Regime-Aware Bitcoin Price Forecasting Using a Gaussian Hidden Markov Model

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Abstract- This study examines the regime-dependent behaviour of Bitcoin prices using a Gaussian Hidden Markov Model. Using daily Bitcoin data, the analysis identifies three distinct latent market regimes: a bullish regime with positive returns and moderate volatility, a stable regime with low volatility and weak returns, and a bearish regime with negative returns and heightened volatility. The findings further show that bullish and bearish regimes are relatively persistent, while the stable regime is more transitional. These results suggest that Bitcoin price dynamics are not constant over time but evolve through recurring shifts in market conditions. By capturing these nonlinear patterns, the Gaussian Hidden Markov Model provides a useful framework for understanding the structure, volatility, and predictability of Bitcoin markets. The study highlights the value of regime-based modelling for analysing cryptocurrency behaviour, especially in emerging economies where exposure to digital asset risks is increasing.

Keywords: Bitcoin, Gaussian Hidden Markov Model, Regime-switching, Price Volatility, Cryptocurrency Markets

I. Introduction

The increasing digitization of financial systems has fundamentally reshaped the structure and dynamics of global asset markets (Nwoke, 2024), with cryptocurrencies emerging as a prominent component of this transformation (El Hajj & Farran, 2024). Among these, Bitcoin has remained the most dominant and widely traded digital currency, attracting sustained attention from investors, policymakers, and researchers (Mourad & Gül, 2025). Its appeal lies in its decentralized architecture, limited supply, and potential as both a speculative asset and a store of value (Baur et. al. 2018). However, these same features contribute to pronounced price volatility, making Bitcoin one of the most unpredictable assets in contemporary financial markets (Baur et al., 2018; Corbet et al., 2019). In recent years, fluctuations in Bitcoin prices have been driven not only by market fundamentals but also by investor sentiment, technological developments, and broader macroeconomic uncertainties, further complicating its behaviour and predictability (Güler, 2023)

Beyond the global financial landscape, Bitcoin's relevance has become increasingly evident in emerging and developing economies, where structural constraints in traditional financial systems continue to drive the adoption of alternative financial instruments (El Hajj & Farran, 2024). In many African economies, including Nigeria, factors such as exchange rate instability, inflationary pressures, and limited access to formal banking services have contributed to the growing utilization of cryptocurrencies for transactions, savings, and cross-border payments (Adedeji, 2024)**. Nigeria, in particular, has consistently ranked among the leading countries in cryptocurrency adoption, reflecting both economic necessity and rapid digital integration** (Irhebhude et al., 2026). Despite this growing significance, Bitcoin's inherent volatility poses substantial risks, especially in environments where financial literacy, regulatory frameworks, and risk management structures are still evolving.

At a more technical level, the challenge of accurately forecasting Bitcoin prices remains unresolved. A key limitation in the existing literature is the widespread reliance on linear, single-regime models, which assume stable relationships over time and are therefore ill-suited to capturing the complex, nonlinear, and regime-dependent nature of cryptocurrency markets. Bitcoin price movements are often characterized by abrupt transitions between bullish, bearish, and relatively stable phases, suggesting the presence of latent regimes that are not directly observable. While some recent studies have introduced machine learning techniques and hybrid forecasting approaches, these methods frequently prioritize predictive performance without adequately modelling the underlying regime-switching structure of the data (Han et. al., 2025). Moreover, although regime-switching frameworks have gained attention, limited emphasis has been placed on applying Gaussian Hidden Markov Models as a probabilistic tool to jointly model state transitions and conditional distributions in Bitcoin price series.

This gap is particularly important in the current context of heightened global financial uncertainty, where market conditions are increasingly unstable and subject to rapid shifts. Ignoring regime dynamics not only reduces forecasting accuracy but also obscures critical information about risk, timing, and market behaviour. A regime-aware modelling approach is therefore essential for capturing the evolving structure of Bitcoin markets and providing more reliable forecasts that can support informed investment and policy decisions.

Against this backdrop, this study examines the extent to which Bitcoin price dynamics are characterized by distinct underlying regimes and evaluates the effectiveness of a Gaussian Hidden Markov Model in capturing these regime shifts for improved forecasting performance. In doing so, the analysis identifies latent market states, models their transition dynamics, and assesses the predictive accuracy of the Gaussian Hidden Markov framework relative to conventional time series approaches. By focusing on regime-dependent behaviour, the study provides deeper insight into the structure, volatility, and predictability of Bitcoin markets, with particular relevance for emerging economies where exposure to cryptocurrency risks continues to increase.

II. LITERATURE REVIEW

Conceptual Review

Bitcoin, as the first decentralized cryptocurrency, operates on a peer-to-peer blockchain network that enables transactions without the need for central authority. Unlike conventional financial assets, Bitcoin does not derive value from underlying cash flows or physical backing; rather, its price is largely driven by market demand, investor sentiment, scarcity, and expectations about future adoption (Guidolin & Ionta, 2026). This unique structure contributes to its classification as both a speculative asset and, in some contexts, a potential hedge against macroeconomic instability.

Bitcoin price volatility refers to the degree of variation in its price over time and is widely recognized as one of its defining characteristics (Gbadebo et al., 2021). Studies have shown that Bitcoin exhibits higher volatility compared to traditional assets such as equities, gold, and foreign exchange instruments (Baur & Dimpfl, 2021). This volatility is often associated with speculative trading, regulatory uncertainty, technological developments, and shifts in global risk sentiment (Omrane et al., 2025).

A central concept in this study is **regime switching**, which describes situations where a time series alternates between different states or regimes, each characterised by distinct statistical properties such as mean, variance, or persistence. In the context of Bitcoin markets, these regimes may correspond to bullish periods (sustained price increases), bearish periods (persistent declines), and relatively stable phases. Traditional models typically assume a single data-generating process, thereby failing to account for these structural shifts.

The **Gaussian Hidden Markov Model (GHMM)** provides a probabilistic framework for modelling such regime dynamics. In this approach, the observed Bitcoin price series is assumed to be generated by an unobservable (hidden) state process that follows a Markov chain, while the observed data are conditionally Gaussian within each regime (Kim et al., 2022). The GHMM allows for the estimation of both the transition probabilities between regimes and the parameters governing each state, making it particularly suitable for capturing nonlinear and time-varying behaviour in financial data.

Forecasting, within this context, refers to the process of predicting future Bitcoin prices based on historical information. While conventional forecasting models rely on linear assumptions, regime-aware approaches such as the GHMM incorporate structural changes, thereby offering the potential for improved predictive performance in highly volatile markets.

Theoretical Framework

The analysis of Bitcoin price dynamics in this study is anchored primarily in market efficiency and regime-switching theories.

The **Efficient Market Hypothesis (EMH)**, as developed by (Fama, 1970), posits that asset prices fully reflect all available information. Under this framework, price movements are assumed to follow a random walk, making systematic prediction difficult (Fama, 1995). However, empirical evidence from cryptocurrency markets has consistently challenged the strict assumptions of market efficiency. Bitcoin markets are often characterised by information asymmetry, speculative bubbles, and behavioural biases, suggesting that prices may not always fully reflect available information (Urquhart, 2016; Nadarajah & Chu, 2017). These deviations from efficiency create opportunities for models that can capture time-varying structures and patterns in price movements.

Complementing this perspective is the **Regime-Switching Theory**, which assumes that financial time series evolve through different states governed by distinct probabilistic processes (Hamilton, 2018). Originally formalized by Hamilton (2018), this framework recognizes that economic and financial systems are subject to structural changes driven by shifts in policy, market sentiment, or external shocks. In the context of Bitcoin, regime-switching behaviour reflects transitions between periods of high growth, sharp decline, and relative stability.

The Gaussian Hidden Markov Model builds on this theoretical foundation by introducing latent state processes that govern observable outcomes. Unlike standard models, it allows for dynamic transitions between regimes, thereby providing a more flexible representation of financial market behaviour. This makes it particularly relevant for cryptocurrency markets, where abrupt changes and nonlinear patterns are common.

Together, these theoretical perspectives suggest that Bitcoin price dynamics cannot be adequately captured by static or single-regime models. Instead, a framework that accommodates structural shifts and latent state transitions is required to better understand and predict its behaviour.

III. Empirical Review

Empirical studies on Bitcoin price behaviour have evolved rapidly, reflecting growing interest in cryptocurrency markets and advancements in modelling techniques (Ünvan, 2024; Moyo & Phiri, 2023; Atree & Tripathy, 2025). Early studies largely on bitcoin and gold focused on traditional econometric models such as GARCH and ARIMA. For instance, Dyhrberg (2016) found that Bitcoin exhibits hedging properties similar to gold's while also exhibiting unique volatility characteristics. However, these models are limited by their assumption of constant parameters over time.

More recent studies on cryptocurrency have shifted towards nonlinear and machine-learning approaches to improve forecasting accuracy (Marwick et al., 2024; Qureshi et al., 2025; Bouteska et al., 2024). Jang and Lee (2018) employed Bayesian neural networks to predict Bitcoin prices and reported improved performance relative to traditional models. Similarly, Mudassir et al. (2020) compared machine learning techniques such as support vector machines and artificial neural networks, concluding that these models outperform classical time series approaches in short-term prediction tasks. Despite their predictive strength, these approaches often function as "black-box" models, offering limited interpretability and failing to explicitly capture regime dynamics.

In response to these limitations, a growing body of literature on Bitcoin has explored regime-switching models (Ballis et al., 2025). Katsiampa (2019) applied Markov-switching GARCH models to Bitcoin returns and demonstrated that volatility dynamics differ significantly across regimes. Bouri et al. (2022) also provided evidence of regime-dependent behaviour in cryptocurrency markets, highlighting the importance of accounting for structural changes in modelling financial time series. These studies reinforce the idea that Bitcoin markets are inherently nonlinear and subject to frequent transitions.

However, while regime-switching frameworks have gained traction, the application of **Gaussian Hidden Markov Models** remains relatively underexplored in the context of Bitcoin price forecasting. Existing studies often focus on volatility modelling rather than direct price prediction, or they employ alternative regime-switching approaches without fully leveraging the probabilistic structure of GHMMs. Furthermore, there is limited evidence on how GHMM-based forecasts compare with conventional models in terms of predictive performance, particularly in environments characterised by heightened uncertainty and rapid market shifts.

Another important limitation in the literature is the insufficient attention given to the implications of regime dynamics for emerging economies. Given the high level of cryptocurrency adoption in countries such as Nigeria, understanding how Bitcoin behaves across different regimes is crucial for risk management and financial decision-making. Yet, most empirical studies are largely global in focus and do not explicitly consider the relevance of their findings for developing economies.

In light of these gaps, this study contributes to the literature by applying a Gaussian Hidden Markov Model to Bitcoin price forecasting, with a focus on capturing latent regime dynamics and evaluating predictive performance. By doing so, it provides a more transparent and theoretically grounded alternative to black-box machine learning models, while also addressing the need for regime-aware analysis in increasingly volatile cryptocurrency markets.

IV. METHODOLOGY

Data Source and Study Scope

This study employs high-frequency Bitcoin price data from Yahoo Finance, a widely used, publicly accessible financial database. The choice of this source is guided by its consistency, transparency, and ease of replication, which are essential requirements in empirical financial research. The dataset consists of **daily Bitcoin price observations** spanning **15 September 2021 to 14 September 2025**. This timeframe captures multiple phases of Bitcoin market behaviour, including periods of extreme volatility, market corrections, and recovery cycles. The high-frequency nature of the data allows for a more detailed examination of short-term dynamics and improves the ability to detect regime transitions that may be obscured in lower-frequency datasets.

Prior to analysis, the raw price series undergoes standard preprocessing. These include the removal of missing observations, the alignment of timestamps, and the filtering of irregular intervals that may arise from market microstructure effects. To stabilize variance and improve statistical properties, the study utilizes **logarithmic returns**, computed as:

$$r_t = ln(P_t) - ln(P_{t-1}) \qquad (1)$$

Where Pt denotes the Bitcoin price at time t, and r_t represents the continuously compounded return. This transformation ensures stationarity and makes the data suitable for regime-switching analysis.

Methodological Framework

Bitcoin price behaviour is widely recognized to exhibit **nonlinearity, volatility clustering, and structural breaks**, features that are not adequately captured by conventional linear models. While machine learning approaches have demonstrated strong predictive performance, they often lack interpretability and provide limited insight into the underlying structure of market dynamics.

To address these limitations, this study adopts a **Gaussian Hidden Markov Model (GHMM)**, which provides a flexible probabilistic framework for modelling time series characterized by unobserved regime changes. The GHMM is particularly well-suited to this context because it allows the data-generating process to switch among multiple latent states, each associated with distinct statistical properties.

This approach offers three key advantages. First, it explicitly models **regime dependence**, allowing for the identification of bullish, bearish, and stable market phases. Second, it captures **time-varying volatility** through state-specific distributions. Third, it combines **interpretability with predictive capability**, thereby offering a more transparent alternative to black-box forecasting models.

Model Specification

The Gaussian Hidden Markov Model assumes that the observed Bitcoin return series r_t is generated by an underlying, unobservable state process Stthat evolves according to a first-order Markov chain.

Hidden State Process

Let $S\_t \in \{1, 2, \ldots, K\}$ denote the latent regime at time t, where K represents the number of possible states. The evolution of these states is governed by transition probabilities defined as:

$$P\big(S_t = j | S_{(t-1)} = i\big) = p_{ij}\,, \quad \sum_{j=1}^{k} p_{ij} = 1 \qquad (2)$$

These probabilities are summarized in a transition matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & & p_{2k} \\ \vdots & & & \\ p_{k1} & p_{k2} & & p_{kk} \end{bmatrix}$$

Observation Equation

Conditional on the regime St = k the observed return follows a Gaussian distribution:

$$r_t |\, S_t = k \sim N(\mu_k, \sigma_k^2) \qquad (3)$$

where μ_k and σ_k^2 denote the mean and variance of returns in regime k, respectively. This specification allows each regime to exhibit distinct return and volatility characteristics.

Likelihood Function

The likelihood of the observed return sequence is defined as:

$$L(\theta) = \sum_{S_1 \ldots, S_T} P(S_1) \prod_{t=2}^{T} P(S_t | S_{t-1}) \prod_{t=1}^{T} f(r_t | S_t) \ (4)$$

where $\theta = \{\mu_k, \sigma_k^2, p_{ij}\}$ represents the set of model parameters. The likelihood accounts for all possible state paths, making direct estimation computationally intensive.

Parameter Estimation

To estimate the model parameters, the study employs the **Expectation–Maximization (EM) algorithm**, which iteratively maximizes the likelihood function.

In the expectation step, the probabilities of the hidden states are estimated using the forward–backward procedure. In the maximization step, the model parameters, including regime-specific means, variances, and transition probabilities, are updated based on these estimated probabilities. This process continues until convergence is achieved.

Forecasting

The GHMM generates forecasts by weighting regime-specific expectations with their corresponding probabilities:

$$\hat{r}_{t+1} = \sum_{k=1}^{K} P(S_{t+1} = k | \Omega_t) \mu_k \qquad (5)$$

where Ω_t represents the available information set at time t. This approach ensures that forecasts incorporate both current market conditions and the likelihood of regime transitions.

Variable Description

Variable	Description	Measurement
P_t	Bitcoin price	USD
r_t	Log return of Bitcoin price	Continuous
S_t	Latent market regime	Discrete (1…k)
p_{ij}	Transition probabilities	Probability

Expected Regime Characteristics

Although the model is data-driven, economic intuition suggests that:

Regime	Mean Behaviour	Volatility
Bullish	Positive returns	Moderate
Bearish	Negative returns	High
Stable	Near-zero returns	Low

V. Results and Discussions

Identification and characterization of latent Bitcoin market regimes

To address the first objective, the Gaussian Hidden Markov Model was used to identify the latent regimes underlying Bitcoin price dynamics. The results reveal that Bitcoin does not follow a single, uniform market process over time. Rather, its behaviour is better explained by three distinct regimes, each with its own return and volatility profile. These regimes are labelled as bullish, stable, and bearish based on their statistical characteristics.

Table 1 presents the regime-specific summary statistics. The bullish regime records a positive mean log return of 0.00194 with a standard deviation of 0.02122, indicating that this state is associated with relatively favourable market performance and moderate price fluctuations. It also contains the largest number of observations (925), suggesting that this is the most frequently observed market condition within the sample period. This pattern implies that Bitcoin experiences extended episodes of positive momentum, although such periods are still accompanied by notable variability.

The stable regime shows the lowest volatility, with a standard deviation of 0.00426, and a slightly negative mean log return of -0.00132. This suggests that the regime is relatively calm in terms of price movement, but not necessarily profitable. In other words, periods of market stability in Bitcoin do not always translate into positive returns. Instead, this regime appears to reflect subdued trading conditions, where price changes remain limited and market direction is weak.

The bearish regime exhibits the weakest performance among the three states. It has the most negative mean log return, at -0.00230, and the highest standard deviation, at 0.05752. The wide spread between the minimum return (-0.17006) and maximum return (0.13576) further highlights the intensity of price swings during this regime. This state therefore captures periods of pronounced market stress, when Bitcoin is exposed to sharp downward movements and heightened uncertainty.

Taken together, these findings provide clear evidence that Bitcoin price dynamics are regime-dependent. The market alternates between states of relative optimism, subdued stability, and heightened distress, each of which reflects a different combination of return and risk. This result is important because it shows that modelling Bitcoin as a single-process series may conceal meaningful structural differences across market conditions. By uncovering these latent states, the Gaussian Hidden Markov Model offers a more realistic representation of Bitcoin behaviour and provides a stronger basis for understanding its volatility and predictability.

Table 1: Regime-Specific Summary Statistics for Bitcoin Price Dynamics

Regime	Mean Log Return	Standard Deviation	Minimum Return	Maximum Return	Observations	Interpretation
Bullish	0.00194	0.02123	-0.05617	0.06021	925	Positive average return with moderate volatility, indicating a growth-oriented market state
Stable	-0.00132	0.00426	-0.01272	0.00854	310	Very low volatility with slightly negative average return, suggesting a relatively calm but weak market condition
Bearish	-0.00231	0.05753	-0.17006	0.13576	220	Negative average return with the highest volatility, reflecting a turbulent and riskier market phase

Table 2: Transition Probabilities and Persistence of Bitcoin Market Regimes

From Regime	To Bullish	To Stable	To Bearish	Persistence (Stay Probability)	Interpretation
Bullish	0.6667	0.2026	0.1307	0.6667	The bullish regime is relatively persistent, with a high likelihood of remaining in the same state once entered
Stable	0.5717	0.4165	0.0117	0.4165	The stable regime is less persistent and tends to shift mainly toward the bullish regime
Bearish	0.3471	0.0000	0.6529	0.6529	The bearish regime is also highly persistent, with a strong tendency to remain in distress once it emerges

The table above address the second objective, the transition probability matrix of the Gaussian Hidden markov Model was examined to understand how Bitcoin transitions among latent market regimes over time. The results show that regime shifts are not random. Instead, each market state exhibits varying degrees of persistence and distinct likelihoods of transitioning to alternative states.

As shown in Table 2, the bullish regime has a self-transition probability of 0.6667, implying that once Bitcoin enters a bullish state, it is highly likely to remain in that regime in the subsequent period. This suggests that positive market conditions are relatively persistent and tend to remain in place over time rather than reversing immediately. The probability of moving from the bullish regime to the stable regime is 0.2026, while the probability of switching directly to the bearish regime is lower, at 0.1307. This pattern indicates that although bullish periods may weaken, they are more likely to moderate gradually before turning fully adverse.

The stable regime, by contrast, is the least persistent of the three states, with a self-transition probability of 0.4165. This implies that periods of relative calm are more short-lived and less structurally durable than either bullish or bearish conditions. Notably, the probability of moving from the stable regime to the bullish regime is 0.5717, which is higher than the probability of remaining stable. This suggests that low-volatility periods in Bitcoin often serve as transitional phases that precede renewed positive momentum. The probability of moving from the stable regime to the bearish regime is extremely low, at 0.0117, indicating that calm market conditions rarely deteriorate directly into distress without first passing through an intermediate strengthening phase.

The bearish regime also exhibits substantial persistence, with a self-transition probability of 0.6529. This result implies that once the Bitcoin market enters a distressed state, negative conditions are likely to endure for some time. The probability of switching from the bearish regime to the bullish regime is 0.3471, suggesting that recovery is possible, though not immediate. The near-zero probability of moving from the bearish regime to the stable regime suggests that market recovery typically does not occur through a calm adjustment process. Rather, the results suggest that Bitcoin tends to move directly from distress into a stronger recovery phase.

Overall, the transition dynamics confirm that Bitcoin price behaviour is strongly regime-dependent, with both bullish and bearish states showing considerable persistence, whereas the stable regime appears more temporary and transitional. These findings reinforce the view that Bitcoin markets are characterized by recurrent phases of momentum and stress, rather than by a constant and uniform adjustment process. This also strengthens the suitability of the Gaussian Hidden Markov Model, as it captures not only the existence of distinct market states but also the dynamics by which the market transitions between them. The transition matrix shows that Bitcoin market regimes are persistent but asymmetric, with bullish and bearish phases exhibiting greater continuity, whereas the stable regime largely serves as a short-lived transitional state.

Evaluation of the Gaussian Hidden Markov Model for Forecasting Bitcoin Price Dynamics

To address the third objective, the Gaussian Hidden Markov Model was evaluated based on its model fit and its ability to capture the regime-dependent structure of Bitcoin price behaviour. The results suggest that the model provides a useful framework for analyzing and forecasting Bitcoin dynamics in an environment characterized by structural shifts and evolving volatility.

The estimated model was fitted using 1,455 observations and a three-regime specification. The model generated a log-likelihood value of -1883.0932, with an Akaike Information Criterion (AIC) of 3794.1863 and a Bayesian Information Criterion (BIC) of 3868.1450. These fit statistics indicate that the model provides a reasonably strong representation of the underlying data while maintaining a parsimonious structure. More importantly, the three-state framework is consistent with the empirical behaviour observed in the Bitcoin series, where bullish, stable, and bearish periods exhibit clearly different return and volatility patterns.

A major advantage of the Gaussian Hidden Markov Model is that it allows the data-generating process to vary across latent states rather than assuming a constant pattern throughout the sample period. This is especially important in the case of Bitcoin, where periods of rapid appreciation, relative calm, and sharp decline tend to alternate over time. By explicitly modelling these shifts, the Gaussian Hidden Markov framework captures the nonlinear and time-varying nature of Bitcoin price behaviour more effectively than conventional single-state approaches that impose fixed parameters across all periods.

The model's forecasting relevance is further strengthened by its ability to assign observations to distinct market regimes and trace the transition path between them. Since each regime is associated with a different return and volatility structure, the model provides a more informative basis for anticipating future market conditions than approaches that treat all observations as arising from the same process. In this sense, the forecasting value of the Gaussian Hidden Markov Model lies not only in statistical fit, but also in its capacity to reflect the underlying economic reality that Bitcoin markets evolve through recurrent phases of optimism, stability, and distress.

Overall, the findings indicate that the Gaussian Hidden Markov Model is a suitable and promising framework for forecasting Bitcoin price dynamics under regime-dependent conditions. Its ability to uncover latent market states, model transition dynamics, and account for time-varying volatility makes it particularly useful for understanding and predicting cryptocurrency market behaviour. However, while the present results support the model's adequacy, a fuller evaluation of forecasting superiority would require a direct comparison with conventional benchmark models such as ARIMA or GARCH. As such, the evidence from this study should be interpreted as providing strong support for the forecasting usefulness of the Gaussian Hidden Markov approach, rather than a definitive claim of overall forecasting dominance.

Table 3: Model Fit Indicators for the Gaussian Hidden Markov Model

Metric	Value
Model	Gaussian HMM
Log Likelihood	-1883.0932
AIC	3794.1863
BIC	3868.1450
Observations	1455
Number of Regimes	3
Covariance Type	Diagonal

VI. Conclusion

This study examined the regime-dependent nature of Bitcoin price dynamics using a Gaussian Hidden Markov Model. The findings show that Bitcoin behaviour is not uniform over time, but instead unfolds across three distinct latent regimes: a bullish regime associated with positive returns and moderate volatility, a stable regime marked by low volatility and weak returns, and a bearish regime characterized by negative returns and heightened market turbulence. The transition results further indicate that bullish and bearish states are relatively persistent, while the stable regime is more short-lived and transitional. Overall, the evidence suggests that the Gaussian Hidden Markov Model offers a useful framework for capturing the nonlinear structure and changing risk conditions that define Bitcoin markets.

VII. Policy Implications

The findings carry important implications for policy and market oversight, particularly in emerging economies where exposure to cryptocurrency markets is gradually increasing. First, the regime-dependent nature of Bitcoin prices suggests that regulators should not treat cryptocurrency risk as constant over time. Periods of market distress are more volatile and persistent, so monitoring systems should be sensitive to abrupt shifts in market conditions. Second, financial authorities may need to strengthen surveillance and early-warning mechanisms to identify transitions into high-risk regimes before instability becomes more pronounced. Third, the results point to the importance of improving investor awareness around the volatile and state-dependent behaviour of cryptocurrency markets. In this regard, policy efforts aimed at financial literacy, risk disclosure, and market transparency may help reduce vulnerability to sudden losses. More broadly, the study suggests that regulatory responses to cryptocurrency markets should be flexible enough to reflect the changing dynamics of these assets rather than relying on static assumptions about their behaviour.

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