights. In capturing U.S. market-specific dynamics, existing research includes broad indices like Dow Jones and SP500, failing to isolate the unique characteristics of each stock index. The NASDAQ is disproportionately affected by monetary policies; some of NASDAQ's listed stocks, being innovative in nature, have an inherent market resilience, allowing them to continue growing in value despite pressures from rising interest rates. Fama and French (2004) highlight that companies with higher growth prospects often exhibit resilience during times of economic tightening. This approach of emphasizing the U.S. stock indices in the context of U.S.-specific monetary policy addresses an essential area of financial research, contributing to original insights. This focused analysis of the U.S. stock indices helps bridge existing literature gaps by providing a U.S.-specific perspective that has been insufficiently explored.

In summary, this study utilizes Bitcoin and Ethereum as an untreated control group within a DiD framework, offering a unique perspective on stock market dynamics in response to shifting interest rates. DiD directly measures the causal effect of the specific policy intervention during COVID-19, which is more policy-relevant. The Fed rate cut during COVID-19 provides a natural experiment to create a clear treatment (stock indices) vs control (cryptocurrencies) comparison. The Fed's decision was largely exogenous to individual asset performance. Campbell and Thompson (2008) have shown that lower relative valuations can provide a margin of safety, which mitigates the adverse effects of increasing interest rates on stock prices. Baker and Wurgler (2006) highlight that investor sentiment has larger effects on stocks, whose valuations are highly subjective and difficult to arbitrage. The NASDAQ index comprises largely growth-oriented stocks that have compelling valuations and thus have an inherent market resilience.

Therefore, by quantifying how stock indices react to Fed rate changes independent of confounding variables, this study could refine predictive models on interest rate effects. Its insights into Bitcoin and Ethereum limitations as a control during monetary shifts may address the literature gaps in cryptocurrency diversification strategies. The DiD framework used in this study allows estimation of differential effects across NASDAQ, DOW, and SP500. Traditional studies typically use Vector Auto Regression(VAR) models and estimate aggregate effects, missing important heterogeneity. For policymakers, the results may highlight the critical importance of Fed policy and potential ripple effects in broader economic contexts. This study, therefore, addresses a gap in the literature.

3. Methodology

A) Data Collection and Preprocessing

To investigate the causal relationship, this study employs a comprehensive data collection and pre-processing strategy. The analysis leverages a comprehensive dataset encompassing financial market data and various macroeconomic indicators. Two distinct subsets represent stock and crypto data, integrated with macroeconomic variables such as the Effective Federal Funds Rate (EFFR), 10-year Treasury yield (DGS), Consumer Price Index (CPI), crude oil prices (CRUDE), Gross Domestic Product (GDP), and the Global Supply Chain Pressure Index

(GSCPI). This study is based on dataset covering the period from January 1, 2019, to December 31, 2021.

1) Financial Market Data

- NASDAQ, DOW, and SP500 Daily Close Price: This serves as the primary metric to measure the performance and response of the stock market. See Fig-1, Fig-2, and Fig-3 for the stock indices trend.
- Bitcoin (BTC) and Ethereum(ETH) Daily Close Price in USD: Utilized as an untreated control group to differentiate the impact of the interest rate policy on the Stock indices. See Fig-4, Fig-5 for the BTC and ETH trend.

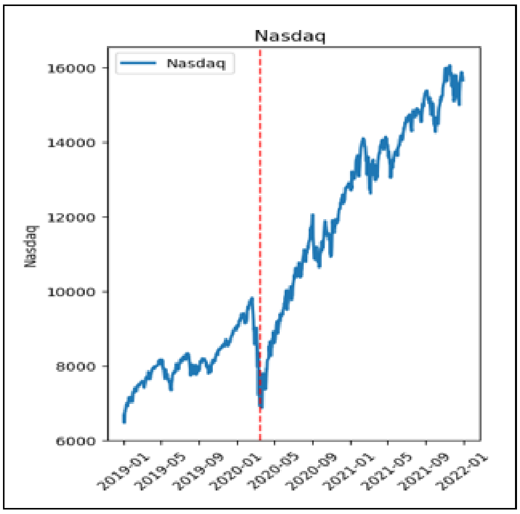

Figure 1: NASDAQ Trend

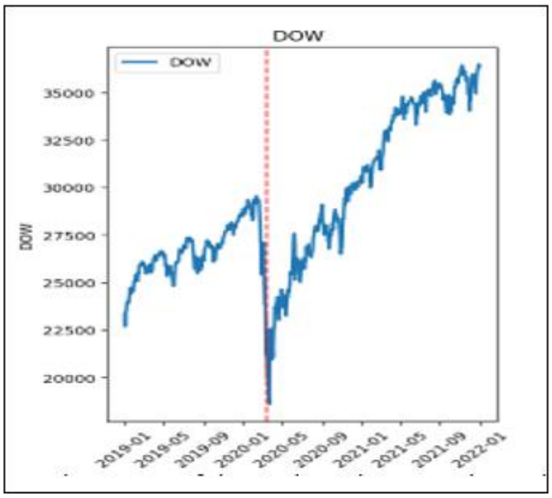

Figure 2: DOW Trend

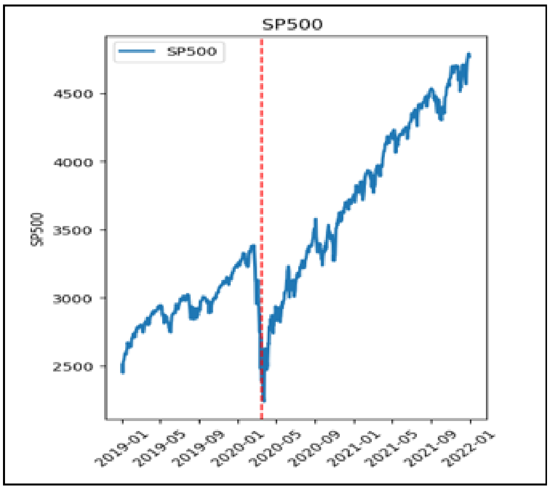

Figure 3: SP500 Trend

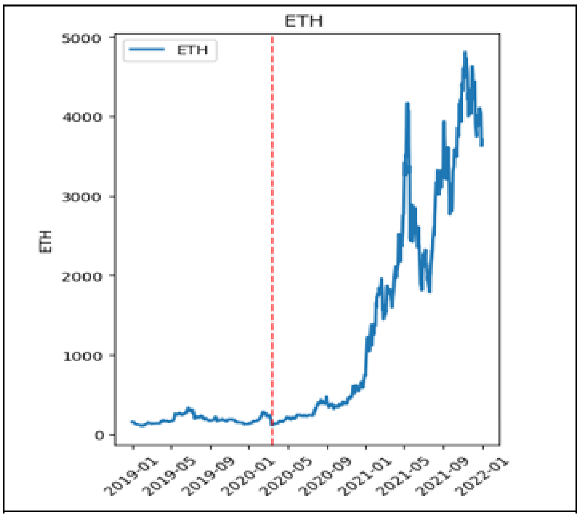

Figure 4: ETH Trend

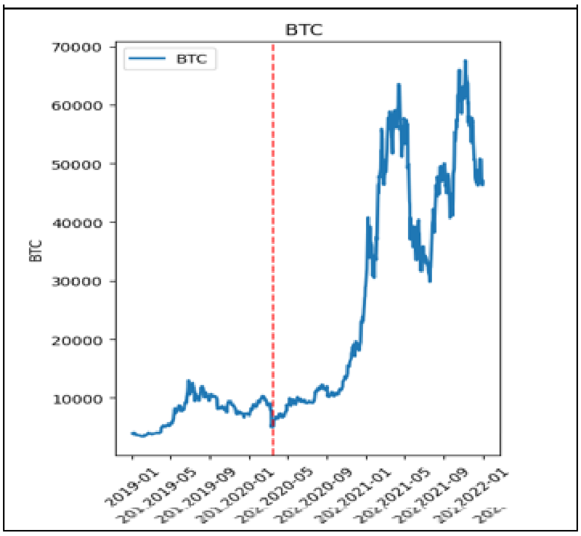

Figure 5: BTC Trend

2) Macroeconomic Indicators

- Effective Federal Funds Rate (EFFR): This is the intervention variable in this study, which captures the Fed's interest rate.
- 10-Year Treasury Yield(DGS): This variable represents the yield on the U.S. government's 10-year Treasury, a benchmark for long-term interest rates. When 10-year

yields surpass certain levels, the cost of borrowing increases, potentially dampening stock market returns as companies face higher financing costs (Estrella & Mishkin, 1998). This data point is used in the study to control influences related to long-term interest rates.

- Consumer Price Index (CPI): This data point serves to control the effects of inflationary pressures. Inflation is pivotal to almost every economic issue(Boskin et al., 1998)
- West Texas Intermediate (WTI) Oil Prices: This variable is an important benchmark in oil pricing, representing the cost of crude oil from the U.S. interior. Included to account for energy price fluctuations, which impact costs for businesses, consumer spending, and broader economic conditions. Oil prices have significant effects on consumption spending and purchases of domestic automobiles in particular(Hamilton, 2009).
- Global Supply Chain Pressure Index (GSCPI): An index representing the level of pressure on global supply chains, affecting the cost and availability of goods. Supply chain disruption can lead to product shortages and increased costs, thereby impacting market dynamics(Riaz et al., 2025). Included for controlling supply chain shocks. Supply-demand imbalances arising from COVID-19 led to a shortage of raw materials, which in turn led to increases in their prices(Guido et al., 2024).
- Gross Domestic Product (GDP): The GDP represents the total economic output and health of an economy, indicating a nation's overall economic performance. This is included to account for broader market sentiment, economic conditions, and investor outlook. Corredor et al. (2013) highlighted that investor sentiment influence stock returns and varies in intensity across markets.

3) Creation of Analysis Groups

- **Treatment Group**: Comprises NASDAQ, DOW, and SP500 data for the period post-March 16, 2020, to assess the effect of the interest rate policy changes.
- **Control Group:** Consists of BTC and ETH data post-March 16, 2020, serving as a benchmark to evaluate stock market's distinct response.

To ensure the stock indices and cryptocurrency daily closing prices are on a comparable scale, they were normalized using min-max normalization. Mathematically, min-max normalization transforms a variable according to the formula.

$$Y_{norm} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}}$$

This is a common data preprocessing step, especially when input data ranges differ significantly, to mitigate scale distortions in analysis, see Fig. 6, Fig. 7, and Fig. 8 for normalized trends. Comparing the normalized trends in Fig. 1 to Fig. 5, we can see that the trends of NASDAQ, DOW, SP500, BTC, and ETH were maintained after normalization. Thus, we conclude that the normalization did not alter any underlying data.

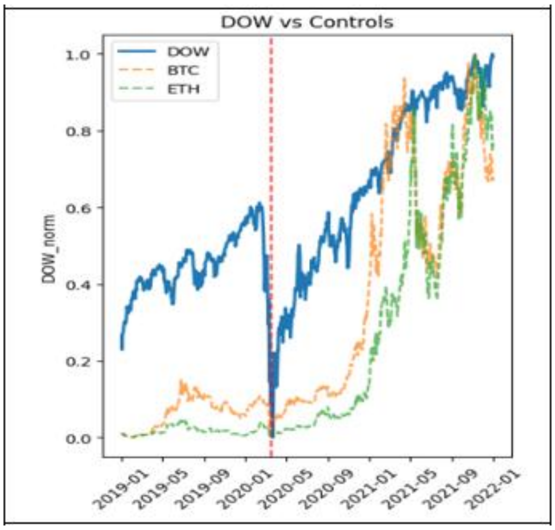

Figure 6: DOW Vs Control

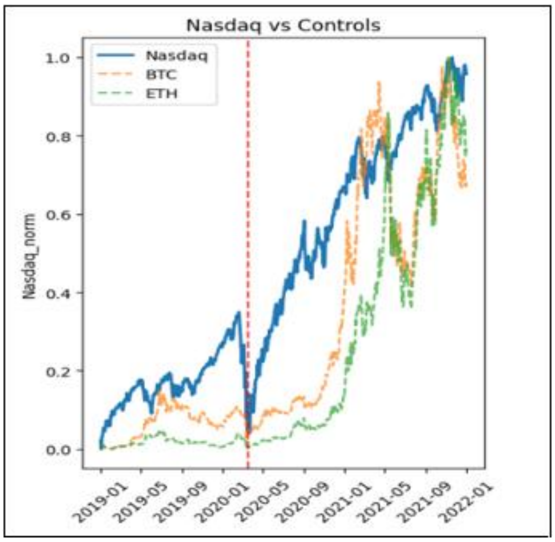

Figure 7: NASDAQ Vs Control

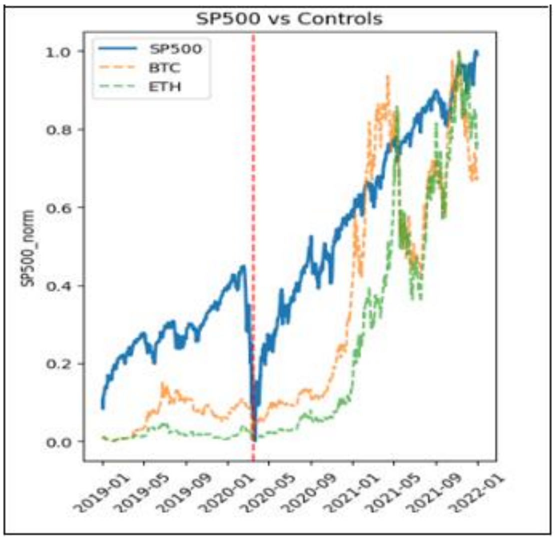

Figure 8: SP500 Vs Control

A treatment variable is assigned a value of 1 for the stock indices to denote the intervention group prices and assigned 0 for cryptos. The data collection and pre-processing approach outlined forms the foundation for dissecting and understanding complex interactions between interest rate policies and stock market behaviour. Data pre-processing ensures temporal alignment and fills in missing information to enable seamless analysis. The daily close prices of the stock indices are explicitly aligned with the macroeconomic data, ensuring all data points share matching dates. For example, the GSCPI is typically released monthly on the fourth business day of each month, reflecting the preceding month. In our dataset, GSCPI is aligned with the stock indices such that the current month stock prices are paired with the GSCPI's previous month values. Similarly, CPI data, which is monthly, is forward-filled to handle any gaps within a given month. GDP, available quarterly, is forward-filled to bridge missing values up to the release of the subsequent GDP index. For the other macroeconomic variables, forward-filling are employed where applicable, specifically focusing on aligning data with varying release frequencies.

B. Evaluation and Empirical Analysis

This study is grounded in Difference-in-Differences (DiD) approach. The study controls for various external factors such as inflation, long-term interest rates, crude oil prices, GDP growth, and supply chain disruptions.

1) Parallel Trends

The parallel trend is a crucial test for causal inference in DiD analysis. The parallel trends test asserts that, in the absence of the policy intervention (changes in interest rate policies), the treatment and control groups would have evolved similarly over time. The study begins by ensuring compliance with the parallel-trend assumption to establish the validity of the DiD methodology. Each of the stock index and crypto return is calculated as the first difference of normalized values within the pre-intervention window to provide a direct comparison. The time difference in days is calculated from the initial date. A statistical test employing ordinary least squares (OLS) regression is performed with an interaction term between time and treatment group. This OLS is conducted on pre-intervention returns against each pair, such as NASDAQ vs BTC, NASDAQ vs ETH, DOW vs BTC, DOW vs ETH, SP500 vs BTC, and SP500 vs ETH.

$$Return_{it} = \beta_0 + \beta_1 \times Time_t + \beta 2 \times Pair\_Treatment_i + \beta 3 \times (Time_t \times Pair\_Treatment_i) + \varepsilon_{i,t} \quad - I$$

This study investigates interaction effects between time and treatment for each stock index against each crypto to confirm the parallel trends assumption rigorously. The Time Treatment coefficient assesses whether, before the event, the returns of the treatment variable diverged in trend from those of the control variable. An insignificant p-value (commonly above 0.05) for this interaction term signals no evidence of differential pre-intervention trends, supporting the validity of the DiD approach.

2) Difference-in-Differences Modelling

Assets are grouped into

Treatment group: NASDAQ, DOW, SP500

Control group: BTC, ETH

For each asset, a dummy variable ($Treatment_i$) is assigned (1 for stock indices, 0 for cryptocurrencies). The post-intervention period is indicated by $Post_t$ (1 for dates on or after intervention, 0 before).

Asset-specific intercepts are included via fixed-effect dummies (γ_i), with restrictions to one from each group to avoid collinearity. All but one dummy from each group (treatment/control) is omitted, so that each asset category is compared to a chosen reference (NASDAQ for treatment; BTC for control). This study has 4 DiD modelling approaches as listed below.

Model-1(Basic DiD): A basic DiD model assesses the differential impact of treatment over time without additional control variables. It focuses on the interaction between treatment status and the post-intervention period.Here, γ_i represents restricted asset fixed effects, included for granularity but subject to the dummy-variable trap (one dropped per group).

$$Y_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \beta_2 \times Post_t + \beta_3 \times (Treatment_i \times Post_t) + \gamma_i + \varepsilon_{i,t} \quad - II$$

Model-2(DiD with Controls): An enhanced DiD model incorporates control variables to account for confounding factors that may influence market returns. By including EFFR, DGS, CPI, CRUDE, GDP, and GSCPI, this model aims for a more nuanced understanding of the Federal Reserve's rate cuts' effects.

$$Y_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \beta_2 \times Post_t + \beta_3 \times (Treatment_i \times Post_t) + \gamma_i + \beta_4 \times EFFR_t + \beta_5 \times DGS_t + \beta_6 \times CPI_t + \beta_7 \times CRUDE_t + \beta_8 \times GDP_t + \beta_9 \times GSCPI_t + \varepsilon_{i,t} \quad - III$$

Model-3(Log-Level): Recognizing potential scale variances and non-linear effects, a third model examines the log-transformed dependent variable (Log Y). This approach mitigates issues surrounding data distribution and provides insights into percentage changes. The financial data (especially for assets like cryptocurrencies) is well-known for extreme skewness and heavy tail behavior. The log transformation reduces these extremes.

$$LogY_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \beta_2 \times Post_t + \beta_3 \times (Treatment_i \times Post_t) + \gamma_i + \beta_4 \times EFFR_t + \beta_5 \times DGS_t + \beta_6 \times CPI_t + \beta_7 \times CRUDE_t + \beta_8 \times GDP_t + \beta_9 \times GSCPI_t + \varepsilon_{i,t} \quad - IV$$

Model-4(With Time Trends): To capture dynamic effects and potential time-variant impacts post-intervention, Model-4 augments the Model-2 specification with a time trend interaction (Time×Post).

$$Y_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \beta_2 \times Post_t + \beta_3 \times (Treatment_i \times Post_t) + \gamma_i + \beta_4 \times EFFR_t + \beta_5 \times DGS_t + \beta_6 \times CPI_t + \beta_7 \times CRUDE_t + \beta_8 \times GDP_t + \beta_9 \times GSCPI_t + \beta_{10} \times (Time_t \times Post_t) + \varepsilon_{i,t} \quad - V$$

For all the models, robust standard errors (cov_type='HC1') are utilized to fortify against heteroscedasticity. Each model presents a unique perspective on the interplay between Monetary policy and stock market performance. The model-2 and model-3 not only chart the immediate implications but also reflect on broader economic conditions. This layered evaluation is poised to enrich the understanding of monetary intervention, particularly during periods of economic instability. In DiD model-1, model-2, and model-4, the dependent variable is the min-max normalized asset price level, where coefficients reflect the estimated change in the normalized scale after the intervention. In the DiD model-3, the dependent variable is log-transformed, and the coefficients approximate proportional or percentage changes in this model.

3) Robustness Check

This study employs robustness checks to validate the findings of the Difference-in-Differences (DiD) analysis. This ensures the reliability of the results by addressing potential biases or spurious correlations that could arise due to specific data configurations. The following robustness checks are employed:

- Propensity score matching.
- Huber regression and Tukey regression.
- Event study analysis.

Propensity Score Matching (PSM): To provide additional validation for the causal analysis, Propensity Score Matching (PSM) is used as a robustness check to ensure that the treatment effect estimated through DiD is not confounded. The assets are grouped as treatment (NASDAQ, DOW, SP500) and control (BTC, ETH). The following pre-treatment characteristics are extracted: normalized asset price, EFFR, DGS, CPI, CRUDE, GDP, GSCPI, and Time. Utilizing only pre-treatment period data (where Post = 0), a logistic regression model is fit where treatment assignment is regressed on the mentioned covariates for each normalized asset: $p_i=P(Treatment_i=1|X_i)$, where X_i includes the normalized asset-specific, macro-financial, and temporal features. For each treated unit, the KNN algorithm is used to match each treated unit to a control unit(BTC, ETH) with the closest propensity score. A DiD dataset is created by combining the treated units with their corresponding matched controls. The primary outcome is then modelled for the basic and controls as below.

$$Y_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \beta_2 \times Post_t + \beta_3 \times (Treatment_i \times Post_t) + \varepsilon_{i,t} \quad \text{- VI}$$

$$Y_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \beta_2 \times Post_t + \beta_3 \times (Treatment_i \times Post_t) + \beta_4 \times EFFR_t + \beta_5 \times DGS_t + \beta_6 \times CPI_t + \beta_7 \times CRUDE_t + \beta_8 \times GDP_t + \beta_9 \times GSCPI_t + \varepsilon_{i,t} \quad \text{- VII}$$

By reconstructing the treated and control groups based on matched pre-policy characteristics, the PSM approach ensures that imbalances in asset properties do not drive the estimated DiD effect. This PSM approach aims to create comparable groups based on pre-treatment characteristics. The PSM may confirm the accuracy of causal inference by DiD and reduce selection bias.

Huber and Tukey regression: Financial markets may be prone to sporadic jumps, unexpected outliers, and volatility clustering. Financial asset returns, especially cryptocurrencies, are known for skewness and heavy tail behavior that can bias standard regression estimates. The Log DiD regression model mitigates outlier and non-normality effects. The log transformation of the dependent variable stabilizes variance. To provide additional support to mitigate the outlier influence and non-normality effects, Huber and Tukey regressions are employed in this study. The Huber M-estimator limits the influence of large residuals by applying "soft trimming" through a loss function that is less sensitive to outliers. The Huber M-estimator is a form of robust regression that minimizes the effect of outliers on parameter estimation. For small residuals, Huber regression behaves identically to OLS (quadratic loss). However, for large residuals, it applies a linear penalty, reducing the impact of outliers. Huber regression provides robustness against outliers while maintaining efficiency for normal observations. It provides estimates that are less sensitive to extreme observations, improving the stability and interpretability of DiD effects in noisy market data.

The Tukey bi-square function gives even less weight to outliers than Huber, providing an additional robustness check. Its loss function is even less sensitive to large residuals. In financial markets, large shocks such as sudden market crashes may occur. The COVID-19 period had extreme market movements that could dominate results. The Tukey regression ensures parameter estimates remain reliable by minimizing the influence of these events. This is particularly valuable for cryptocurrency data where extreme price movements can dominate the analysis.

Event study analysis: To complement the DiD analysis, this study employs a detailed event study analysis to examine how stock indices evolve around the time of a key policy intervention. The event study framework is rigorously designed to track temporal changes in normalized stock prices around a pivotal policy intervention. Each observation is assigned a period category according to its number of days relative to the intervention date (March 16, 2020). The study adopts a systematic approach with period categories such as 'pre_180', 'pre_90', 'pre_60', 'event', 'post_60', 'post_90', 'post_180', 'post_360', and 'post long'. These windows are defined in the Table 1 below.

Table 1: Event analysis time periods

Label	Time Period
pre_180	-91 to -180 days (September 18,2019 to December 16,2019)
pre_90	-90 to -61 days (December 17,2019 to January 15, 2020)
pre_60	-60 to -1 days (January 16 to March 15, 2020)
event	Event day (March 16, 2020)
post_60	1 to 60 days (March 17 to May 15, 2020)
post_90	61 to 90 days (May 16 to June 14, 2020)
post_180	91 to 180 days (June 15 to September 12, 2020)
post_360	181 to 270 days (September 13 to December 11, 2020)
post_long	After 360 days (after March 11, 2021)

The pre-treatment periods provide insight into changes immediately prior to the intervention, controlling for baseline dynamics and potential anticipatory effects. This categorical period labelling aids in comparing pre- and post-event impacts. The event period ('event') isolates the days immediately surrounding the intervention date, capturing the immediate impact of the policy shock. Interaction terms are created for each period to indicate the presence of the treatment. The post-treatment periods extend into the aftermath, enabling analysis of quarterly and lagged impacts on asset returns. The pre-event period('pre_90') is used as the baseline reference category for regression analyses, ensuring that effect estimates are interpreted relative to a robust pre-intervention window. A regression model then assesses the effect of the intervention across these defined periods. The model estimates for each period allow us to interpret the intervention's differential impacts.

$$Y_{i,t} = \beta_0 + \beta_1 \times Treatment_i + \sum k \beta_{2k} (Treatment_i \times Period_k) + \beta_3 \times EFFR_t + \beta_4 \times DGS_t + \beta_5 \times CPI_t + \beta_6 \times CRUDE_t + \beta_7 \times GDP_t + \beta_8 \times GSCPI_t + \varepsilon_{i,t} \quad \text{- VIII}$$

Where

- $Period_k$: dummy variable for each event period *k*
- β_k: treatment effect for period k, interpreted against the baseline pre-event period ('pre_90')

By implementing robustness checks, this study aims not only to confirm the robustness of its primary findings but also to offer nuanced insights into the intervention's characteristics. These checks act as crucial components in establishing the study's validity and reliability of causal analysis.

4. Results and Discussion

A. Parallel Trends Test

The parallel trends test asserts that, without intervention, stocks and cryptos would have followed similar trajectories. The trend (slope) of the outcome variable follows the same pattern for both the treated and control groups in pre-intervention. Across all tested pairs, the respective Time-Treatment coefficients are close to zero, and all p-values are above conventional significance thresholds ($p > 0.05$), indicating no statistically significant difference in trends between each stock index and digital currency. This provides robust evidence in favor of the parallel trends assumption for every group considered.

The OLS indicates the Time Treatment Interaction, which checks whether the trend in returns differs between the treatment and control groups before treatment, see Table 2. The lack of significance in the Time Treatment interaction term indicates that there was no significant pre-intervention differential trend between the treatment and control groups. The OLS test provides evidence in favor of the parallel trend assumption, suggesting that the DiD analysis is valid and unbiased.

NASDAQ vs. BTC: No significant difference in pre-intervention trends; parallel trends assumption supported
Coefficient: -0.000004, P-value: 0.5065
NASDAQ vs. ETH: Parallel trends assumption upheld.
Coefficient: -0.000008, P-value: 0.1878
DOW vs. BTC: No significant pre-treatment difference; parallel trends assumption supported
Coefficient: -0.000013, P-value: 0.1578
DOW vs. ETH: Though marginally lower than others, the p-value does not indicate a significant trend difference; the assumption holds.
Coefficient: -0.000017, P-value: 0.0648
SP500 vs. BTC: No evidence of divergent pre-intervention trends; assumption supported.
Coefficient: -0.000009, P-value: 0.2566
SP500 vs. ETH: Pre-treatment trends are statistically similar; assumption upheld.
Coefficient: -0.000012, P-value: 0.0903

Table 2: Parallel Trends OLS results

Index	Crypto	Time:Treatment Coefficient	P-value
Nasdaq	BTC	-0.000004	0.5065
Nasdaq	ETH	-0.000008	0.1878
DOW	BTC	-0.000013	0.1578
DOW	ETH	-0.000017	0.0648
SP500	BTC	-0.000009	0.2566
SP500	ETH	-0.000012	0.0903

B. Difference in Differences (DiD)

Pre-intervention parallel trends diagnostics provide support for the validity of the DiD framework, indicating that subsequent deviations in returns can be attributed more confidently to the policy intervention. The study's results support the hypotheses, indicating that the Federal Reserve's rate cut impacted the stock indices during the post-treatment period and that there is a differential effect of interest rates on the crypto market vs the stock market, see Table 3 for the results of all DiD models.

In the basic DiD model, for NASDAQ, the Treatment_Post variable was associated with a positive and significant effect on the index (Coefficient = 0.1211, SE = 0.0156, $p < 0.001$). For DOW, the effect was negative and significant (Coefficient = -0.1180, SE = 0.0157, $p < 0.001$). For SP500, the estimate was negative but not significant (Coefficient = -0.0171, SE = 0.0157, $p = 0.2779$). The Basic DiD model provides an initial understanding of the effect of interest rate intervention on asset returns, contrasting stock indices and cryptocurrencies.

In the DiD Model with Controls, the results for each asset are robust and significant: NASDAQ, DOW, and SP500 (NASDAQ: Coefficient = 0.1211, SE = 0.0067, $p < 0.001$; DOW: Coefficient = -0.1180, SE = 0.0067, $p < 0.001$; SP500: Coefficient = -0.0171, SE = 0.0063, $p = 0.0066$). The persistence of significant coefficients after controlling economic variables supports the assertion that monetary policy shocks have direct and heterogeneous effects on stock indices. A significant negative coefficient of the Interest Rate(EFFR) indicates that higher effective federal funds rates are associated with lower asset returns across groups. Other controls such as CPI, CRUDE, DGS, GDP, and GSCPI, demonstrate statistically significant coefficients.

In the Log-Level DiD Model, the effects remain significant for all indices (NASDAQ: Coefficient = 0.0619, DOW: Coefficient = -0.1264, SP500: Coefficient = -0.0447). The log transformation offers robustness against outlier influences and affirms trend consistency across modeling approaches. All the controls CPI, CRUDE, DGS, GDP, and GSCPI demonstrate statistically significant coefficients, though effect sizes are slightly attenuated due to log transformation.

In the DiD with Time Trend, with the inclusion of time trends to capture evolving market dynamics, the results remain broadly consistent: strong positive effect for NASDAQ, strong negative for DOW, and moderate negative for SP500, with improved model fit (R-squared = 0.9359). The Time×Post though small, is statistically significant (Coeff = 0.0011, $p < 0.001$). This Time×Post suggests growing divergence between asset groups over time.

From the DiD analysis, Treatment_Post interaction shows a distinct response to each of the stock indices. The NASDAQ shows a statistically significant positive effect, implying that the rate cut catalysed an upward shift in its returns relative to the cryptocurrency control group during the post-intervention period. This could reflect NASDAQ's composition, with a higher weight in technology stocks, which are more sensitive to financing costs and macroeconomic stimulus. The DOW exhibits a significant negative effect. DOW's constituent firms, often more exposed to cyclical sectors, may have faced different risk and opportunity profiles following the rate adjustment. The SP500 also shows a significant but relatively small negative effect, suggesting a balanced net response, potentially due to its broad sectoral diversity. The DiD analysis reveals strong support for Hypothesis-1. The negative and highly significant coefficients of EFFR in the expanded models demonstrate that higher Fed interest rates are associated with lower asset returns. This confirms that the Fed's interest rate impacts the stock market and is consistent with economic theory. Critically, the expanded multi-asset approach uncovers

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pronounced heterogeneity across stock indices. The Fed's intervention actively contributed to stabilizing and enhancing returns for the NASDAQ during the period following the rate cut. The DOW index exhibited a significant negative treatment impact, and the SP500 showed a modest negative response. This demonstrates that the Fed's policy interventions did not affect all segments of the stock market identically. The findings highlight the importance of asset-specific analysis and indicate that the stabilizing role of monetary policy during crisis periods is nuanced and varies according to index composition.

Hypothesis 2 is supported by the observed results, which indicate that cryptocurrencies demonstrate distinct responses compared to stock indices. The Treatment variable ($Treatment_i$) is a dummy coded as 1 for stock indices (Nasdaq, DOW, SP500) and 0 for cryptocurrencies (BTC, ETH). The $Treatment_i$ is positive and highly significant across all models (Basic DiD: 0.0932***, DiD Control: 0.0932*** Log DiD: 0.0875*** DiD with Time Trend: 0.0932***). The statistically significant Treatment coefficient confirms that, on average, cryptos and stocks move differently**.** The results validate crypto as an appropriate control for this study. All stock indices show significant differential responses vs crypto. Inclusion of both BTC and ETH as control assets solidifies the observed divergence; ETH's pattern largely mimics BTC, thus supporting the robustness of group comparison. There is clear evidence of monetary policy transmission to stocks. The stock indices and cryptocurrencies both exhibit sensitivity to monetary policy (EFFR), but in differing directions and magnitudes, with stocks overall more affected. For example, the Treatment_Post coefficient suggests that the crypto effect is differentiated from the stock indices. Even controlling for EFFR and other factors, post-treatment response remains significant. This evidence reinforces the hypothesis that cryptocurrencies are not as tightly coupled to conventional monetary policy as stock indices. Their market dynamics may be influenced more by alternative factors such as investor sentiment and/or technological developments, rather than direct interest rate interventions. The monetary policy shocks tend to propagate differently and with less uniformity in crypto markets compared to equity markets. Overall, the results of the DiD analysis provide strong empirical support for both hypotheses.

The control variables used to parse out additional macroeconomic factors throw light on the broader economic influences and how they interact with or confound the primary treatment effects. The DGS representing the 10-year yield showed positive coefficients (DiD Control: 0.0538***, Log DiD: 0.0278***, DiD with Time Trend: 0.0029). It indicates that increases in long-term interest rates are associated with rises in market values. The CPI coefficient (DiD Control: 0.0121***, Log DiD: 0.0064***, DiD with Time Trend: -0.0070***). Therefore, model-2 and model-3 indicate that Higher inflation (CPI) is typically associated with increased nominal asset returns. The positive and significant coefficients of CRUDE (DiD Control: 0.0058***, Log DiD: 0.0047***, DiD with Time Trend: 0.0042***) indicate that higher crude oil prices are positively associated, potentially reflecting that economic growth may influence market perception. Furthermore, the GDP coefficient, though very small is significant in both control and log models, confirming that economic growth positively influences market performance. Finally, the GSCPI coefficients (DiD Control: 0.0111***, Log DiD: 0.0056***, DiD with Time Trend: 0.0122***) being positive and significant indicate that supply chain pressures correlate with higher market values. The controls CPI, CRUDE, DGS, GDP, and GSCPI adjust for confounding, time-varying influences that could otherwise bias estimates of interest rate policy and asset class effects. These controls ensure that the unique impact of Fed interest rate policies on stocks versus cryptocurrencies is not overstated due to simultaneous macro shocks.

C. Robustness check

Propensity Score Matching (PSM): To reinforce the causal relationship and to minimize confounding influences, this study implemented a propensity score matching (PSM) approach using K-nearest neighbours (KNN). The propensity score distributions for both treatment and control groups are highly similar, with near-identical means and minimal standard deviation (mean ≈ 0.5998, std ≈ 0.0011). This balance indicates effective matching, reducing the risk of systematic differences between groups that could confound treatment effects. See Table 4 for the stock index-specific PSM results.

NASDAQ**:** These results reaffirm the conclusion that the Federal Reserve's rate cuts during the pandemic had a statistically significant positive impact on the NASDAQ index. The basic DiD model produces a coefficient of 0.1053 (SE = 0.0190, $p < 0.001$), which is significantly positive and consistent with earlier unmatched findings. The positive impact also persists when controls are included (coefficient = 0.1053, SE = 0.0088, $p < 0.001$).

DOW**:** The sustained negative response indicates sectoral or compositional sensitivities within the DOW index. This further supports the notion of heterogeneity within stock market responses. In contrast to NASDAQ, the DOW index exhibits a significant and negative treatment effect in all specifications (basic: coefficient = -0.1337, SE = 0.0191, $p < 0.001$; with controls: coefficient = -0.1337, SE = 0.0089, $p < 0.001$).

SP500**:** These findings suggest that while the SP500 did not benefit as strongly as NASDAQ, there remains a statistically robust negative effect attributable to the intervention, emphasizing the importance of asset-level analysis over market-wide aggregation. The SP500's treatment effect is negative but smaller in size (basic: coefficient = -0.0328, SE = 0.0191, p = 0.0852). This effect becomes highly significant when additional controls are included (coefficient = -0.0328, SE = 0.0085, $p < 0.001$).

The application of PSM significantly enhances the evidence for the causal effects of interest rate policy, matching for pre-treatment characteristics, and controlling for potential sources of bias. The persistence of treatment effects after matching suggests the results are not driven purely by pre-existing differences between treatment and control groups. The PSM results align with insights from the DiD analysis. The approach also demonstrates that the impact of interest rate cuts during the COVID-19 pandemic was not uniform, but rather differentiated across major indices, confirming Hypothesis-1. The distinction between control assets (cryptocurrencies) and stock market indices persists after matching, supporting Hypothesis-2 that cryptocurrencies do not respond to interest rate policy in the same way as conventional equity markets.

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Huber and Tukey: The coefficients of Huber and Tukey regressions have the same sign as that of the DiD Model-3(Log). Consistent results across Huber and Tukey methods provide confidence in our findings. Huber M-estimator and Tukey bi-square methods ensure our results are robust to outliers and non-normal error distributions. The scale parameters were similar in Huber and Tukey. Huber (0.0446) vs Tukey (0.0420) – This suggests consistent robust estimation. Huber and Tukey methods address the inherent volatility and extreme movements characteristic of asset classes during the COVID-19 period. See Table 6 for the results.

NASDAQ**:** The Huber and Tukey results reaffirm that the Federal Reserve's rate cuts during the pandemic had a substantial and statistically significant positive impact on the NASDAQ index. The Huber model produces a Treatment_Post coefficient of 0.0836 ($p < 0.001$), significantly positive and consistent with DiD findings. The positive impact also persists with the Tukey model (coefficient = 0.1028, $p < 0.001$).

DOW**:** The Huber and Tukey confirm the negative impact of interest rate changes on DOW. This further confirms heterogeneity within stock market responses. In contrast to NASDAQ, the DOW index exhibits a negative treatment effect in all specifications (Huber: coefficient = -0.0240, $p < 0.001$; Tukey: coefficient = -0.0052, $p = 0.2077$).

SP500**:** The Huber and Tukey methods confirm that there remains a statistically robust negative effect attributable to the intervention. The SP500's treatment effect is negative and significant (Huber: coefficient = -0.1045,$p < 0.001$). This effect is negative and highly significant with the Tukey as well (coefficient = -0.0862, $p < 0.001$).

The overall conclusions from Huber and Tukey confirm the robustness of DiD findings, with effect directions remaining largely unchanged. Covariates like CPI, oil prices, and GDP effects are highly consistent across the different estimation methods. The control parameters such as CPI, CRUDE, GDP, and GSCPI, are all highly significant and positive, consistent across models, suggesting inflation, oil, economic growth, and supply chain issues impact returns, and these results are not driven by outliers. Overall, the use of Huber and Tukey affirms that our main DiD findings are not driven by atypical return episodes.

Event study analysis: The event study analysis examines asset-specific effects of the Federal Reserve's interest rate intervention by evaluating changes across multiple pre-event and post-event windows for each stock index (NASDAQ, DOW, SP500), using the pre_90 period as the baseline. For all indices, the estimated coefficients in pre-event periods are generally small and statistically insignificant ($p > 0.05$). All pre-event effects are insignificant, providing key empirical support for the parallel trend assumption. This finding suggests that, before the intervention, the indices did not exhibit abnormal behavior relative to their baseline trends. The DOW's event date shows a modest negative and significant effect (coefficient = -0.1098, $p = 0.0157$). Index-specific post event results are as follows.

NASDAQ**:** Following the intervention, NASDAQ displays a clear and statistically significant pattern of positive treatment effects in all post-event windows. The post_60 Coefficient rises sharply to 0.1376 ($p < 0.001$), marking the immediate impact of the intervention. From post_90 to post_360, the effect increases progressively, peaking at 0.2481 ($p < 0.001$) at one year post-event post_long, the effect remains positive and significant (coefficient = 0.0759, $p < 0.001$), indicating lasting stabilization. These findings provide robust evidence for the sustained positive impact of monetary policy on the NASDAQ index.

DOW**:** In contrast, the DOW index demonstrates significant and persistent negative effects following the intervention: post_60 to post_long, all coefficients are negative and highly significant, ranging from -0.0945 to -0.1538 (all $p < 0.001$ except event date), suggesting the rate cut had a lasting impact on the DOW. This sustained negative response highlights asset-specific heterogeneity, with DOW underperforming relative to the baseline after the policy event.

SP500**:** SP500 shows a mixed trajectory post-intervention. post_60 and post_90 are Positive, and significant effects appear early (0.0180, $p = 0.0394$; 0.0328, $p = 0.0003$). post_180 and post_360: The effect remains positive and significant, though smaller than for NASDAQ. post_long, the effect turns negative (coefficient = -0.0567, $p < 0.001$), suggesting some reversal or loss of initial gains over the extended horizon. This mixed response points to a more complex adjustment in the SP500, reflecting its broader and more diversified market exposure.

The event study's post-treatment windows reveal a progressive and significant impact of the Fed's rate cuts, with the NASDAQ index experiencing the most pronounced positive shift, the DOW seeing a sustained negative response, and the SP500 showing initial growth followed by a later decline. The absence of significant abnormal returns prior to the intervention confirms the parallel trends assumption and strengthens the overall validity of the analysis. The event study highlights that monetary policy's influence is persistent and markedly positive for some indices, particularly NASDAQ, which aligns with its larger concentration of technology and growth stocks.

This study empirically investigates the differential effects of central bank interest rate policy changes on traditional equity indices (NASDAQ, DOW, SP500) and leading digital currencies (Bitcoin, Ethereum). The findings reveal that equity markets exhibit a pronounced sensitivity to interest rate adjustments. In contrast, Bitcoin and Ethereum show markedly muted responses, with statistical insignificance or minimal price movements around policy announcements.

Overall, our empirical results reveal nuanced patterns in how interest rate policies are transmitted through financial asset markets, reflecting the distinctive characteristics of stocks and cryptocurrencies. For conventional stock indices such as the NASDAQ, DOW, and SP500, the observed responses align closely with established channels of monetary policy transmission. In the liquidity channel, monetary policy (rate cuts), such as those seen during the COVID-19 crisis, led to increased liquidity within traditional equity markets. However, the cryptocurrency markets (BTC, ETH) exhibited a more muted initial liquidity response, underscoring their limited direct linkage to conventional banking. The less regulated, decentralized structure of crypto assets may diminish the potency of monetary-policy-driven liquidity expansions. Additionally, our results reveal that expectations may have manifested divergently across asset classes. For traditional equities, interest rate signals from the Federal Reserve shaped investor expectations about future economic growth, thereby exerting pronounced effects on asset pricing. The study's results suggest that crypto market valuations were somewhat less tethered to central bank signaling, with price movements probably driven by sentiment shifts and speculation, rather than expectations shaped by monetary authorities. In terms of risk-taking, lower interest rates may have encouraged greater appetite for risk among investors in the stock market, leading to sectoral rotation and increased demand for growth assets. The findings indicate that crypto price dynamics may be especially sensitive to rapid changes in global risk perception and market sentiment, amplified by news and social media influences. Unlike equities, where risk-taking is constrained by institutional oversight and macroprudential policy, crypto markets display more volatile, sentiment-driven reactions—a pattern evident in periods of monetary policy uncertainty or heightened economic stress.

Finally, the wealth effects could be observed in traditional markets, where asset price appreciation following rate cuts stimulated consumption. In the case of digital assets, the heightened volatility of crypto assets suggests that wealth effects may be episodic or intertwined with sentiment cycles, rather than a stable transmission mechanism for monetary policy. The comparative analysis underscores the greater influence of behavioral and sentiment mechanisms in crypto markets relative to stocks, with implications for financial stability and policy effectiveness. Overall, the findings suggest that traditional markets exhibit robust responses along the standard transmission vectors of liquidity, expectations, and wealth effects, while digital currencies may be influenced more by behavioral and sentiment-driven processes with limited direct exposure to central bank actions. This contrast underscores the importance of incorporating behavioral finance perspectives into interpreting the macro-financial implications for digital assets. The findings motivate further research into the unique frictions and drivers that characterize crypto market dynamics.

In summary, the PSM analysis, Huber regression, Tukey regression, and the event study analysis support the robustness of the DiD estimation. The robustness checks in the study provide more confidence that observed effects, strengthening the study's causal claims around monetary policy impacts. Overall, the additional robustness checks provide evidence of robust, asset-specific responses to monetary policy shocks, further elucidating the heterogeneous impacts discovered in prior DiD analyses and validating the study's central hypotheses

D. Limitations

This study provides important insights into the effects of monetary policy interventions on major U.S. stock indices. However, we acknowledge certain limitations to inform future research. These limitations stem from methodological choices, scope of analysis, and the inherent complexity of financial markets. The following aspects suggest directions for further analysis.

Asset Coverage and Generalizability: The study is limited to a select set of major U.S. stock indices and two cryptocurrencies (BTC, ETH). Broader inclusion could capture a wider spectrum of market responses. The focus on U.S. financial markets means results may not generalize to international markets. The monetary policy transmission and asset composition may differ for international markets.

Cryptocurrency Dynamics and bubbles: Cryptocurrencies are utilized as controls, but their own market dynamics, including episodes of speculative bubbles, may confound the interpretation of results. Research has identified speculative bubbles in Bitcoin (Baek & Elbeck, 2015; Cheah & Fry, 2015; Cheung et al., 2015; Li et al., 2022; Podhorsky, 2024). However, this study does not explicitly test such bubble phenomena. Furthermore, fully characterizing the channels of monetary policy transmission in digital assets is complex. Unlike equities, cryptocurrencies may not rely on traditional credit markets or banking infrastructure, which may limit the transmission of liquidity shocks to digital assets. Our study focuses primarily on price responses and does not directly disentangle investor expectations, liquidity flows, or risk appetites within crypto markets.

Macro Variables: While several controls are included, there may be unobserved confounders(for example, industrial production) affecting both treatment and outcome. Furthermore, since the macroeconomic data such as GDP used in this study were aligned to match the daily frequency of asset data, the ability to capture short-run fluctuations in economic activity may be reduced. As a result, the analysis may miss fine cyclical dynamics that could otherwise influence asset sensitivity to monetary policy interventions.

Sample Size: The use of propensity score matching, while improving comparability, reduces the overall sample size, which may affect statistical power and generalizability.

Unconventional monetary policy tools: While this study focuses on the effects of interest rate cuts, particularly the March 16, 2020, event, it does not consider other elements of monetary policy such as quantitative easing (QE). The simultaneous use of QE and other liquidity management tools during the COVID-19 period may have had independent and/or interactive effects on financial markets.

Market Volatility: Market volatility is referenced in the manuscript to characterize the financial environment during the study period. While the study refers to market volatility for context, it does not empirically analyze the impact of monetary policy on volatility itself.

Behavioral and Sentiment effects: This study did not employ sentiment or behavioral models, which could disentangle other drivers behind asset price movements in response to monetary policy, particularly under stressed conditions. Recent literature indicates that asset prices are amplified by sentiment-driven trading, behavior, and other adjustment processes (Barberis et al., 2018).

Crisis vs. Policy Effects: While the analysis centers on the March 16, 2020, Federal Reserve emergency rate cut, we recognize that this event coincided with the peak of the

COVID-19 shock and exceptionally high market uncertainty. As such, the observed effects should be interpreted as reflecting the differential sensitivity of asset classes to monetary policy during a crisis environment, rather than serving as definitive causal estimates of policy impact under normal conditions. The overlap between crisis dynamics and policy interventions poses challenges for fully disentangling the effect of monetary policy alone. This study does not assess whether similar asset-class responses would occur outside of periods of acute stress, so it remains unclear whether these findings are unique to the emergency context or can be generalized to more typical market conditions. Therefore, the causal inference drawn from this study is specific to the extraordinary circumstances of the period examined.

Table 3: DiD Results

Variable	PSM_Nasdaq_ Basic	PSM_Nasdaq_ Control	PSM_DOW_ Basic	PSM_DOW_ Control	PSM_SP500_ Basic	PSM_SP500_ Control
Intercept	0.0558***	-3.5487***	0.0558***	-3.2530***	0.0558***	-4.0513***
Pair_Treatment	0.1191***	0.1191***	0.3944***	0.3944***	0.2278***	0.2278***
Post	0.3509***	0.1151***	0.3509***	0.0925***	0.3509***	0.0950***
Treatment_Post	0.1170***	0.1170***	-0.1221***	-0.1221***	-0.0212	-0.0212***
CPI	N/A	0.0081***	N/A	0.0082***	N/A	0.0116***
CRUDE	N/A	0.0060***	N/A	0.0065***	N/A	0.0055***
DGS	N/A	0.0519***	N/A	0.0767***	N/A	0.0607***
EFFR	N/A	-0.0797***	N/A	-0.1085***	N/A	-0.0820***
GDP	N/A	0.0001***	N/A	0.0000***	N/A	0.0000***
GSCPI	N/A	0.0212***	N/A	0.0173***	N/A	0.0183***
R-squared	0.5204	0.9112	0.5029	0.9105	0.4594	0.9093
Adj. R-squared	0.5194	0.9106	0.5019	0.91	0.4583	0.9088

Table 4: PSM Results

Variable	Basic DiD_ Co_eff	BasicDiD_ P-value	DiD_ Controls_ Coeff	DiD_ Controls_ P-value	DiDLog_ Controls_ Coeff	DiDLog_ Controls_ P-value	DiD_Time Trend_ Coeff	DiD_Time Trend_P-value
Intercept	0.0817***	0.0000	-4.0108***	0.0000	-2.2954***	0.0000	1.7737***	0.0000
Post	0.3468***	0.0000	0.0823***	0.0000	0.0670***	0.0000	-0.7098***	0.0000
Treatment_Post_Nasdaq	0.1211***	0.0000	0.1211***	0.0000	0.0619***	0.0000	0.1211***	0.0000
Treatment_Post_DOW	-0.1180***	0.0000	-0.1180***	0.0000	-0.1264***	0.0000	-0.1180***	0.0000
Treatment_Post_SP500	-0.0171	0.2779	-0.0171***	0.0066	-0.0447***	0.0000	-0.0171***	0.0038
Treatment	0.0932***	0	0.0932***	0.0000	0.0875***	0.0000	0.0932***	0.0000
CPI	N/A	N/A	0.0121***	0.0000	0.0064***	0.0000	-0.0070***	0.0000
CRUDE	N/A	N/A	0.0058***	0.0000	0.0047***	0.0000	0.0042***	0.0000
DGS	N/A	N/A	0.0538***	0.0000	0.0278***	0.0000	0.0029	0.6267
EFFR	N/A	N/A	-0.0898***	0.0000	-0.0767***	0.0000	-0.1203***	0.0000
GDP	N/A	N/A	0.0000***	0.0000	0.0000***	0.0000	0.0000	0.2971
GSCPI	N/A	N/A	0.0111***	0.0003	0.0056**	0.0166	0.0122***	0.0000
DOW[T.True]	0.2753***	0.0000	0.2753***	0.0000	0.2108***	0.0000	0.2753***	0.0000
ETH[T.True]	-0.0801***	0.0000	-0.0801***	0.0000	-0.0637***	0.0000	-0.0801***	0.0000
SP500[T.True]	0.1087***	0.0000	0.1087***	0.0000	0.0884***	0.0000	0.1087***	0.0000
Time_Post	N/A	N/A	N/A	N/A	N/A	N/A	0.0011***	0.0000
R-squared	0.5228	N/A	0.9245	N/A	0.9184	N/A	0.9359	N/A
Adj. R-squared	0.5218	N/A	0.9243	N/A	0.9181	N/A	0.9356	N/A

Note ***p<0.01, **p<0.05, * p<0.10

Table 5: Event Study Results

Huber & Tukey						
Variable	DiD_LogY_ Coeff	DiD_Log Y_P-value	Model_Huber_ Coeff	Model_Huber_ P-value	Model_Tukey_ Coeff	Model_Tukey_ P-value
Intercept	-2.2954***	0.0000	-2.3829***	0.0000	-2.3537***	0.0000
Treatment_Post_Nasdaq	0.0619***	0.0000	0.0836***	0.0000	0.1028***	0.0000
Treatment_Post_DOW	-0.0447***	0.0000	-0.0240***	0.0000	-0.0052	0.2077
Treatment_Post_SP500	-0.1264***	0.0000	-0.1045***	0.0000	-0.0862***	0.0000
Treatment	0.0875***	0.0000	0.0905***	0.0000	0.0919***	0.0000
CPI	0.0064***	0.0000	0.0047***	0.0000	0.0038***	0.0000
CRUDE	0.0047***	0.0000	0.0037***	0.0000	0.0031***	0.0000
DGS	0.0278***	0.0000	0.0104***	0.0059	0.0056	0.1104
EFFR	-0.0767***	0.0000	-0.0347***	0.0000	-0.0207***	0.0000
GDP	0.0000***	0.0000	0.0001***	0.0000	0.0001***	0.0000
GSCPI	0.0056**	0.0166	0.0158***	0.0000	0.0202***	0.0000
Post	0.0670***	0.0000	0.1073***	0.0000	0.1093***	0.0000
Asset_DOW[T.True]	0.2108***	0.0000	0.2135***	0.0000	0.2139***	0.0000

Asset_ETH[T.True]	-0.0637***	0.0000	-0.0560***	0.0000	-0.0543***	0.0000
Asset_SP500[T.True]	0.0884***	0.0000	0.0897***	0.0000	0.0899***	0.0000

Table 6: Huber & Tukey

Event Study						
Period	NASDAQ_Coef	NASDAQ_P-Value	DOW_Coef	DOW_P-Value	SP500_Coef	SP500_P-Value
pre_180	0.0093	0.0783	-0.0006	0.9205	-0.0056	0.3083
pre_60	-0.0009	0.8357	0.0055	0.224	0.0029	0.4528
event	0.021	0.4823	-0.1098**	0.0157	-0.045	0.2083
post_60	0.1376***	0.0000	-0.0945***	0.0000	0.018*	0.0394
post_90	0.1516***	0.0000	-0.0621***	0.0000	0.0328***	0.0003
post_180	0.2232***	0.0000	-0.0412***	0.0000	0.064***	0.0000
post_360	0.2481***	0.0000	-0.0586***	0.0000	0.0388***	0.0001
post_long	0.0759***	0.0000	-0.1538***	0.0000	-0.0567***	0.0000
Asset_SP500[1.True]	0.0884***	0.0000	0.0897***	0.0000	0.0899***	0.0000

5. Contributions & Future Research

5.1 Contribution

This study contributes to the body of literature by providing insights into the Federal Reserve's role through interest rate adjustments. Utilizing cryptocurrencies as an untreated control group in a DiD framework, this study offers a fresh perspective. This study contrasts the differential responses to interest rate changes between stock markets and decentralized cryptocurrencies. Unlike aggregate or market-wide models, this study deliberately models each of the major U.S. stock indices (NASDAQ, DOW, and SP500) separately. By modelling each stock index separately, the framework identifies that the response to the policy shock is not monolithic, enabling richer analysis of market dynamics. This approach recognizes that financial markets are heterogeneous, with individual indices reflecting distinct sectoral compositions, investor bases, and risk profiles. The findings reveal a robust, sustained positive impact on the NASDAQ index, a significant negative impact on the DOW, and a nuanced negative effect on the SP500. These results underscore that the financial market's reaction to monetary policy is shaped by sectoral compositions, asset characteristics, and underlying market structure.

The study's empirical rigor is further strengthened by the inclusion of key macroeconomic controls. By supplementing the primary analysis with key macroeconomic controls, the study provides enhanced causal inference and a comprehensive perspective on how monetary policy interacts with both market sentiment and real economic influences. Insights from this analysis thus extend to broader discussions about financial stability, asset allocation, and the future of central bank policy in increasingly diversified financial environments. In summary, this study advances the field with nuanced empirical evidence, enriching our understanding of monetary policy impact in an era marked by rapid market evolution.

5.2 Future Research

Future research could expand on this study by examining other financial indices and a wider range of cryptocurrencies to determine if similar patterns hold across different financial ecosystems. Expanding research to include additional financial indices could illuminate whether the heterogeneous responses identified in U.S. markets persist across different market segments. Researchers could examine international markets to determine if the Fed's influence extends globally with a similar magnitude. Such studies could provide a more holistic view of the broader impacts of monetary policy on diverse asset classes. Similarly, incorporating a wider array of cryptocurrencies, including emerging tokens and altcoins, may reveal whether the observed comparative resilience or sensitivity to monetary policy is a generalized property of digital assets. Future research could explore the impact of monetary policy shocks using alternative macroeconomic controls, such as industrial production, to assess robustness and sensitivity to variable selection, particularly in studies emphasizing short-run market dynamics.

Furthermore, with the increasing prominence of digital currencies and the potential rollout of central bank digital currencies (CBDCs), future research could explore how these developments interact with traditional monetary policy. Understanding CBDC's relationship with interest rates can be crucial as central banks navigate the evolving landscape of digital finance. The significant coefficients on control variables in our models suggest complex interactions between monetary policy and real economic factors that could evolve as digital currencies reshape monetary transmission mechanisms. Additionally, future research may delve into behavioral finance; analyzing behavioral factors alongside economic variables can provide a more nuanced understanding of market dynamics. Complementary research incorporating behavioral finance perspectives could offer nuanced insight into how investor sentiment, psychological biases, and collective market behavior respond to monetary policy announcements. By pursuing these directions, researchers can contribute to a richer, more comprehensive understanding of monetary policy's multifaceted impact across global financial systems, incorporating technological innovation, market complexity, and behavioral dynamics as key elements of future inquiry.

6. Conclusion

This study provides a comprehensive analysis of the Fed's interest rate cuts and their impact on financial markets. The confluence of economic pressures during COVID-19 provided an opportunity to evaluate the efficacy of monetary policy interventions in markets amidst unprecedented turmoil. This study provides causal identification, validating the "parallel trends" assumption, isolating the treatment effect of the specific EFFR cut on March 16, 2020. The findings are substantiated through multiple methodological approaches, which include Difference-in-Differences (DiD) analysis, Propensity Score Matching (PSM), Huber & Tukey regressions, and Event Study analysis. The findings demonstrate the significant role of the Federal Reserve's rate cuts in influencing the stock indices. The parallel trends test addressed no pre-existing differences between the Stock and Cryptocurrency, ensuring the strength of our causal inference. The Treatment_Post coefficient across models suggests a positive effect of Fed intervention on the stock market, supported by different modeling perspectives. The interaction terms in our models consistently showed that the treated period experienced marked changes in stock market outcomes, thus affirming Hypothesis 1. The negative EFFR coefficients in the DiD analysis confirm conventional wisdom that interest rates impact stock market performance. Exploring the differential impacts between traditional stock and cryptocurrency markets represented by BTC and ETH yielded nuanced insights. There is a difference between the cryptocurrency and conventional stock markets regarding monetary policy responsiveness. While the stock indices showed significant responses to the Federal Reserve's interventions, as shown by consistent and significant coefficients in the interaction terms, the event study analysis provided inferred evidence for the differential nature of monetary policy effects on crypto markets. There is clear support for Hypothesis 2. However, this study recommends further scrutiny to comprehensively gauge cryptocurrency resilience against conventional monetary measures. Additionally, the event study analysis contextualized the temporal progression of the treatment effect beyond the immediate post-intervention period, showcasing impacts that align with long-term market stabilization narratives.

In conclusion, this study highlights the role of monetary policy tools in navigating financial uncertainties, emphasizing central banks' influence on market dynamics. The Fed's actions exert distinct, asset-specific effects within the stock market, while cryptocurrencies demonstrate a differentiated and independent reaction to interest rate changes. Future research could delve deeper into the asymmetric impacts of such policies across different asset classes, particularly within cryptocurrencies. These insights could provide actionable guidance for policymakers, investors, and scholars in strategizing amidst variable economic conditions.

Statements & Declarations
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