

**Louvain School of Management
and NOVA School of Business & Economics**

What is the impact of macroeconomic factors, including economic uncertainty, on the price and volatility of Bitcoin, in comparison to gold and US stocks through a comparative regression analysis?

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Abstract

This thesis investigates how macroeconomic factors, including economic uncertainty, affect the price and volatility of Bitcoin. The analysis compares Bitcoin's behavior to gold and the S&P 500 in order to understand whether Bitcoin functions as a speculative asset, a hedge, or a hybrid instrument. Using monthly data from 2012 to 2025, the study applies linear regressions to assess the influence of inflation, interest rates, money supply, exchange rate volatility, oil prices, and several uncertainty indices (VIX, MPU, GEPU, GPR) on asset returns. The results show that Bitcoin is largely unresponsive to inflation, monetary aggregates, and interest rates. In contrast, it reacts negatively to financial market volatility, with the VIX being significantly associated with its returns. The explanatory power of macroeconomic variables is much lower for Bitcoin than for gold or equities. These findings suggest that Bitcoin does not behave like a macro sensitive asset or a safe haven, but rather like a speculative instrument influenced by non-traditional factors.

Keywords: Bitcoin, Macroeconomic variables, Economic uncertainty, Asset volatility, Safe haven assets, Comparative regression analysis, Speculative financial instruments.

Contents

1	Introduction	1
2	Literature review	3
2.1	Macroeconomic Factors and Bitcoin Price Behavior	3
2.2	Bitcoin's Response to Inflation	4
2.3	Monetary Policy, Interest Rates, and Bitcoin	6
2.4	Comparing Bitcoin, Gold, and U.S. Stocks	8
2.5	Economic Uncertainty and Bitcoin Volatility	10
2.6	Bitcoin's Correlation and Regime Dependence	12
2.7	Hypotheses	14
3	Methodology	15
3.1	Research objective	15
3.2	Data collection and transformation	15
3.3	Econometric framework	19
4	Statistical results	22
4.1	Multiple OLS regression on Bitcoin	22
4.2	Multiple OLS regression on Gold	23
4.3	Multiple OLS regression on S&P500	25
4.4	Comparative analysis of the three regressions	27
5	Discussion	29
5.1	Empirical validation of theoretical hypotheses and interpretation	29
5.2	Limitations of the research	32
5.3	Recommendations for future research and practice	34
6	Conclusion	36
7	References	39
8	Appendix	42
8.1	Stata code	42

List of Tables

1	Augmented Dickey-Fuller (ADF) Test Results	17
2	Pearson Correlation Matrix	18
3	Breusch-Pagan Test Results for Heteroskedasticity	20
4	Durbin-Watson Test Results	21
5	OLS Regression Results for Bitcoin Log Returns	22
6	OLS Regression Results for Gold Log Returns	24
7	OLS Regression Results for S&P 500 Log Returns	26

1 Introduction

The relationship between macroeconomic factors and financial asset prices has been widely studied, particularly in the context of Bitcoin, gold, and U.S. stocks. Bitcoin, as an emerging asset class, presents unique characteristics that differentiate it from traditional financial instruments such as equities and commodities (Nakagawa & Sakemoto, 2022). Unlike gold, which has historically served as a store of value (Erdoğan, 2017), and stocks, which derive their valuation from corporate earnings and economic growth (Hsing, 2011), Bitcoin remains highly speculative and subject to extreme volatility (Aharon et al., 2022). Unlike traditional assets such as gold, known for its safe haven properties (Sun, 2018), or equities, which are fundamentally tied to corporate earnings and economic growth (Danso, 2020), Bitcoin exhibits high levels of volatility and is shaped by a complex interplay of macroeconomic forces and speculative behavior (Sovbetov, 2018). Understanding Bitcoin's sensitivity to economic conditions is critical for academics, investors, and policymakers, particularly given its unpredictable behavior in response to macroeconomic shifts (Aharon et al., 2022).

This study addresses the following question in financial economics: *“What is the impact of macroeconomic factors, including economic uncertainty, on the price and volatility of Bitcoin, in comparison to gold and US stocks?”* Additionally, it explores how these effects compare to those observed in gold and U.S. stocks, thereby situating Bitcoin within the broader financial ecosystem. The study aims to provide a nuanced understanding of whether Bitcoin behaves more like a speculative instrument, a safe haven, or if it represents a hybrid category within financial markets (Nakagawa & Sakemoto, 2022).

Bitcoin's price dynamics are influenced by non-traditional factors such as market sentiment and speculative trading (Sovbetov, 2018), in contrast to gold, which responds more reliably to inflation and monetary policy changes (Sun, 2018). U.S. stocks, represented here by the S&P 500 index, are closely tied to economic fundamentals such as corporate earnings and GDP growth (Danso, 2020). These distinct behaviors underscore the need for a systematic comparison to determine whether Bitcoin aligns more closely with speculative equities or safe haven assets during periods of economic uncertainty (Erdoğan, 2017). This study builds upon existing literature, which highlights the speculative nature of Bitcoin and its sensitivity to non-economic drivers, such as fear and greed indices and market sentiment (Bashir & Kumar, 2023; Aharon et al., 2022). While some studies suggest that Bitcoin may act as a hedge under

certain conditions (Mokni et al., 2022; Corbet et al., 2018), its high volatility and dependence on investor sentiment distinguish it from traditional financial assets (Nakagawa & Sakemoto, 2022). Conversely, gold has consistently demonstrated its role as a reliable hedge against inflation and currency fluctuations (Erdoğan, 2017).

To address this question, this study employs a robust econometric approach covering the period from 2012 to 2025. The analysis focuses on the monthly returns of Bitcoin, gold, and the S&P 500 index. Key macroeconomic indicators such as inflation (CPI), monetary aggregates (M2), short-term and long-term interest rates (Federal Funds Rate and 10-Year Treasury Yield), and exchange rate fluctuations (DXY) are included. In addition, measures of market sentiment and uncertainty namely the VIX, the Global Economic Policy Uncertainty (GEPU) index, the Monetary Policy Uncertainty (MPU) index, the Geopolitical Risk (GPR) index as well as oil prices (OIL), are integrated into the regression model to capture both traditional and non-traditional influences on asset performance. The methodology relies on multiple linear regression models applied separately to each asset, enabling a direct comparison of their respective sensitivities to macroeconomic and uncertainty related variables. This framework follows established practices in empirical finance (Nakagawa & Sakemoto, 2022; Erdoğan, 2017) and offers a consistent way to quantify how different asset classes behave under varying macro financial conditions.

Preliminary results are that Bitcoin does not exhibit strong or consistent responses to traditional macroeconomic variables such as inflation, money supply, or interest rates. In contrast, gold and the S&P 500 demonstrate clearer and more theoretical reactions to shifts in key macroeconomic indicators. However, Bitcoin shows a negative and significant response to financial market volatility as measured by the VIX, indicating that it tends to decline during periods of heightened uncertainty. These findings suggest that Bitcoin is not entirely disconnected from macroeconomic forces but reacts selectively and often more like a speculative asset than a stable hedge.

The structure of the thesis is as follows. Chapter 2 provides a literature review with theoretical framework and outlines hypotheses based on it. Chapter 3 presents the methodology, data used and the model. Chapter 4 details the empirical results, followed by a discussion through the hypotheses, including limitations and recommendations, in Chapter 5. Chapter 6 concludes the thesis with a synthesis of the findings and implications for future research.

2 Literature review

2.1 Macroeconomic Factors and Bitcoin Price Behavior

Sovbetov (2018) and Aharon et al. (2022) investigated the relationship between macroeconomic factors and Bitcoin's price dynamics, highlighting the complex and often inconsistent influence of traditional indicators such as inflation, interest rates, and exchange rates. Sovbetov (2018) concluded that these variables generally exhibit limited explanatory power over Bitcoin's price, in contrast to traditional financial assets like gold or equities. Aharon et al. (2022) expanded this view by showing that uncertainty related measures, particularly those tied to policy shifts and investor sentiment, play a more statistically significant role in shaping Bitcoin returns, but with inconsistent directions. Unlike gold and stocks, which are driven by intrinsic value through cash flows or commodity fundamentals, Bitcoin's valuation is speculative and primarily driven by investor expectations, technological narratives, and liquidity conditions. Mokni et al. (2022) and Corbet et al. (2018) emphasized this speculative component, noting that while Bitcoin can occasionally imitate hedging behavior, especially during isolated crises or monetary expansions, it remains largely disconnected from conventional macro financial transmission channels. For instance, interest rate announcements affect equities through discount rate adjustments and future earnings revisions (Hsing, 2011), and gold through inflation expectations and fiat currency depreciation (Sun, 2018; Erdoğdu, 2017). Bitcoin, by contrast, reacts via changes in risk appetite, market sentiment, and social media driven momentum, lacking the structural valuation mechanisms of traditional markets (Nakagawa & Sakemoto, 2022; Bashir & Kumar, 2023).

As institutional participation in the cryptocurrency market has grown, researchers have observed an increase in Bitcoin's sensitivity to global macroeconomic shocks. Aharon et al. (2022) found that macroeconomic and geopolitical uncertainty increasingly impact Bitcoin, especially during periods of heightened volatility. However, the mode of transmission remains different from that of conventional assets, instead of absorbing economic news through fundamental valuation, Bitcoin's reaction is mediated by speculative liquidity flows and investor positioning (Danso, 2020). For example, expansionary monetary policies may encourage risk-on behavior and capital inflows into Bitcoin, but Mokni et al. (2022) demonstrated that this relationship is neither linear nor stable over time. Similarly, Corbet et al. (2018) showed that macroeconomic announcements produce irregular and sometimes counterintuitive reactions in Bitcoin markets.

This behavior becomes especially pronounced under stress. Ruhiyat and Terzaghi (2023) found that Bitcoin's responses to negative macroeconomic shocks such as interest rate hikes or financial volatility spikes are stronger than its responses to positive developments, indicating an asymmetric sensitivity that distinguishes it from gold (Sun, 2018) and aligns it more closely with high volatility equities (Hsing, 2011). Nakagawa and Sakemoto (2022) further argued that Bitcoin exhibits regime dependent behavior, it may act as a diversifier during periods of market calm, but tends to move in tandem with equities when uncertainty increases. Corbet et al. (2018) and Ruhiyat and Terzaghi (2023) supported this, observing that Bitcoin's correlation with equities intensifies during crises, while gold's negative correlation with risky assets remains consistent (Erdoğan, 2017). These findings collectively underscore Bitcoin's dual nature, increasingly exposed to macroeconomic dynamics, but still largely governed by speculative behavior and short-term investor sentiment.

2.2 Bitcoin's Response to Inflation

Sovbetov (2018) conducted one of the earliest studies on Bitcoin's reaction to inflation and found that while Bitcoin sometimes displays behavior consistent with inflation hedging, this relationship is neither stable nor robust. His results showed that speculative demand plays a far more important role in explaining Bitcoin's returns than inflation related fundamentals. Aharon et al. (2022) similarly noted that Bitcoin's performance during inflationary periods lacks consistency, often driven more by sentiment and market noise than by macroeconomic variables themselves. This stands in contrast to gold, whose inflation hedging role is well established. Erdoğan (2017) and Sun (2018) demonstrated a strong positive correlation between gold prices and inflation indicators like the Consumer Price Index (CPI), highlighting gold's ability to preserve value during periods of fiat currency depreciation. While Bitcoin shares certain supply characteristics with gold, most notably its capped issuance, its behavior under inflationary pressure does not consistently mirror that of traditional inflation hedges.

Nakagawa and Sakemoto (2022) argue that Bitcoin's speculative nature prevents it from responding predictably to inflation. Their analysis emphasizes that Bitcoin's price fluctuations tend to follow investor sentiment, social narratives, and external shocks rather than macroeconomic fundamentals. In some cases, Bitcoin has appreciated during inflationary periods, but these increases often coincide with episodes of technological enthusiasm, increased retail interest, or accommodative monetary policy, making it difficult to isolate inflation as a

causal driver. Danso (2020) examined the relationship between inflation and U.S. equities and found that while moderate inflation may support stock returns due to rising corporate revenues, higher inflation tends to harm equities by eroding purchasing power and increasing production costs. Bitcoin, however, does not follow this kind of earnings based logic. It lacks cash flows and is not tied to corporate fundamentals, which means it cannot adjust to inflationary environments through valuation channels used by traditional assets.

Mokni et al. (2022) provided further insights by linking Bitcoin's performance not directly to inflation, but to the liquidity conditions often associated with inflationary pressures. They found that during periods of monetary expansion, characterized by low interest rates and increased money supply, Bitcoin tends to benefit from elevated speculative inflows. These findings suggest that Bitcoin's value rises not because it protects against inflation in a fundamental sense, but because easy monetary policy encourages risk taking. This aligns with Sun (2018), who showed that gold also appreciates under expansionary monetary regimes, but due to its safe haven characteristics rather than speculation. However, Bitcoin's reaction to inflation becomes more irregular in tightening cycles. As interest rates rise and liquidity decreases, Bitcoin tends to experience sharp corrections, particularly when inflation is accompanied by increased financial market uncertainty. Ruhayat and Terzaghi (2023) found that Bitcoin's reaction to macroeconomic shocks, including inflation related events, is asymmetrical, negative shocks such as unexpected rate rises often provoke disproportionately strong responses compared to positive ones.

The volatility of Bitcoin in inflationary environments is also reinforced by policy driven uncertainty. Aharon et al. (2022) demonstrated that Bitcoin's price is highly sensitive to episodes of inflation related policy announcements, especially when central banks signal tightening. Rather than acting as a stable hedge, Bitcoin becomes more volatile, reacting to perceived shifts in liquidity rather than inflation data itself. Bashir and Kumar (2023) showed that investor attention, based on social media activity, increases during such periods and contributes to short-term price surges or crashes, suggesting that psychological and speculative forces dominate Bitcoin's behavior in inflationary contexts. In contrast, gold's response to inflation is steadier and more rooted in its historical role as a reserve asset. Danso (2020) noted that while equities suffer from inflation shocks due to earnings compression, gold tends to retain its value due to its negative correlation with real interest rates, a dynamic that Bitcoin has not demonstrated consistently.

2.3 Monetary Policy, Interest Rates, and Bitcoin

Mokni et al. (2022) and Corbet et al. (2018) both examined Bitcoin's sensitivity to monetary policy, particularly to interest rate changes. Their findings suggest that Bitcoin tends to decline in response to interest rate rises, as higher yields on traditional fixed income securities reduce the attractiveness of speculative assets. This behavior mirrors equity markets, where Hsing (2011) demonstrated that rising interest rates negatively impact stock prices due to increased borrowing costs and lower profit expectations. In the context of monetary tightening, liquidity becomes scarcer, and capital tends to rotate away from risk assets like Bitcoin, leading to price corrections. Danso (2020) also confirmed that restrictive monetary conditions can suppress speculative investment, which is essential for sustaining Bitcoin's upward momentum. Nakagawa and Sakemoto (2022) further highlighted that Bitcoin lacks a consistent or predictable reaction to interest rate changes. Unlike gold, which typically benefits from inflationary expectations and maintains a stable response to monetary developments (Sun, 2018), Bitcoin's behavior is shaped by shifts in sentiment, trading volume, and market positioning.

Expansionary monetary environments appear more favorable for Bitcoin, as shown by Mokni et al. (2022), who observed that lower interest rates and abundant liquidity create conditions conducive to increased risk taking and speculative investment. Under such circumstances, Bitcoin often experiences upward price movements, not because of improved fundamentals, but due to capital searching for higher yields outside of traditional assets. Danso (2020) reported similar patterns for U.S. equities, which tend to rise during periods of accommodative policy because of reduced financing costs and higher expected earnings. However, unlike equities, Bitcoin lacks cash flows or intrinsic valuation supports, and its upward response is more fragile. Bashir and Kumar (2023) noted that Bitcoin's reaction to expansionary monetary conditions is also mediated by social sentiment and media narratives, particularly during global events such as the COVID-19 pandemic. Therefore, while Bitcoin may rise alongside other assets during loose monetary regimes, its underlying drivers differ significantly, rooted in speculative dynamics rather than economic fundamentals.

Nakagawa and Sakemoto (2022) argued that Bitcoin's inconsistent reaction to monetary policy stems from its dual identity as both a speculative vehicle and a potential alternative store of value. In low interest rate environments, Bitcoin may be perceived as an attractive alternative

to fiat currencies, especially in regions with depreciating national currencies or inflationary pressures. However, this perception does not always translate into market stability. Corbet et al. (2018) found that macroeconomic announcements, including interest rate decisions, often generate irregular responses in Bitcoin prices, as markets struggle to interpret their implications without the guidance of traditional valuation models. Ruhiyat and Terzaghi (2023) supported this by observing that Bitcoin reacts more strongly to contractionary monetary signals than to expansionary ones, indicating an asymmetrical sensitivity. This asymmetry implies that markets are more reactive to perceived threats to liquidity and risk appetite than to supportive policy moves. Sun (2018) reported that gold, in contrast, behaves more symmetrically and predictably, especially when central banks adopt inflation targeting or easing strategies.

Another layer of complexity lies in Bitcoin's reaction to global liquidity cycles. Monetary tightening not only affects domestic liquidity but also international capital flows, which increasingly influence Bitcoin due to its global trading structure. Danso (2020) emphasized that during periods of global monetary contraction, speculative flows into alternative assets like Bitcoin tend to decrease rapidly. Ruhiyat and Terzaghi (2023) noted that Bitcoin's volatility increases significantly under such conditions, as traders react quickly to perceived shifts in global risk appetite. Meanwhile, U.S. stocks tend to correct more gradually, supported by earnings resilience and market depth. Gold, while sensitive to real interest rates, often benefits from tightening cycles that coincide with financial uncertainty, as investors move toward traditional safe havens (Erdoğan, 2017; Sun, 2018). Bitcoin does not consistently benefit from such rotations, suggesting that its appeal during tightening cycles remains weak and context dependent.

The speculative and sentiment driven nature of Bitcoin becomes particularly visible during interest rate transition periods. As noted by Aharon et al. (2022), Bitcoin's price behavior becomes more erratic during moments of central bank uncertainty, when policy direction is unclear or contested by markets. Bashir and Kumar (2023) found that investor attention surges in such periods, often contributing to short-lived rallies or sell-offs disconnected from macro fundamentals. This volatility further distances Bitcoin from assets that react through rational expectation channels. Nakagawa and Sakemoto (2022) argued that these characteristics make Bitcoin poorly suited for stable asset allocation in response to policy changes, unlike equities or gold, which display more stable patterns under similar conditions. Hsing (2011) showed that monetary policy signals translate into predictable earnings adjustments for stocks, while

Sun (2018) illustrated gold's steady response to monetary easing and tightening through its relationship with real yields. Bitcoin's lack of response consistency underlines its speculative core, especially when compared to these traditional instruments.

2.4 Comparing Bitcoin, Gold, and U.S. Stocks

Erdoğan (2017) and Sun (2018) demonstrated that gold functions consistently as a hedge against inflation and financial instability. According to Erdoğan (2017), gold shows a positive correlation with inflation and a negative correlation with the U.S. dollar, reinforcing its role as a protective asset during economic downturns. Sun (2018) also found that gold reacts positively to inflationary pressures and maintains price stability when interest rates fluctuate, confirming its safe haven status. In contrast, Nakagawa and Sakemoto (2022) emphasized that Bitcoin does not exhibit the same stable relationship with macroeconomic variables. Their study showed that Bitcoin's sensitivity to inflation and interest rates is irregular and highly dependent on market sentiment, making its behavior distinct from gold. Sovbetov (2018) similarly found limited explanatory power of macroeconomic variables such as inflation, exchange rates, and interest rates over Bitcoin's returns, in contrast to the more systematic responses observed in traditional assets.

Ruhiyat and Terzaghi (2023) found that Bitcoin's volatility increases significantly during financial crises, while gold tends to experience a gradual appreciation. Their findings highlighted that Bitcoin responds more abruptly to economic shocks, particularly during periods of market stress, in part due to the speculative nature of its investor base. Corbet et al. (2018) confirmed that during crisis episodes, Bitcoin's price tends to decline sharply, unlike gold which typically attracts investor capital in such environments. Sun (2018) documented gold's role as a preferred asset during turbulence, showing its positive performance during monetary easing and uncertainty. Aharon et al. (2022) noted that Bitcoin's behavior becomes more erratic under policy uncertainty, while gold continues to display a more predictable defensive pattern. These studies collectively show that although both assets may be affected by similar macroeconomic conditions, gold reacts in a stable and consistent way, while Bitcoin's reactions are more volatile and less reliable.

In comparison to equities, Bitcoin also behaves differently in response to macroeconomic indicators. Hsing (2011) showed that U.S. stock prices are closely tied to fundamental variables

such as GDP growth, corporate earnings, and interest rates. Stocks generally decline when interest rates rise and perform well during periods of economic expansion due to increased consumption and investment. Danso (2020) found that equities benefit from moderate inflation through improved revenues, but suffer under excessive inflation due to reduced purchasing power and declining profitability. Nakagawa and Sakemoto (2022) emphasized that Bitcoin does not respond through these same transmission mechanisms, as it is not backed by productive output or corporate fundamentals. Bashir and Kumar (2023) highlighted the influence of investor attention and sentiment on Bitcoin prices, particularly through social media dynamics, which differentiates Bitcoin from equities whose valuations are driven primarily by forward looking earnings expectations.

Although Bitcoin has at times exhibited upward trends during periods of monetary easing, as observed by Mokni et al. (2022), its responses are highly context dependent and not fundamentally linked to economic indicators. Mokni et al. (2022) found that Bitcoin's appreciation during loose monetary policy phases reflects increased speculative activity rather than fundamental valuation shifts. While equities also respond positively to expansionary policies due to lower borrowing costs and stronger earnings potential (Danso, 2020), Bitcoin's price is influenced more by risk appetite and liquidity flows than by macroeconomic fundamentals. Corbet et al. (2018) found that macroeconomic announcements affect Bitcoin unpredictably, with price swings that are not aligned with typical financial market responses. This contrasts with the more structured and delayed reactions in stock markets, as described by Hsing (2011), where prices adjust gradually based on new macroeconomic data and expectations.

Corbet et al. (2018) also showed that Bitcoin's correlation with equities tends to rise during periods of financial stress, undermining its potential as a portfolio diversifier. Ruhayat and Terzaghi (2023) observed that in crisis conditions, Bitcoin moves more closely with stock markets than with safe haven assets like gold. This behavior differs from gold, which maintains or strengthens its negative correlation with equities in the same periods, according to Erdoğan (2017). Aharon et al. (2022) supported this by documenting Bitcoin's increased volatility and equity like behavior during policy uncertainty, while gold remained stable. These findings suggest that Bitcoin aligns more with risk assets during economic downturns, whereas gold serves a stabilizing role in portfolios. Danso (2020) also confirmed that equities respond predictably to macroeconomic trends and policy decisions, particularly through the earnings

channel, while Bitcoin lacks such mechanisms.

Bashir and Kumar (2023) identified social media driven sentiment as a key driver of Bitcoin's price, particularly in response to global events. Their research showed that investor attention surges during periods of uncertainty, and that Bitcoin prices become more volatile when media intensity increases, regardless of macroeconomic fundamentals. Aharon et al. (2022) similarly found that Twitter based uncertainty indexes are significantly correlated with Bitcoin returns, highlighting a channel of influence that does not exist in gold or equities. While gold and stocks are influenced by macroeconomic indicators through established valuation models and institutional expectations (Sun, 2018; Hsing, 2011), Bitcoin's price formation is more reactive to psychological triggers and speculative momentum.

2.5 Economic Uncertainty and Bitcoin Volatility

Aharon et al. (2022) examined the influence of economic policy uncertainty on Bitcoin and showed that the asset responds with increased volatility during periods of rising uncertainty, particularly when using Twitter based measures or conventional indices such as the Economic Policy Uncertainty (EPU) index. Their analysis revealed that Bitcoin reacts more erratically to uncertainty shocks than traditional assets such as gold or equities, displaying significant price swings without consistent directional outcomes. Gold, in contrast, tends to behave predictably in the face of economic uncertainty, as Erdoğan (2017) documented through its positive response to inflationary pressure and its negative correlation with the U.S. dollar. Gaies et al. (2023) supported Aharon et al.'s findings by demonstrating that spikes in the Global Economic Policy Uncertainty index lead to significant increases in Bitcoin's volatility, reflecting its high sensitivity to investor sentiment and macroeconomic ambiguity. The authors also emphasized that while gold maintains stable behavior under uncertain macro conditions, Bitcoin's market reactions tend to be speculative and unpredictable, often resulting in volatility rather than stability.

The VIX index, representing market expectations of volatility in the U.S. stock market, has also been examined in the context of Bitcoin. Ruhayat and Terzaghi (2023) found that increases in the VIX are closely followed by heightened Bitcoin price fluctuations, particularly during financial stress events. Corbet et al. (2018) similarly observed that Bitcoin becomes more volatile and its correlation with equities intensifies during such periods, indicating that Bitcoin does not behave

as a safe haven but rather mirrors risk asset dynamics. Unlike gold, which Erdoğan (2017) showed to gain value during times of increased market stress, Bitcoin experiences amplified drawdowns. Aharon et al. (2022) confirmed that Bitcoin's volatility under policy uncertainty conditions deviates from traditional hedging behavior, showing no consistent appreciation or depreciation trend, but rather increased risk exposure.

The Geopolitical Risk (GPR) index has been used to analyze Bitcoin's behavior in response to political and conflict related events. Aharon et al. (2022) showed that Bitcoin does not exhibit a systematic response to increases in geopolitical risk, unlike gold, whose price typically increases during global instability as shown by Erdoğan (2017). Nakagawa and Sakemoto (2022) found that in specific national contexts such as countries with unstable currencies or political repression Bitcoin has occasionally functioned as a vehicle for capital preservation. However, this function remains inconsistent on a global scale. According to their study, Bitcoin's price response depends on local accessibility and regulatory conditions rather than on the broader geopolitical context, which limits its reliability as a global hedge. In contrast, gold's international recognition and monetary neutrality contribute to its uniform reaction during geopolitical stress.

The effect of monetary policy uncertainty (MPU) on Bitcoin has also been investigated. Nakagawa and Sakemoto (2022) reported that Bitcoin shows strong reactions to unexpected changes in monetary outlook, particularly when market participants are caught off guard by central bank decisions. However, they found that these reactions were not directionally stable, Bitcoin may surge or dive depending on concurrent factors such as investor positioning and market sentiment. Danso (2020) found that in periods of mixed or unclear macroeconomic signals, Bitcoin's volatility increases as investors reallocate capital based on perceived rather than fundamental risks. Bashir and Kumar (2023) further emphasized the role of investor attention in shaping Bitcoin's reaction to uncertainty. They showed that during periods of heightened media coverage or policy speculation, investor attention intensifies and correlates with increased short term volatility in Bitcoin prices, particularly during global crises such as the COVID-19 pandemic. These findings contrast with Hsing (2011), who demonstrated that equity markets react to uncertainty via structured adjustments in earnings forecasts and discount rates, creating more predictable responses compared to Bitcoin's sentiment driven behavior.

Ruhiyat and Terzaghi (2023) concluded that Bitcoin is particularly vulnerable to uncertainty

driven volatility, especially when uncertainty emerges across multiple macroeconomic dimensions, such as inflation, monetary policy, and geopolitical risk. Their study found that Bitcoin's volatility increases more sharply than that of gold or U.S. equities under such conditions, reaffirming its classification as a high risk asset rather than a hedge. Aharon et al. (2022) and Bashir and Kumar (2023) both noted that this volatility is often amplified by behavioral factors such as fear, speculation, and media driven investor response, which play a dominant role in Bitcoin's short term dynamics. In contrast, Sun (2018) showed that gold's reaction to uncertainty is more fundamentally linked to macroeconomic variables like interest rates and inflation and less influenced by behavioral or media driven mechanisms. Corbet et al. (2018) and Gaies et al. (2023) demonstrated that Bitcoin's volatility during uncertainty shocks is not accompanied by stabilizing capital inflows as seen with traditional hedging assets, but instead by increased correlation with risky markets and sudden selloffs.

2.6 Bitcoin's Correlation and Regime Dependence

Corbet et al. (2018) investigated the correlation between Bitcoin and traditional financial assets and found that Bitcoin's relationship with equities and gold is time varying and dependent on market conditions. Their analysis demonstrated that during stable financial periods, Bitcoin exhibited low correlation with both gold and U.S. stock indices, suggesting a potential role as a diversification tool. However, in times of market stress, such as financial crises or periods of elevated uncertainty, the correlation between Bitcoin and equities significantly increased, reducing its effectiveness as a hedge. These findings were reinforced by Ruhayat and Terzaghi (2023), who observed that Bitcoin tends to behave more like a high risk asset during financial turbulence, amplifying losses rather than insulating portfolios. Their results showed that Bitcoin's correlation with equities becomes especially pronounced during global shocks, including periods of elevated VIX or systemic market uncertainty, while its correlation with gold remains weak or inconsistent.

Nakagawa and Sakemoto (2022) analyzed the evolution of Bitcoin's behavior over time and emphasized the importance of market regimes in understanding its correlation patterns. They found that Bitcoin displays regime dependent dynamics, alternating between low correlation phases and periods of high synchronization with other financial markets, particularly equity markets. Their results indicated that Bitcoin does not maintain a stable long term relationship with any traditional asset class. Instead, its correlation coefficients vary according to changes

in monetary conditions, investor sentiment, and global liquidity cycles. This observation distinguishes Bitcoin from gold, which maintains relatively stable inverse correlations with risk assets during periods of market stress, as demonstrated by Erdoğan (2017) and Sun (2018). Ruhayat and Terzaghi (2023) also confirmed that Bitcoin's behavior is strongly influenced by external shocks, and that its volatility and correlation patterns change rapidly in response to monetary policy signals, geopolitical risks, and financial market disruptions.

Aharon et al. (2022) studied the impact of uncertainty shocks on the co-movement between Bitcoin and other asset classes and found that during periods of rising policy uncertainty, Bitcoin's correlation with U.S. equities increases. This result suggests that in uncertain environments, Bitcoin behaves similarly to other speculative assets, reacting to changes in investor risk appetite rather than serving as a store of value. Their analysis also showed that Bitcoin's correlation with gold remains insignificant in most regimes, reinforcing the argument that the two assets respond to fundamentally different drivers. While gold's correlation structure is relatively stable and counter-cyclical, Bitcoin's is pro-cyclical and varies based on the intensity of external shocks and the speculative activity in its markets. Corbet et al. (2018) further observed that Bitcoin's correlation with major indices such as the S&P 500 increases during high volatility regimes, which undermines its potential as a hedge in diversified portfolios.

Bashir and Kumar (2023) contributed additional insights by examining how investor attention and sentiment influence Bitcoin's correlation patterns. They showed that during periods of heightened investor attention, often triggered by global events or macroeconomic shifts, Bitcoin tends to align more closely with equity markets, particularly in terms of intraday volatility and reaction to news. Their findings suggest that Bitcoin's perceived independence from traditional assets is not persistent, but conditional on media cycles and retail trading intensity. This behavior contrasts with U.S. stocks, which Hsing (2011) found to be consistently influenced by macroeconomic fundamentals such as GDP growth, inflation, and monetary policy, regardless of media or sentiment fluctuations. Danso (2020) similarly demonstrated that equities respond systematically to macroeconomic signals through changes in expected earnings and risk premiums, while Bitcoin's market is driven more by speculative dynamics that amplify correlation during turbulent periods.

Gaies et al. (2023) examined correlation structures under different macroeconomic regimes and

found that Bitcoin's response to global macro shocks is asymmetric and shifts depending on the prevailing risk environment. Their study showed that in high uncertainty regimes, Bitcoin's correlation with both equities and commodities increases, while in low volatility periods, it regains a degree of independence. This regime dependency was not observed in gold, which maintained its hedging role across different volatility states, and only marginally changed its correlation structure in response to macro shocks (Erdoğan, 2017). Nakagawa and Sakemoto (2022) also emphasized that Bitcoin lacks the institutional stability and historical legitimacy of gold, which may explain why investors do not systematically turn to it during crises. Instead, its behavior reflects that of a speculative instrument whose linkage to other assets intensifies in the presence of shocks and uncertainty.

2.7 Hypotheses

Based on the literature review, five different hypotheses were formulated for this research:

H1: Changes in inflation (CPI) have no consistent effect on Bitcoin returns, reflecting its speculative and sentiment driven nature rather than any hedging function (Sovbetov, 2018; Aharon et al., 2022; Nakagawa & Sakemoto, 2022).

H2: Expansionary monetary policies, such as increasing money supply (M2), tend to boost Bitcoin's price due to increased speculative investments (Mokni et al., 2022; Danso, 2020).

H3: Rising interest rates (Federal Funds Rate and 10-Year Treasury Yield) generally lead to Bitcoin price declines, as higher yields on traditional financial assets reduce demand for speculative investments (Corbet et al., 2018; Nakagawa & Sakamoto, 2022).

H4: Macroeconomic variables explain less of Bitcoin's volatility compared to traditional assets, reflecting its stronger exposure to idiosyncratic and sentiment driven shocks. (Aharon et al., 2022; Nakagawa & Sakemoto, 2022; Corbet et al., 2018)

H5: A surge in financial market volatility (VIX) is associated with increased Bitcoin price fluctuations, but unlike gold, Bitcoin does not consistently act as a safe haven and often follows risk assets like stocks in times of market distress (Ruhayat & Terzaghi, 2023; Corbet et al., 2018).

3 Methodology

3.1 Research objective

The objective of this research is to examine the influence of macroeconomic factors and economic uncertainty on the returns of Bitcoin, gold, and the S&P 500 over time by assessing to what extent Bitcoin reacts to key macroeconomic variables, and how its sensitivities compare to those observed for traditional assets like gold and equities. The analysis covers the period from 2012 to 2025 and is based on 157 monthly observations, capturing major economic developments such as interest rate cycles, inflation surges, and periods of elevated policy uncertainty. All empirical estimations and data manipulations are performed using Stata, a standard software in applied econometrics. By incorporating variables related to monetary policy, inflation, market sentiment, and uncertainty (both economic and geopolitical), this study contributes to a deeper understanding of how macroeconomic forces affect different asset classes in a comparative framework.

3.2 Data collection and transformation

The three dependent variables in this study are the prices of Bitcoin, gold, and the S&P 500 index at a monthly frequency. Bitcoin, as the largest cryptocurrency by market capitalization, represents the broader cryptocurrency market. Gold is included due to its traditional role as a safe haven asset, while the S&P 500 index serves as a proxy for the broader equity market. These assets allow the analysis of how macroeconomic shocks impact speculative digital assets, conventional stores of value, and traditional equities. Price data for Bitcoin are sourced from Investing.com, while gold and S&P 500 data are obtained from Yahoo Finance, ensuring reliability and consistency across financial time series. The dependent variables Bitcoin, gold, and the S&P 500 index are transformed into logarithmic returns to ensure comparability across different asset classes and stabilize variance over time. This transformation is standard practice in financial econometrics to improve comparability across assets and correct for heteroskedasticity. As highlighted by Nakagawa and Sakemoto (2022), the use of logarithmic returns facilitates the application of linear econometric models by converting multiplicative price changes into additive and stationary processes, thus improving the statistical properties of the series. Logarithmic returns also allow for a consistent interpretation of coefficients across different assets, making the comparative analysis more robust and meaningful.

The independent variables selected in this study reflect key macroeconomic indicators frequently analyzed in financial literature and available at a monthly frequency. The dataset is sourced primarily from FRED, the Federal Reserve Bank of St. Louis, and Economic Policy Uncertainty, ensuring consistency and reliability across time series. Inflation, captured through the Consumer Price Index (CPI) and sourced from FRED, plays a crucial role in determining asset prices, influencing investment decisions and portfolio rebalancing. Erdoğan (2017) highlights the impact of inflation on asset allocation, emphasizing its role in shaping investor expectations and risk tolerance. Similarly, exchange rate fluctuations, represented by the U.S. Dollar Index (DXY) and sourced from FRED, affect global liquidity flows and investment preferences. The study by Erdoğan (2017) also acknowledges the influence of exchange rate volatility on capital flows and portfolio allocations, reinforcing its importance in financial modeling. Crude oil prices (OIL), another vital macroeconomic factor, are sourced from FRED and serve as an indicator of inflationary pressures and broader economic stability. Danso (2020) examines the effect of oil price fluctuations on financial markets, demonstrating how variations in crude oil costs influence production expenses, corporate earnings, and investment sentiment. Liquidity conditions in the economy are captured by the M2 Money Supply (M2), sourced from FRED, which reflects monetary expansion and contraction. Nakagawa and Sakemoto (2022) discuss the role of monetary aggregates in influencing asset valuations, particularly in speculative markets where capital availability dictates investment trends. Interest rates, specifically the Federal Funds Rate (FedRate) and 10-Year Treasury Yields (DGS10), sourced from FRED, provide insights into monetary policy stances. Hsing (2011) highlights their role in shaping investment strategies, noting that changes in risk-free rates affect asset returns across financial markets, from equities to commodities and digital assets.

This study incorporates economic uncertainty and market sentiment through robust monthly indices. The Global Economic Policy Uncertainty (GEPU) Index, sourced from Economic Policy Uncertainty, measures global economic policy uncertainty by analyzing newspaper coverage and economic forecasts. Huang & al. (2024) demonstrate that the GEPU Index significantly influences Bitcoin's volatility, making it a suitable measure of policy related uncertainty in financial markets. Similarly, the Monetary Policy Uncertainty (MPU) Index, also sourced from Economic Policy Uncertainty, tracks uncertainty in monetary policy decisions, particularly those of the Federal Reserve. Sakariyahu & al. (2024) employ the MPU Index in their study to evaluate its effect on financial assets, highlighting its role in shaping Bitcoin price

fluctuations. The Geopolitical Risk (GPR) Index, obtained from Economic Policy Uncertainty, developed to quantify geopolitical instability arising from conflicts, terrorism, and diplomatic tensions, is another key uncertainty measure. Sakariyahu & al. (2024) demonstrate its impact on market behavior, making it a crucial factor in analyzing Bitcoin's reaction to global uncertainty. The CBOE Volatility Index (VIX), sourced from FRED, is a standard proxy for market uncertainty, representing expected volatility in the S&P 500. Huang & al. (2024) utilize the VIX to assess financial market uncertainty and its influence on asset prices, including Bitcoin. Their findings highlight the relevance of VIX in capturing shifts in investor sentiment and market risk perception, making it a crucial indicator in the analysis of Bitcoin's price dynamics.

To ensure the validity of the regression analysis, it is essential to verify the stationarity of the time series variables. Stationarity refers to the property of a time series where its mean, variance, and autocovariance remain constant over time. Non-stationary variables can lead to spurious regression results, where apparent relationships between variables are purely driven by shared trends rather than genuine economic linkages. Consequently, prior to estimation, stationarity tests are a critical step in empirical research, particularly in macroeconomic and financial studies (Sirucek, 2012; Aharon et al., 2022). Following the methodology adopted by Sirucek (2012) and Aharon et al. (2022), the Augmented Dickey-Fuller (ADF) test was conducted on each independent variable included in the analysis. The ADF test examines the null hypothesis that a unit root is present in a time series, implying non-stationarity. Rejecting the null hypothesis at conventional significance levels indicates that the series is stationary.

Table 1: Augmented Dickey-Fuller (ADF) Test Results

Variable	CPI	FedRate	DGS10	DXY	VIX	OIL	M2	GEPU	MPU	GPR
ADF Statistic	-0.576	-1.861	-1.530	-2.771	-4.798	-2.456	-1.504	-3.410	-4.453	-5.345
p-value	0.9802	0.6745	0.8187	0.2078	0.0005	0.3502	0.8278	0.0500	0.0018	0.0000
Stationarity	No	No	No	No	Yes	No	No	Yes	Yes	Yes

The results in Table 1 reveal that the Consumer Price Index (CPI), the Federal Funds Rate, the 10-Year Treasury Yields (DGS10), the U.S. Dollar Index (DXY), crude oil prices (OIL) and the M2 money supply (M2) are non-stationary in levels, as indicated by p-values greater than 0.05. Consistent with standard econometric practices (Sirucek, 2012), the first differences of these variables were computed to achieve stationarity. Transforming the variables into their first differences allows the analysis to focus on relative changes rather than absolute levels,

mitigating the risk of spurious regression results. A distinction is made between macroeconomic variables expressed as indices of levels and those already in percentage form. For the CPI, M2, OIL and the DXY, the log of the series was first computed before applying the first difference, resulting in log-differenced variables. This transformation is widely adopted in time series analysis to stabilize variance and allow for direct interpretation in percentage terms (Tsay, 2010). In the case of the Consumer Price Index (CPI), this transformation effectively converts the series into a proxy for monthly inflation, expressed as a percentage change in the general price level. Conversely, the Volatility Index (VIX), the Global Economic Policy Uncertainty (GEPU) Index, the Monetary Policy Uncertainty Index (MPU) and the Geopolitical Risk Index (GPR) were retained in level form, as they are already standardized, statistically stationary and economically meaningful without further transformation.

Before estimating the regression model, it is essential to assess the relationships between the independent variables to detect any potential multicollinearity issues. High multicollinearity among regressors can distort the estimation of individual coefficients, inflate standard errors, and undermine the reliability of the statistical inference. Therefore, a preliminary correlation analysis was conducted, following the methodological recommendations of Sirucek (2012) and Sovbetov (2018), who both emphasized the importance of evaluating inter-variable correlations prior to running multivariate regressions. A Pearson correlation matrix was computed to quantify the linear relationship between each pair of independent variables. The Pearson correlation coefficient measures the strength and direction of the linear association between two continuous variables, ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no linear relationship.

Table 2: Pearson Correlation Matrix

Variable	$\Delta \ln(\text{CPI})$	$\Delta \text{FedRate}$	ΔDGS10	$\Delta \ln(\text{DXY})$	VIX	$\Delta \ln(\text{OIL})$	$\Delta \ln(\text{M2})$	GEPU	MPU	GPR
$\Delta \ln(\text{CPI})$	1.0000	0.2871	0.4266	-0.2046	-0.0277	-0.5250	-0.2582	0.1481	0.0550	0.2138
$\Delta \text{FedRate}$	0.2871	1.0000	0.2074	-0.1888	-0.1391	-0.2663	-0.4978	0.0214	0.0320	0.2047
ΔDGS10	0.4266	0.2074	1.0000	0.1191	-0.0883	0.4002	-0.1988	-0.0216	-0.0950	0.1714
$\Delta \ln(\text{DXY})$	-0.2046	-0.1888	0.1191	1.0000	0.1842	-0.3969	0.0416	0.5543	0.0182	0.1238
VIX	-0.0277	-0.1391	-0.0883	0.1842	1.0000	-0.2675	0.4045	0.2131	0.5496	0.0308
$\Delta \ln(\text{OIL})$	-0.5250	-0.2663	0.4002	-0.3969	-0.2675	1.0000	-0.2141	0.0067	-0.1578	-0.0023
$\Delta \ln(\text{M2})$	-0.2582	-0.4978	-0.1988	0.0416	0.4045	-0.2141	1.0000	0.2446	0.1273	-0.2114
GEPU	0.1481	0.0214	-0.0216	0.5543	0.2131	0.0067	0.2446	1.0000	0.7033	0.1334
MPU	0.0550	0.0320	-0.0950	0.0182	0.5496	-0.1578	0.1273	0.7033	1.0000	0.2105
GPR	0.2138	0.2047	0.1714	0.1238	0.0308	-0.0023	-0.2114	0.1334	0.2105	1.0000

The results of the correlation analysis in Table 2 indicate that no pair of variables exhibits a correlation coefficient exceeding 0.8 or falling below -0.8, thresholds commonly used to signal

problematic multicollinearity (Sirucek, 2012). The highest observed correlation is between MPU and GEPU (0.7033). While the MPU–GEPU relationship indicates a strong association between these two uncertainty indices, it remains below the critical threshold. Overall, the relatively low correlation values across the dataset confirm that multicollinearity is unlikely to pose a significant problem for the Ordinary Least Squares (OLS) estimation. Therefore, all independent variables were retained for the subsequent regression analysis.

3.3 Econometric framework

To analyze the impact of macroeconomic factors on the returns of Bitcoin, gold, and the S&P 500, this study employs the Ordinary Least Squares (OLS) regression method. OLS is a widely used econometric technique for estimating the relationships between dependent and independent variables due to its simplicity, interpretability, and efficiency under classical assumptions. Following the methodologies of Sirucek (2012) and Mokni et al. (2022), OLS is deemed appropriate for this study as it provides unbiased and consistent estimates when residuals exhibit no heteroskedasticity or autocorrelation. The use of OLS allows for quantifying the sensitivity of asset returns to key macroeconomic variables, thereby facilitating comparative analysis across asset classes. To address potential violations of standard assumptions, diagnostic tests for heteroskedasticity and autocorrelation were conducted, and appropriate corrections were applied where necessary. The regression is conducted three times, once for each dependent variable, allowing for a comparative analysis of how macroeconomic factors influence Bitcoin, gold, and U.S. equities. The econometric model is specified as follows:

$$r_{i,t} = \alpha + \beta_1 \Delta \ln(CPI_t) + \beta_2 \Delta FedRate_t + \beta_3 \Delta DGS10_t + \beta_4 \Delta \ln(DXY_t) + \beta_5 VIX_t \\ + \beta_6 \Delta \ln(OIL_t) + \beta_7 \Delta \ln(M2_t) + \beta_8 GEPU_t + \beta_9 MPU_t + \beta_{10} GPR_t + \varepsilon_t$$

- $r_{i,t}$: Logarithmic monthly return of one of the three assets analyzed (Bitcoin, gold, or the S&P 500).
- α : Intercept term of the equation.
- $\Delta \ln(CPI_t)$: Monthly growth rate of the Consumer Price Index.
- $\Delta FedRate_t$: Monthly change in the Federal Funds Rate.

- $\Delta DGS10_t$: Monthly change in the 10-Year Treasury Yield.
- $\Delta \ln(DXY_t)$: Monthly growth rate of the U.S. Dollar Index.
- VIX_t : Monthly level of the CBOE Volatility Index.
- $\Delta \ln(OIL_t)$: Monthly growth rate of crude oil prices (WTI).
- $\Delta \ln(M2_t)$: Monthly growth rate of the M2 money supply.
- $GEPU_t$: Monthly level of the Global Economic Policy Uncertainty Index.
- MPU_t : Monthly level of the Monetary Policy Uncertainty Index.
- GPR_t : Monthly level of the Geopolitical Risk Index.
- ε_t : Error term capturing unobservable factors.

Where $r_{i,t}$ represents the logarithmic monthly return of Bitcoin, gold, or the S&P 500. The coefficients β_i measure the sensitivity of asset returns to macroeconomic changes, while α captures baseline returns. The error term ε_t accounts for unobservable factors.

Heteroskedastic errors, characterized by non-constant residual variance across observations, violate a fundamental assumption of the classical linear model and can lead to biased standard errors and invalid hypothesis testing. In addressing this risk, the Breusch-Pagan-Godfrey test was conducted to detect potential heteroskedasticity, following the methodology employed by Sovbetov (2018). The Breusch-Pagan-Godfrey test evaluates whether the variance of the residuals is systematically related to the independent variables, with the null hypothesis assuming homoskedasticity. A rejection of the null hypothesis suggests the presence of heteroskedasticity and the need for corrective measures. The results of the Breusch-Pagan tests for the three models are summarized below in Table 3.

Table 3: Breusch-Pagan Test Results for Heteroskedasticity

Model	$\chi^2(1)$	p-value	Heteroskedasticity
Bitcoin	9.46	0.0021	Yes
Gold	0.65	0.4188	No
S&P 500	11.01	0.0009	Yes

The test findings in Table 3 reveal significant heteroskedasticity in the Bitcoin and S&P 500 models, where the null hypothesis of homoskedasticity is rejected at the 5% significance level

(p-values of 0.0021 and 0.0009, respectively). Conversely, the gold model does not exhibit heteroskedasticity, as evidenced by a p-value of 0.4188. In light of these results, robust standard errors are applied to all regressions to correct for heteroskedasticity. This practice is consistent with Mokni et al. (2022) and Corbet et al. (2018), who emphasize the necessity of employing heteroskedasticity-robust standard errors in empirical analyses of financial and cryptocurrency markets, where variance instability is a recurrent feature.

Beyond variance concerns, it is equally important to verify the independence of residuals across time. Serial correlation among residuals can introduce inefficiencies in OLS estimates and compromise the overall validity of the model. Following the approach of Sirucek (2012), the Durbin-Watson (DW) test was utilized to assess the presence of first-order autocorrelation in the residuals. The DW statistic ranges from 0 to 4, with values close to 2 indicating the absence of autocorrelation. Values substantially below or above 2 suggest positive or negative autocorrelation, respectively, both of which can undermine the efficiency of estimators. The Durbin-Watson statistics computed for the Bitcoin, gold, and S&P 500 models are presented below.

Table 4: Durbin-Watson Test Results

Model	Durbin-Watson Statistic	Autocorrelation
Bitcoin	1.835	No significant
Gold	2.235	No significant
S&P 500	2.616	No significant

The DW results in Table 4 indicate statistics of 1.835 for Bitcoin, 2.235 for gold, and 2.616 for the S&P 500. These values are sufficiently close to 2, suggesting no significant autocorrelation in the residuals. Although the S&P 500 model exhibits a slightly higher statistic, indicating a minor tendency toward negative autocorrelation, the deviation remains within acceptable limits and does not warrant corrective action. Therefore, based on the absence of severe autocorrelation and the adjustment for heteroskedasticity, the OLS estimates employed in this study are deemed robust and reliable for subsequent analysis.

4 Statistical results

4.1 Multiple OLS regression on Bitcoin

The regression presented in Table 5 investigates the relationship between Bitcoin's monthly log-returns and a set of macroeconomic indicators over the period spanning from January 2012 to December 2024, using 156 observations. The R-squared value is 0.0798, indicating that approximately 8.0% of the variability in Bitcoin's log-returns is explained by the included regressors. The model's overall significance, as measured by an F-statistic of 1.72 and a p-value of 0.0805, does not reach the conventional 5% threshold but lies close to the 10% level. While this suggests limited explanatory power for the model as a whole, one coefficient is statistically significant, allowing for a more detailed examination of its individual effect.

Table 5: OLS Regression Results for Bitcoin Log Returns

Variable	Coefficient	Std. Err.	t	P> t	95% Conf. Int.	Signif.
$\Delta \ln(CPI)$	-10.8123	9.3686	-1.15	0.250	[-29.3290, 7.7045]	No
$\Delta FedRate$	-0.1329	0.1142	-1.16	0.246	[-0.3587, 0.0928]	No
$\Delta DGS10$	0.0767	0.1078	0.71	0.479	[-0.1359, 0.2881]	No
$\Delta \ln(DXY)$	-0.1432	1.7192	-0.08	0.934	[-3.5412, 3.2547]	No
VIX	-0.0108	0.0039	-2.76	0.006	[-0.0185, -0.0030]	Yes
$\Delta \ln(OIL)$	0.2669	0.2157	1.24	0.218	[-0.1593, 0.6932]	No
$\Delta \ln(M2)$	1.7589	2.8571	0.62	0.539	[-3.8879, 7.4059]	No
GEPV	-0.0002	0.0005	-0.39	0.697	[-0.0015, 0.0007]	No
MPV	0.0009	0.0006	2.13	0.122	[0.0001, 0.0018]	No
GPR	-0.0007	0.0007	-0.95	0.346	[-0.0020, 0.0007]	No
Constant	0.2929	0.1375	2.13	0.035	[0.0211, 0.5647]	Yes
<i>R-squared</i> = 0.0798, <i>F</i> (10, 145) = 1.72, <i>Prob</i> > <i>F</i> = 0.0805, <i>Root MSE</i> = 0.25822						

Among the explanatory variables, the VIX index exhibits the most statistically robust relationship with Bitcoin's returns. The coefficient is -0.0108 and is significant at the 1% level ($p = 0.006$), implying that a one point increase in the VIX is associated with an average decrease of approximately 1.08% in Bitcoin's monthly return. This negative effect is relatively strong in magnitude compared to the other variables in the model.

The remaining variables do not exhibit statistically significant effects at conventional levels. The

coefficient on the monthly growth rate of the Consumer Price Index ($\Delta \ln(CPI)$) is -10.8123 with a p-value of 0.250, indicating that short-term inflation dynamics are not systematically associated with Bitcoin's returns over the sample period. Likewise, the coefficient on the monthly change in the Federal Funds Rate ($\Delta FedRate$) is -0.1329 ($p = 0.246$), and the coefficient on the change in the 10-Year Treasury Yield ($\Delta DGS10$) is 0.0767 ($p = 0.479$), neither of which are statistically significant. These results suggest that variations in interest rates, both short and long term, do not exert a measurable effect on Bitcoin's return dynamics. The monthly growth rate of the U.S. Dollar Index ($\Delta \ln(DXY)$) also fails to show significance, with a coefficient of -0.1432 and a p-value of 0.934, indicating that exchange rate fluctuations do not play a systematic role in explaining Bitcoin returns in this model. Oil prices, proxied by the monthly growth rate in WTI crude oil ($\Delta \ln(OIL)$), also do not appear to have a statistically significant relationship with Bitcoin returns. The coefficient is 0.2669 ($p = 0.218$), indicating a very small and imprecise estimate. Similarly, the coefficient on the growth rate in the M2 money supply ($\Delta \ln(M2)$) is 1.7589 with a p-value of 0.539. The magnitude of this effect is negligible, and its lack of statistical significance confirms that changes in money supply do not explain much of Bitcoin's return variation. The Global Economic Policy Uncertainty index (GEPU), used in level form, also shows no significant relationship with Bitcoin's returns; its coefficient is -0.0002 with a p-value of 0.697. Similarly, the Monetary Policy Uncertainty index (MPU) has a coefficient of 0.0009 with a p-value of 0.122, which doesn't meet the conventional 5% threshold. Finally, the Geopolitical Risk Index (GPR) displays no significant effect, with a coefficient of -0.0007 and a p-value of 0.346, indicating that geopolitical events, at least as captured by this index, are not a key driver of Bitcoin's short-term performance.

The constant term in the regression is estimated at 0.2929 and is statistically significant at the 5% level ($p = 0.035$), suggesting that in the absence of variation in the explanatory variables, the model predicts a baseline monthly return of approximately 29.3%.

4.2 Multiple OLS regression on Gold

The regression results presented in Table 6 focus on explaining the monthly log-returns of gold using a selection of macroeconomic variables over the period from January 2012 to December 2024, based on 156 observations. The model yields an R-squared of 0.2299, indicating that approximately 23.0% of the variation in gold's monthly returns is accounted for by the included regressors. The F-statistic for the model is 4.81, with a p-value of 0.0000, confirming that the

set of explanatory variables is jointly significant at the 1% level. While the explanatory power remains moderate, this specification provides a clearer structure than in the Bitcoin model, and several individual variables are found to be statistically significant.

Table 6: OLS Regression Results for Gold Log Returns

Variable	Coefficient	Std. Err.	t	P> t	95% Conf. Int.	Signif.
$\Delta \ln(CPI)$	-0.2726	1.4265	-0.19	0.849	[-3.0920, 2.5469]	No
$\Delta FedRate$	-0.0219	0.0203	-1.08	0.282	[-0.0615, 0.0182]	No
$\Delta DGS10$	-0.0574	0.0207	-2.77	0.006	[-0.0984, -0.0161]	Yes
$\Delta \ln(DXY)$	-0.8600	0.2621	-3.28	0.001	[-1.3784, -0.3412]	Yes
VIX	-0.0001	0.0007	-0.17	0.863	[-0.0015, 0.0012]	No
$\Delta \ln(OIL)$	0.0098	0.0259	0.39	0.697	[-0.0398, 0.0594]	No
$\Delta \ln(M2)$	0.1469	0.3787	0.39	0.699	[-0.6017, 0.8953]	No
GEPV	0.0000	0.0006	0.82	0.414	[-0.0007, 0.0018]	No
MPV	0.0001	0.0014	1.50	0.137	[-0.0000, 0.0024]	No
GPR	0.0002	0.0001	1.84	0.068	[-0.0000, 0.0004]	No
Constant	-0.0297	0.0136	-2.18	0.031	[-0.0567, -0.0028]	Yes
<i>R-squared</i> = 0.2299, <i>F</i> (10, 145) = 4.81, <i>Prob</i> > <i>F</i> = 0.0000, <i>Root MSE</i> = 0.03719						

From the independent variables, two stand out with statistically significant coefficients at conventional thresholds. The change in the 10-year Treasury yield ($\Delta DGS10$) has a coefficient of -0.0574 and a p-value of 0.006. This indicates that a one percentage point increase in long-term interest rates is associated with a 5.74% decrease in the monthly return on gold. Similarly, the coefficient on the monthly growth rate in the U.S. Dollar Index ($\Delta \ln(DXY)$) is -0.8600 and statistically significant at the 1% level ($p = 0.001$), implying that a 1% increase in the dollar index correlates with an average 0.86% decrease in gold returns. These two effects are among the strongest in the model and reflect short-term sensitivities of gold returns to interest rate movements and exchange rate fluctuations.

The remaining variables do not show significant associations with the dependent variable. The coefficient on $\Delta \ln(CPI)$ is -0.2726, with a p-value of 0.849, which suggests that the monthly growth rate in consumer prices does not systematically affect gold returns. $\Delta FedRate$ has a coefficient of -0.0219 and a p-value of 0.282, meaning that short-term interest rate changes do not show a meaningful link to gold's log-returns in this specification. VIX, which measures

market volatility, has a coefficient of -0.0001 ($p = 0.863$), indicating no clear short-term relationship between volatility in financial markets and the performance of gold over the sample period. Oil prices ($\Delta \ln(OIL)$) also do not appear significant in this regression, with a coefficient of 0.0098 and a p-value of 0.697 . Similarly, the coefficient on $\Delta \ln(M2)$ (money supply) is 0.1469 and statistically insignificant ($p = 0.699$), suggesting that the monthly growth rate of liquidity measured by M2 has little explanatory power for short-term movements in gold prices. The broader uncertainty indices also fail to show strong effects in this model. The Global Economic Policy Uncertainty index (GEPU) yields a coefficient of 0.0001 and a p-value of 0.414 , while the Monetary Policy Uncertainty index (MPU) has a coefficient of 0.0001 and a p-value of 0.137 , which estimates that it has no significant effect. The Geopolitical Risk Index (GPR), included in levels, has a coefficient of 0.0002 and a p-value of 0.068 . Although the sign of all three coefficients is positive, none reaches the 10% significance threshold, and thus they are not retained as statistically meaningful predictors of gold returns in this setting.

The constant term in the regression is estimated at -0.0297 and is statistically significant at the 5% level ($p = 0.031$). This negative intercept suggests a baseline decrease of 2.97% in monthly gold returns when all explanatory variables are held constant.

4.3 Multiple OLS regression on S&P500

Table 7 presents the regression output assessing the impact of macroeconomic variables on the monthly log-returns of the S&P 500 over the period from January 2012 to December 2024, based on 156 observations. The set of explanatory variables is identical to that used in the Bitcoin and gold specifications, comprising ten macroeconomic indicators expressed in either first differences or levels depending on their stationarity properties. The model yields an R-squared of 0.2563 , meaning that approximately 25.6% of the variation in the S&P 500's monthly returns is accounted for by these variables. With an F-statistic of 4.77 and a p-value of 0.0000 , the joint significance of the model is well supported at the 1% level.

Volatility and liquidity related variables exhibit particularly notable effects in this regression. The VIX index, which represents market expectations of future volatility, has a negative and highly significant coefficient of -0.0033 ($p = 0.000$). This implies that a one point increase in the VIX is associated with a 0.33% decrease in the S&P 500's monthly log-return, confirming the sensitivity of equity markets to short-term shifts in investor risk aversion. The monthly

Table 7: OLS Regression Results for S&P 500 Log Returns

Variable	Coefficient	Std. Err.	t	P> t	95% Conf. Int.	Signif.
$\Delta \ln(CPI)$	-0.4028	1.3804	-0.29	0.771	[-3.1311, 2.3255]	No
$\Delta FedRate$	0.0169	0.0313	0.54	0.590	[-0.0449, 0.0787]	No
$\Delta DGS10$	-0.0076	0.0234	-0.32	0.746	[-0.0538, 0.0386]	No
$\Delta \ln(DXY)$	-0.4991	0.3432	-1.45	0.148	[-1.1774, 0.1792]	No
VIX	-0.0033	0.0007	-4.79	0.000	[-0.0046, -0.0019]	Yes
$\Delta \ln(OIL)$	0.0430	0.0439	0.98	0.328	[-0.0436, 0.1296]	No
$\Delta \ln(M2)$	1.4960	0.6009	2.49	0.014	[0.3084, 2.6838]	Yes
GEPV	0.0001	0.0006	1.41	0.160	[-0.0019, 0.0021]	No
MPV	0.0001	0.0007	1.67	0.098	[-0.0012, 0.0015]	No
GPR	-0.0009	0.0011	-0.88	0.381	[-0.0028, 0.0010]	No
Constant	0.0433	0.0149	2.91	0.004	[0.0139, 0.0728]	Yes
<i>R-squared</i> = 0.2563, <i>F</i> (10, 145) = 4.77, <i>Prob</i> > <i>F</i> = 0.0000, <i>Root MSE</i> = 0.03637						

growth rate in the M2 money supply ($\Delta \ln(M2)$) is positively associated with S&P 500 returns, with a coefficient of 1.4960 and a p-value of 0.014. A 1% increase in the money supply (M2) is associated with an average increase of approximately 1.50% in the monthly return of the S&P 500. The significance of this coefficient suggests that increases in monetary liquidity coincide with improved equity performance.

The remaining variables do not show significant associations with the dependent variable. The coefficient for $\Delta \ln(CPI)$ is negative but not statistically significant (-0.4028; $p = 0.771$), implying no clear relationship between month to month inflation and returns on the S&P 500 within this model. Similarly, the coefficient on the Federal Funds Rate ($\Delta FedRate$) is 0.0169, with a p-value of 0.590. While positive in sign, it is not statistically meaningful. Long-term interest rates, captured by the 10-year Treasury yield ($\Delta DGS10$), show a negative coefficient of -0.0076 and remain non-significant ($p = 0.746$). These results suggest that within the sample and frequency used, short-term movements in nominal interest rates are not consistently reflected in equity market returns. Exchange rate effects appear to be limited. The coefficient on the monthly growth rate in the U.S. Dollar Index ($\Delta \ln(DXY)$) is negative (-0.4991), but statistically non-significant ($p = 0.148$). This implies that shifts in the value of the dollar, measured monthly, do not exert a systematic influence on equity returns in this framework. Oil prices ($\Delta \ln(OIL)$),

with a coefficient of 0.0430 and a p-value of 0.328, do not exhibit a statistically significant effect on the index. The Global Economic Policy Uncertainty Index (GEPU), with a coefficient of 0.0001 ($p = 0.160$) and the Monetary Policy Uncertainty index (MPU), with a coefficient of 0.0001 ($p = 0.098$), both display positive but statistically insignificant effects. The Geopolitical Risk Index (GPR), entered in levels, shows a coefficient of -0.0009 with a p-value of 0.381. This result implies that geopolitical events, captured through this index, do not significantly alter the month to month performance of the S&P 500 in this regression setting.

The constant term, with a value of 0.0433 and a p-value below 1%, is statistically significant. It implies a baseline log-return of 4.3% per month in periods where all explanatory variables remain stable.

4.4 Comparative analysis of the three regressions

In terms of model performance, a clear gradient emerges in the explanatory strength of the regressions. The S&P 500 regression demonstrates the highest R-squared at 0.2563, suggesting that roughly 25.6% of the variability in the index's monthly returns is captured by the macroeconomic variables included. The gold model follows with an R-squared of 0.2299, while Bitcoin's regression explains only 8% of return variation by far the lowest. All three models are statistically significant overall, with the S&P 500 and gold regressions exhibiting strong F-statistics (4.77 and 4.81 respectively, both $p < 0.01$), while the Bitcoin regression yields a weaker F-statistic of 1.72 and a p-value of 0.0805, failing to pass the 5% significance threshold. This relative weakness in the Bitcoin model reflects a structural limitation in capturing its return dynamics through standard macroeconomic indicators.

For Bitcoin, the most influential explanatory variable is the VIX, with a coefficient of -0.0108 ($p = 0.006$). This association implies that Bitcoin's returns are negatively affected by increased financial market volatility, with a one point rise in the VIX corresponding to a decrease of approximately 1.08% in monthly log-returns. Interestingly, this effect is much stronger than the corresponding impact of the VIX on the S&P 500, where the coefficient is -0.0033 ($p = 0.000$), showing a less pronounced but still negative relationship. For gold, the VIX has no statistically significant effect, which reinforces the interpretation that its short-term behavior is less driven by stock market volatility. When examining liquidity and monetary indicators, differences become even more apparent. The monthly growth rate in the M2 money supply is

significantly associated with returns only in the case of the S&P 500, where a positive coefficient of 1.4960 ($p = 0.014$) indicates that a 1% increase in monetary liquidity corresponds to a 1.5% increase in equity returns. Neither Bitcoin nor gold shows a significant relationship with M2 in the regression results. Similarly, short-term interest rates ($\Delta FedRate$) do not reach significance in any of the models, and long-term rates ($\Delta DGS10$) are significant only for gold (coefficient -0.0574, $p = 0.006$), where a one percentage point increase in the 10-year Treasury yield is associated with a 5.74% decline in monthly gold returns. This absence of significance in the Bitcoin model and to a lesser extent in the S&P 500, may suggest a weaker or more unstable relationship between conventional interest rate movements and these asset classes over short horizons. Regarding exchange rate effects, only the gold model includes a significant coefficient on the US Dollar Index ($\Delta \ln(DXY)$), with a value of -0.8600 ($p = 0.001$). The variable is insignificant in both the Bitcoin and S&P 500 regressions, suggesting that gold returns remain more sensitive to dollar fluctuations. Oil prices ($\Delta \ln(OIL)$) and the monthly growth rate of the Consumer Price Index ($\Delta \ln(CPI)$) are statistically insignificant across the three regressions, suggesting that monthly oil price and inflation movements do not exert a consistent effect on asset returns. The Global Economic Policy Uncertainty Index (GEPU), the Monetary Policy Uncertainty Index (MPU), and the Geopolitical Risk Index (GPR) do not exhibit significant effects in any of the models. While GPR is positive and nearly significant in the gold regression ($p = 0.068$), the coefficients elsewhere remain statistically weak. These findings indicate that uncertainty shocks captured through broad policy or geopolitical indices do not consistently explain the short-term returns of the three assets, at least at a monthly frequency.

Finally, these differences in explanatory power are mirrored in the volatility of returns observed across the three assets. Bitcoin's regression yields a low R-squared of 0.0798, indicating that only a small portion of its return variance is explained by macroeconomic variables. In addition, the Root Mean Squared Error (Root MSE) of its model reaches 0.2582 (Table 5), considerably higher than those of gold (0.03719, Table 6) and the S&P 500 (0.03637, Table 7). The combination of a weak explanatory fit and a large residual dispersion suggests that Bitcoin's monthly returns are both more volatile and less predictable within the macroeconomic framework employed. In contrast, the lower Root MSE and higher R-squared values observed for gold and the S&P 500 point to more stable return patterns and a closer alignment with conventional economic indicators. These results support the view that, at least in this empirical setting, Bitcoin behaves as a more erratic asset compared to traditional financial instruments.

5 Discussion

5.1 Empirical validation of theoretical hypotheses and interpretation

As previously discussed, this study investigates whether Bitcoin responds to core macroeconomic variables in a way that reflects traditional financial logic or if its behavior remains more speculative and sentiment driven. The results support the assumption that changes in inflation do not exhibit a consistent effect on Bitcoin returns (H1), as suggested by Sovbetov (2018), Aharon et al. (2022), and Nakagawa and Sakemoto (2022). The estimated coefficient for the growth rate of the CPI is negative but statistically insignificant, indicating that inflationary movements do not have a meaningful influence on Bitcoin's performance. This is consistent with Sovbetov's (2018) conclusion that Bitcoin is largely disconnected from macroeconomic fundamentals, and with Aharon et al. (2022), who found that Bitcoin fails to behave as an inflation hedge, even during periods of rising prices. Nakagawa and Sakemoto (2022) also observed that Bitcoin's role in inflationary contexts remains ambiguous, often diverging from assets like gold that investors traditionally turn to in such periods. The result suggests that investors do not consider inflation when valuing Bitcoin, likely because of its volatile, non-yielding nature and lack of intrinsic value. While some narratives present Bitcoin as "digital gold," the evidence in this study reinforces that such comparisons remain theoretical rather than empirical. Bitcoin continues to act more like a speculative instrument, influenced by factors such as hype cycles, network developments, and investor behavior, rather than by shifts in the price level of goods and services. Therefore, the analysis confirms hypothesis (H1), indicating that Bitcoin's return dynamics are not shaped by inflation in any statistically or economically significant way.

Turning to hypothesis (H2), which posits that expansionary monetary policies such as increases in the money supply (M2) tend to boost Bitcoin's price due to increased speculative investment (Mokni et al., 2022; Danso, 2020), the results are less conclusive. Although the coefficient for M2 is positive, which is consistent with the theoretical expectation, it is not statistically significant. As a result, the hypothesis must be rejected based on the data. This finding diverges from Mokni et al. (2022), who documented a positive and significant link between M2 growth and cryptocurrency prices during periods of monetary easing, and Danso (2020), who suggested that abundant liquidity encourages risk taking and speculative activity in markets such as Bitcoin. A possible explanation for the difference lies in the temporal or situational nature

of the link between liquidity and crypto prices. For example, during specific events like the COVID-19 pandemic, central bank interventions coincided with Bitcoin rallies, but such effects may not persist across broader timeframes. It is also possible that M2, as a monetary aggregate focused on the U.S. economy, does not adequately capture global liquidity conditions that affect an international asset like Bitcoin. Moreover, the decentralized structure of Bitcoin markets and the limited role of institutional investors during much of the sample period may reduce the influence of traditional monetary policy instruments. Retail investors, who make up a significant portion of market activity, may be more influenced by media narratives or price momentum than by macro level indicators such as money supply changes. This finding suggests that Bitcoin's relationship to liquidity is complex and may not follow the linear mechanisms often observed in traditional asset classes. Although monetary expansion may influence asset prices in general, Bitcoin appears to respond to liquidity conditions in ways that are less systematic and more context dependent, which limits the explanatory power of this variable in the regression model.

The third hypothesis (H3) assumes that rising interest rates both in terms of the Federal Funds Rate and the 10-Year Treasury Yield should reduce Bitcoin prices, as higher yields on traditional financial assets decrease the attractiveness of speculative investments (Corbet et al., 2018; Nakagawa & Sakemoto, 2022). This expectation follows classic financial theory, which holds that interest rates serve as a benchmark for evaluating the opportunity cost of holding riskier assets. However, the findings do not confirm this assumption. Both the short-term and long-term interest rate coefficients are statistically insignificant, indicating no robust link between interest rate changes and Bitcoin returns. This leads to a rejection of hypothesis (H3). Although Corbet et al. (2018) observed that speculative markets generally react negatively to interest rate increases, the same pattern does not apply here. Similarly, Nakagawa and Sakemoto (2022) found that while some cryptocurrencies may show interest rate sensitivity, Bitcoin's behavior remains more ambiguous, often reflecting market specific sentiment rather than broader financial conditions. Several explanations can be considered. First, Bitcoin's unique features, including its decentralized nature, capped supply, and lack of ties to economic fundamentals, make it less responsive to conventional monetary tools. Second, Bitcoin markets are still in a transitional stage, with growing but still limited institutional participation, which means the asset may not yet be incorporated into the typical portfolio decisions that respond to interest rate changes. Third, the valuation of Bitcoin is not based on future cash flows, so the standard discounting mechanisms that make interest rates so important for equity and bond

markets do not apply in the same way. This distinction could explain why the results do not show a significant connection, despite theoretical expectations. In practice, Bitcoin prices seem to be more influenced by factors such as market news, adoption announcements, and speculative trading waves than by movements in central bank policy rates. These findings support the idea that Bitcoin is still not fully integrated into the broader financial system and behaves differently from assets that are strongly influenced by interest rate policies.

The fourth hypothesis (H4) assumes that macroeconomic variables explain less of Bitcoin's volatility compared to traditional assets, such as gold and the S&P 500, because Bitcoin is more exposed to idiosyncratic and sentiment driven shocks. This assumption is supported by Aharon et al. (2022), who showed that Bitcoin's return structure remains highly dependent on internal market dynamics, and by Nakagawa and Sakemoto (2022), who argued that traditional macroeconomic indicators fail to capture a large portion of the variability in crypto asset prices. Corbet et al. (2018) also emphasized the role of sentiment, regulation, and speculative waves in shaping the volatility of cryptocurrencies. In the present study, this hypothesis is clearly confirmed by the comparative R^2 values of the regression models: macroeconomic variables account for only 8% of the variation in Bitcoin returns, compared to 23% for gold and 25.6% for the S&P 500. This gap in explanatory power highlights a structural distinction between Bitcoin and more established financial instruments. For gold and equity markets, macroeconomic indicators such as inflation, interest rates, and money supply explain a substantial part of price behavior, reflecting their integration into the broader economic and monetary system. In contrast, Bitcoin's volatility appears much less connected to those fundamentals. This suggests that most of the fluctuations in Bitcoin returns come from other sources such as retail investor sentiment, regulatory announcements, social media driven momentum, and crypto specific developments. Unlike traditional assets, Bitcoin lacks a mature valuation model, institutional anchoring, or predictable cash flows, which limits the relevance of macroeconomic forces in explaining its price movements. The result validates hypothesis (H4) and reinforces the idea that Bitcoin remains driven largely by idiosyncratic shocks rather than systematic factors.

Hypothesis (H5) adds a further layer to this discussion by examining how Bitcoin responds to financial market volatility, particularly through the VIX index, and whether it can be considered a safe haven in times of stress. The hypothesis builds on the findings of Ruhiyat and Terzaghi (2023), who show that Bitcoin does not behave like gold during periods of financial uncertainty, and Corbet et al. (2018), who argue that cryptocurrencies often behave like high beta risk assets

during market downturns. The results of this study confirm that interpretation. For Bitcoin, the coefficient on VIX is negative and statistically significant, meaning that increases in financial market volatility are associated with declines in Bitcoin returns. This suggests that, during risk-off episodes, Bitcoin tends to fall alongside equities rather than offer protection. In contrast, the effect of VIX on gold is insignificant, which is in line with gold's traditional role as a safe haven asset. The S&P 500, as expected, also reacts negatively to VIX, but Bitcoin's response is even more pronounced. These findings clearly show that Bitcoin does not act as a reliable hedge or safe haven during periods of financial stress. Instead, it appears to amplify volatility in the same direction as other risky assets. This undermines the narrative, often seen in media and investor circles, that Bitcoin can serve as a refuge in times of uncertainty. While gold tends to attract capital during market sell-offs, Bitcoin seems to be treated more like a speculative vehicle that investors exit quickly when volatility rises. The explanation for this may lie in investor behavior and market structure. Since Bitcoin lacks an intrinsic value and is subject to rapid price swings, investors may perceive it as too risky when uncertainty increases. Furthermore, because Bitcoin markets operate globally and largely without regulation, they can become even more volatile when traditional financial markets are under stress. The findings support hypothesis (H5), confirming that Bitcoin's price fluctuations increase with market volatility, but its behavior contrasts sharply with that of safe haven assets. Overall, the evidence points to Bitcoin's tendency to move in line with risky assets rather than protect against them, particularly in periods of heightened financial instability.

5.2 Limitations of the research

Despite the empirical insights offered by this research, several limitations must be acknowledged. From a methodological perspective, the use of a linear Ordinary Least Squares (OLS) regression imposes structural constraints on the model. This framework assumes constant relationships between macroeconomic variables and asset returns across the entire distribution and over time. However, as highlighted in the literature review (Nakagawa & Sakemoto, 2022; Aharon et al., 2022), Bitcoin is known for its high volatility, asymmetric behavior, and irregular reaction to economic shocks, making it unlikely that a linear model can fully capture its dynamics. The rejection of several hypotheses despite theoretical support in prior studies may partly reflect these modeling limitations. In particular, the OLS approach is not designed to accommodate potential regime shifts, non-linearities, or time varying

sensitivities that are particularly relevant for highly speculative and sentiment driven assets such as Bitcoin. Additionally, the choice of explanatory variables, although grounded in the macroeconomic literature, omits factors that may have more explanatory power in the context of cryptocurrencies. As explained in section 2.6 of the literature review, Bitcoin evolves in distinct market cycles, often characterized by momentum effects, self-reinforcing trends, and investor sentiment driven by the media (Nakagawa & Sakemoto, 2022; Corbet et al., 2018). These dynamics suggest that variables such as social media activity, Google Trends data, or the Fear & Greed Index may be more relevant than traditional indicators like CPI or interest rates in certain contexts. Furthermore, on-chain metrics such as transaction volumes, active address growth, or hashrate development are widely used in the crypto finance field. The omission of these potentially influential variables limits the model's ability to explain Bitcoin's idiosyncratic behavior, as also suggested by the low R^2 in the Bitcoin regression (H4).

Another limitation concerns the frequency of the data. This research relies on monthly observations, which are well suited for capturing macroeconomic trends but less effective for analyzing fast moving assets such as Bitcoin. The crypto market is highly sensitive to short-term news, regulatory shocks, and liquidity fluctuations that unfold at a daily or even hourly scale. As a result, the monthly frequency may smooth out critical short-term reactions and understate the true responsiveness of Bitcoin to both macroeconomic and non-macroeconomic shocks. This temporal granularity mismatch may partly explain why certain relationships expected from theory do not appear in the regression results (e.g., for interest rates in H3). Moreover, the period covered by the dataset, from 2012 to early 2025, raises concerns regarding structural shifts in the Bitcoin market. During this time, Bitcoin's price has increased from less than \$10 to \$100,000, accompanied by dramatic changes in trading infrastructure, investor composition, and public perception. The early years of Bitcoin were dominated by retail and ideological investors, while the later years have seen growing institutional participation and regulatory scrutiny. These transitions may have fundamentally altered how Bitcoin interacts with macroeconomic factors, yet the linear model assumes temporal consistency. As a result, the aggregated estimates may mask important differences across sub-periods or phases of the Bitcoin cycle.

Finally, while Bitcoin operates as a global asset, most of the macroeconomic data used in the model reflect U.S. based conditions (e.g., U.S. CPI, Federal Funds Rate, M2). Although the U.S. remains a dominant actor in global finance, Bitcoin is traded 24/7 across international platforms with users and investors from all regions. Relying solely on American macroeconomic

indicators may introduce geographic bias and limit the generalizability of the findings to the broader global context. More comprehensive studies could integrate global aggregates, such as central bank balance sheet indices or cross-country measures of monetary policy stance, to better capture Bitcoin's truly international exposure.

5.3 Recommendations for future research and practice

Building on the findings and limitations of this study, several recommendations can be made to improve future research and inform practical decisions. First, from a methodological standpoint, future studies should consider moving beyond the traditional linear OLS framework. Given Bitcoin's high volatility, asymmetric return distribution, and regime dependent behavior, more flexible models are needed. One promising alternative is quantile regression, which allows the estimation of relationships at different points of the return distribution. This approach is especially relevant for assets like Bitcoin that exhibit sharp upside or downside movements, enabling researchers to capture whether macroeconomic variables matter more during crashes, rallies, or stable periods. Unlike OLS, quantile regression does not rely on the assumption of homoscedasticity or normality, and it offers more detailed insights into tail behaviors, an important feature in crypto markets. Additionally, future models could incorporate regime switching techniques or time varying parameter models to reflect the distinct phases of Bitcoin market cycles, as discussed in section 2.6 of the literature review. This would allow the estimation process to adapt to bullish, bearish, or sideways periods, which appear to have very different drivers.

Second, expanding the set of explanatory variables is recommended. As suggested in the literature and reinforced by the results of this study, traditional macroeconomic variables such as CPI, interest rates, or M2 provide only limited explanatory power, especially for Bitcoin. Future research should therefore include non-traditional factors that better capture the idiosyncratic and sentiment driven nature of crypto assets. For example, sentiment indicators derived from Google Trends and Twitter activity could help assess the influence of investor mood and media exposure. Data from platforms such as the Fear & Greed Index could also reflect psychological shifts that are not detected by macroeconomic aggregates. Furthermore, on-chain metrics such as transaction volume, address growth, miner behavior, hashrate or exchange inflows offer unique insights into network activity and user adoption, both of which are key drivers of price dynamics in blockchain based assets.

From a practical standpoint, these findings have clear implications for both investors and policymakers. Investors should be prudent in viewing Bitcoin as a hedge against inflation or other macroeconomic risks, as the results show no consistent or significant relationship with those variables. Instead, Bitcoin behaves more like a speculative asset whose performance is highly sensitive to financial market volatility and investor sentiment. Risk management strategies should therefore incorporate Bitcoin's pro-cyclical nature and vulnerability to volatility spikes, as highlighted by its negative reaction to increases in the VIX. Portfolio managers may consider treating Bitcoin as a distinct risk asset class, with its own set of drivers and risk return profile, rather than integrating it directly within traditional macro hedging strategies. Meanwhile, policymakers and regulators should recognize that Bitcoin does not react to conventional levers of monetary or fiscal policy in the same way as other financial instruments. This non-responsiveness implies that market dynamics may not stabilize automatically through macroeconomic adjustment, which increases the importance of monitoring liquidity, leverage, and speculative activity within the crypto space.

Finally, future studies should consider a more targeted and dynamic investigation into Bitcoin's macroeconomic behavior. A potential direction would be to examine how different factors influence Bitcoin returns across various market regimes, thereby aligning econometric tools with the asset's known cyclicity. Specifically, a research question such as "*Among macroeconomic, sentiment driven, and on-chain variables, which factors most effectively explain Bitcoin returns across different volatility states?*" could serve as a guiding framework. This would not only account for the unique properties of Bitcoin but also help identify context dependent sensitivities. Such studies could test whether sentiment dominates during speculative booms, while macroeconomic signals gain relevance in more mature or institutional phases.

6 Conclusion

This thesis examines the impact of macroeconomic factors, including economic uncertainty, on the price and volatility of Bitcoin, in comparison to gold and U.S. stocks. It assesses Bitcoin's function whether as a hedge, a speculative vehicle, or an emerging safe haven through a structured empirical comparison with two benchmark assets: gold and the S&P 500. To answer this question, three multiple linear regressions were applied to monthly data covering the period from 2012 to 2025. Five hypotheses were developed from existing academic literature, focused on inflation, monetary expansion, interest rates, macroeconomic explanatory power, and the asset's response to financial uncertainty in terms of financial market volatility. Bitcoin's behavior was analyzed in parallel with that of gold and equities, in order to assess both its distinctiveness and its possible convergence with more established financial instruments.

The results of the analysis provide a clear answer to the research question. First, Bitcoin returns show no significant relationship with inflation, rejecting the idea that it serves as a hedge against consumer price increases. Second, the effects of monetary expansion, measured by growth in the M2 money supply, were not statistically significant, and third, interest rates, both short- and long-term, also failed to exhibit any meaningful influence on Bitcoin returns. These findings jointly indicate that Bitcoin does not follow the monetary or pricing logic observed in traditional financial assets. By contrast, gold and the S&P 500 respond in more predictable ways to these same macroeconomic drivers, reinforcing Bitcoin's departure from standard economic sensitivities. However, the analysis does reveal that Bitcoin reacts to a specific form of financial market uncertainty: the VIX, which captures investor expectations of short-term stock market volatility. The coefficient for the VIX was negative and statistically significant, suggesting that Bitcoin tends to decline when anticipated volatility rises. This contrasts with gold, whose returns remain unaffected by the same variable, reinforcing its role as a safe haven. In contrast, broader measures of uncertainty, including the Monetary Policy Uncertainty (MPU) index, the Global Economic Policy Uncertainty (GEPU) index and the Geopolitical Risk Index (GPR), do not exhibit statistically significant effects on Bitcoin returns. These results suggest that Bitcoin's responsiveness to uncertainty is concentrated on short-term financial market stress rather than influenced by broader institutional or geopolitical factors. Instead, its negative reaction to financial market volatility further supports the conclusion that Bitcoin behaves more like a high risk speculative asset than like gold. Above all, the model's explanatory power

varied considerably between assets. The macroeconomic variables used in this study explained only 8% of the variation in Bitcoin returns, compared to 23% for gold and 25.6% for the S&P 500. This divergence suggests that traditional macroeconomic indicators fail to capture the key drivers of Bitcoin's return behavior. This validates the fourth hypothesis and supports the idea that Bitcoin remains primarily driven by idiosyncratic factors such as speculative interest, sentiment waves, and internal market developments.

Taken together, these findings suggest that Bitcoin occupies a hybrid space in the financial system. It is not completely decoupled from macroeconomic reality, its reaction to the VIX shows some responsiveness but it is also far from behaving like a standard asset class governed by inflation, interest rates, or monetary supply. The asset's behavior appears to be highly context dependent, shaped by cycles of market optimism and fear, and potentially more sensitive to internal or behavioral triggers than to external economic policies. These characteristics support the view that Bitcoin is not a reliable hedge or safe haven, but rather a structurally unstable asset that may mimic riskier segments of traditional markets during times of stress.

While these results provide meaningful insights, they are subject to several limitations. The linear regression framework employed assumes stable and symmetric relationships between variables across time, which is difficult to justify in the case of Bitcoin, whose return structure is widely recognized as regime dependent. As discussed in the literature review, Bitcoin moves in clear cycles often driven by speculative momentum and media narratives making it likely that macroeconomic variables influence the asset differently depending on market phase. In addition, the study focuses solely on monthly data, which while appropriate for macroeconomic indicators, may overlook the high frequency dynamics and sudden shocks that characterize Bitcoin markets. The analysis also omits alternative explanatory factors that are particularly relevant for crypto assets, such as on-chain indicators and investor sentiment variables. These limitations do not invalidate the findings but rather suggest that further refinement is necessary to better capture the specificities of the asset.

Building on these limitations, several recommendations can be made for future research. First, models that allow for asymmetric and regime sensitive responses such as quantile regression should be considered to better reflect Bitcoin's complex behavior. Second, future studies should integrate variables that are more intrinsic to the crypto ecosystem, including on-chain metrics and sentiment based indicators. A useful research question for future work might

be: *“Among macroeconomic, sentiment driven, and on-chain variables, which factors most effectively explain Bitcoin returns across different volatility states?”*

In conclusion, this thesis demonstrates that Bitcoin does not conform to the standard macroeconomic logic that governs traditional assets. Its limited response to inflation, interest rates, and monetary policy, combined with its sensitivity to volatility and low explanatory coherence, suggests that it behaves more like a speculative instrument than a stable macro responsive asset. At the same time, its partial responsiveness to uncertainty, by its reaction to financial market volatility, shows that it cannot be dismissed as entirely disconnected from economic reality. Bitcoin’s evolving nature underscores the need for adaptive analytical tools capable of capturing the behavior of decentralized financial assets outside conventional macroeconomic frameworks.

7 References

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8 Appendix

8.1 Stata code

```

1
2 // ---Download daily data dependant variable---
3
4 // Set the working directory
5 cd "C:\Users\arthu\OneDrive\Documents\Thesis\"
6 clear
7
8 // Import the BTC CSV file
9 import delimited "BTC_monthly", clear
10 keep v1 v2
11 rename v1 date_stata
12 rename v2 BTC_price
13 drop if date == "Date"
14 gen date = date(date_stata, "MDY")
15 format date %td
16 sort date
17 drop date_stata
18 replace BTC_price = substr(BTC_price, 1, 10)
19 gen BTC_price_clean = ustrregexr(BTC_price, "[^0-9.]", "")
20 destring BTC_price_clean, replace
21 drop BTC_price
22 rename BTC_price_clean BTC_price
23
24 // Calculate log returns Log return formula:  $\ln(P_t / P_{t-1})$ 
25 gen log_return_btc = ln(BTC_price / BTC_price[_n-1])
26 // Save data
27 save "BTC_monthly.dta", replace
28
29
30 // Fetch S&P 500 data
31 getsymbols ^GSPC, fm(1) fd(1) fy(2012) lm(1) ld(1) ly(2025) frequency(m) yahoo clear
32 keep daten adjclose__GSPC
33 rename daten date
34 rename adjclose__GSPC SP500_price

```

```

35
36 // Calculate log returns
37 gen log_return_sp500 = ln(SP500_price / SP500_price[_n-1])
38 // Save data
39 save "sp500_monthly.dta", replace
40
41
42 // Import the gold CSV file
43 import delimited "GOLDINV_monthly", clear
44 keep v1 v2
45 rename v1 date_stata
46 rename v2 GOLD_price
47 drop if date == "Date"
48 gen date = date(date_stata, "MDY")
49 format date %td
50 sort date
51 drop date_stata
52 replace GOLD_price = substr(GOLD_price, 1, 10, .)
53 gen GOLD_price_clean = ustrregexr(GOLD_price, "[^0-9.]", "")
54 destring GOLD_price_clean, replace
55 drop GOLD_price
56 rename GOLD_price_clean GOLD_price
57
58 // Calculate log returns
59 gen log_return_gold = ln(GOLD_price / GOLD_price[_n-1])
60 // Save data
61 save "gold_monthly.dta", replace
62
63
64 // --- Gather them ---
65
66
67 // Load the BTC dataset
68 clear
69 use "BTC_monthly.dta", clear
70
71 // Merge with the S&P 500 dataset
72 merge 1:1 date using "sp500_monthly.dta", keepusing(SP500_price log_return_sp500)

```



```

73
74 // Keep only matched dates (drop unmatched dates)
75 drop if _merge != 3
76 drop _merge
77
78 // Merge with the Gold dataset
79 merge 1:1 date using "gold_monthly.dta", keepusing(GOLD_price log_return_gold)
80
81 // Keep only matched dates (drop unmatched dates)
82 drop if _merge != 3
83 drop _merge
84
85 // Save the merged dataset
86 save "final_monthly_prices.dta", replace
87
88
89
90 // --- Download data independent variables ---
91
92
93
94 // Import the CPI data from FRED
95 import delimited "CPI_monthly", clear
96 gen date = date(observation_date, "YMD")
97 format date %td
98 drop observation_date
99 rename cpiaucsl CPI
100 gen lCPI = log(CPI)
101 gen Ldelta_CPI = lCPI - lCPI[_n-1]
102 gen delta_CPI = CPI - CPI[_n-1]
103 save "monthly_deltaCPI.dta", replace
104
105
106 // Import the interest rate data from FRED
107 import delimited "FEDRATE_monthly", clear
108 gen date = date(observation_date, "YMD")
109 format date %td
110 drop observation_date

```

```

111 rename fedfunds FedRate
112 gen delta_FedRate = FedRate - FedRate[_n-1]
113 save "monthly_FedRate.dta", replace
114
115 // Import the interest rate 10 years data from FRED
116 import delimited "DGS10_monthly", clear
117 gen date = date(observation_date, "YMD")
118 format date %td
119 drop observation_date
120 rename dgs10 DGS10
121 gen delta_DGS10 = DGS10 - DGS10[_n-1]
122 save "monthly_DGS10.dta", replace
123
124 // Import the DXY data from FRED
125 import delimited "DXY_monthly", clear
126 gen date = date(observation_date, "YMD")
127 format date %td
128 drop observation_date
129 rename twexbgsmth DXY
130 gen lDXY = log(DXY)
131 gen Ldelta_DXY = lDXY - lDXY[_n-1]
132 gen delta_DXY = DXY - DXY[_n-1]
133 save "monthly_deltaDXY.dta", replace
134
135 // Import the VIX data from FRED
136 import delimited "VIX_monthly", clear
137 gen date = date(observation_date, "YMD")
138 format date %td
139 drop observation_date
140 rename vixcls VIX
141 gen delta_VIX = VIX - VIX[_n-1]
142 save "monthly_VIX.dta", replace
143
144
145 // Import the OIL data from FRED
146 import delimited "OIL_monthly", clear
147 gen date = date(observation_date, "YMD")
148 format date %td

```

```

149 drop observation_date
150 rename dcoilwtico OIL
151 gen lOIL = log(OIL)
152 gen Ldelta_OIL = lOIL - lOIL[_n-1]
153 gen delta_OIL = OIL - OIL[_n-1]
154 save "monthly_deltaOIL.dta", replace
155
156
157 // Import the M2 data from FRED
158 import delimited "M2_monthly", clear
159 gen date = date(observation_date, "YMD")
160 format date %td
161 drop observation_date
162 rename wm2ns M2
163 gen lM2 = log(M2)
164 gen Ldelta_M2 = lM2 - lM2[_n-1]
165 gen delta_M2 = M2 - M2[_n-1]
166 save "monthly_deltaM2.dta", replace
167
168 // Import the GEPU data from FRED
169 import delimited "GEPU_monthly", clear
170 gen date = date(observation_date, "YMD")
171 format date %td
172 drop observation_date
173 rename gepucurrent GEPU
174 gen delta_GEPU = GEPU - GEPU[_n-1]
175 save "monthly_GEPU.dta", replace
176
177 // create a dataset of monthly date
178 drop GEPU
179 gen id = _n
180 save "monthly_date.dta", replace
181
182 // Import the MPU data from Economic Policy Uncertainty
183 import delimited "MPU_monthly", clear
184 keep in 325/481 // Keep only the relevant MPU observations
185 drop year month bbdmpuindexbasedon10majorpapers
186 rename bbdmpuindexbasedonaccessworldnew MPU

```

```

187 gen id = _n
188 save "MPU_withoutdate.dta", replace
189 // Load the monthly dates
190 use "monthly_date.dta", clear
191 merge 1:1 id using "MPU_withoutdate.dta", keepusing(MPU)
192 drop id _merge
193 gen delta_MPU = MPU - MPU[_n-1]
194 save "monthly_MPU.dta", replace
195
196
197 // Import the GRP data from Economic Policy Uncertainty
198 import delimited "GPR_monthly", clear
199 keep in 325/481
200 drop v3 v4
201 rename v1 date
202 rename v2 GPR
203 destring GPR, replace dpcomma
204 gen id = _n
205 drop date
206 save "GPR_withoutdate.dta", replace
207 // Load the monthly dates
208 use "monthly_date.dta", clear
209 merge 1:1 id using "GPR_withoutdate.dta", keepusing(GPR)
210 drop id _merge
211 gen delta_GPR = GPR - GPR[_n-1]
212 save "monthly_GPR.dta", replace
213
214
215 // --- Gather all data ---
216
217
218 clear
219 use "final_monthly_prices", clear
220
221 // Merge CPI
222 merge 1:1 date using "monthly_deltaCPI", keepusing(delta_CPI CPI Ldelta_CPI)
223 drop _merge
224

```

```

225 // Merge Fed Rate
226 merge 1:1 date using "monthly_FedRate", keepusing(delta_FedRate FedRate)
227 drop _merge
228
229 // Merge Interest Rate 10 years
230 merge 1:1 date using "monthly_DGS10", keepusing(delta_DGS10 DGS10)
231 drop _merge
232
233 // Merge DXY
234 merge 1:1 date using "monthly_deltaDXY", keepusing(delta_DXY DXY Ldelta_DXY)
235 drop _merge
236
237 // Merge VIX
238 merge 1:1 date using "monthly_VIX", keepusing(delta_VIX VIX)
239 drop _merge
240
241 // Merge Oil
242 merge 1:1 date using "monthly_deltaOIL", keepusing(delta_OIL OIL Ldelta_OIL)
243 drop _merge
244
245 // Merge M2
246 merge 1:1 date using "monthly_deltaM2", keepusing(delta_M2 M2 Ldelta_M2)
247 drop _merge
248
249 // Merge GEPU
250 merge 1:1 date using "monthly_GEPU", keepusing(delta_GEPU GEPU)
251 drop _merge
252
253 // Merge MPU
254 merge 1:1 date using "monthly_MPU", keepusing(delta_MPU MPU)
255 drop _merge
256
257 // Merge GPR
258 merge 1:1 date using "monthly_GPR", keepusing(delta_GPR GPR)
259 drop _merge
260
261 // Save final file
262 save "All_Final_Data.dta", replace

```

```

263
264
265 // --- Load the final dataset ---
266
267 clear
268 use "All_Final_Data.dta", clear
269
270 describe
271 summarize
272
273 gen date_monthly = mofd(date) // Transform date to monthly frequency
274 format date_monthly %tm
275 tsset date_monthly
276 tsreport
277
278 //ADF test to check if stationary
279 dfuller CPI, lags(1) trend
280 dfuller Ldelta_CPI, lags(1) trend // ok
281 dfuller FedRate, lags(1) trend
282 dfuller delta_FedRate, lags(1) trend // ok
283 dfuller DGS10, lags(1) trend
284 dfuller delta_DGS10, lags(1) trend // ok
285 dfuller DXY, lags(1) trend
286 dfuller Ldelta_DXY, lags(1) trend // ok
287 dfuller VIX, lags(1) trend // ok
288 dfuller OIL, lags(1) trend
289 dfuller Ldelta_OIL, lags(1) trend // ok
290 dfuller M2, lags(1) trend
291 dfuller Ldelta_M2, lags(1) trend // ok
292 dfuller GEP, lags(1) trend // ok
293 dfuller MPU, lags(1) trend // ok
294 dfuller GPR, lags(1) trend // ok
295
296 //Pearson test to check collinearity
297 correlate Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL Ldelta_M2
    ↪ GEP MPU GPR
298
299 //Test of heteroscedasticity

```

```

300 reg log_return_btc Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL
    ↪ Ldelta_M2 GEPU MPU GPR
301 estat hettest
302
303 reg log_return_gold Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL
    ↪ Ldelta_M2 GEPU MPU GPR
304 estat hettest
305
306 reg log_return_sp500 Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL
    ↪ Ldelta_M2 GEPU MPU GPR
307 estat hettest
308
309 // Perform the regression with the specified independent variables
310 reg log_return_btc Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL
    ↪ Ldelta_M2 GEPU MPU GPR, robust
311 estat dwatson
312
313 reg log_return_gold Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL
    ↪ Ldelta_M2 GEPU MPU GPR, robust
314 estat dwatson
315
316 reg log_return_sp500 Ldelta_CPI delta_FedRate delta_DGS10 Ldelta_DXY VIX Ldelta_OIL
    ↪ Ldelta_M2 GEPU MPU GPR, robust
317 estat dwatson
318
319
320
321
322
323
324

```

