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Regime-Dependent Relationships between Bitcoin Market Capitalization, Financial Stability, and Economic Growth in OECD Member Countries

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Highlights

- **Bitcoin is negatively associated with financial stability in both regimes, with a stronger relationship during recession.**
- **Bitcoin has a weak and regime-dependent association with economic growth, becoming negative and statistically significant during expansions.**
- **Bitcoin is associated with a small deterioration in financial stability, without evidence of a destabilizing relationship with OECD financial systems.**

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Abstract

This study employs a one-lag Markov-Switching Pooled VAR model to examine the empirical relationship between Bitcoin, economic growth, and financial stability in OECD member countries . Preliminary analyses confirmed the stationarity of the variables and revealed two distinct regimes, corresponding to recession and expansion. The results indicate that Bitcoin is negatively and statistically significantly associated with financial stability in both regimes. During recessions, Bitcoin is positively but statistically insignificantly associated with economic growth, whereas in expansions its association with economic growth becomes negative and statistically significant. Interest rates are positively and significantly associated with economic growth only in the recession regime, while their associations with financial stability and Bitcoin market capitalization remain statistically insignificant. Unemployment is generally insignificant across regimes; however, at the 10% significance level, it is negatively associated with economic growth during recessions, consistent with economic theory. Overall, Bitcoin market capitalization is negatively associated with financial stability in both regimes, while its relationship with economic growth is regime-dependent. Policymakers and investors should take these dynamics into account when designing regulatory frameworks and investment strategies related to cryptocurrency markets. Future research is encouraged to investigate the relationships between cryptocurrencies and macro-financial variables in developing countries and other emerging financial systems.

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1. Introduction

Cryptocurrency is a type of virtual currency that uses cryptographic technology in its design and is usually managed in a decentralized manner. Since cryptocurrencies are an emerging phenomenon and new examples continue to be created, various definitions of them can be found in the literature. Blockchain technology was first introduced in the 1990s, and in 2009, following the global financial crisis, a decentralized cryptocurrency called Bitcoin, based on blockchain technology, was introduced by an unknown individual or group under the pseudonym Satoshi Nakamoto and entered the financial world.

The important feature of digital currencies is that they were created and launched with the aim of replacing conventional monetary units. Therefore, their main use is as a means of payment and value transfer, although as this industry has expanded, more applications have been added to the field of cryptocurrencies.

Bitcoin, as the first digital currency, has two main goals: to create a decentralized monetary system controlled by individuals and to reduce inflationary pressures in economies. The decentralized nature of Bitcoin is a unique feature in the history of digital currencies. Overall, Bitcoin not only offers an innovative means of payment, but also has unique features that may be associated with changes in financial and economic systems.

Another goal of Bitcoin is to control inflation because its limited supply on the blockchain network prevents unlimited expansion. However, the implications of Bitcoin's predetermined supply for inflation, financial crises, and financial stability are not straightforward. Bitcoin's price volatility, speculative trading, and integration into financial markets may also be associated with financial risks. Accordingly, one of the objectives of this research is to examine the relationship between Bitcoin market capitalization and financial stability. On the other hand, Bitcoin has grown rapidly over a relatively short period and has gained substantial value in financial markets. According to statistics for 2023, it is considered the ninth most valuable asset in the world, with a market value of approximately $848 billion. These developments raise questions about the relationship between Bitcoin market capitalization and economic growth, which constitutes another objective of this research.

Given its rapid growth and the volume of capital attracted worldwide, how is Bitcoin market capitalization associated with financial stability across different business-cycle regimes? Furthermore, how does its relationship with economic growth vary between recessionary and expansionary conditions? These are the main questions addressed in this research.

Based on the theoretical arguments and empirical evidence discussed in the literature, the following hypotheses are formulated:

H1: Bitcoin market capitalization is positively associated with economic growth across business-cycle regimes.

H2: Bitcoin market capitalization is associated with financial stability, potentially reflecting both its store-of-value characteristics and its speculative nature.

H3: The relationships between Bitcoin market capitalization, economic growth, and financial stability differ across business-cycle regimes.

The study of financial stability is important because countries are constantly exposed to economic shocks that can lead to crises, and certain innovations may also create shocks and instability. These crises can directly affect the economy of any country. In a general sense, financial stability may refer to the absence of financial crises, the proper functioning of key elements of the financial system, or the ability of the financial system to withstand various shocks. According to Mishkin (2013), financial crises can take several forms, including banking crises, currency crises, and disruptions in financial markets. When banking crises occur alongside currency and stock market crises, their combined effects may generate severe financial instability and contribute to deep recessions in the real economy. Paying attention to various factors associated with instability and preparing continuous reports can help prevent potential risks from developing into systemic risks and ultimately into crises.

Various factors may be associated with financial crises, including developments in digital currency markets. Several considerations motivate the present study: the growing presence of digital currencies in the global financial system, their potential role as a store of value, and their emergence as a relatively new financial phenomenon. Between 2015 and 2023, the cryptocurrency market experienced substantial fluctuations and gained considerable market value within a relatively short period. The volatility of this market raises questions about its relationship with financial stability and economic growth. These considerations highlight the importance of examining the relationship between fluctuations in Bitcoin market capitalization, financial stability, and economic growth. Accordingly, this study focuses on OECD countries and investigates how these relationships vary across business-cycle regimes, particularly during recessionary and expansionary periods.

2. Literature Review

Theoretical Perspectives on the Relationships between Digital Currencies, Financial Stability, and Economic Growth have been examined from three complementary perspectives: (1) financial stability and its theoretical foundations, (2) digital currencies, financial innovation, and economic growth, and (3) asymmetric and regime-dependent macro-financial relationships. These theoretical foundations provide the conceptual basis for examining the dynamic interactions among financial stability, economic growth, and Bitcoin market capitalization.

2.1. Financial Stability and Cryptocurrency Markets

The Relationship between Digital Currencies and Financial Stability :In the financial literature, financial stability is one of the most frequently discussed concepts in public policy and economic research. Despite its widespread use, there is no universally accepted definition of financial stability. The concept gained increasing attention following the financial crises of the 1990s and became a central

topic in economic research and the policy discussions of financial institutions (Crockett, 2000; Das et al., 2004; Arner, 2007).

There is no universally accepted definition or consensus regarding the concept and nature of financial stability in the academic literature. The concept has evolved over time, particularly in response to major financial crises, and has become a central focus of both academic and policy debates. These debates also include institutional questions regarding whether supervisory responsibilities over the financial system should be assigned to central banks or to independent regulatory authorities (De Haan, & Oosterloo, (2004); Crockett, 2000; Schinasi, 2004).

Traditional Financial Theories: According to Allen and Wood (2006), financial stability is considered the ability of the financial system to withstand shocks and maintain optimal performance. Digital currencies, due to characteristics such as high volatility, may pose a threat to financial stability. The integration of financial stability theories with digital currencies is a relatively new and dynamic topic in the economic literature. The following section explains the relationship between financial stability theories and the role of digital currencies in promoting or threatening financial stability.

1. Financial Fragility Theory: Minsky's (1986 , 1992), in his Financial Fragility Theory, explains that long-term stability in financial markets gradually gives rise to instability. He argues that during periods of economic prosperity, firms and investors increase their debt levels and, as the margin of safety declines, the economy becomes more vulnerable to shocks.

In the new environment of financial markets, particularly with the emergence of digital currencies, recent research (Kanu, 2025) has shown that speculative behavior in cryptocurrencies can be viewed as an example of the Minsky cycle. During periods of rising prices, debt and leverage increase, while during periods of decline, liquidity crises and financial instability emerge. According to Minsky's theory, financial innovations such as digital currencies, DeFi, and NFTs may increase systemic risk, which can ultimately contribute to financial instability.

According to Minsky's (1986 , 1992) theory of financial fragility, financial markets typically pass through three stages: a prudent financing stage, a speculative stage, and finally a Ponzi stage. The cryptocurrency market appears to have followed this pattern. In its early stages, it operated under prudent financing conditions; however, as prices grew rapidly and investors sought substantial profits, it entered speculative and Ponzi-like stages, ultimately leading to financial instability. The extreme price fluctuations of Bitcoin and the collapse of the cryptocurrency market in 2018 and 2022 are clear examples of this inherent instability (Manahov, V. (2023)).

2. Financial Cycle Theory: According to Miranda-Agrippino and Rey (2020) and Borio (2014), Financial Cycle Theory suggests that fluctuations in credit, asset prices, and financial leverage occur in cyclical patterns that have profound effects on macroeconomic stability. Global monetary policies and international financial developments have caused financial markets to move in tandem. Recent studies have shown that the cryptocurrency market is also part of the global financial cycle

and, in response to changes in global interest rates, undergoes fluctuations similar to those observed in traditional markets. Consequently, cryptocurrency price changes resulting from interest rate fluctuations may contribute to financial instability.

3. Imperfect Markets Perspective: According to Stiglitz (1987), real-world financial markets often deviate from the assumptions of perfect competition due to the presence of information asymmetries and transaction costs. These market imperfections may lead to inefficiencies in resource allocation and increase the vulnerability of financial markets to economic shocks. Consistent with this view, Kikkawa et al. (2017) show that imperfect competition can strengthen the transmission of shocks through economic networks. In cryptocurrency markets, information asymmetry, limited transparency, and weak regulatory oversight may similarly increase systemic risk and financial instability (Kanu, 2025). This perspective highlights the importance of effective regulatory frameworks in reducing market vulnerabilities.

4. Shock Transmission Theory and Financial Networks: According to Allen and Gale (2000), financial institutions transmit shocks throughout the system through their interconnected networks. The denser the network, the greater the likelihood of crisis contagion. In recent years, studies such as Hansen (2021) and Ramadiah et al. (2018) have shown that the network structure of cryptocurrency transactions exhibits similar characteristics and can serve as a new channel for the transmission of financial instability.

Cryptocurrencies are connected to the traditional financial system through global exchanges, blockchain payment networks, and smart contracts. The collapse of a stablecoin (e.g., UST in 2022) sent shockwaves throughout the entire ecosystem. The linkage between cryptocurrencies and traditional assets, such as stocks, bonds, and digital dollars, has enabled small shocks to become amplified, thereby facilitating the transmission of financial disturbances and ultimately contributing to financial instability.

5. Prudential and Regulatory Perspectives: The prudential perspective, emphasized by international institutions such as the IMF and BIS, highlights the importance of preventing the accumulation of systemic risks. The IMF (2024) discusses financial stability risks associated with digitalization and the potential implications of growing links between digital assets and the broader financial system. These concerns underline the importance of monitoring potential channels of financial contagion and strengthening appropriate regulatory frameworks.

A recent study published in 2025 also suggests that the lack of a coherent regulatory framework in the cryptocurrency market could intensify financial instability. Accordingly, instruments such as holding limits on stablecoins and capital requirements for cryptocurrency platforms have been proposed.

Behavioral finance theories suggest that investors' decisions are influenced not only by rational expectations but also by psychological biases, emotions, and social interactions (Barberis & Thaler, 2003). In cryptocurrency markets, these behavioral factors may encourage herd behavior and speculative trading,

particularly during periods of rapid market expansion. Extreme price volatility and unusually high returns can further intensify speculative activities and contribute to the formation of price bubbles, thereby increasing financial instability and systemic risk (Haykir & Yagli, 2022).

2.2. Digital Currencies, Financial Innovation, and Economic Growth

From the perspective of Financial Innovation Theory, financial innovations can enhance market efficiency, increase competition, and transform financial intermediation processes (Schumpeter, 1934; Frame & White, 2004). As a recent form of financial innovation, cryptocurrencies have the potential to reshape market structures and financial behavior by providing alternative mechanisms for payments, investment, and value transfer.

From the perspective of Monetary Theory (Friedman, 1969), money serves three primary functions: a medium of exchange, a store of value, and a unit for speculative investment. Depending on their design and underlying support mechanisms, digital currencies can fulfill some of these functions (Adrian and Mancini-Griffoli, 2019).

Central banks and international institutions have also emphasized that the introduction of central bank digital currencies (CBDCs) may have both positive and negative effects on the stability and efficiency of the monetary system (IMF, CBDC, 2021). According to monetary theories, digital currencies, as a new form of money, can serve as an alternative to traditional money and financial instruments due to features such as transparency, transaction speed, and reduced transaction costs.

According to Classical and Neoclassical Growth Theory (Solow, 1956), economic growth is driven by capital accumulation, labor input, and technological progress. From this perspective, digital currencies may contribute to higher economic efficiency by reducing transaction costs, facilitating access to financial services, and potentially improving the velocity of money, which can indirectly support productivity growth.

Digital currencies, as an emerging form of financial innovation, may contribute to economic growth by reducing transaction costs, improving the efficiency of payment systems, and expanding access to financial services. Furthermore, digital currencies can facilitate faster and more transparent financial transactions, promote financial inclusion, and improve resource allocation, thereby enhancing productivity and supporting long-term economic growth (Ozili, 2018; Frame & White, 2004).

According to Keynesian theories of money and economic activity, aggregate demand plays a central role in determining economic activity. From this perspective, the use of Bitcoin as a transactional currency may facilitate transactions and affect monetary behavior, potentially influencing economic activity. (Keynes, 1936), (Pagano & Sedunov, 2020)

In addition to financial and digital asset-related factors, macroeconomic conditions play an important role in determining economic growth and financial

stability. Among these conditions, labor market dynamics are particularly important because changes in unemployment can reflect underlying fluctuations in economic activity. Unemployment is widely recognized as a lagging indicator of business cycles because labor market adjustments generally occur after changes in economic activity. Employment decisions by firms often respond with delay to variations in production, demand conditions, and overall economic performance. Consequently, changes in unemployment may not immediately capture their full effects on financial stability and economic growth. Higher unemployment can gradually reduce household income, weaken consumption, increase credit risks, and contribute to financial vulnerabilities. Therefore, the unemployment rate is incorporated as an exogenous control variable in the empirical model

2.3. Regime Dependence in Macro-Financial Relationships

In the macroeconomic and financial literature, the assumption of symmetry in the response of variables to positive and negative shocks has long been questioned. Recent theories suggest that the response of macroeconomic variables to positive and negative shocks is not necessarily the same, a phenomenon known as the "asymmetric effect." Particularly in the context of financial fluctuations, negative shocks often have stronger and more persistent effects on economic growth than positive shocks because they exacerbate uncertainty, credit constraints, and precautionary behavior.

In this regard, regime-switching models, such as Markov-switching models first introduced by Hamilton (1989), allow researchers to examine the different behavior of variables under recessionary and expansionary regimes. More recent studies on asymmetric effects have shown that distinguishing between positive and negative shocks can contribute to a better understanding of the dynamics of economic growth and financial stability (Shin et al., 2014).

Therefore, a regime-dependent framework is appropriate for examining how the relationships among Bitcoin market capitalization, economic growth, and financial stability vary across recessionary and expansionary conditions in OECD countries. Differences between these regimes reflect variation in the estimated relationships across business-cycle conditions and do not necessarily imply different responses to positive and negative shocks. This provides the theoretical motivation for applying a Markov-switching pooled VAR framework, which allows the dynamic relationships among financial stability, economic growth, and Bitcoin market capitalization to vary across regimes.

3. Research Background

3.1. Empirical Evidence on Cryptocurrency, Financial Stability, and Economic Growth

The first study examined the correlation between the cryptocurrency market and traditional financial markets in order to assess its impact on financial stability. To analyze the relationship between Bitcoin and three traditional assets—gold, the S&P 500, and EUR/USD—the TVP-VAR model and daily data from 2015 to 2023

were used. The results showed that the correlation between traditional assets, particularly stocks (S&P 500), gold, and Bitcoin, increased significantly over the study period. However, other indicators, such as exchange rates, were not significantly correlated with cryptocurrencies. Therefore, the findings suggest that the cryptocurrency market may pose risks to financial stability by amplifying shocks and risks transmitted from traditional financial markets (Donoiu & Iacob, 2023).

The next study analyzed the global drivers behind the development of cryptocurrencies using a combination of analytical and comparative methods to examine their impact on the global financial market. The analytical approach was used to assess structural dynamics, market trends, and capital growth within the cryptocurrency market, while the comparative method facilitated the evaluation of differences and similarities in cryptocurrency adoption across countries and financial systems. The results highlighted the dominance of Bitcoin and its evolution into a global asset, as well as the expanding role of altcoins, utility tokens, and stablecoins. The analysis also revealed the increasing use of cryptocurrencies in commercial payments, the issuance of national digital currencies, and the growing adoption of blockchain technologies by global corporations. However, the study identified significant challenges, including regulatory ambiguities, security vulnerabilities, and systemic risks related to financial stability (Nechyporchuk, 2025).

Another study examined the relationship between the expansion of digital currencies and the challenges they pose to the global financial system. The study highlighted several risks associated with the increasing use of digital currencies, including cybersecurity threats, fraud, and money laundering, which may disrupt traditional financial structures and threaten financial stability. The findings indicated that while some regulatory measures have improved market transparency and investor protection, regulatory frameworks have often struggled to keep pace with the rapid evolution of digital currencies. The study emphasized the need for a comprehensive and internationally coordinated regulatory framework that balances innovation, investor protection, and financial stability (Laucius, 2025).

A subsequent study examined the impact of the cryptocurrency industry on stock market returns in the Middle East and North Africa (MENA) region using panel data econometric techniques and generalized method of moments (GMM) estimation over the period 2014–2019. The results indicate a significant relationship between cryptocurrency returns and stock market performance in the region, with heterogeneous effects across Gulf and non-Gulf countries. Overall, the findings suggest that cryptocurrency market developments may have differential impacts on stock market returns depending on country-specific financial conditions (Sami & Abdallah, 2020).

Another study examined the effect of Bitcoin on inflation using monthly data. Based on monthly data on Bitcoin trading volume, as the most widely traded and accepted digital currency, and the Consumer Price Index (CPI) in the United States, which is considered one of the most reliable measures of inflation, the results

showed that the inflation rate does not have a significant impact on the supply of traded Bitcoin. Ultimately, changes in inflation may themselves be a source of instability (Bendiba, 2023).

In the next study, the effects of financial instability on Iran's macroeconomic variables during the period 1360–1400 were investigated using the Time-Varying Vector Autoregression (TVP-VAR) method. The results showed a significant relationship between financial instability and macroeconomic variables. Financial instability shocks led to increases in interest rates, inflation, exchange rates, and liquidity growth, while simultaneously reducing consumption, investment, and GDP growth. The study concluded that financial instability results from inefficiencies in resource allocation and disruptions in the flow of financial resources from savers to investors (Mohammadifard, Mehrara, and Barkhordari, 2023).

A number of studies have shown that cryptocurrencies can significantly influence financial markets, including stock markets, highlighting their growing role in financial system dynamics (Corbet et al., 2019).

A study using panel data from 37 countries during the period 2020–2023 examined the factors influencing cryptocurrency adoption as well as its economic and social consequences. Under conditions of monetary and exchange-rate instability, individuals tend to adopt digital currencies more readily. However, the study found a negative relationship between cryptocurrency adoption and economic growth, indicating that countries with higher economic growth rates tended to exhibit lower levels of cryptocurrency adoption (Gao et al., 2025).

In a subsequent study using quarterly data from Nigeria from 2012 to 2019, the relationship between cryptocurrencies and economic growth was examined. The results obtained from the Engle–Granger and Dynamic Ordinary Least Squares (DOLS) models revealed a long-run negative relationship between Bitcoin trading volume and GDP. The study suggested that the Nigerian government and the Central Bank of Nigeria should mitigate the negative effects of cryptocurrencies while benefiting from their innovative potential through effective legal and regulatory frameworks (Ngong, 2025).

Another study investigated the effects of cryptocurrency mining on economic growth and unemployment using panel data from the top ten crypto-trader countries over the period 2015–2023 and applying the System Generalized Method of Moments (System GMM). The findings revealed a positive relationship between cryptocurrency mining activities and GDP per capita growth, suggesting that the expansion of mining activities may contribute to economic growth. Furthermore, the results indicated a negative relationship between cryptocurrency mining and unemployment rates, implying that the development of the cryptocurrency sector may support employment generation and economic development (Imran et al., 2024).

Another study assessed the relationship between several national development indicators and cryptocurrency adoption across 137 countries using a linear regression model. The findings indicated that cryptocurrency adoption is positively

associated with indicators such as education, human development, the Gini index, and gross domestic product (Bhimani et al., 2022).

Another study examined the economic significance of cryptocurrency trading using FMOLS and DOLS panel cointegration models, as well as a vector error correction model (VECM), for the period 2013–2020. The results indicated that increased cryptocurrency trading contributed to higher levels of real gross fixed capital formation, gross domestic product, and global economic integration. These findings suggest that the expansion of cryptocurrency trading may stimulate investment activity and support economic growth (Miśkiewicz et al., 2022).

A recent study investigated the macroeconomic and financial determinants of cryptocurrency adoption using data from 165 countries over the period 2019–2021. Employing several econometric and machine-learning techniques, the findings revealed that cryptocurrency adoption is more prevalent in countries with higher levels of economic development, more developed financial markets, and better educational outcomes. The results suggest that economic and financial development play a significant role in shaping the diffusion of cryptocurrencies across countries (Magazzino et al., 2025).

The next study examined the spillover effects of cryptocurrencies on other digital currencies and gold during the pre- and post-COVID-19 periods. The results showed that Bitcoin, as a representative cryptocurrency, exerted the greatest spillover effects on Litecoin, Ethereum, and Dash, while the smallest spillover effects were observed for Dogecoin and Ripple. The study also found that gold serves as a safe-haven asset for investors during periods of market uncertainty (Hajilomoghaddam, Shokri, & Zisti, (2023)).

3.2. Methodological Advances and Asymmetric/Regime-Dependent Evidence

Another line of research has examined the asymmetric effects of macroeconomic shocks on capital markets and financial indicators under crisis and non-crisis conditions. Aliyev et al. (2020) showed that stock markets in the United States respond asymmetrically to negative shocks, with stronger reactions than those observed for positive shocks. This difference becomes even more pronounced during periods of financial crisis.

Omane-Adjepong and Alagidede (2021) showed that major cryptocurrencies, including Bitcoin, exhibit asymmetric volatility behavior that differs from that observed in traditional financial markets.

The literature on macroeconomic fluctuations provides substantial evidence that economic activity and inflation respond asymmetrically to different types of shocks, with negative shocks typically having stronger and more persistent adverse effects on output than positive shocks of comparable magnitude (Kandil, 2010).

Furthermore, evidence from regime-switching VAR literature suggests that macroeconomic and monetary policy shocks can have asymmetric effects depending on the state of the economy, with stronger impacts typically observed during adverse economic regimes (Kole & van Dijk, 2023).

This empirical evidence suggests that asymmetric and regime-switching models provide a more appropriate framework than standard linear models for analyzing the nonlinear behavior of variables in response to shocks. Consequently, this body of research provides a methodological foundation for employing the Markov-Switching model to analyze the relationship between Bitcoin, economic growth, and financial stability, since sudden fluctuations and major shocks in cryptocurrency markets may be associated with asymmetric responses and regime-dependent behavior in macroeconomic variables.

3.3. Research Gap

Despite the growing literature on cryptocurrency markets, financial stability, and economic growth, previous studies have largely examined these relationships separately, focused on individual countries or traditional financial-market linkages, or employed linear and single-regime econometric approaches. Limited attention has been given to the joint regime-dependent interaction among financial stability, economic growth, and Bitcoin market capitalization within a panel framework for OECD economies. The present study addresses this gap by employing a Markov-Switching Panel VAR framework to examine whether these dynamic relationships differ across macro-financial regimes.

4. The Model and Discussion

4.1. The Model and Data Analysis

In this study, the Markov-Switching Panel Vector Autoregression (MS-PVAR) econometric method is employed to examine fluctuations in business cycles. The Markov-Switching method, as a modern econometric tool, is capable of evaluating the relationships among variables within a flexible nonlinear framework during different phases of business cycles. In this model, changes in regimes and variations in the behavior of variables occur endogenously and flexibly over time.

The Vector Autoregression (VAR) model is one of the most widely used time-series models, in which all variables are treated as endogenous. Each variable is estimated based on its own lagged values as well as the lagged values of the other variables included in the model.

If the time series under investigation is assumed to experience regime changes over time, the assumption of constant parameters in the standard VAR model becomes inappropriate. In such cases, Markov-Switching VAR (MS-VAR) models can be employed. The structure and application of these models are described below.

Nonlinear models were first introduced by Hamilton (1989) to study the nonlinear behavior of variables and their relationships with business cycles. Following Hamilton's contribution, Markov-Switching models became widely used in economic and financial analyses. The MS-VAR framework was later developed and examined by (Krolzig 1997, Krolzig1999).

In the Markov-Switching Vector Autoregression model, the model parameters depend on the regime variable, denoted by (St.), and only the probabilities associated with each regime can be estimated. To complete the modeling process, it is necessary to specify how regime transitions occur. In the Markov-Switching framework, it is assumed that (St.) is generated by a first-order Markov process, which can be expressed as follows:

$$PT\left\{ S_t|[S_{t-1}]_{j=1}^{n}, [Y_{t-1}]_{j=1}^{n} \right\} = PT\{S_t|S_{t-1};\rho\} \quad (1)$$

Where (P) denotes a vector consisting of the parameters of the regime probabilities. By arranging these probabilities in an (n \times n) matrix, the transition probability matrix is obtained. By allowing the model parameters to vary across different regimes, the standard VAR model is transformed into a Markov-Switching VAR (MS-VAR) model, which can be expressed as follows:

$$y_t = \begin{cases} v_1 + A_{11}\, y_{t-1} + \cdots + A_{P1}\, y_{t-p} + \sum_{1}^{\frac{1}{n}} u_t, if\ s_t = 1 \\ v_{t1} + A_{1n}\ y_{t-1} + \cdots + A_{pn} y_{t-p} + \sum_{1}^{\frac{1}{n}} u_t, if\ s_t = n \end{cases} \quad (2)$$

The Markov-switching Vector Autoregression (MS-VAR) framework was originally developed to capture nonlinear relationships and regime-dependent dynamics in time-series data. However, since this study examines the dynamic interactions among variables across multiple OECD countries, a panel extension of the Markov-switching framework is required. Therefore, the Markov-switching Panel Vector Autoregression (MS-PVAR) model is employed, which combines the advantages of VAR models in capturing dynamic interactions among variables with the ability of panel models to incorporate cross-country heterogeneity. This framework allows the analysis of how the relationships among variables differ across recessionary and expansionary regimes.

Following this extension, the MS-PVAR framework allows the parameters of the VAR system to vary across unobserved regimes, thereby capturing nonlinear and asymmetric relationships among variables under different economic conditions. The model is specified as:

$$Y_{i,t} = A_{s_t} Y_{i,t-1} + B_{s_t} X_{i,t} + u_{i,t} \quad (3)$$

Here, (i) denotes countries, (t) represents time periods, and (s_t) denotes the common latent regime in the pooled MS-PVAR framework. The latent regime follows a first-order Markov process over time and is shared by all countries within a given year. Accordingly, the regime-specific coefficients are common across countries in each year, and the model does not estimate separate country-specific transition matrices or independent country-specific Markov processes.

Since the regime variable is latent, the model parameters were estimated using a customized Expectation-Maximization (EM) algorithm developed in the R

environment. The estimation procedure consists of two iterative steps .In the E-step, the probabilities associated with the common latent regime are estimated conditional on the current parameter estimates and the pooled panel likelihood. In the M-step, regime-specific coefficient matrices and covariance matrices are updated using these posterior probabilities. The iterations continue until convergence is achieved.

The empirical analysis is conducted using annual panel data for 36 OECD member countries over the period 2015–2023. The initial balanced panel consists of 324 country-year observations. After constructing the one-period lagged variables required by the VAR (1) specification, the estimation sample contains 288 observations, corresponding to 36 countries over eight annual periods. This distinction is maintained when describing the dataset and the final estimation sample.

The empirical model includes three endogenous variables: the Financial Stability Index (FSI), economic growth (GDGrowth), and the logarithm of Bitcoin market capitalization (logBIT). The endogenous variable vector is defined as (Y_{i,t}=(FSI_{i,t}, GDGrowth_{i,t}, logBIT_{i,t})'). The vector of control variables is defined as (X_{i,t}=(InterestRate_{i,t}, Unemployment_{i,t})'), comprising the interest rate and unemployment rate.

logBIT: The natural logarithm of Bitcoin market capitalization. Bitcoin market capitalization data were obtained from CoinMarketCap. Given the substantial variation in Bitcoin market capitalization over time, a logarithmic transformation was applied to reduce scale effects and improve the statistical properties of the series. Since Bitcoin is a global asset, annual logBIT values are identical across the 36 OECD countries. Consequently, its coefficient captures the relationship between changes in global Bitcoin market capitalization and financial and macroeconomic variables in the pooled OECD sample, with identification arising from time-series rather than cross-country variation. The common nature of this variable may also contribute to cross-sectional dependence in the panel system, which is taken into account when interpreting the MS-PVAR estimates.

FSI and FSI2: Two alternative versions of the Financial Stability Index constructed using different weighting methods.

GDGrowth: Economic growth indicator.

To account for other macroeconomic influences, the final empirical specification also includes two control variables: the interest rate and the unemployment rate. These variables were selected because they are widely recognized in the literature as important macroeconomic determinants of financial stability and economic growth. The interest rate captures monetary policy conditions and the cost of capital, whereas the unemployment rate reflects labor market conditions and aggregate economic activity. The final specification was selected based on the principles of model stability, estimation reliability, and parsimony. The Financial Stability Index (FSI) was constructed based on previous studies and the existing literature. In this study, financial stability is represented by four dimensions: capital adequacy, asset quality, earnings and profitability, and

liquidity. The classification of the indicators into these dimensions follows Al-Rjoub (2021), which also guided the initial selection of indicators. However, some indicators were excluded because of overlap with other indicators or the lack of sufficiently comparable data for the 36 OECD countries over the 2015–2023 period. To ensure consistency in data sources and cross-country comparability, the final nine sub-indicators were extracted from the IMF Financial Soundness Indicators (FSI) database. These indicators cover all four dimensions of financial stability, and the corresponding indicators and data sources are reported in Table 1.

To ensure comparability across indicators measured on different scales, all sub-indicators were normalized to a [0, 1] range using the Min–Max procedure. For indicators positively associated with financial stability, the standard Min–Max formula was applied, so that higher values indicate greater stability. For indicators negatively associated with financial stability, the complementary Min–Max formula was applied. This procedure reverses the direction of the negatively associated indicators, ensuring that higher normalized values consistently indicate greater financial stability across all dimensions.

Table 1. Financial Stability Sub-Indices and Other Variables Used in the Present Study

Row	index	Variable / Sub-index	Data Source
1	Capital Adequacy	Non-performing loans to total loans	IMF, Financial Soundness indicators
2	Asset Quality	Coverage ratio	IMF, Financial Soundness indicators
3	Asset Quality	Non-performing loans net of reserves to equity	IMF, Financial Soundness indicators
	Asset Quality	Capital adequacy ratio	IMF, Financial Soundness indicators
5	Asset Quality	Leverage ratio	IMF, Financial Soundness indicators
6	Earnings and Profitability	Return on equity	IMF, Financial Soundness indicators
7	Earnings and Profitability	Return on assets	IMF, Financial Soundness indicators
8	Earnings and Profitability	Interest margin to gross income	IMF, Financial Soundness indicators
9	Liquidity	Liquidity ratio	IMF, Financial Soundness indicators
10	Macroeconomic control	GDP growth	OECD
11	Macroeconomic control	Unemployment rate	OECD
12	Macroeconomic control	Interest rate	Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis; originally sourced from OECD Main Economic Indicators
13	Cryptocurrency variable	Bitcoin market capitalization(logBIT)	CoinMarketCap

Source: *Author's compilation based on the IMF, OECD, Federal Reserve Economic Data (FRED), and CoinMarketCap. The classification of financial stability dimensions follows Al-Rjoub (2021)*

Following normalization, the indicators within each dimension were aggregated using their arithmetic mean to obtain four dimension-specific sub-

indices. These sub-indices were then combined using two alternative weighting schemes. For the baseline FSI, equal weights of 25% were assigned to each of the four dimensions. For the alternative FSI2, dimension-specific weights derived from Principal Component Analysis (PCA) were applied. The weights used in both approaches are reported in Table 2. The PCA procedure and corresponding results are reported in Appendix A. Comparing these two indices provides a robustness assessment of the baseline results under an alternative weighting scheme .The Markov-Switching Pooled VAR model was then estimated for each specification.

Table 2. Weights Assigned to the Four Financial Stability Dimensions under the Equal-Weight and PCA-Based Methods

Row	Financial stability dimension	Equal weight method	PCA-based FSI2 weight
1	(CA)Capital adequacy	0.25	0.170213
2	(EQ)Earnings and Profitability	0.25	0.185305
3	(LQ) Liquidity	0.25	0.386232
4	(AQ)Asset quality	0.25	0.258249

***Source**: Research findings*

The descriptive statistics of the variables examined over the period 2015–2023 provide an overview of the distributional characteristics of the cryptocurrency market, the real economy, and financial stability across the OECD countries included in the sample. The results indicate that Bitcoin-related variables, including Bitcoin price and the logarithm of market capitalization (logBIT), exhibit substantial variation over the study period. These descriptive patterns highlight the considerable fluctuations in the cryptocurrency market but do not, by themselves, establish that Bitcoin generates short-term financial shocks.

From the perspective of the cryptocurrency market, Bitcoin prices exhibit a considerable difference between their mean and median values, suggesting a positively skewed distribution in which periods of sharp price increases influence the overall distribution. The wide range of observed prices and relatively high standard deviation further reflect substantial fluctuations in Bitcoin prices during the sample period. Similarly, the dispersion of logBIT indicates considerable variation in Bitcoin market capitalization over time. Unlike Bitcoin price, which reflects the market value of an individual unit, logBIT captures changes in the overall size of the Bitcoin market and provides a measure of its changing market scale.

Regarding the real economy, the economic growth rates of OECD countries exhibit a skewed distribution, as indicated by their positive skewness value. The high kurtosis and Jarque–Bera statistic further suggest that the distribution departs substantially from normality, reflecting the presence of extreme observations and unusually large deviations from average growth rates. These characteristics are consistent with the possibility that exceptional economic events and crisis periods generated substantial fluctuations in economic performance across the sample countries.

The Financial Stability Index constructed in this study exhibits a relatively moderate distribution within the sample. Its mean value should be interpreted in

relative terms and does not represent an absolute threshold for financial stability. Higher values indicate relatively stronger financial stability conditions compared with lower values within the sample. The relatively low skewness and kurtosis values suggest that the distribution of the Financial Stability Index is approximately symmetric, with a degree of kurtosis only slightly above that of a normal distribution. Furthermore, the Jarque–Bera test does not reject the hypothesis of normality for the Financial Stability Index at the 5% significance level.

A comparison of the descriptive statistics reveals substantial differences in the distributional characteristics of the research variables. In particular, GDP and the interest rate exhibit pronounced deviations from normality, while Bitcoin price, economic growth, and financial stability display different degrees of dispersion and asymmetry. These differences highlight the importance of considering the distributional characteristics of the variables when examining their economic relationships. Nevertheless, descriptive statistics cannot identify the direction, magnitude, or dynamic nature of the relationships among Bitcoin market capitalization, economic growth, and financial stability. Therefore, the Markov-Switching Panel VAR framework provides an appropriate approach for investigating their dynamic interactions and potential regime-dependent associations. Table 3 presents the descriptive statistics of the research variables.

Table 3. Descriptive Statistics of the Study Variables

Statistic	FSI	GDP **USD billion**	logBIT	BITPrice	GDGrowth	Interestrate	Unemloyment
Mean	0.4332	1,460	4.8019	14993.5	2.350470	3.269093	6.758954
Median	0.4283	415	4.8766	7622.08	2.330650	1.613121	5.890500
Maximum	0.9783	27,400	7.0722	46306.4	24.47525	46.41700	24.98100
Minimum	0.0642	17.5	1.3374	271.952	-11.16730	-0.732500	2.015000
Std. Dev.	0.1438	3,67۰	1.8529	15104.8	3.633676	5.389632	3.644136
Skewness	0.1592	5.1357	—	0.89348	0.065247	3.802626	1.890713
Kurtosis	3.33577	30.4654	—	2.468689	8.891488	22.52293	7.856735
Jarque–Bera	2.89175	11608.0	—	46.91945	468.8099	5926.293	511.4754
Observations	324	324	324	324	324	324	324

Note: *GDP and Bitcoin price (BITPRICE) are reported for descriptive purposes and are not included as separate variables in the final MS-PVAR specification. The endogenous variables in the final model are FSI, GDGrowth, and logBIT, while the interest rate and unemployment rate are included as control variables.*
Source*: Author's calculations based on data from the IMF, OECD, and coinMarketCap using R software."*

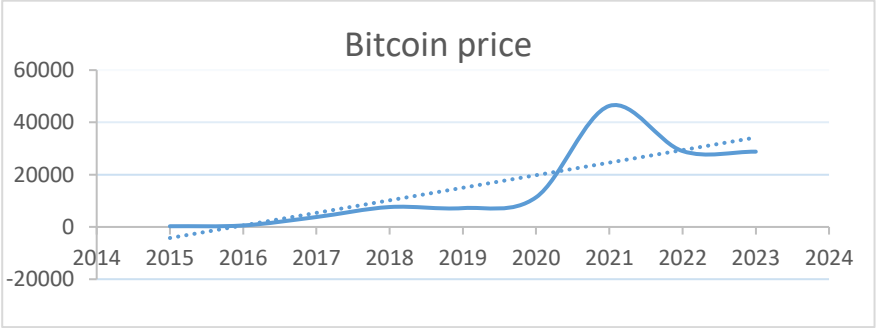

Chart No. 1. Bitcoin price changes during the period 2015-2023
Source: *Author's compilation based on CoinMarketCap data*

4.2. Model Estimation

Prior to estimating the Markov-Switching Pooled VAR model, several preliminary diagnostic procedures were conducted, including stationarity tests and regime specification analysis. Among these procedures, examining the stationarity properties of the variables is a fundamental requirement to avoid spurious regression relationships and ensure the reliability of the estimated nonlinear model.

Accordingly, panel unit root tests were conducted for the variables included in the empirical analysis, namely Bitcoin market capitalization in logarithmic form (logBIT), economic growth (GDGrowth), the Financial Stability Index (FSI), the interest rate, and the unemployment rate. To examine the stationarity properties of these variables, the Levin–Lin–Chu (LLC) and Maddala–Wu Fisher-ADF panel unit root tests were employed. In both tests, the null hypothesis assumes the presence of a unit root, whereas the alternative hypothesis indicates stationarity.

The results reported in Table 4 indicate that the null hypothesis of a unit root is rejected for all variables at conventional significance levels, confirming that the variables are stationary in levels. For the interest-rate variable, the LLC test could not be computed because the interest-rate series is time-invariant for Estonia. Therefore, the Fisher-ADF test was used to assess the stationarity of the interest-rate variable after excluding the time-invariant country from this specific test. The Fisher-ADF result strongly rejects the unit-root null hypothesis, confirming that the interest-rate series is stationary at levels. For unemployment, both the LLC and Fisher-ADF tests reject the unit-root null hypothesis. Overall, the stationarity results support the use of the variables in the Markov-Switching Panel VAR model without additional differencing. These findings also reduce the potential risk of spurious regression relationships.

Table 4. Results of Panel Unit Root Tests for the Model Variables

Variable	LLC Statistic	LLC p-value	Fisher-ADF Statistic	Fisher-ADF p-value	Conclusion
FSI	−4.7503	0.000001	139.98	0.000003	Stationary
logBIT	−17.3300	<0.0001	294.89	<0.0001	Stationary
GDGrowth	−12.7510	<0.0001	333.79	<0.0001	Stationary
Interest Rate	—	—	602.13*	<2.2e−16*	Stationary
Unemployment	−10.152	<2.2e−16	400.82	<2.2e−16	Stationary

**For the interest-rate variable, the LLC test could not be computed because the series is time-invariant for Estonia. The Fisher-ADF test was therefore computed using the remaining 35 countries. The test strongly rejects the unit-root null hypothesis, indicating stationarity at levels.*
***Source*:** *Author's calculations based on research data.*

Before estimating the nonlinear model, the appropriate panel specification was determined. Given the panel structure of the OECD dataset, the F-Limer (Chow) test was employed to examine whether country-specific fixed effects were statistically significant. The test results indicate that the null hypothesis of no individual-specific effects cannot be rejected, as the F-statistic is 0.31441 with a p-value of 0.9999. Therefore, the country-specific fixed effects are not statistically significant, and the pooled specification is selected as the appropriate panel framework. Accordingly, the nonlinear model is estimated under a pooled panel specification using the Markov-Switching Panel Vector Autoregressive (MS-Pooled VAR) framework.

Table 5. Results of the F-Limer (Chow) Test for Poolability

Test	F-statistic	df1	df2	p-value	Decision
F-Limer (Chow) Test	0.31441	35	247	0.9999	Pooled specification

***Source**: Research findings*

To assess the appropriate lag structure of the Markov-Switching Panel VAR model, alternative lag specifications were initially explored. The VAR (1) specification achieved satisfactory convergence and stable estimation, whereas the VAR (2) specification did not achieve satisfactory convergence and was therefore not retained for the final analysis. Accordingly, the final empirical specification was based exclusively on the converged VAR (1) model.

Table 6. Lag Specification Assessment in the Markov-Switching Panel VAR Model

Lag order	Estimation status	Final specification
VAR (1)	Converged satisfactorily and provided stable parameter estimates	Retained
VAR (2)	Did not achieve satisfactory convergence	Not retained

***Source**: Author's estimation results.*

The VAR (2) specification was explored as an alternative lag structure but was not used for inference because satisfactory convergence was not achieved. Therefore, its likelihood-based information criteria are not used for direct comparison with the converged VAR (1) model. All empirical results reported in this study are based on the converged VAR (1) specification, which also provides a parsimonious and stable model structure.

To determine the optimal number of regimes, alternative Markov-switching specifications with different numbers of regimes were estimated and compared using the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The specification with the lowest information criterion values was selected as the preferred model. Both criteria supported the selection of a two-regime model, which is consistent with the objective of distinguishing recessionary and expansionary economic conditions.

Within this framework, the variables are allowed to switch between unobserved regimes over time. The model parameters, including regression coefficients and error variances, vary across regimes, allowing the model to capture regime-dependent relationships under different economic conditions.

To assess the relative fit of the regime-switching specification, the two-regime MS-PVAR model was compared with the corresponding linear specification using the likelihood-ratio (LR) statistic. The LR value was 2025.726, indicating a substantially better fit of the regime-switching model relative to the linear alternative. However, because the asymptotic distribution of LR statistics in Markov-switching models is non-standard, the LR statistic is reported as a model-comparison measure rather than interpreted as a conventional significance test.

Following the selection of the pooled panel specification, the final nonlinear model was estimated in R using an EM-based estimation procedure for the pooled Markov-Switching Panel VAR framework. The estimation process provides regime-specific coefficients, variance parameters, and regime probabilities. The results presented in the following section are based on this final estimation.

In the MS-Pooled VAR framework, financial stability, economic growth, and Bitcoin market capitalization are treated as endogenous variables. Each variable is modeled as a function of its own lagged value, the lagged values of the other endogenous variables, and the lagged control variables. The estimated one-lag MS-PVAR model can be represented as follows:

(4)

$$\begin{aligned}
\mathrm{FSI}_{i,t} &= \alpha_{1,s_t} + a_{11,s_t}\mathrm{FSI}_{i,t-1} + a_{12,s_t}\mathrm{GDGrowth}_{i,t-1} + a_{13,s_t}\mathrm{logBIT}_{i,t-1} \\
&\quad + B_{1,s_t}^{T}X_{i,t-1} + \varepsilon_{1,i,t} \\
\mathrm{GDGrowth}_{i,t} &= \alpha_{2,s_t} + a_{21,s_t}\mathrm{FSI}_{i,t-1} + a_{22,s_t}\mathrm{GDGrowth}_{i,t-1} + a_{23,s_t}\mathrm{logBIT}_{i,t-1} \\
&\quad + B_{2,s_t}^{T}X_{i,t-1} + \varepsilon_{2,i,t} \\
\mathrm{logBIT}_{i,t} &= \alpha_{3,s_t} + a_{31,s_t}\mathrm{FSI}_{i,t-1} + a_{32,s_t}\mathrm{GDGrowth}_{i,t-1} + a_{33,s_t}\mathrm{logBIT}_{i,t-1} \\
&\quad + B_{3,s_t}^{T}X_{i,t-1} + \varepsilon_{3,i,t}
\end{aligned}$$

Here, (X_{i,t-1}) denotes the vector of lagged control variables, comprising the interest rate and unemployment rate for country (i) in period (t-1). Consistent with the VAR(1) specification, the control variables enter each equation with a one-period lag.

In the adopted specification, regime transitions are assumed to follow a first-order Markov process with constant transition probabilities. Therefore, the model focuses on estimating regime-dependent relationships among the variables rather than modeling the determinants of regime transitions.

The Markov-Switching Pooled Vector Autoregressive (MS-PVAR) model was estimated in the R environment using a customized estimation procedure. First, the balanced panel dataset was prepared, Bitcoin market capitalization was transformed into logarithmic form (logBIT), and the required lagged variables were constructed. Based on lag-length selection criteria, a VAR (1) specification was adopted. The model includes Financial Stability Index (FSI), Economic Growth (GDGrowth), and Bitcoin market capitalization (logBIT) as endogenous variables, while Interest Rate and Unemployment are incorporated as exogenous controls. Two latent regimes were specified to capture recessionary and expansionary states of the economy. Initial parameter values were obtained from a linear pooled VAR (1) model. Model estimation was then carried out using the Expectation–Maximization (EM) algorithm. In the E-step, probabilities associated with the common latent regime were estimated conditional on the current parameter estimates and the pooled panel likelihood. In the M-step, regime-specific coefficient matrices, covariance matrices, and transition probabilities were updated. The iterative procedure continued until convergence of the log-likelihood function was achieved. Following convergence, the smoothed posterior regime probabilities were used to summarize the estimated regime classification over the effective sample. These probabilities refer to the common latent regime and do not imply separate country-specific regime processes.

The standard errors of the regime-specific coefficient estimates were calculated within the estimation procedure and were used to assess statistical significance. The estimated regime-specific parameters were subsequently employed in the impulse response function (IRF) and forecast error variance decomposition (FEVD) analyses.

To assess the possibility of multicollinearity in the final MS-PVAR specification, Variance Inflation Factors (VIFs) were calculated for the explanatory variables. As reported in Table (7), all VIF values are close to one and well below the conventional thresholds of 5 and 10. These results indicate that there is no evidence of problematic multicollinearity among the explanatory variables in the final model.

Table 7. Variance Inflation Factor (VIF) Diagnostics for the Final MS-PVAR Specification

Variable	VIF
FSI(-1)	1.034
GDGrowth(-1)	1.127
logBIT(-1)	1.047
Interest Rate	1.144
Unemployment	1.078

***Source*:** *Author's calculations based on the final MS-Pooled VAR specification.*

To assess the adequacy of the final MS-Pooled VAR specification, the Ljung–Box test was applied to the residuals of each endogenous-variable equation. As reported in Table (8), the test results do not indicate statistically significant first-order autocorrelation in the residuals of the FSI, GDGrowth, or logBIT equations, as all p-values exceed the 5% significance level. These results support the adequacy of the dynamic specification of the final model.

Table 8. Ljung–Box Test for Residual Autocorrelation

Equation	Ljung–Box Q(1)	p-value	Conclusion
FSI	1.5309	0.2160	No significant autocorrelation
GDGrowth	2.3818	0.1228	No significant autocorrelation
logBIT	0.2283	0.6328	No significant autocorrelation

***Note**: The Ljung–Box test is applied to the residuals of the final MS-PVAR model estimated using logBIT.*

The MS-PVAR model was initially estimated using the Financial Stability Index constructed through the equal-weighting approach. The results presented in Tables (1-9), (2-9) indicate the existence of two distinct economic regimes. Since the regimes are unobservable, their economic interpretation is based on regime-specific characteristics, including economic growth dynamics, error variances, transition probabilities, and regime-specific coefficients.

The regression results for the recessionary and expansionary regimes are reported in Tables (1-9), (2-9) and (1-10), (2-10) respectively, using two alternative measures of the Financial Stability Index. These estimations examine the regime-dependent relationships of Bitcoin market capitalization on financial stability and economic growth across different economic states.

The identified regimes represent common latent nonlinear regimes for the pooled OECD sample and should not be interpreted as country-specific or synchronized business-cycle regimes. Instead, they capture common nonlinear economic conditions affecting the countries included in the pooled sample.

4.3. Results and Discussion

As shown in Tables 9-1, 9-2, 10-1, and 10-2, the results of the Markov-switching pooled VAR model indicate that the relationships between Bitcoin market capitalization, financial stability, and economic growth vary across the two

regimes.

During the recession regime, Bitcoin market capitalization in logarithmic form (logBIT) has a negative and statistically significant association with financial stability with a one-period lag. The estimated coefficient (-0.0413) indicates that an increase in Bitcoin market capitalization is associated with a decline in the Financial Stability Index. In the expansion regime, Bitcoin also exhibits a negative and statistically significant association with financial stability at a one-period lag, although the magnitude of the coefficient (-0.0152) is smaller than that observed in the recession regime .The negative relationship between Bitcoin and financial stability may be consistent with the speculative characteristics and high volatility of cryptocurrency markets. During periods of economic uncertainty, investors may increase their exposure to alternative assets such as Bitcoin, which may amplify market uncertainty and create additional channels of financial risk. However, the relatively small magnitude of the estimated coefficients suggests that, in OECD economies with developed financial systems and stronger regulatory institutions, Bitcoin does not represent a dominant source of systemic financial instability.

The results further indicate that the negative association between Bitcoin and financial stability is stronger during recessionary periods compared with expansionary periods. This finding highlights the importance of considering nonlinear and regime-dependent relationships when analyzing the interaction between cryptocurrency markets and macro-financial conditions.

The Association of Bitcoin with Economic Growth under the Equal -Weight Financial Stability Index: The results indicate that, in the first regime, Bitcoin has a positive but statistically insignificant association with economic growth at a one-period lag. The estimated coefficient (0.0900) indicates that the relationship between Bitcoin market capitalization and economic growth is not statistically significant during recessionary periods.

This result may indicate that although cryptocurrency markets attract financial resources, their connection with productive economic activities remains limited in developed economies. Therefore, fluctuations in Bitcoin market capitalization may not immediately translate into measurable changes in aggregate economic growth.

In contrast, in the expansion regime, Bitcoin has a negative and statistically significant association with economic growth at a one-period lag. The estimated coefficient (-0.3165) indicates that higher Bitcoin market capitalization is associated with lower economic growth. This relationship may be consistent with the possibility that rapid growth of speculative asset markets could temporarily alter capital allocation patterns. Nevertheless, given the institutional strength of OECD economies, the magnitude of this association should be interpreted cautiously.

The association of the interest rate with the model variables was examined using the Financial Stability Index constructed with equal weights. The results indicate that, in the first regime, the association between the interest rate and Bitcoin is positive but statistically insignificant. The association between the interest rate and financial stability is also statistically insignificant, while its association with economic growth is positive and statistically significant. Specifically, a one-

percentage-point increase in the interest rate is associated with an approximately 0.238-percentage-point increase in economic growth. Although the positive relationship between interest rates and economic growth may appear inconsistent with conventional monetary theory, it may reflect the economic conditions of OECD countries, where higher interest rates can be associated with stronger economic performance, monetary normalization, and improved investor confidence rather than only restrictive monetary policy.

In the expansion regime, the associations of the interest rate with Bitcoin, financial stability, and economic growth are statistically insignificant.

Regarding the unemployment rate, the estimated coefficients are generally statistically insignificant across both regimes and all three equations, suggesting no strong evidence of a systematic relationship between unemployment and financial stability, economic growth, or Bitcoin market capitalization in the pooled OECD sample. In Regime 1, the unemployment coefficient in the GDP growth equation is negative (-0.142752) and marginally significant at the 10% level ($p = 0.071$), indicating a weak negative association between unemployment and economic growth. However, this relationship is not statistically significant at the conventional 5% level. In Regime 2, the corresponding coefficient remains negative (-0.036796) but is statistically insignificant ($p = 0.112$). The coefficients in the FSI and logBIT equations are also statistically insignificant in both regimes. Overall, these findings suggest that the relationship between unemployment and the endogenous variables is relatively weak and does not exhibit robust statistical significance across the two regimes.

The robustness analysis using the PCA-based Financial Stability Index (FSI2) provides partially consistent evidence with the equal-weight specification. In Regime 1, the association between lagged Bitcoin market capitalization and financial stability remains negative and statistically significant under the FSI2 specification, supporting the main finding for this regime. However, the results differ in Regime 2, where the corresponding coefficient under FSI2 is positive but statistically insignificant. Thus, the robustness of the estimated relationship depends on the regime and the index-construction method. Overall, the PCA-based specification supports the negative association between Bitcoin market capitalization and financial stability in Regime 1, but does not establish an equivalent relationship in Regime 2.

Under the second specification, in which the Financial Stability Index is constructed using Principal Component Analysis (PCA), the relationships between the interest rate, unemployment, financial stability, economic growth, and Bitcoin market capitalization were examined across the recessionary and expansionary regimes. The results indicate that most of the estimated coefficients associated with the control variables are statistically insignificant, although some differences emerge across regimes and equations.

The association between the interest rate and Bitcoin market capitalization is negative in both regimes but statistically insignificant at the 5% level. Specifically, the coefficient on the lagged interest rate is -0.005716 ($p=0.535$) in the recessionary

regime and −0.017491 (p=0.062) in the expansionary regime. Although the latter estimate is statistically insignificant at the 5% level, it provides relatively weak evidence of a negative association at the 10% level. Overall, the estimates do not establish a statistically significant relationship between lagged interest rates and Bitcoin market capitalization at the conventional 5% threshold.

The association between the interest rate and financial stability is positive in the recessionary regime (0.001922, (p=0.347)) and negative in the expansionary regime (−0.003026, (p=0.806)). Neither coefficient is statistically significant. Consequently, the PCA-based specification does not provide sufficient evidence of a systematic relationship between lagged interest rates and financial stability in either regime.

The relationship between the interest rate and economic growth is positive and statistically significant in the recessionary regime, with a coefficient of (0.076538 (p=0.035). In the expansionary regime, the coefficient is also positive (0.091681), but statistically insignificant (p=0.439). Although the positive association in the recessionary regime differs from the conventional expectation that higher interest rates constrain economic activity, it should be interpreted as a regime-specific empirical association rather than as evidence of a causal effect. It may reflect the endogenous response of monetary policy to prevailing economic conditions and the interaction of interest rates with other macroeconomic factors.

The association between unemployment and Bitcoin market capitalization is positive in both the recessionary and expansionary regimes. The estimated coefficients are 0.008642 (p=0.381) and 0.011418 (p=0.475), respectively. Neither estimate is statistically significant at the 5% level. Thus, the results do not provide sufficient evidence of a systematic relationship between lagged unemployment and Bitcoin market capitalization under the PCA-weighted specification.

The association between unemployment and financial stability is negative in the recessionary regime (−0.001285, (p=0.557)) and positive in the expansionary regime (0.016809, (p=0.424)). Both coefficients are statistically insignificant. Therefore, despite the difference in their estimated signs, the results do not establish a statistically significant relationship between lagged unemployment and financial stability in either regime.

Finally, the coefficient on lagged unemployment in the economic growth equation is positive in the recessionary regime (0.075239, (p=0.053)) and close to zero in the expansionary regime (0.002220, (p=0.991)). Neither coefficient is statistically significant at the 5% level. Although the recessionary-regime estimate is close to the conventional significance threshold, it does not provide sufficient evidence of a systematic relationship between lagged unemployment and subsequent economic growth.

The sample period encompasses several major macro-financial and cryptocurrency market events, including the COVID-19 pandemic, the 2018 cryptocurrency market downturn, and the 2022 FTX collapse. These events may have influenced the financial and macroeconomic environment and may therefore be reflected in the regime-dependent dynamics identified by the MS-PVAR model.

However, the objective of this study is to examine regime- dependent relationships rather than to identify the causal effects of individual events. A COVID-excluded subsample estimation was not conducted because the annual sample is relatively short, and this limitation is acknowledged. Accordingly, the identified regimes should not be interpreted as being driven exclusively by COVID-19 or any single cryptocurrency market event.

To assess the economic significance of the estimated relationships, the magnitude of the coefficients was evaluated using a one-standard-deviation increase in logBIT. The standard deviation of logBIT is 1.852945. Accordingly, a one-standard-deviation increase in logBIT is associated with an approximately 0.077-unit decline in the Financial Stability Index (FSI) in Regime 1 and a 0.028-unit decline in Regime 2. Regarding economic growth, the same increase in logBIT is associated with an approximately 0.167-percentage-point increase in GDP growth in Regime 1; however, this coefficient is statistically insignificant. In Regime 2, a one-standard-deviation increase in logBIT is associated with an approximately 0.587-percentage-point decline in GDP growth, and this relationship is statistically significant. These magnitudes provide additional evidence on the practical significance of the estimated relationships beyond statistical significance, suggesting that the effects of Bitcoin market capitalization on financial stability and economic growth vary across regimes in both magnitude and statistical significance.

Table 9-1. Results of the MS-Pooled VAR Model under the Equal-Weight Financial Stability Index (FSI): Regime 1 (Recession)

Variable	FSI Equation				GDP Growth Equation				logBIT Equation			
	Coefficient	Std. Error	t-Statistic	Prob	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.140425	0.048121	2.918143	0.003805	2.399179	0.989114	2.425584	0.015912	2.853799	0.078674	36.273807	0.000000
FSI(-1)	0.970868	0.016115	60.247294	0.000000	0.590945	0.331231	1.784086	0.075485	0.159856	0.026346	6.067571	0.000000
GDGrowth(-1)	-0.008554	0.002855	-2.996414	0.002975	-0.267452	0.058675	-4.55815	0.000008	-0.052871	0.004667	-11.32869	0.000000
logBIT(-1)	-0.041269	0.007580	-5.444722	0.000000	0.090017	0.155797	0.577785	0.563870	0.635076	0.012392	51.248721	0.000000
Interest Rate	-0.000213	0.002668	-0.079681	0.936548	0.237707	0.054847	4.334025	0.000020	0.006799	0.004362	1.558475	0.120242
Unemployment	0.005463	0.003833	1.425176	0.155212	-0.142752	0.078785	-1.81192	0.071062	-0.009629	0.006267	-1.536599	0.125513

Source: *Computed by the author using R software based on OECD panel data (2015–2023) and the estimated MS-Pooled VAR model*

Table 9-2. Results of the MS-Pooled VAR Model under the Equal-Weight Financial Stability Index (FSI): Regime 2 (Expansion)

Variable	FSI Equation				GDP Growth Equation				logBIT Equation			
	Coefficient	Std. Error	t-Statistic	Prob	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.422780	0.032930	12.83878	0.000000	2.065721	0.308033	6.706174	0.000000	1.435613	0.050292	28.545627	0.000000
FSI(-1)	0.167066	0.022520	7.418558	0.000000	0.181514	0.210656	0.861661	0.389606	-0.084932	0.034393	-2.469418	0.014126
GDGrowth(-1)	-0.007402	0.005090	-1.45427	0.146983	0.546967	0.047613	11.487641	0.000000	0.007207	0.007774	0.927127	0.354668
logBIT(-1)	-0.015176	0.004429	-3.42649	0.000702	-0.316549	0.041430	-7.640509	0.000000	0.727106	0.006764	107.492410	0.000000
Interest Rate	0.000773	0.001579	0.489565	0.624822	-0.000437	0.014766	-0.029581	0.976422	-0.003640	0.002411	-1.509825	0.132208
Unemployment	0.003799	0.002469	1.538429	0.125065	-0.036796	0.023099	-1.592965	0.112288	-0.000525	0.003771	-0.139325	0.889293

Source: *Computed by the author using R software based on OECD panel data (2015–2023) and the estimated MS-Pooled VAR model*

Table 10-1. Results of the MS-Pooled VAR Model under the Equal-Weight Financial Stability Index (FSI2): Regime 1 (Recession)

Variable	FSI Equation				GDP Growth Equation				logBIT Equation			
	Coefficient	Std. Error	t-Statistic	Prob	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.513968	0.028293	18.166	0.000	2.785067	0.502155	5.546	0.000	1.963025	0.127670	15.376	0.000
FSI(-1)	0.015937	0.004050	3.935	0.000	-0.100141	0.071887	-1.393	0.164	0.000700	0.018277	0.038	0.969
GDGrowth(-1)	-0.008612	0.002168	-3.973	0.000	-0.217185	0.038475	-5.645	0.000	-0.068304	0.009782	-6.982	0.000
logBIT(-1)	-0.019549	0.004226	-4.626	0.000	-0.016783	0.075010	-0.224	0.823	0.731602	0.019071	38.362	0.000
Interest Rate	0.001922	0.002044	0.940	0.347	0.076538	0.036280	2.110	0.035	-0.005716	0.009224	-0.620	0.535
Unemployment	-0.001285	0.002188	-0.587	0.557	0.075239	0.038836	1.937	0.053	0.008642	0.009874	0.875	0.381

Source: *Computed by the author using R software based on OECD panel data (2015–2023) and the estimated MS-Pooled VAR model*

Table 10-2. Results of the MS-Pooled VAR Model under the Equal-Weight Financial Stability Index (FSI2): Regime 2 (Expansion)

Variable	FSI Equation				GDP Growth Equation				logBIT Equation			
	Coefficient	Std. Error	t-Statistic	Prob	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.754878	0.332544	-2.270	0.023	-2.894145	3.198924	-0.905	0.366	2.319206	0.253139	9.162	0.000
FSI(-1)	1.019232	0.071302	14.295	0.000	-0.978820	0.685890	-1.427	0.154	0.084335	0.054276	1.554	0.120
GDGrowth(-1)	-0.062240	0.025825	-2.410	0.016	0.901605	0.248427	3.629	0.000	-0.003817	0.019659	-0.194	0.846
logBIT(-1)	0.038667	0.061068	0.633	0.527	0.002818	0.587451	0.005	0.996	0.640848	0.046486	13.786	0.000
Interest Rate	-0.003026	0.012322	-0.246	0.806	0.091681	0.118529	0.773	0.439	-0.017491	0.009379	-1.865	0.062
Unemployment	0.016809	0.021020	0.800	0.424	0.002220	0.202204	0.011	0.991	0.011418	0.016001	0.714	0.475

Source: *Computed by the author using R software based on OECD panel data (2015–2023) and the estimated MS-Pooled VAR model*

4.3.1. Model Convergence and Stability Analysis

As an additional robustness check, the MS-Pooled VAR model was also estimated with two lags. However, the two-lag specification did not achieve satisfactory convergence of the estimation algorithm. Therefore, the one-lag specification was retained as the final model. To assess the stability of the estimated MS-Pooled VAR model, the regime-specific lag coefficient matrices were examined and their corresponding eigenvalues were calculated. For Regime 1, the eigenvalues were 0.9490, 0.6465, and −0.2570, while for Regime 2, they were 0.7136, 0.5603, and 0.1673. Since the modulus of the largest eigenvalue in each regime is less than unity, the estimated model satisfies the stability condition in both regimes. Therefore, shocks to the system are expected to dissipate over time without generating explosive dynamics. These results confirm the dynamic stability of the relationships among financial stability, economic growth, and Bitcoin market capitalization across both regimes.

Regime1 Lag coefficient matrix $A_1 = \begin{bmatrix} 0.9709 & -0.0086 & -0.0413 \\ 0.5909 & -0.2675 & 0.0900 \\ 0.1599 & -0.0529 & 0.6351 \end{bmatrix}$

Eigenvalues: $\lambda 1 = 0.9490$,$\lambda 2 = 0.6465$, $\lambda 3 = -0.2570$

Regime2 Lag coefficient matrix $A_2 = \begin{bmatrix} 0.1671 & -0.0074 & -0.0152 \\ 0.1815 & 0.5470 & -0.3165 \\ -0.0849 & 0.0072 & 0.7271 \end{bmatrix}$

Eigenvalues: $\lambda 1 = 0.7136$, $\lambda 2 = 0.5603$, $\lambda 3 = 0.1673$

Source: *Author's calculations using R software based on the estimated MS-PVAR model*

4.3.2. Transition Probability Matrix of the MS-Pooled VAR Model:

As reported in Table (11), the transition probability matrix indicates relatively limited regime persistence. The probability of remaining in Regime 1 is 53.81%, while the probability of remaining in Regime 2 is 46.78%. At the same time, the relatively high probabilities of switching to the alternative regime (46.19% from Regime 1 and 53.22% from Regime 2) indicate that transitions between the two regimes occur with considerable frequency. Therefore, the model suggests that the economy under study experiences relatively dynamic transitions between the recessionary and expansionary states, with no evidence of prolonged persistence in either regime. These findings indicate the presence of distinct regime-dependent dynamics and support the appropriateness of the Markov-Switching VARX framework for capturing nonlinear relationships among financial stability, economic growth, and Bitcoin market development

Table 11. Transition Probability Matrix of the MS-Pooled VAR Model

Row	Regime1	Regime2
Regime1	0.5381	0.4619
Regime2	0.5322	0.4678

Source: *Author's calculations using R software based on the estimated MS-Pooled VAR model*

4.3.3. Conditional Estimation Strategy and Inference

Given the computational complexity of estimating the regime-dependent pooled VAR model using a custom algorithm, a conditional estimation strategy was adopted to obtain the model estimates. Previous studies have examined regime-dependent impulse response analysis in Markov-switching VAR models (Ehrmann et al., 2003; Droumaguet, 2012), while Bayesian panel Markov-switching VAR specifications have also been developed in the literature (Billio et al., 2016).

In this study, regime-specific impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) were used to examine the dynamic relationships among Bitcoin market capitalization, financial stability, and economic growth. The IRFs were accompanied by pointwise 95% simulation-based confidence intervals, constructed using a conditional parametric simulation procedure described in the following subsection. The interpretation of these intervals takes into account the conditional nature of the simulation procedure.

4.3.4. Impulse Response Functions and Confidence Intervals

To quantify uncertainty in the impulse response functions (IRFs), pointwise 95% simulation-based confidence intervals were constructed using a conditional parametric simulation procedure with 5,000 replications. In each replication, the regime-specific error covariance matrices ((\Sigma_s)) were simulated from Wishart distributions parameterized to have means equal to the corresponding estimated covariance matrices. The degrees of freedom were set according to the regime-specific posterior-weighted effective sample sizes (153 for Regime 1 and 135 for Regime 2), obtained by aggregating the smoothed posterior regime probabilities across the pooled country-year sample. The regime-specific coefficient matrices ((A_1) and (A_2)) were held fixed at their point estimates, and the IRFs were recomputed using the simulated covariance matrices. The confidence limits were defined by the 2.5th and 97.5th percentiles of the simulated IRF distributions at each horizon. Accordingly, these intervals quantify covariance-matrix uncertainty conditional on the estimated coefficient matrices and the adopted regime classification; they do not account for uncertainty in the coefficient estimates or regime probabilities.

4.3.5. Response of FSI to a log BIT Shock

The impulse response analysis indicates that a positive shock to Bitcoin market capitalization is associated with a negative response of financial stability in both regimes. In Regime 1, the response becomes increasingly negative over the initial horizons, reaching its largest absolute magnitude (approximately −0.125) around horizons 6–7, before gradually moving back toward zero. In Regime 2, the response is also negative but smaller in magnitude, reaching its largest absolute value (approximately −0.023) at horizon 2 and then declining rapidly toward zero.

The response is substantially stronger in Regime 1 than in Regime 2, suggesting that the dynamic association between Bitcoin market capitalization and financial stability is more pronounced in Regime 1. This pattern is consistent with

the regime-specific coefficient estimates reported in Tables 9-1 and 9-2, where the coefficient on lagged logBIT in the FSI equation is more negative in Regime 1 (−0.0413) than in Regime 2 (−0.0152). The reported 95% simulation-based confidence intervals exclude zero at horizons 2–10 in both regimes. This indicates that the estimated responses are statistically distinguishable from zero under the conditional covariance-simulation procedure, although the intervals do not incorporate uncertainty in the coefficient estimates or regime probabilities.

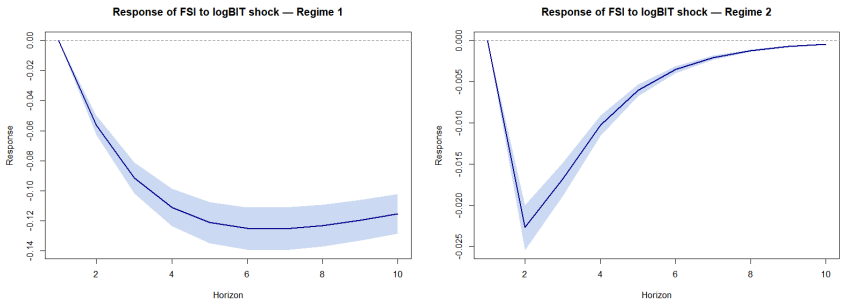

Figure 1. Impulse Response of Financial Stability (FSI) to a Shock in Bitcoin Market Capitalization (logBIT)

***Source**: Author's calculations using R software based on the estimated MS-Pooled VAR model*

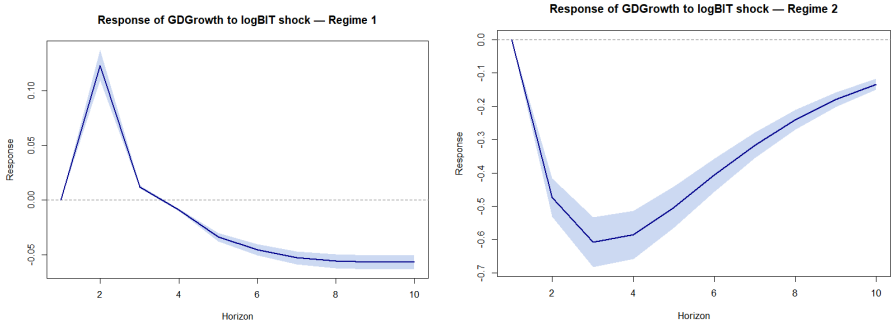

Figure 2. Impulse Response of GDP Growth to a Shock in Bitcoin Market Capitalization (logBIT)

***Source**: Author's calculations using R software based on the estimated MS-Pooled VAR model*

Table 12. Impulse Response of FSI to a logBIT Shock with 95% Confidence Intervals

Horizon	Estimate		Lower95		Upper95	
	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2
1	0	0	0	0	0	0
2	-0.05629	-0.02267	-0.06271	-0.02546	-0.05	-0.02002
3	-0.09145	-0.01677	-0.10188	-0.01883	-0.08122	-0.01481
4	-0.11096	-0.01027	-0.12361	-0.01154	-0.09855	-0.00907
5	-0.12103	-0.00604	-0.13483	-0.00679	-0.10749	-0.00534
6	-0.125	-0.00354	-0.13926	-0.00397	-0.11102	-0.00312
7	-0.12519	-0.00208	-0.13947	-0.00233	-0.11119	-0.00183
8	-0.12305	-0.00123	-0.13709	-0.00138	-0.10929	-0.00109
9	-0.11952	-0.00074	-0.13315	-0.00083	-0.10615	-0.00065
10	-0.1152	-0.00045	-0.12834	-0.0005	-0.10231	-0.00039

Source: *Authors' calculations using R based on the estimated MS-Pooled VAR model.*

4.3.6. Regime-Specific Forecast Error Variance Decomposition (FEVD)

The regime-specific forecast error variance decomposition (FEVD) results reported in Tables 13-1 and 13-2 show that the relative contributions of shocks to Bitcoin market capitalization (logBIT), financial stability (FSI), and economic growth (GDGrowth) differ across the two regimes and forecast horizons.

In Regime 1, the contribution of logBIT shocks to the forecast error variance of FSI increases with the forecast horizon, reaching 9.32% at horizon 10. By comparison, logBIT shocks account for only 0.22% of the forecast error variance of GDGrowth at the same horizon. Thus, Bitcoin market capitalization shocks contribute more to financial stability forecast uncertainty than to economic growth forecast uncertainty in this regime, although FSI's own shocks remain the dominant source of its forecast error variance.

In Regime 2, logBIT shocks account for 0.53% of the forecast error variance of FSI and 7.01% of that of GDGrowth at horizon 10. This contrasts with Regime 1, where the contribution of logBIT shocks is greater for FSI than for GDGrowth. The results therefore indicate that the relative importance of Bitcoin market capitalization shocks differs across regimes, with a larger contribution to financial stability forecast uncertainty in Regime 1 and a larger contribution to economic growth forecast uncertainty in Regime 2.

The decomposition also indicates that own-variable shocks account for most of the forecast error variance of logBIT in both regimes. At horizon 10, its own shocks explain 95.77% of its forecast error variance in Regime 1 and 95.83% in Regime 2. Overall, the FEVD results complement the impulse response analysis by illustrating regime-dependent differences in the relative contributions of Bitcoin market capitalization shocks to forecast uncertainty in financial stability and economic growth. These variance shares should be interpreted as measures of forecast uncertainty rather than as direct evidence of causal effects.

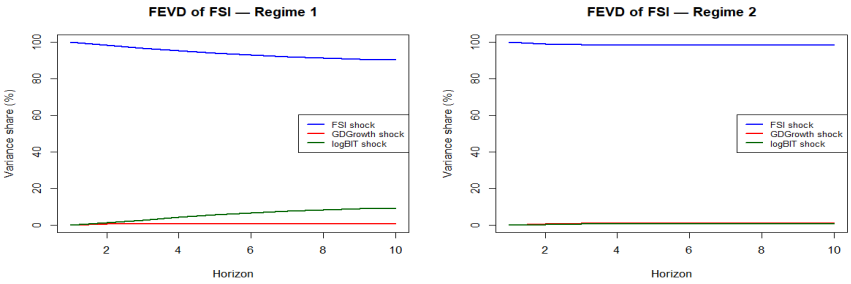

Figure 3. Forecast Error Variance Decomposition of FSI: Regime 1 and Regime 2
***Source**: Author's calculations using R software based on the estimated MS-Pooled VAR model.*

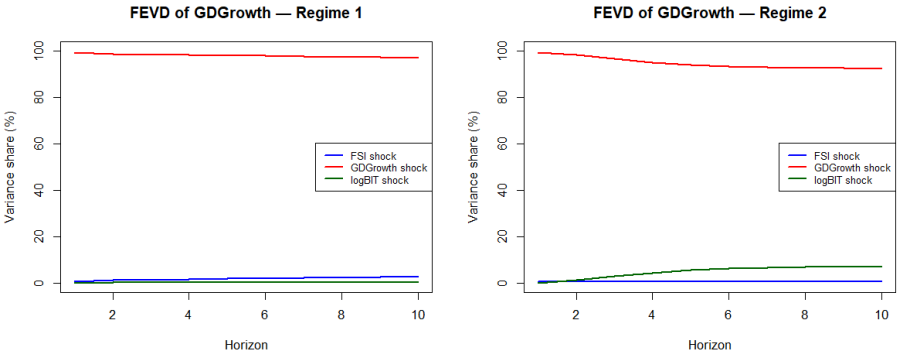

Figure 4. Forecast Error Variance Decomposition of GDgrowth Regime 1and Regime 2
***Source**: Author's calculations using R software based on the estimated MS-Pooled VAR model.*

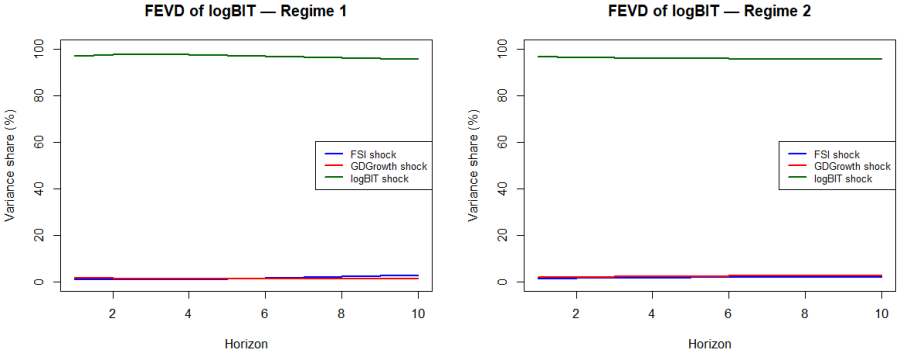

Figure 5. Forecast Error Variance Decomposition of logBIT Regime 1 and Regime 2
***Source**: Author's calculations using R software based on the estimated MS-Pooled VAR model.*

Table 13-1. FEVD Regime1 (%)

Response	Horizon	FSI shock	GD Growth shock	Log BIT shock
FSI	1	100.0	0.0	0.00
	2	98.43	0.4	1.09
	3	96.87	0.4	2.66
	4	95.34	0.4	4.18
	5	94.02	0.48	5.50
	6	92.92	0.4	6.60
	7	92.02	0.4	7.50
	8	91.30	0.47	8.23
	9	90.70	0.47	8.83
	10	90.22	0.47	9.32
GD Growth	1	0.62	99.38	0.00
	2	1.18	98.71	0.11
	3	1.33	98.56	0.11
	4	1.56	98.32	0.11
	5	1.76	98.11	0.12
	6	1.96	97.91	0.14
	7	2.13	97.71	0.16
	8	2.29	97.53	0.18
	9	2.44	97.36	0.20
	10	2.57	97.21	0.22
Log BIT	1	1.22	1.72	97.06
	2	0.89	1.42	97.68
	3	0.84	1.28	97.88
	4	0.97	1.25	97.78
	5	1.23	1.23	97.54
	6	1.56	1.23	97.21
	7	1.93	1.23	96.84
	8	2.30	1.23	96.47
	9	2.66	1.22	96.11
	10	3.01	1.22	95.77

Note*: *FEVD is based on regime-specific MS-PVAR estimates using the Cholesky ordering FSI → GD Growth → log BIT. Values are percentages of forecast error variance attributable to each shock. The reported n = 153 is used for covariance calculations and does not imply country-specific regime assignments.

Table 13-2. FEVD — Regime 2 (%)

Response	Horizon	FSI shock	GD Growth shock	Log BIT shock
FSI	1	100.00	0.00	0.00
	2	99.16	0.55	0.29
	3	98.72	0.84	0.44
	4	98.56	0.95	0.50
	5	98.50	0.98	0.52
	6	98.49	0.99	0.52
	7	98.48	1.00	0.52
	8	98.48	1.00	0.53
	9	98.48	1.00	0.53
	10	98.48	1.00	0.53
GD Growth	1	0.62	99.38	0.00
	2	0.48	98.36	1.15
	3	0.46	96.71	2.83
	4	0.47	95.19	4.34
	5	0.48	94.09	5.43
	6	0.49	93.38	6.14
	7	0.50	92.94	6.56
	8	0.50	92.70	6.80
	9	0.50	92.56	6.94
	10	0.50	92.48	7.01
Log BIT	1	1.22	1.72	97.06
	2	1.51	1.96	96.53
	3	1.63	2.14	96.23
	4	1.69	2.26	96.05
	5	1.71	2.34	95.95
	6	1.73	2.38	95.89
	7	1.73	2.41	95.86
	8	1.74	2.42	95.84
	9	1.74	2.43	95.83
	10	1.74	2.43	95.83

Note*: *FEVD is based on regime-specific MS-PVAR estimates using the Cholesky ordering FSI → GD Growth → log BIT. Values are percentages of forecast error variance attributable to each shock. The reported n = 135 is used for covariance calculations and does not imply country-specific regime assignments

4.3.7. Smoothed Regime Probabilities and Regime Classification

To provide additional evidence on regime identification, the smoothed posterior regime probabilities obtained from the final MS-Pooled VAR model estimation were examined at the time-series level. Because the latent regime s_t is common to all countries within a given year, the probabilities are reported on an annual basis rather than at the country-year level. As reported in Table 14, Regime

1 was the dominant regime in four of the eight annual periods (2017, 2020, 2021, and 2022), while Regime 2 was dominant in the remaining four periods (2016, 2018, 2019, and 2023). The average posterior probability of Regime 1 over the eight annual periods was 0.5335, and that of Regime 2 was 0.4665. The mean maximum posterior probability was 0.9476, indicating a high degree of classification certainty. The regime classification is therefore presented at the time-series level, consistent with the common-regime specification of the model, and does not imply independent country-specific regime processes.

Table 14. Smoothed Posterior Regime Probabilities by Year

year	Probability of Regime 1	Probability of Regime 2	Classified Regime
2016	0.0556	0.9444	2
2017	1.0000	0.0000	1
2018	0.0693	0.9307	2
2019	0.0283	0.9717	2
2020	0.9583	0.0417	1
2021	1.0000	0.0000	1
2022	0.9659	0.0341	1
2023	0.1905	0.8095	2

Source: *Author's calculations using R software based on the estimated MS-Pooled VAR model.*

4.3.8. Robustness Check

To assess the robustness of the baseline findings, the pooled MS-PVAR model was re-estimated using an alternative Financial Stability Index constructed through Principal Component Analysis (FSI2). The results provide partial support for the baseline findings. In the recession regime, the relationship between Bitcoin market capitalization and financial stability remains negative and statistically significant under both the baseline equal-weight specification and the alternative PCA-based specification. In the expansion regime, however, the coefficient becomes positive and statistically insignificant under the alternative FSI2 specification, in contrast to the negative and statistically significant association obtained using the baseline FSI. This difference suggests that the estimated relationship between Bitcoin market capitalization and financial stability in the expansion regime is sensitive to the construction of the financial stability index. Therefore, the robustness analysis supports the baseline finding in the recession regime, while providing no statistically significant confirmation of the negative association in the expansion regime. Given the partial consistency between the baseline and alternative specifications, additional analyses, including impulse response functions, forecast error variance decomposition, and regime diagnostics, were not repeated for the FSI2 specification

4.3.9. Supplementary Robustness Check Using Driscoll–Kraay Standard Errors

Because Bitcoin market capitalization is a common time-varying variable across countries, potential cross-sectional dependence warrants additional consideration when assessing the robustness of statistical inference. Accordingly, as a supplementary robustness check, we estimate a linear pooled VAR(1) specification using Driscoll–Kraay standard errors. This approach is designed to provide inference robust to heteroskedasticity, serial correlation, and general forms of cross-sectional dependence (Driscoll & Kraay, 1998; Hoechle, 2007). Its use as a robustness procedure is consistent with previous empirical studies. For example, Ullah et al. (2021) employed Driscoll–Kraay standard-errors regression to validate their two-step System-GMM findings on sustainable development in Belt and Road Initiative countries. Similarly, Beylik et al. (2022) applied the Driscoll–Kraay standard-error approach to examine the relationship between health expenditure indicators and economic growth across 21 OECD countries. More recently, an OECD-country study of artificial intelligence, digital finance, and climate resilience used Driscoll–Kraay fixed-effects estimation as a robustness check alongside System-GMM and bootstrapped quantile regression (Kashif et al., 2026).

In our supplementary specification, the estimated coefficient on lagged Bitcoin market capitalization in the financial stability equation remains negative across alternative Driscoll–Kraay covariance lag lengths. This consistency provides supplementary evidence that the estimated negative association is not sensitive to the selected covariance lag length.

5. Conclusion and Policy Recommendations

The main objective of this study was to investigate the relationship between Bitcoin, economic growth and financial stability in developed OECD countries using a Markov-Switching pooled VAR approach. Based on preliminary diagnostic tests, including stationarity tests, optimal lag selection and regime determination, the estimated model was found to be stationary and characterized by two distinct regimes (recession and expansion).

Overall, the results provide evidence of heterogeneous and regime-dependent associations between Bitcoin and macro-financial variables. The main findings are summarized as follows:

In the recession regime, Bitcoin has a negative and statistically significant lagged association with financial stability, although the magnitude is relatively small. This finding suggests that the relationship between Bitcoin market capitalization and financial stability remains limited in magnitude, even during recessionary periods, without creating large systemic instability. This pattern may reflect temporary portfolio reallocation behavior under uncertainty. In the expansion regime, Bitcoin is also negatively and statistically significantly associated with financial stability, albeit with limited magnitude. This result indicates that financial systems in developed OECD countries exhibit resilience

against shocks originating from cryptocurrency markets, likely due to strong regulatory frameworks and deep financial markets.

During recessionary periods, Bitcoin is positively associated with economic growth at the one-period lag, although this relationship is statistically insignificant. In expansionary periods, Bitcoin exhibits a negative and statistically significant association with economic growth at the one-period lag. These regime-dependent results indicate that the relationship between Bitcoin market capitalization and economic growth differs across economic conditions, with no statistically significant positive association during recessionary periods and a statistically significant negative association during expansionary periods.

The interest rate is not statistically significantly associated with Bitcoin market capitalization in either regime. The interest rate is negatively but statistically insignificantly associated with financial stability during the recessionary period, while its association remains statistically insignificant during expansionary periods. Moreover, the interest rate is positively associated with economic growth during the recessionary period, while its association with economic growth is not statistically significant in the expansionary regime.

The unemployment rate is negatively but statistically insignificantly associated with Bitcoin market capitalization in both regimes. However, unemployment is not statistically significantly associated with financial stability in either regime. In addition, unemployment is negatively and statistically significantly associated with economic growth during recessions at the 10% significance level, while its association with economic growth is statistically insignificant during expansions.

5.1. Policy Implications

The regime-dependent findings suggest that the policy implications of Bitcoin market capitalization are conditional on the prevailing macro-financial regime. Therefore, policymakers should avoid a uniform policy response to cryptocurrency-market developments. In periods characterized by weaker financial conditions, closer macroprudential monitoring of crypto-related exposures and their potential transmission to financial stability is warranted. By contrast, under more stable conditions, policy should focus primarily on monitoring systemic exposures while allowing financial innovation to develop.

For OECD economies, these findings imply that macroprudential authorities should incorporate crypto-asset exposures into broader financial-stability monitoring, while the intensity of such monitoring should reflect differences in financial-system development and market structure across countries. Thus, rather than adopting identical policy responses, regulatory authorities should account for country-specific financial conditions and the regime-dependent nature of the relationship identified in this study.

The findings also support a cautious and risk-based approach to cryptocurrency regulation. In this context, existing prudential and regulatory initiatives, including the Basel framework for banks' crypto-asset exposures and the

EU's MiCA framework, provide relevant institutional references. However, the empirical results do not imply that a specific regulatory framework or instrument is superior; rather, they highlight the importance of adapting regulatory and supervisory responses to prevailing financial conditions and country-specific characteristics.

5.2. Limitations and Future Research

Several limitations of the present study provide directions for future research. First, the relatively short annual sample limits the possibility of conducting detailed event-specific analyses of major episodes such as the COVID-19 pandemic, the 2018 cryptocurrency downturn, and the 2022 FTX collapse. Future studies could examine these events using higher-frequency data where sufficiently long and consistent series are available. Second, future research could extend the analysis to developing and emerging economies to further investigate cross-country heterogeneity in the relationship between cryptocurrency markets, financial stability, and economic growth. Third, the analysis could be extended to other major digital assets, including Ethereum and stablecoins, within a multi-regime framework. Finally, alternative measures of financial stability and alternative specifications of the cryptocurrency market could be examined to further assess the robustness and generalizability of the findings.

Author Contributions

Conceptualization, all authors; methodology, all authors. formal analysis, all authors; resources, all authors. writing—original draft preparation, Fereshteh Haji fathali. writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data were obtained from the IMF (FSI; https://data.imf.org), OECD (macroeconomic variables; https://data.oecd.org), FRED (interest rate; https://fred.stlouisfed.org), and CoinMarketCap (Bitcoin market capitalization: https://coinmarketcap.com). Data are available from the corresponding Author upon reasonable request

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Appendix A. PCA-Based Construction of the Alternative Financial Stability Index (FSI2)

To assess the robustness of the baseline financial stability index (FSI), an alternative financial stability index (FSI2) was constructed using Principal Component Analysis (PCA). PCA was applied to four financial stability dimensions: capital adequacy (CA), Earnings and Profitability (EQ), liquidity (LQ), and asset quality (AQ).

Before aggregation, the underlying individual indicators were normalized using the Min–Max transformation to ensure comparability across indicators. The normalized indicators were then aggregated into the four financial stability dimensions. PCA was subsequently applied to these dimensions using their correlation matrix to derive the alternative index weights. $X_{it}^{*} = \frac{X_{it} - X_{\min}}{X_{\max} - X_{\min}}$

A.1. Selection of Principal Components

The Kaiser criterion was used to determine the number of principal components to retain. Under this criterion, components with eigenvalues greater than one are retained. The PCA results indicate that the first two principal components satisfy this criterion and are therefore retained for the weighting procedure.

Table A1. PCA Eigenvalues and Explained-Variance Ratios

Component	Eigenvalue	Explained variance (%)	Decision
PC1	1.538100	38.45	Retained
PC2	1.008704	25.22	Retained
PC3	0.853149	21.33	Not retained
PC4	0.600047	15.00	Not retained
Total	4.000000	100.00	—

Note: *The PCA was based on the correlation matrix of the four financial-stability dimensions using complete observations. The Kaiser criterion retains components with eigenvalues greater than one. Accordingly, PC1 and PC2 are used to derive the dimension weights.*
Source: *Author's calculations using R software based on the correlation matrix of the four financial stability dimensions.*

A.2. PCA Eigenvector Coefficients

The eigenvector coefficients represent the coefficients of the four financial-stability dimensions in the linear combinations defining the principal components. The coefficients for all four components are reported in Table A2. Only the first two components are used to calculate the dimension contributions for FSI2.

Table A2. PCA Eigenvector Coefficients for the Four Financial-Stability Dimensions

Dimension	PC1	PC2	PC3	PC4
CA	0.523354	−0.110044	0.738594	−0.410451
EQ	0.546226	−0.113633	−0.673467	−0.484940
LIQ	0.067372	0.983996	0.007283	−0.164803
AQ	0.650537	0.082036	−0.029470	0.754455

Note: *The signs of eigenvector coefficients are arbitrary. Because the weighting procedure uses squared coefficients, the signs do not affect the calculated contribution scores.*
Source: *Author's calculations using R software based on the correlation matrix of the four financial stability dimensions.*

A.3. Calculation of PCA-Based Dimension Contributions and Weights

The contribution of each financial-stability dimension was calculated using its squared eigenvector coefficients on the two retained principal components, weighted by the corresponding eigenvalues. For dimension j, the contribution is defined as:

$$C_j = \lambda_1 v_{j1}^2 + \lambda_2 v_{j2}^2$$

where C_j denotes the contribution of dimension j, λ_1 and λ_2 are the eigenvalues associated with PC1 and PC2, respectively, and v_(j1) and v_(j2) are the corresponding eigenvector coefficients.

The contributions were normalized to obtain dimension weights summing to one:

$$w_j = \frac{C_j}{C_1 + C_2 + C_3 + C_4}$$

The resulting contributions and normalized weights are reported in Table A3.

Table A3. PCA-Based Contributions and Final Dimension Weights

Dimension	Contribution (C_j)	Final weight (w_j)	Weight (%)
CA	0.433500	0.170213	17.02
EQ	0.471937	0.185305	18.53
LIQ	0.983658	0.386232	38.62
AQ	0.657711	0.258249	25.82
Total	2.546804	1.000000	100.00

***Note**: Contributions are calculated from the reported eigenvalues and eigenvector coefficients. Final weights are obtained by normalizing the contributions. Displayed values may differ slightly from calculations using full-precision values because of rounding.*

***Source**: Author's calculations using R software based on the correlation matrix of the four financial stability dimensions.*

A.4. Construction of the PCA-Based Financial Stability Index

The PCA-based alternative financial stability index is constructed as a weighted sum of the four dimensions:

$$FSI2_{it} = 0.170213\, CA_{it} + 0.185305\, EQ_{it} + 0.386232\, LIQ_{it} + 0.258249\, AQ_{it}$$

The weights indicate that liquidity receives the largest weight, followed by asset quality, equity, and capital adequacy. Unlike the baseline equal-weight index, FSI2 assigns different weights to the four dimensions according to the PCA-based weighting procedure.

When one dimension is unavailable for an observation, the index is calculated using the available dimensions and the corresponding weights are renormalized to sum to one. The resulting FSI2 measure is used as an alternative financial-stability indicator in the robustness analysis. The corresponding Markov-Switching Pooled VAR estimates are reported in Tables 10-1 and 10-2.

Appendix B. Robustness Check Using Driscoll–Kraay Standard Errors

B.1. Motivation and estimation procedure

Bitcoin market capitalization is identical across countries in a given year, creating a common time-varying regressor in the country-year panel. Consequently, the effective variation identifying its coefficient is primarily temporal rather than cross-sectional. To assess the sensitivity of the estimated relationship to a covariance estimator designed to accommodate cross-sectional and serial dependence, a supplementary linear pooled VAR (1) model was estimated using Driscoll–Kraay standard errors.

The specification includes lagged financial stability, GDP growth, and log Bitcoin market capitalization, together with lagged interest rates and unemployment. The analysis uses alternative maximum covariance lag lengths of 1, 2, and 3. The coefficients remain unchanged across these specifications, while the estimated standard errors vary with the covariance lag length.

B.2. Results

Table B1. Robustness of the lagged Bitcoin market capitalization coefficient to alternative Driscoll–Kraay lag lengths

Equation	DK maxlag	Coefficient of logbit_lag	DK standard error	t-statistic	p-value
Financial stability (FSI)	1	−0.01855	0.00393	−4.72	0.0000037
Financial stability (FSI)	2	−0.01855	0.00305	−6.09	0.0000000037
Financial stability (FSI)	3	−0.01855	0.00293	−6.33	0.00000000096
GDP growth	2	0.0063	0.2446	0.026	0.980

Notes: *The table reports the coefficient on lagged log Bitcoin market capitalization from the supplementary linear pooled VAR (1) specification. Driscoll–Kraay standard errors were calculated using the indicated maximum covariance lag lengths. The GDP growth equation is reported for the specification with a maximum lag length of 2. The reported t-statistics and p-values are those produced by the R coeftest procedure, which in this implementation uses 282 residual degrees of freedom. Given the short time dimension of the panel, the reported statistical significance should be interpreted cautiously.*

Source: *Author's calculations using R software based on the supplementary linear pooled VAR (1) specification.*

B.3. Interpretation

The estimated coefficient on lagged Bitcoin market capitalization in the financial stability equation is negative and remains similar in magnitude across all three covariance lag specifications. Its reported statistical significance is also preserved across these alternatives. In contrast, the coefficient in the GDP growth equation is close to zero and statistically insignificant in the supplementary pooled specification with a maximum covariance lag length of 2.

These results provide complementary evidence that the negative estimated relationship between lagged Bitcoin market capitalization and financial stability is not driven by the particular Driscoll–Kraay covariance lag length considered. Nevertheless, the sample contains only nine annual periods before lagging and approximately eight usable annual periods after the first lag. The resulting short time dimension limits the reliability of conventional large-time-dimension

approximations. Accordingly, the supplementary estimates are interpreted as a sensitivity analysis rather than a definitive resolution of cross-sectional dependence in the baseline Markov-switching pooled VAR model.