Interplay of Traditional and Digital Finance: An Analysis of Stock and Cryptocurrency Markets Under Divergent Economic Policies

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Spring 2024

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[1] Thesis submitted to the Division of Social Sciences at New York University Abu Dhabi for the Economics Capstone Project in 2024

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Abstract

The interplay between digital and traditional financial assets can be observed through their periodic coupling and decoupling trends. These dynamics were particularly evident during the COVID-19 pandemic, marked by significant policy interventions. The U.S. federal government implemented quantitative easing measures to inject liquidity into the market, followed by an increase in policy rates aimed at tempering an overheating economy El Montasser et al. [2022]. This capstone project seeks to rigorously analyze the relationship between the stock market, represented by the S&P 500 index, and the cryptocurrency market, proxied by the market capitalization of stablecoins—digital assets designed to mirror the value stability of the U.S. dollar, often referred to as 'crypto dollars.'

This analysis will explore two distinct monetary policy environments to understand their impact on these financial sectors. Furthermore, the study will investigate investor behavior, focusing on preference shifts between the traditional stock market and cryptocurrency market under varying economic conditions. The objective is to elucidate the factors that influence these preferences and to develop a foundational understanding of the underlying mechanisms driving investor decisions in these divergent financial landscapes.

Keywords: *Coupling and Decoupling, Monetary Policy Impact, Pandemic, Quantitative Analysis, Cryptocurrency Markets and Stock Market Interplay*

1 Introduction

the concept of "coupling" between two assets refers to a situation where their price movements exhibit significant correlation. As global financial markets become ever more interconnected, the relationship between emerging digital assets, such as cryptocurrencies, and well-established traditional financial instruments has drawn considerable scholarly attention Feng et al. [2018]. This project is dedicated to a thorough examination of this complex interplay, focusing particularly on the role of policy rates in influencing the dynamic phenomena of coupling and its antithesis, decoupling, where market movements are synchronized or divergent, respectively. Central to our research is the exploration of whether policy rates serve to bind these distinct financial realms during certain periods or drive them apart during others.

Our analysis is particularly relevant in the context of recent significant events in the global financial landscape, notably the disruptions caused by the COVID-19 pandemic and the ensuing monetary policy adjustments Weber [2016]. These critical moments have tested the robustness of financial systems and marked a period of unparalleled uncertainty and transformation. Against this backdrop, our study seeks to illuminate the influence of monetary policies on the interaction between cryptocurrency and traditional financial markets during these transformative times.

To empirically test our hypothesis, we will utilize a suite of quantitative analytical techniques applied to a carefully selected dataset comprising policy rates, stablecoin market cap, and traditional market indices. This methodological approach is designed to uncover latent patterns and correlations that potentially reflect coupling or decoupling behaviors in response to shifts in monetary policy during the pandemic and its aftermath. This analysis aims to contribute valuable insights into the evolving dynamics of financial markets under varied policy conditions.

1.1 Literature Review

Recent scholarly investigations into the proliferation and impact of stablecoins on the banking sector suggest that these digital assets are increasingly regarded as safe havens during market distress, akin to traditional safe assets International Monetary Fund [2022]. This characterization implies an inverse relationship between stablecoin holdings and interest rate fluctuations, as well as market turbulence, prompting investors to acquire more stablecoins as a defensive strategy Feng et al. [2018]. Furthermore, the literature explores the potential for stablecoins to integrate within a two-tiered banking system, aligning with fractional reserve banking practices International Monetary Fund [2021]. This integration could enhance credit intermediation, thereby expanding the balance sheets of commercial banks without unduly impacting central bank reserves. Such developments could lead to a closer and more interwoven relationship between cryptocurrency markets and traditional financial sectors.

In addition, a report from the European Central Bank scrutinizes the multifaceted implications of stablecoins within the euro area, particularly concerning monetary policy, financial stability, and the banking industry. This analysis underscores the urgent need for stringent regulatory frameworks to manage the growing adoption of stablecoins. The prevailing negative interest rate environment may bolster the attractiveness and viability of non-interest-bearing stablecoins, significantly altering their market dynamics.

These insights collectively signal the escalating adoption of stablecoins and their emergence as a novel asset class for investors Weber [2016]. Within the analyses presented by these documents, a critical underlying variable is the Policy Rate. This rate fundamentally influences market dynamics, whether through its role in fractional reserve banking systems or by regulating market liquidity, thereby affecting the profitability of holding both crypto and traditional financial assets. Under varying policy rate scenarios, the increasing popularity of stablecoins underscores their utility in reflecting the crypto market's volatility and dynamics. This utility makes stablecoin transaction volumes a viable metric for exploring the interconnectedness—or the lack thereof—of crypto assets with traditional financial mechanisms during and after the COVID-19 pandemic.

2 Data and Methodology

To elucidate the complex interplay between cryptocurrency assets and traditional financial markets, our research employs a comprehensive and rigorous methodology. This approach is meticulously designed to reveal the patterns and correlations that characterize the interactions—both coupling and decoupling—between these two distinct financial spheres.

2.1 Data Collection and Selection:

Our investigation commences with a thorough process of data collection and selection. We have compiled an extensive dataset that includes a variety of critical variables essential for our analysis. This dataset features daily data points for the Federal Funds Rate, sourced from the Federal Reserve, which serves as our proxy for policy interest rates. It also includes the daily calculated market capitalization for major stablecoins, obtained from CoinMarketCap, daily closing values of the S&P 500 index, Brent oil prices, and daily yields of 10-year U.S. Treasury bills, all sourced from Investing.com. The choice of daily data frequency is strategic, allowing us to capture short-term market fluctuations during and post the COVID-19 pandemic. This high-frequency data is crucial for understanding market responses to policy shifts and economic events, which are essential for isolating and controlling variables that elucidate the impacts of changes in the policy rate environment. Furthermore, the inherent volatility and quick reaction of the cryptocurrency market to external changes make this daily approach particularly valuable. The datasets are denominated in U.S. dollars and cover the period from January 2020 to December 2023, excluding non-trading days to ensure consistency.

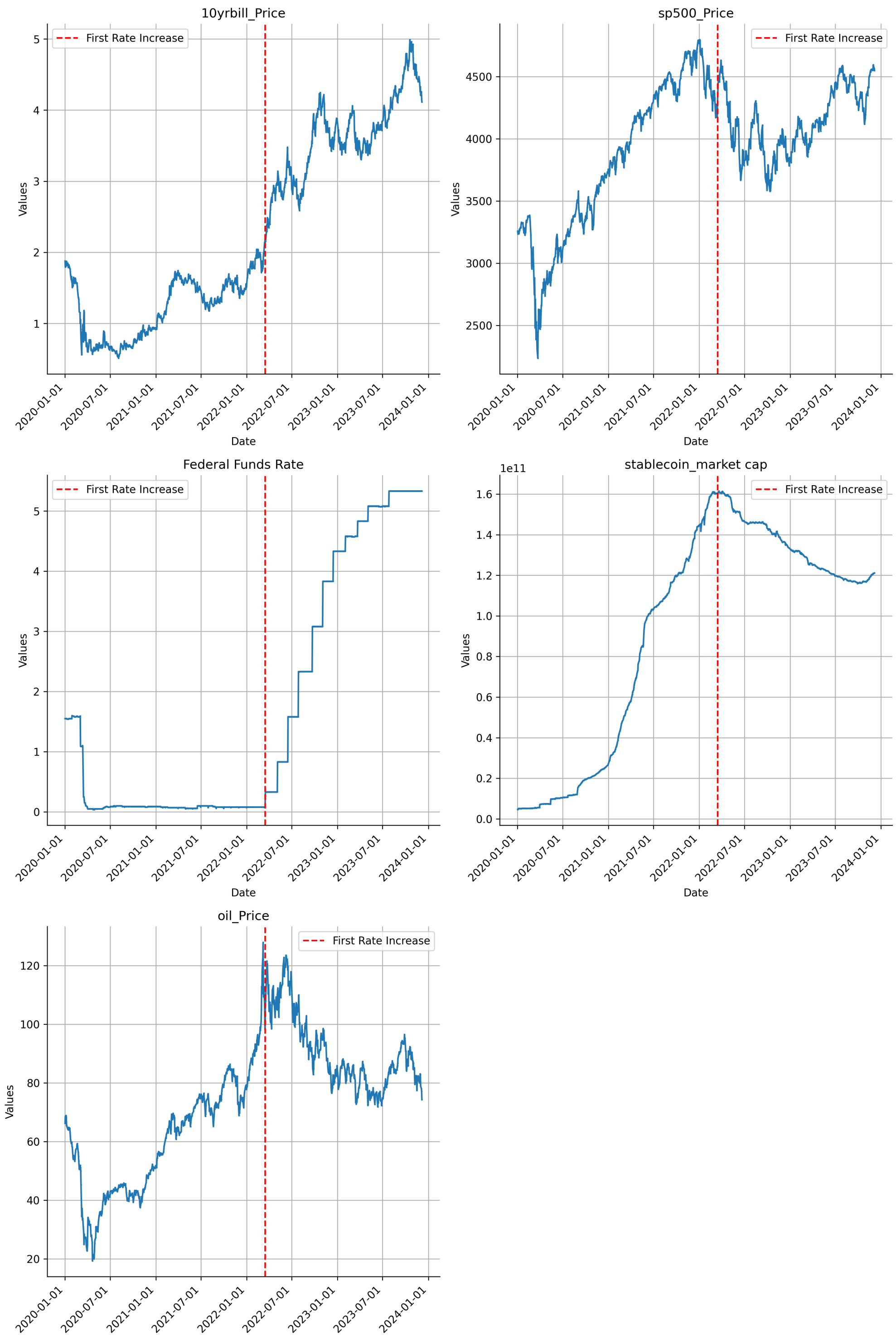

Figure 1: Trend of the variables

It is not hard to observe that the S&P 500 price graph displays a trend of general upward movement until the point marked by the first rate increase, suggesting a bullish market condition leading up to this monetary tightening. Post the initial rate increase, there is a visible fluctuation in the index with a trend towards stabilization and subsequent recovery. This pattern indicates a market reaction to the tightening of monetary policy, likely reflecting investor uncertainty about future economic conditions and the impact of higher borrowing costs on corporate profitability.

In contrast, the stablecoin market capitalization exhibits a steep ascendancy prior to the rate increase, reaching its peak coincidentally at or near the policy shift. The peak is followed by a significant decline, which then stabilizes but remains on a slight downward or flat trajectory. The initial growth can be interpreted as investors possibly flocking to stablecoins, perhaps perceiving them as a more risker but more profitable investment opportunities as the liquidity in the makret boomed amidst declining or the anticipation of continuous declines of the monetary policy. The subsequent decline post-rate increase may reflect a recalibration of investor expectations as stablecoins, despite their peg to stable assets like the USD, do not entirely escape the repercussions of broader financial market adjustments.

2.2 Methodology

In order to meticulously account for the structural shifts prompted by changes in policy rates within our analysis, this study adopts a phased analysis approach. This methodology entails partitioning the comprehensive dataset into two distinct temporal phases that align with periods characterized by either expansionary or contractionary monetary policies. The initial phase spans from March 2020 to March 2022, a period of relatively loose monetary conditions, while the subsequent phase extends through August 2023, marking the dataset's terminus during a phase of tighter monetary policy.

Our analytical strategy employs a dual-phase Ordinary Least Squares (OLS) regression framework to rigorously examine the interdependencies between cryptocurrency market dynamics and traditional financial metrics across these varied monetary environments. This bifurcated approach allows for a tailored analysis that accommodates the distinct economic climates of each phase, thereby enhancing the precision of our insights into how different policy regimes influence market behaviors.

To ensure the reliability of our findings and to address potential non-stationarity in the data—which could bias the OLS estimations—the dataset will undergo a transformation into percentage growth rates, a format generally acknowledged for its stationarity properties. This transformation is critical as it mitigates the risk of spurious regression results that are commonplace in time series data where unit roots might exist. Prior to conducting the regression analyses, the study will implement the Augmented Dickey-Fuller (ADF) Test to confirm stationarity of the transformed data. Additionally, the Variance Inflation Factor (VIF) checks will be conducted to assess the presence of multicollinearity among the independent variables, ensuring that the regression results are both valid and interpretable.

1. ***Model 1: Impact on Traditional Stock Market***
   The initial Ordinary Least Squares (OLS) regression model seeks to elucidate the determinants of the S&P 500 index prices, posited as the dependent variable. This model hypothesizes that the index prices are influenced by key economic indicators: the 10-year U.S. Treasury bill yields, changes in Brent oil prices, and the Federal Funds Rate. The model is formally represented by the equation:

   $$S\&P500_t = \alpha + \beta_1 \times 10yrBill_t + \beta_2 \times Oil_Price_Change_t + \beta_3 \times PolicyRate_t + \varepsilon_t \quad (1)$$

   where α denotes the intercept, $\beta_1, \beta_2, \beta_3$ are the coefficients for the respective independent variables reflecting their impact, and ε_t is the stochastic error term capturing unobserved influences at time t.

2. ***Model 2: Impact on Cryptocurrency Market***
   Concurrently, the second OLS regression model addresses the market capitalization of stablecoins, designated as the dependent variable, to assess its responsiveness to the

same set of economic indicators. This approach ensures consistency in examining the effect of macroeconomic variables across different financial sectors. The specification for this model is as follows:

$$Stablecoin_t = \alpha' + \beta_1' \times 10yrBill_t + \beta_2' \times Oil_{P}rice_{C}hange_t + \beta_3' \times PolicyRate_t + \varepsilon_t' \quad (2)$$

where α' represents the model's intercept, $\beta_1', \beta_2', \beta_3'$ are the coefficients quantifying the impact of each independent variable on the stablecoin market, and ε_t' is the error term at time t, capturing unobserved factors specific to the cryptocurrency market.

The coefficients β_3 and β_3', corresponding to the Federal Funds Rate, will be meticulously analyzed to discern their respective impacts—whether positive or negative—on the S&P 500 index and stablecoin market capitalization, thereby providing insights into how monetary policy influences diverse financial markets.

In advancing our econometric analysis to a more comprehensive framework, we employ a Vector Autoregression (VAR) model to explore the intricate dynamics and interrelations among selected economic indicators and cryptocurrency market variables across diverse monetary policy regimes. The VAR model is instrumental in capturing the simultaneous interactions and mutual influences among multiple interdependent time series, thereby facilitating a nuanced understanding of economic phenomena.

In this study, the VAR model is utilized to assess how each variable within our dataset is influenced not only by its own historical values but also by the past values of other variables, encompassing a broader set of economic indicators. These include the Federal Funds Rate, S&P 500 index prices, 10-year U.S. Treasury bill yields, stablecoin market capitalization, and Brent oil prices. This comprehensive approach allows for the assessment of direct and indirect effects within and across the financial sectors under study.

The model is structured as a VAR(p), where p denotes the optimal lag order chosen based on empirical data characteristics. The specification for our VAR model involving the vector of time series

$$Y_t = [S\&P500_t, Stablecoin_t, 10yrBill_t, oilPrice_t, PolicyRate_t]^T$$

The model can be spcified as:

$$\mathbf{Y}_t = \mathbf{A}_0 + \mathbf{A}_1\mathbf{Y}_{t-1} + \ldots + \mathbf{A}_p\mathbf{Y}_{t-p} + \varepsilon_t \quad (3)$$

$$= \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \\ \alpha_{30} \\ \alpha_{40} \\ \alpha_{50} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} & \phi_{14} & \phi_{15} \\ \phi_{21} & \phi_{22} & \phi_{23} & \phi_{24} & \phi_{25} \\ \phi_{31} & \phi_{32} & \phi_{33} & \phi_{34} & \phi_{35} \\ \phi_{41} & \phi_{42} & \phi_{43} & \phi_{44} & \phi_{45} \\ \phi_{51} & \phi_{52} & \phi_{53} & \phi_{54} & \phi_{55} \end{bmatrix} \mathbf{Y}_{t-1} \quad (4)$$

$$+ \ldots + \mathbf{A}_p\mathbf{Y}_{t-p} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \quad (5)$$

Here, $\mathbf{A}_0$ is the vector of constants α_{i0}, $\mathbf{A}_1, \ldots, \mathbf{A}_p$ are the matrices of coefficients ϕ_{ij} to be estimated, and ε_t is the vector of error terms at time t for each equation in the system.

The lag length p will be selected based on the lowest value of the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC), or Hannan-Quinn Information Criterion (HQIC), which can be represented as:

$$AIC(p) = \log|\hat{\Sigma}| + \frac{2}{T}pK^2 \quad (6)$$

$$SBIC(p) = \log|\hat{\Sigma}| + \frac{\log(T)}{T}pK^2 \quad (7)$$

$$HQIC(p) = \log|\hat{\Sigma}| + \frac{2\log(\log(T))}{T} pK^2 \tag{8}$$

where $\hat{\Sigma}$ is the estimated covariance matrix of the VAR residuals, $\boldsymbol{T}$ is the sample size, and $\boldsymbol{K}$ is the number of endogenous variables in the VAR model.

Upon fitting the VAR model, we will perform various diagnostic checks, including tests for serial correlation, non-normality, and heteroscedasticity of residuals, to ensure the model's reliability. Additionally, the stability of the VAR will be verified to ensure that the model is suitable for impulse response analysis and variance decomposition.

Impulse response functions (IRFs) and forecast error variance decomposition (FEVD) will be used to interpret the VAR model. IRFs will trace the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. FEVD will decompose the variance of forecast errors of each variable into proportions attributable to shocks to each variable in the VAR.

3 Results and discussions

In the datasets selected for this study, the presence of outliers is an expected phenomenon during certain periods, particularly noticeable in the instances of abrupt fluctuations in policy rates. Such spikes or declines are inherent characteristics of monetary policy adjustments, which can occur rapidly and with substantial magnitude. However, unlike the policy rate data, other time series in the dataset—represented in returns rather than raw values—typically exhibit properties conducive to stationarity, mitigating concerns related to non-stationary data that might otherwise affect the robustness of econometric analyses.

Given the differentiated nature of the data, it is crucial to establish a consistent framework for the analysis. To this end, the study delineates the periods of monetary policy into two distinct phases based on the prevailing economic conditions: Phase 1, referred to as the "loose monetary environment," and Phase 2, termed the "tight monetary environment." This terminological standardization facilitates a structured analysis, allowing for a clearer comparison and interpretation of the economic impacts associated with each phase. This dichotomy not only aids in simplifying the analytical process but also ensures that the effects of disparate monetary conditions on the financial markets are more accurately discerned and reported.

3.1 ADF and VIF Checks

Variable	ADF Statistic	P-value	Critical Value (1%)	Critical Value (5%)
Phase 1				
10yr Bill	-11.632666	0.000000	-3.443470	-2.867326
S&P500	-29.391775	0.000000	-3.443366	-2.867280
PolicyRate	-10.942722	0.000000	-3.443418	-2.867303
OilPrice_Change %	-6.735171	0.000000	-3.443794	-2.867469
Stablecoin	-22.090516	0.000000	-3.443366	-2.867280
Phase 2				
10yr Bill	-18.807670	0.000000	-3.449447	-2.869954
S&P500	-19.133020	0.000000	-3.449447	-2.869954
PolicyRate	-1.267213	**0.644036**	-3.449447	-2.869954
OilPrice_Change %	-12.049007	0.000000	-3.449560	-2.870004
Stablecoin	-18.396682	0.000000	-3.449447	-2.869954

Table 1: ADF Results for Two Phases

Phase 1	VIF Phase 1	Phase 2	VIF Phase 2
PolicyRate	1.004683	PolicyRate	1.001751
OilPrice_Change %	1.024755	OilPrice_Change	1.011857
10yrbill_Change %	1.027478	10yrbill_Change %	1.012779

Table 2: VIF Results for Two Phases

The Augmented Dickey-Fuller (ADF) test was rigorously applied to evaluate the stationarity of economic indicators within two distinct monetary environments delineated in our analysis. According to the results summarized in Table 1, the variables within Phase 1 demonstrated stationarity. This is evidenced by significantly negative ADF statistics, which not only fall below the critical values for both the 1% and 5% significance levels but also correspond with p-values that approach zero ($p = 0.00000$). This group includes the percentage changes in the 10-year Treasury bill yields, S&P 500 index, oil prices, and the market capitalization of stablecoins.

Conversely, in Phase 2, all variables maintained their stationarity except for the Federal Funds Rate. The ADF test for this variable yielded a p-value of 0.644036, which significantly exceeds conventional thresholds for rejecting the null hypothesis of a unit root, suggesting non-stationarity. This anomalous result likely reflects the exceptional adjustments to monetary policy during this period, characterized by abrupt increases in the Federal Funds Rate in response to inflationary pressures following extended periods of Quantitative Easing.

Given these findings, it is essential to consider the nature and role of the Federal Funds Rate within the broader economic system. Unlike market-driven variables, the Federal Funds Rate is directly set by monetary authorities and is thus less prone to random fluctuations typical of traded assets. This intrinsic characteristic—often described as 'stickiness' in economic literature International Monetary Fund [2021] —implies that conventional methods to induce stationarity, such as differencing, may not be appropriate or necessary for this series. Therefore, in our econometric modeling, we will treat the Federal Funds Rate as exogenously determined by the Federal Reserve, acknowledging its distinct behavior from other market-responsive variables.

This approach ensures that our econometric analysis remains grounded in the economic realities governing monetary policy instruments, thereby enhancing both the validity and interpretability of our findings.

3.2 OLS Regressions

	Phase 1		Phase 2	
	Stablecoin	S&P 500	Stablecoin	S&P 500
Constant	0.8935*	0.8406	-0.0646*	-0.1220
	(0.4232)	(0.6449)	(0.0259)	(0.1861)
	[0.0348]	[0.1924]	[0.0130]	[0.5120]
PolicyRate	-4.5215	-9.6947	-0.0078	0.0467
	(4.7022)	(8.1762)	(0.0070)	(0.0439)
	[0.3363]	[0.2357]	[0.2720]	[0.2874]
OilPrice_Change%	0.0526	0.0646*	0.0022	0.1056***
	(0.0429)	(0.0261)	(0.0047)	(0.0277)
	[0.2205]	[0.0134]	[0.6410]	[0.0001]
10yrbill_Change%	-0.0447	0.1263***	0.0062	-0.0808*
	(0.0295)	(0.0269)	(0.0050)	(0.0373)
	[0.1297]	[0.0000]	[0.2205]	[0.0301]
No. Observations	506	506	346	346
R-squared	0.0145	0.2419	0.0095	0.0609
F-statistic	0.8020	11.4429	1.0913	6.0106
Durbin-Watson	1.9831	2.0336	1.9847	2.1280
Omnibus (p-value)	0.000	0.000	0.000	0.015
Jarque-Bera (p-value)	0.00	6.46e-233	9.02e-43	0.00167

t statistics in ()
P-value in [ ]
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3: Regression Results For the Four Models in Two Phases

The regression outcomes displayed in Table 3, derived from a structured analysis detailed in the methodology section, yield critical insights into the influence of monetary policy while controling other economic indicators on the traditional stock market and the cryptocurrency market during two distinct monetary policy phases.

In Phase 1, characterized by a more relaxed monetary policy, the Policy Rate's coefficients are non-significant across both the stock market and the stablecoin market. **This suggests that during a looser monetary policy phase, the markets in question did not exhibit a significant immediate response to changes in the policy rate even though the two markets seem to move in the similar direction as both coefficients have negative signs.** It is notable, however, that the 10-year Treasury bill changes have a substantial positive impact on the S&P 500, marked by three asterisks indicating a significance level below 0.001, which may indicate a higher market sensitivity to long-term interest rates rather than the short-term policy rate.

During Phase 2, under a stricter monetary regime, the Policy Rate continues to demonstrate a non-significant influence on both market types. **However, the relationship between the Policy Rate and the two respective markets seems to suggest a decoupling effect where the stock and crypto markets are swayed by the short-term federal funds rate, inversely.** Nonetheless, the oil price change percentage shows a robust positive relationship with the S&P 500, denoted by the three stars, revealing that commodity prices may play a more crucial role in this phase.

The central aim of the study is to assess whether the stock and cryptocurrency markets are coupling or decoupling based on the reaction to the Policy Rate across different monetary environments. Yet the absence of statistically significant results for all the predictors in both phases four models on the crypto market indicates that the immediate reactions to monetary policy and the macro economic factors are somehow attenuated or transmitted through a lagged mechanism, warranting further investigation.

3.2.1 Diagnostic Check

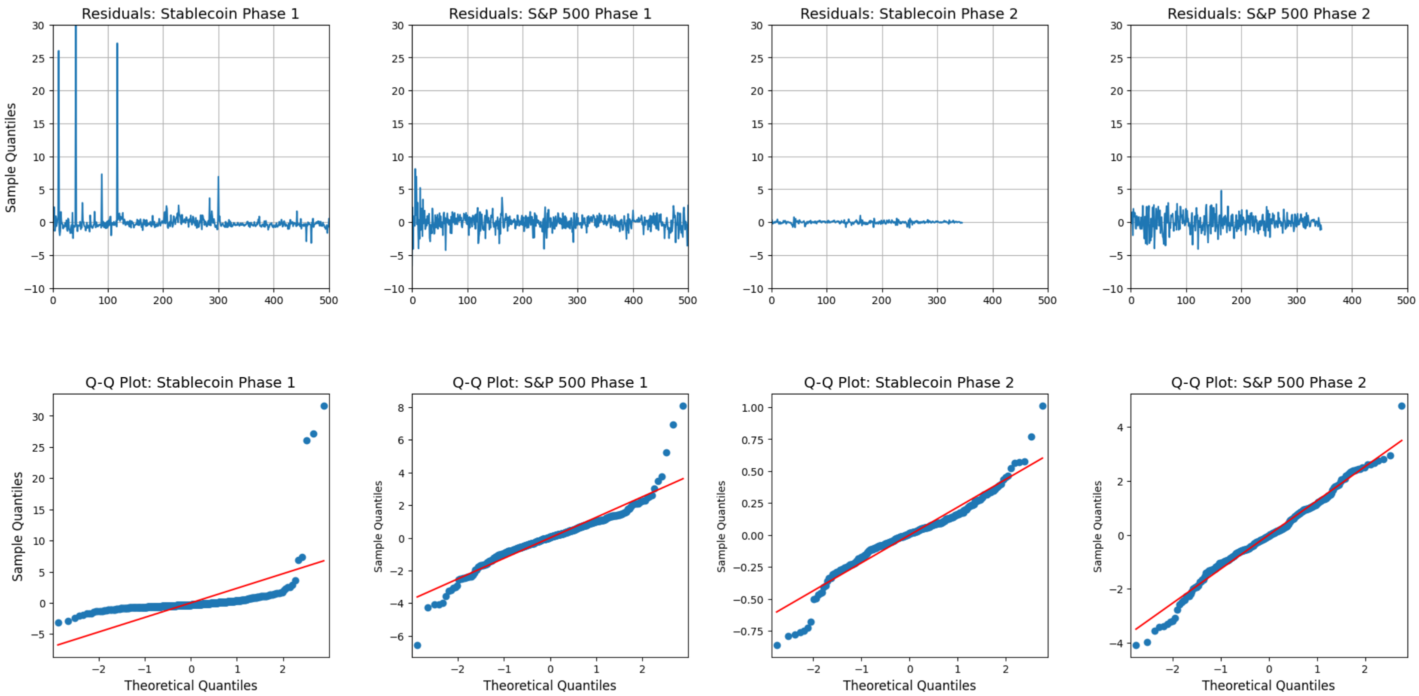

Figure 2: Residuals_Plots

	Model			
Model	Stablecoin Phase 1	S&P500 Phase 1	Stablecoin Phase 2	S&P500 Phase 2
Lagrange multiplier	7.58574	31.2849	1.55725	32.3907
p-value	0.0553959	7.40384e-07	0.669121	4.32939e-07
f-value	2.54677	11.0277	0.515402	11.7743
f p-value	0.0552833	5.0581e-07	0.67193	2.33242e-07

Table 4: Breusch-Pagan Test Results for Four Models

Model	Stablecoin Phase 1	S&P500 Phase 1	Stablecoin Phase 2	S&P500 Phase 2
10yrbill_Change%	0.0000	0.0000	-0.0000	-0.0000
Policy Rate	0.0000	0.0000	-0.0000	0.0000
OilPrice_Change%	0.0000	0.0000	0.0000	-0.0000

Table 5: Correlation between residuals and independent variables

The analysis of residuals (Figure 2) reveals no apparent patterns or systematic deviations, suggesting that the models do not suffer from misspecification errors. For both the stablecoin and S&P 500 models across both phases, the residuals fluctuate randomly around the zero line, indicative of well-specified models. While outliers are present, they do not display an orderly pattern that would suggest model inadequacies.

The Q-Q plots provide further insight into the distribution of residuals. In all models, we observe some deviation from normality in the tails, with Phase 1 showing a slightly more pronounced effect. These heavy tails point towards the presence of larger-than-expected extreme values. However, this departure from normality does not necessarily imply biased estimators, though it may affect efficiency and the robustness of standard error estimates. This might be due to the sudden change in the Policy Rate in response to the Pandemic at the stage creating more deviations on tails.

The Breusch-Pagan test results (Table 4) indicate heteroscedasticity in the residuals of the S&P 500 models for both phases, as suggested by the significant Lagrange multiplier statistics and corresponding p-values. On the other hand, the stablecoin models show p-values bordering on conventional significance levels, suggesting a borderline case for the assumption of homoscedasticity. While heteroscedasticity challenges the efficiency of estimators, it does not inherently bias them.

An essential consideration for unbiasedness is the correlation between residuals and independent variables. Table 5 unequivocally demonstrates a zero correlation, which strongly supports our claim of unbiasedness. The absence of correlation indicates that the regressors do not have omitted variable bias and that the conditional mean of the error term is zero. However, in practice, the close to 0 correlation seems quite unusual. At this stage we ought to stay cautious as the model might be subject to non-linear factors so the negligent linear correlation.

Meanwhile, as seen in Table 3, the Durbin-Watson statistics are near the value of 2, which suggests that autocorrelation is not present in the residuals. Moreover, the Omnibus test in Phase 1 and the Jarque-Bera test in Phase 2 provide a mixed bag of results, indicating that non-normality might be a concern in our models. Nonetheless, these tests do not disprove unbiasedness but rather point towards the non-normality of the error term, which could affect the validity of hypothesis tests based on the assumption of normally distributed errors.

Given the thorough diagnostic checks, the study concludes that the estimators of the regression models are unbiased. This conclusion is predicated on the absence of autocorrelation, the lack of systematic patterns in residuals, and the zero correlation between the residuals and independent variables. Although heteroscedasticity and non-normality are detected, they are more indicative of efficiency loss and potential violations of the OLS assumptions rather than biased estimation. As such, the relationships observed in the regression coefficients—particularly the coefficient of the policy rate—can be interpreted as reflecting the true underlying economic phenomena of market coupling or decoupling, unaffected by biases in model estimation.

3.3 VAR Model

In addressing the potential stickiness of the Policy Rate across various time periods, our econometric approach strategically incorporates lags that span a reasonable time horizon. This decision is rooted in the necessity to capture the temporal dynamics of monetary policy adjustments and to assess their propagative effects across other economic variables within the model. Given our primary interest in examining the impact of shocks in one variable on others, and particularly in forecasting these effects accurately, the model's specification must be adept at reflecting such interactions over time. To this end, AIC has been chosen as the guiding metric for determining the optimal lag structure. Consequently, an initial lag length of 30 days has been established, which aligns with our analytical objective to trace and forecast the ripple effects of financial shocks within a defined temporal window.

	10yr Bill	S&P 500	PolicyRate	Oil_Change %	Stablecoin
Constant	-2.6730	0.6081	0.0047*	2.038454*	1.211291
	(1.6091)	0.4388	(0.0019)	(0.9532)	(0.857093)
	[0.097]	[0.166]	[0.012]	[0.032]	[0.158]
PolicyRate_{t-1}	42.8377	-6.3881	0.5957***	37.661866	23.328137
	(45.4670)	(12.3980)	(0.0529)	(26.9335)	(24.218547)
	[0.346]	[0.606]	[0.000]	[0.162]	[0.335]
$\text{Oil\_Change\%}_{t-1}$	0.1308	-0.0062	-0.000070	0.0007	-0.027877
	(0.0876)	(0.0239)	(0.000102)	(0.0519)	(0.046664)
	[0.135]	[0.796]	[0.494]	[0.990]	[0.550]
10yr Bill_{t-1}	-0.1231*	0.0061	0.000026	0.0071	-0.023102
	(0.0542)	(0.0148)	(0.000063)	(0.0321)	(0.028870)
	[0.023]	[0.680]	[0.681]	[0.824]	[0.424]
$\text{S\&P 500}_{t-1}$	-0.2273	-0.0096	-0.000253	-0.0290	0.059813
	(0.2047)	(0.0558)	(0.000238)	(0.1213)	(0.109037)
	[0.267]	[0.864]	[0.289]	[0.811]	[0.583]
Stablecoin_{t-1}	-0.1290	0.0146	0.000123	-0.0119	-0.035521
	0.1008	(0.0275)	(0.000117)	(0.0597)	(0.053685)
	[0.201]	[0.596]	[0.296]	[0.843]	[0.508]
PolicyRate_{t-13}	32.5807	6.6687	-0.0126	5.2549	-10.730
	(51.972)	(14.172)	(0.0605)	(30.787)	(27.683)
	[0.531]	[0.638]	[0.836]	[0.864]	[0.698]
$\text{Oil\_Change\%}_{t-13}$	-0.0476	0.0088	-0.0001	0.0391	-0.1251**
	(0.0828)	(0.0226)	(0.0001)	(0.0490)	(0.0441)
	[0.565]	[0.696]	[0.564]	[0.425]	[0.005]
10yr Bill_{t-13}	0.0162	-0.1144	0.0001	0.0208	0.0702*
	(0.0571)	(0.1952)	(0.0605)	(0.0338)	(0.0304)
	[0.777]	[0.558]	[0.332]	[0.538]	[0.021]
$\text{S\&P 500}_{t-13}$	-0.1144	-0.1004	0.0001	0.0804	0.1594
	(0.1952)	(0.0532)	(0.0605)	(0.1156)	(0.1040)
	[0.558]	[0.059]	[0.626]	[0.487]	[0.125]
Stablecoin_{t-13}	0.1724	-0.0272	0.0000	0.0591	0.0591
	(0.0950)	(0.0259)	(0.0001)	(0.0563)	(0.0506)
	[0.070]	[0.294]	[0.827]	[0.243]	[0.243]
PolicyRate_{t-26}	-22.1405	13.7983	-0.0219	32.9436	-22.686
	(38.376)	(13.797)	(0.0447)	(29.972)	(20.441)
	[0.564]	[0.317]	[0.623]	[0.272]	[0.267]
$\text{Oil\_Change\%}_{t-26}$	0.0209	0.0488*	-0.0001	0.0772	-0.0010
	(0.0787)	(0.0225)	(0.0001)	(0.0488)	(0.0419)
	[0.790]	[0.030]	[0.572]	[0.114]	[0.985]
10yr Bill_{t-26}	-0.0309	0.0114	0.0000	-0.0909**	0.0071
	(0.0516)	(0.0141)	(0.0001)	(0.0323)	(0.0275)
	[0.549]	[0.418]	[0.919]	[0.005]	[0.798]
$\text{S\&P 500}_{t-26}$	-0.1102	-0.0649	-0.0003	0.0119	0.1178
	(0.1892)	(0.0516)	(0.0002)	(0.1121)	(0.0981)
	[0.560]	[0.196]	[0.162]	[0.915]	[0.230]
Stablecoin_{t-26}	-0.0512	0.0140	0.0002*	-0.1048	-0.0175
	(0.0924)	(0.0252)	(0.0001)	(0.0547)	(0.0478)
	[0.579]	[0.578]	[0.044]	[0.055]	[0.715]
No. Equations	5				
Durbin-Watson	1.9755	1.9785	2.0109	2.0105	2.0217
Jarque-Bera (p-value)	3.326e-04	1.7147e-02	0.00e+00	6.92466e-29	0.000e+00

standard errors in ()
P-value in [ ]
${}^{*}p < 0.05$, ${}^{**}p < 0.01$, ${}^{***}p < 0.001$

Table 6: VAR Results for the First Phase

Variable Lag	Coefficient	p-value
10yrbill_Change %		
L1.10yr Bill	-0.123145	0.023
L4.10yr Bill	-0.216246	0.000
L4.Stablecoin	0.202164	0.045
L5.Oil_Change%	0.175737	0.040
L9.Oil_Change %	0.193573	0.031
L15.Stablecoin	0.235187	0.013
L17.Oil_Change %	0.183927	0.019
L24.Stablecoin	0.258941	0.003
S&P500_Change %		
L3.S&P 500	-0.101110	0.064
L3.Stablecoin	-0.065424	0.017
L4.10yr Bill	-0.029737	0.043
L5.Stablecoin	-0.061375	0.024
L6.oil_Change %	-0.063414	0.008
L7.10yr Bill	-0.034098	0.025
L8.10yr Bill	-0.036804	0.016
L15.Oil_Change %	0.044025	0.049
L15.Stablecoin	0.060183	0.019
L21.Stablecoin	0.072186	0.004
L22.Oil_Change %	0.048770	0.030
Policy Rate		
L1.PolicyRate	0.595685	0.000
L2.PolicyRate	0.238238	0.000
L9.Oil_Change %	0.000234	0.025
L21.PolicyRate	0.212543	0.000
L22.Stablecoin	0.000216	0.044
L23.PolicyRate	-0.156249	0.007
L25.10yr Bill	0.000129	0.033
L26.Stablecoin	-0.000286	0.006
Oil_Change %		
L2.S&P 500	0.338751	0.005
L2.PolicyRate	-62.457792	0.045
L4.10yr Bill	-0.099896	0.002
L4.Oil_Change %	0.123391	0.015
L5.10yr Bill	-0.084564	0.010
L6.PolicyRate	68.153556	0.026
L7.Oil_Change %	-0.192665	0.000
L11.Oil_Change %	0.176809	0.001
L14.Stablecoin	-0.149253	0.008
L16.PolicyRate	-78.696876	0.010
L17.S&P 500	0.345665	0.002
L17.Oil_Change %	-0.262135	0.000
L19.Oil_Change %	0.121192	0.012
L21.Oil_Change %	0.144953	0.003
L22.10yr Bill	-0.090877	0.005
L24.10yr Bill	0.092333	0.003
L25.S&P 500	0.255788	0.021
L26.Oil_Change %	-0.093074	0.046
Stablecoin_Growth%		
L6.Oil_Change %	-0.113253	0.015
L10.Oil_Change %	0.166371	0.000
L13.10yr Bill	0.070193	0.021
L14.10yr Bill	0.085589	0.004
L17.Oil_Change %	-0.202434	0.000
L18.10yr Bill	0.061032	0.038
L19.S&P 500	0.210496	0.039
L22.Stablecoin	-0.095748	0.052
L23.Stablecoin	-0.122101	0.026

Table 7: Significant Lags and Their Coefficients from Phase 1 VAR Results

	10yr Bill	S&P 500	PolicyRate	Oil_Change %	Stablecoin
Constant	0.550932	-0.368012	0.101307***	0.163143	0.008771
	(0.579782)	(0.336022)	(0.024111)	(0.640211)	(0.058243)
	[0.342]	[0.273]	[0.000]	[0.799]	[0.880]
PolicyRate_{t-1}	-0.607352	0.402797	0.891119***	-0.948410	0.145824
	(1.743962)	(1.010740)	(0.072524)	(1.925728)	(0.175192)
	[0.728]	[0.690]	[0.000]	[0.622]	[0.405]
$\text{Oil\_Change\%}_{t-1}$	0.007034	-0.005478	0.002775	0.057582	0.009415
	(0.070149)	(0.040656)	(0.002917)	(0.077460)	(0.007047)
	[0.920]	[0.893]	[0.342]	[0.457]	[0.182]
10yr Bill_{t-1}	0.010132	-0.014761	-0.003494	-0.025946	-0.002767
	(0.078836)	(0.045690)	(0.003278)	(0.087052)	(0.007920)
	[0.898]	[0.747]	[0.287]	[0.766]	[0.727]
$\text{S\&P 500}_{t-1}$	-0.396628**	-0.049473	0.002118	0.130934	0.027013*
	(0.130350)	(0.075547)	(0.005421)	(0.143936)	(0.013095)
	[0.002]	[0.513]	[0.696]	[0.363]	[0.039]
Stablecoin_{t-1}	0.455644	-0.119288	0.002782	0.068665	-0.070985
	(0.726110)	(0.420828)	(0.030196)	(0.801790)	(0.072942)
	[0.530]	[0.777]	[0.927]	[0.932]	[0.330]
PolicyRate_{t-13}	-0.928337	-0.528581	-0.051680	-0.002153	-0.043692
	(2.327582)	(1.348987)	(0.096794)	(0.002955)	(0.030432)
	[0.690]	[0.695]	[0.593]	[0.466]	[0.151]
$\text{Oil\_Change\%}_{t-13}$	0.061159	0.023704	-0.002153	0.061159	-0.003900
	(0.071054)	(0.041180)	(0.002955)	(0.071054)	(0.808054)
	[0.389]	[0.565]	[0.466]	[0.085]	[0.996]
10yr Bill_{t-13}	0.043595	-0.011124	0.001038	0.012519	0.008372
	(0.074787)	(0.043344)	(0.003110)	(0.082582)	(0.007513)
	[0.560]	[0.797]	[0.739]	[0.880]	[0.265]
$\text{S\&P 500}_{t-13}$	-0.022851	-0.033905	-0.528581	0.023704	-1.116773**
	(0.131752)	(0.076359)	(1.348987)	(0.041180)	(0.424116)
	[0.862]	[0.657]	[0.695]	[0.565]	[0.008]
Stablecoin_{t-13}	0.045062	-1.116773**	-0.043692	-0.003900	0.045062
	(0.731783)	(0.424116)	(0.030432)	(0.808054)	(0.731783)
	[0.951]	[0.008]	[0.151]	[0.996]	[0.951]
PolicyRate_{t-26}	-0.557792	0.889520	0.116417	-0.002076	0.039089
	(1.731601)	(1.003576)	(0.072010)	(0.002546)	(0.031197)
	[0.747]	[0.375]	[0.106]	[0.415]	[0.210]
$\text{Oil\_Change\%}_{t-26}$	-0.014702	-0.021623	-0.002076	-0.094760	-0.021623
	(0.061217)	(0.035479)	(0.002546)	(0.067597)	(0.035479)
	[0.810]	[0.542]	[0.415]	[0.161]	[0.542]
10yr Bill_{t-26}	0.008973	0.080990*	-0.017993	0.012956	-0.011836
	(0.064722)	(0.037511)	(0.073424)	(0.081076)	(0.006502)
	[0.890]	[0.031]	[0.806]	[0.873]	[0.069]
$\text{S\&P 500}_{t-26}$	0.073866	-0.040339	0.007777	0.041493	0.000312
	(0.128185)	(0.074292)	(0.005331)	(0.145078)	(0.012877)
	[0.564]	[0.587]	[0.375]	[0.775]	[0.981]
Stablecoin_{t-26}	0.197783	-0.346098	0.039089	-0.027275	0.010901
	(0.750190)	(0.434785)	(0.031197)	(0.075803)	(0.075361)
	[0.792]	[0.426]	[0.210]	[0.719]	[0.885]
No. Equations	5				
Durbin-Watson	1.9732	2.009	2.0275	2.0106	2.0033
Jarque-Bera (p-value)	0.05157019	0.54600097	0.0	0.04545834	0.00058931

standard errors in ()
P-value in [ ]
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 8: VAR Results for the Second Phase

Variable Lag	Coefficient	p-value
10yrbill_Change %		
L1.S&P 500	-0.396628	0.002
L3.S&P 500	-0.282082	0.037
L3.PolicyRate	-4.882166	0.042
L6.PolicyRate	6.195655	0.006
L7.PolicyRate	-5.396811	0.019
L7.Oil_Change %	0.150677	0.031
L7.Stablecoin	1.580201	0.030
L10.Oil_Change %	-0.168741	0.017
L11.Stablecoin	1.469452	0.043
L15.Stablecoin	-1.512322	0.041
L17.S&P 500	-0.289543	0.026
L23.10yr Bill	-0.131106	0.047
S&P500_Change %		
L8.Oil_Change %	0.097729	0.016
L13.Stablecoin	-1.116773	0.008
L15.Oil_Change %	0.082570	0.036
L20.S&P 500	0.148391	0.046
L23.Stablecoin	0.853613	0.047
L26.10yr Bill	0.080990	0.031
Policy Rate		
L1.PolicyRate	0.891119	0.000
L12.Oil_Change %	-0.006811	0.019
L13.S&P 500	0.013575	0.013
L15.S&P 500	0.013219	0.013
L17.Oil_Change %	-0.006546	0.021
Oil_Change %		
L2.10yr Bill	0.179224	0.036
L2.PolicyRate	-5.078741	0.050
L2.Stablecoin	-1.587669	0.047
L15.Stablecoin	-2.068378	0.012
L16.PolicyRate	-6.041341	0.019
L20.10yr Bill	-0.152628	0.046
L24.Oil_Change %	-0.129653	0.067

Table 9: Significant Lags and Their Coefficients from Phase 2 VAR Results

In our Phase 1, characterized by a loose monetary policy environment with declining policy rates, the VAR model analysis focuses on immediate (Lag 1), medium-term (Lag 13), and long-term (Lag 26) effects on various economic indicators. The VAR results indicate a slight positive autocorrelation in policy rates, suggesting a tendency for the rates to follow their immediate past trends. In the meantime, it demonstrates a positive immediate impact on the S&P 500 and a medium-term positive impact on stablecoin valuation due to the inverse relationship, suggesting that lower interest rates may encourage investment in both traditional and digital asset markets but at different timing.

With the closer examination of this phenomenon, the medium to long term periods seems to suggest the muted effects of the policy rate on the stock market. It indicates that the stock market is more sensitive to the swift changes of policy rates and gradually internalize such rate change expectations while the crypto market has shown the opposite patterns, at least within the 26 periods that we examine. As many of these coefficients, while not statistically significant, could hold economic significance, indicating subtle market shifts that may not be immediately apparent but are relevant for long-term investment strategies. This also suggests that the short-term decoupling might hold given the different response time to the Macro market indicators between the two markets. While some coefficients are statistically significant, their economic significance might be limited due to the subtlety of day-to-day fluctuations in this environment. Potentially, there might be a spillover effect of the traditional financial market on crypto's ups and downs. This could be supported from Table 7 where the stablecoin as factors of S&P500_Change % shows the delayed coupling effects at higher lags but decoupled for the near term. Additionally, we cannot find any significant factors of S&P500_Change % as a factor for Stablecoin.

In Phase 2, with a tightening monetary policy, the immediate effects of policy rate changes are again significant on the policy rate itself at Lag 1, highlighting the persistence of policy decisions. However, unlike in Phase 1, we see a negative impact on the S&P 500 at the medium lag (L13), while positive impacts on the near term and the long term. This indicates that the stock market contrary to Phase 1 tends to demonstrate the delayed response to the rising policy rate until the medium term and quickly adjust the expectations to adopt the tight monetary environment.

The crypto market surprisingly demonstrates the similar moving trends. However, we cannot find any significant factors, not even its own lagged terms to be able to better predict the changing directions of the crypto market. This inconsistency suggests that unlike in Phase1, stablecoins may not directly correlate with traditional economic indicators like policy rates in a straightforward manner during tightening phases. The crypto market might become more speculative during this time period and seems to be cut off from the traditional trading markets with its own trend and development.

So by and large, the VAR analysis over two distinct monetary policy phases reveals that the stock market and stablecoins react differently to changes in policy rates across various time lags. In a loose monetary policy environment (Phase 1), the stock market shows strong immediate reaction to policy rate changes, whereas stablecoins display significant positive responses but with a delay. This suggests that while traditional markets may be probe to swiftly react to monetary easing, the cryptocurrency market may benefit from increased liquidity and lower rates over time.

Interestingly, in a tight monetary policy environment (Phase 2), the stock market reacts positively to policy rate increases, particularly over the near and long term, reflecting stickiness of stock growh momentum and the ability to adapt to the changing expectations about the impact of higher borrowing costs on equity investments. However, albeit showing the similar movements, the lack of any significance of the stablecoins seems to be less predictable, with mixed responses that might reflect their complete decoupling from the active traditional financial markets.

3.3.1 Diagnostic Check

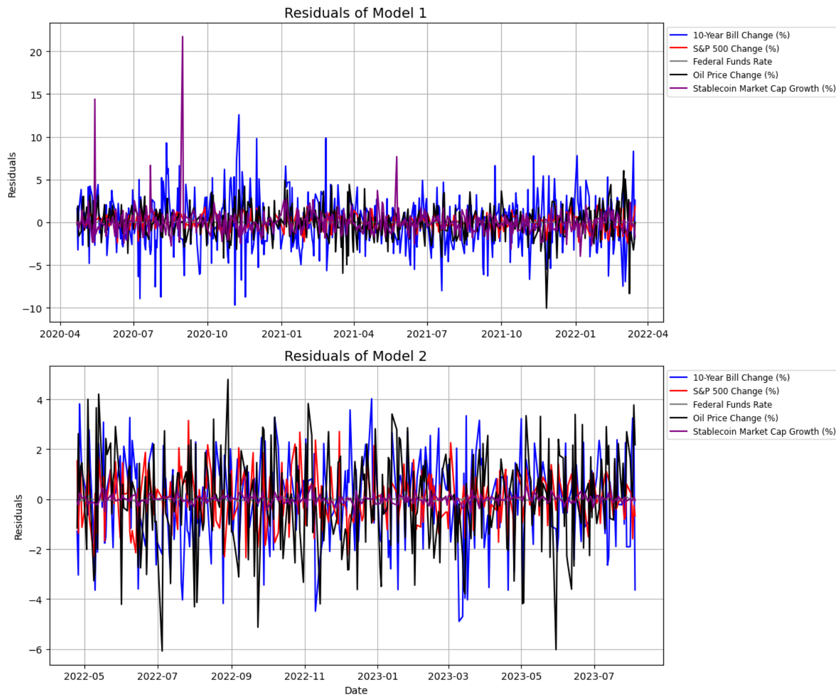

Figure 3: VAR Model Residuals

The diagnostic examination of the residuals from two VAR models suggests that the models are reasonably well-specified, capturing the underlying dynamics of the financial variables. In Model 1, the residuals exhibit a considerable degree of volatility with occasional large spikes, which might indicate specific events or outliers that the model does not fully account for. On the other hand, Model 2 presents a tighter distribution of residuals with fewer and less pronounced spikes, suggesting a potentially better fit or differing market conditions that affect the model's performance. From this perspective, the model tries to suggest that during the loose monetary environment, the market has more transactional activities that contribute to more outliers and spikes on the chart as huge amount of liquidity has been injected to the economy and it takes time to digest.

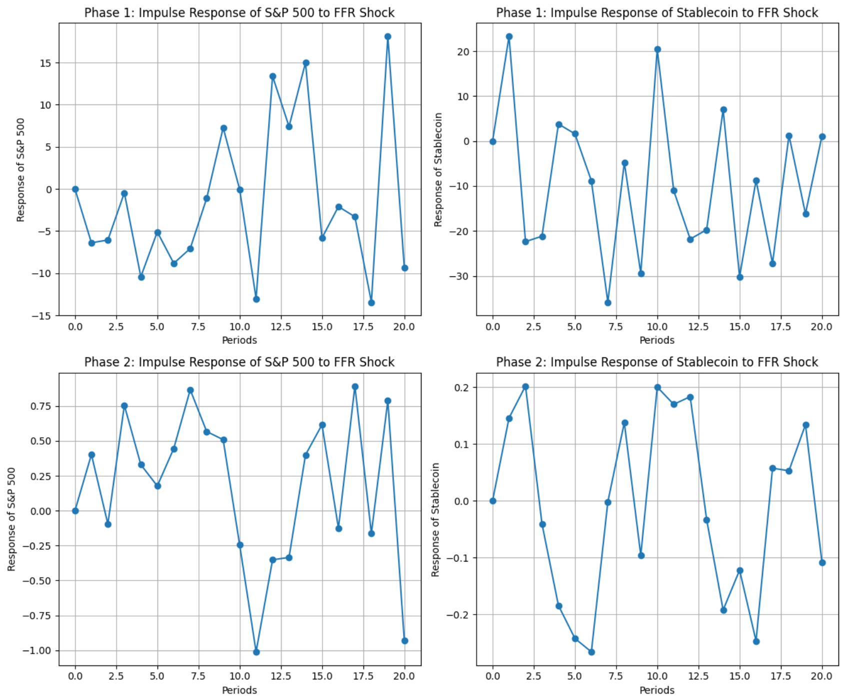

Figure 4: Impute Response Analysis

The impulse responses of the S&P 500 and stablecoins to shocks in the Federal Funds Rate (FFR) demonstrate varied sensitivities across two distinct phases. During Phase 1, both the S&P 500 and stablecoins show highly volatile reactions to FFR shocks, characterized by significant and rapid fluctuations and large scales on the vertical axis. This volatility suggests a heightened sensitivity to changes in monetary policy during this phase, potentially reflecting the financial markets' uncertainties or adjustments to new economic conditions. Over time, the magnitudes of these responses diminish, yet they remain significant, pointing to a persistent impact of monetary policy over the analyzed period. Meanwhile, the crypto response seems to lag behind that of the stock market with each period of it repreating the trend of the stock market in the last period.

Contrary to Phase 1, Phase 2 shows moderated responses for both the S&P 500 and stablecoins, with the magnitudes of fluctuations being comparatively lower on scale. This reduced volatility could indicate that the markets have adapted to the monetary environment or that other macroeconomic factors are buffering the impact of FFR shocks during this phase. The crypto market becomes less volatile to the changes of the FFR at this stage, potentially validating the finding before that the market during this time period began to be cut off from other macro economic markets.

Period (Cumulative)	10yr Bill	S&P 500	PolicyRate	Oil_Change %	Stablecoin_growth %
Phase 1					
FEVD for Stablecoin_growth %					
0	0.003103	0.006664	0.000090	0.004390	0.985754
20	0.074687	0.032793	0.027400	0.104926	0.760194
FEVD for S&P 500					
0	0.032498	0.967502	0.000000	0.000000	0.000000
20	0.095042	0.766023	0.022593	0.042277	0.074066
Phase 2					
FEVD for Stablecoin_growth %					
0	0.020354	0.011430	0.018239	0.000773	0.949204
20	0.083994	0.089476	0.071828	0.045082	0.709620
FEVD for S&P 500					
0	0.015853	0.984147	0.000000	0.000000	0.000000
20	0.067140	0.742410	0.022530	0.091368	0.076552

Table 10: FEVD for Stablecoin Market Cap Growth % and S&P 500 Change %

The FEVD results, which show that the forecast error variances for both the S&P 500 and stablecoins are primarily influenced by their own shocks, suggest that most of the variability in these series is explained by their own past values rather than external influences. This aligns with the observation from the residuals analysis, where both models display residuals that do not exhibit clear patterns or trends, indicating that the models have effectively captured the primary dynamics of the data series.

However, the presence of large spikes in the residuals of Model 1 could be indicative of specific events or outliers not captured by the model. These anomalies in the residuals might be times when exogenous shocks (not included in the model) influenced the market, which were not fully accounted for in the FEVD. The FEVD shows a minor contribution from other economic variables, suggesting that while the models capture the bulk of the dynamics, there could be additional external factors at specific points in time that affect the markets beyond the scope of what was modeled.

Also, the variability in response can be further understood through the FEVD results here, which suggest that while the markets' own shocks are the dominant source of variance, the increasing influence of other variables over time (e.g., policy rate, oil price changes) seen in the FEVD could explain some of the observed responses in the impulse analysis.

For instance, the impulse response analysis in Phase 1 shows a highly volatile reaction of both the S&P 500 and stablecoins to FFR shocks, which might partially be accounted for by the FEVD's indication that other variables (like oil price changes) start to play a more significant role in explaining the variance. In Phase 2, where the impulse responses appear more subdued, the FEVD also shows a slightly increased contribution from the policy rate and other variables, suggesting a more integrated or moderated market reaction to shocks, likely due to adaptations in the market or changes in economic conditions.

The comprehensive analysis of VAR model residuals, impulse responses, and FEVD highlights the complexity and dynamic nature of the relationship between monetary policy changes and financial market reactions. The findings suggest that while the financial markets, represented by the S&P 500 and stablecoins, exhibit significant sensitivity to policy rate shocks, the degree and nature of these responses can vary significantly over different phases. These variations could be influenced by broader economic conditions, market sentiment, and the adaptive behaviors of market participants.

4 Conclusion

Meticulously conducted through the application of advanced quantitative methods including Ordinary Least Squares and Vector Autoregression models, this paper has explored the intricate relationship between the traditional stock market and the cryptocurrency market under varying policy rate environments

This study has underscored the complexity of the interaction between policy rates and market behavior, demonstrating that these relationships are not only influenced by immediate policy changes but also by the broader economic context, especially under the special Pandemic circumstances. The empirical findings suggest that the coupling and decoupling dynamics between the two markets are subtle and significantly impacted by the prevailing monetary policy environment. The stock market showed immediate reactions to policy adjustments, whereas the cryptocurrency market responses were more staggered and less predictable, indicating potential delays in the transmission of policy effects or a different sensitivity to such changes.

Furthermore, the analysis highlighted the nuanced role of stablecoins in the financial ecosystem, particularly under stress conditions influenced by macroeconomic policies. These insights contribute to the understanding of how digital assets might interact with or diverge from traditional financial assets during periods of monetary tightening or easing.

However, one of the limitations of this analysis is its reliance on the assumption that historical market responses to policy changes will continue under future conditions. This may not account for unprecedented market shocks or the introduction of new financial technologies and regulations, which can fundamentally alter market dynamics. Additionally, the use of linear models may not capture the complex, non-linear interactions within financial markets, potentially oversimplifying the relationships between variables. Therefore, additional studies could be conducted to explore the relationship between cryptocurrency assets and key financial market benchmarks. This would enhance the relatively scarce body of research on the separation of cryptocurrency from traditional markets.

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