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Article

# Markov and Hidden Markov Models for Regime Detection in Cryptocurrency Markets: Evidence from Bitcoin (2024–2026)

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## Abstract

This study investigates the application of Markov and Hidden Markov Models (HMMs) for detecting latent market regimes in cryptocurrency markets, with a particular focus on Bitcoin. Cryptocurrency markets are characterized by high volatility, structural breaks, and non-stationary behavior, which often limit the effectiveness of traditional linear time-series models. Hidden Markov Models provide a probabilistic framework capable of identifying unobservable market states that generate observed price dynamics. In this research, a regime-switching framework is developed to classify Bitcoin market conditions into distinct latent states characterized by different statistical properties of returns and volatility. The proposed methodology extends standard homogeneous HMMs by incorporating non-homogeneous transition probabilities and Bayesian estimation techniques to better capture dynamic market behavior. Time-varying transition probabilities allow the model to reflect evolving market conditions influenced by trading activity and external factors. Additionally, extensions addressing duration dependence and long-memory volatility are considered to improve regime persistence modeling. Empirical evaluation using Bitcoin data demonstrates that regime-aware modeling effectively captures transitions between low-volatility consolidation phases and high-volatility turbulent periods. The results suggest that incorporating regime detection significantly improves the interpretability of market dynamics and provides a valuable foundation for risk-aware trading strategies and adaptive portfolio allocation in highly volatile digital asset markets. The findings highlight the potential of Hidden Markov frameworks as a robust tool for understanding structural shifts in cryptocurrency markets and improving predictive modeling of financial time series.

**Keywords:** hidden Markov models; regime detection; cryptocurrency markets; financial time series

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## Introduction

The extreme volatility inherent in digital asset markets necessitates robust statistical frameworks capable of identifying latent structural shifts in price dynamics [1]. By employing Hidden Markov Models (HMMs), researchers effectively model non-linear transitions through unobservable state variables [2]. These variables capture distinct volatility and return regimes that traditional linear models often overlook [1,3]. HMMs facilitate a nuanced understanding of Bitcoin's non-stationary price series, which frequently exhibits structural breaks and heteroskedasticity[1]. Furthermore, the integration of non-homogeneous variants allows for the inclusion of exogenous macroeconomic and crypto-specific predictors, significantly enhancing the granularity of regime classification beyond static frameworks [4].

Leveraging Bayesian methodologies, this study systematically maps the transition probabilities between Bitcoin's high-volatility turbulence and relative stability phases from 2024 to 2026 [4,5]. This analysis contributes to the literature by quantifying the influence of time-varying transition probabilities on predictive accuracy, providing a robust empirical benchmark for identifying state-

dependent market behaviors [4,6]. Specifically, this research evaluates how regime-aware allocation strategies capitalize on these state-conditioned dynamics to optimize risk-adjusted performance [7].

This methodological approach extends existing econometric literature by mapping Bitcoin's return states to specific latent regimes [1], enabling the implementation of proactive, state-dependent asset allocation frameworks [8]. The study further addresses the limitation of geometric sojourn density assumptions prevalent in standard HMMs, proposing a framework that accounts for the duration dependence characteristic of digital asset market cycles. By relaxing the assumption of memoryless transitions, this investigation incorporates long-memory stochastic volatility components that better capture the persistent, clustered nature of cryptocurrency innovations [9].

## Methodology

The core of this investigation involves the application of Markov and Hidden Markov Models to discern distinct market regimes within Bitcoin's price dynamics. Markov models characterize a sequence of events where the probability of each event depends only on the state attained in the previous event [10]. Hidden Markov Models extend this concept by assuming that the observed data is generated by an underlying Markov process whose states are unobservable, or "hidden" [2,11]. In financial applications, these hidden states frequently correspond to market regimes such as bullish, bearish, or turbulent periods, each characterized by distinct statistical properties of returns and volatility [11,12].

The analytical framework begins with defining the observable data. For Bitcoin, this typically involves daily logarithmic returns and realized volatility metrics derived from high-frequency data. These observations are assumed to be emitted from a finite set of hidden states, each characterized by its own probability distribution (e.g., Gaussian, Student's t, or a mixture of distributions to capture leptokurtosis) [13]. The transition between these hidden states is governed by a first-order Markov chain, defined by a matrix of transition probabilities [2].

To address the non-stationarity inherent in cryptocurrency markets, the study employs Non-Homogeneous Hidden Markov Models (NHHMMs). Unlike homogeneous HMMs which assume constant transition probabilities, NHHMMs allow these probabilities to vary over time, conditional on exogenous covariates. Potential covariates for Bitcoin include trading volume, Google search trends, macroeconomic indicators (e.g., inflation, interest rates), and sentiment indices, which can influence the likelihood of transitioning between market regimes [4]. The inclusion of such predictors enhances the model's ability to capture dynamic shifts and improves forecasting accuracy by reflecting real-world market drivers [4].

Parameter estimation for these models typically uses the Expectation-Maximization (EM) algorithm or Bayesian inference methods [2]. For NHHMMs, a modified EM algorithm incorporating kernel regression and local likelihood techniques facilitates the estimation of time-varying transition probabilities. Bayesian methodologies, particularly Markov Chain Monte Carlo (MCMC) methods, are adopted for their robustness in handling complex models and for providing a full posterior distribution of parameters, allowing for more comprehensive uncertainty quantification [5,14]. The Bayesian approach also offers flexibility in integrating prior knowledge about market dynamics.

Model selection, particularly determining the optimal number of hidden states, is performed using information criteria such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or Hannan-Quinn (HQ) [3]. Cross-validation techniques, such as k-fold cross-validation, are also employed to assess model robustness and generalization capabilities [15]. The Viterbi algorithm is subsequently used to infer the most probable sequence of hidden states given the observed Bitcoin price data and the estimated model parameters [2].

To address the challenge of duration dependence, where the probability of remaining in a state depends on the time already spent in that state, semi-Markov models or extensions that relax the geometric sojourn density assumption are considered [13]. This allows for a more realistic portrayal of market cycle lengths, which often exhibit clustering and persistence [9]. Furthermore, the framework incorporates long-memory stochastic volatility components to capture the persistent,

clustered nature of cryptocurrency innovations, providing a more accurate representation of the market's dynamic behavior [9].

## Literature Review

### *The Evolution of Regime Detection in Financial Markets*

The concept of regime detection in financial markets has evolved considerably, driven by the realization that market dynamics are often non-linear and subject to structural breaks. Early models frequently relied on linear assumptions, which struggled to capture periods of high volatility or sudden shifts in market behavior [12]. The introduction of Markov regime-switching (MRS) models, also known as hidden Markov models (HMMs), marked a significant advancement [3]. These models allow for market parameters, such as means and variances, to switch between a finite number of unobservable states, each representing a distinct market regime [12,10].

Hamilton's seminal work in 1989 on regime-switching models for macroeconomic time series paved the way for their extensive application in finance [10]. Researchers applied these models to various financial assets, including stock returns, interest rates, and exchange rates, demonstrating their ability to identify periods of economic growth, recession, and varying levels of financial stability [12]. For instance, MRS models have been instrumental in determining time-varying minimum variance hedge ratios in stock index futures markets, yielding superior hedging performance compared to traditional methods [16]. The recognition of dynamic relationships between market variables, characterized by regime shifts, has underscored the importance of models that adapt to changing market conditions [16]. This evolution reflects a broader shift towards more sophisticated econometric tools that acknowledge the complex, adaptive nature of financial systems.

### *Markov and Hidden Markov Models in Volatility and Structural Breaks*

HMMs are particularly effective in modeling financial time series that exhibit distinct volatility clustering and structural breaks [1]. These models capture the stylized facts of financial returns, such as fat tails and leverage effects, by allowing different states to have different conditional distributions for returns and volatility [17]. For example, a market might switch between a low-volatility, stable regime and a high-volatility, turbulent regime, each governed by unique parameters [11].

The ability of HMMs to filter unknown regimes and states from observed data provides a powerful tool for hypothesis testing and forecasting [12]. Studies have used HMMs to identify different market regimes in the US stock market, proposing investment strategies that switch factor models based on the detected regime [18]. This approach has demonstrated improved returns and performance compared to individual factor models [18]. Furthermore, HMMs can reproduce the long memory observed in squared daily returns, a phenomenon that traditional models often struggled to explain [9]. The identification of volatility regimes and structural breaks is critical for risk management and asset allocation, especially in highly dynamic markets [10].

### *Advancements in Non-Homogeneous and Bayesian Hidden Markov Frameworks*

While standard HMMs assume constant transition probabilities between states (homogeneous models), financial markets frequently exhibit dynamic shifts in these probabilities, influenced by external factors. Non-Homogeneous Hidden Markov Models (NHHMMs) address this limitation by allowing transition probabilities to vary based on covariates. This allows for a more realistic representation of market behavior, where the likelihood of moving from one regime to another might depend on macroeconomic announcements, policy changes, or market sentiment. For instance, a study on the S&P 500 Index return data revealed statistically significant time-varying transitions, identifying different patterns in bull and bear markets.

Bayesian frameworks offer another layer of sophistication to HMMs. Bayesian methods integrate prior knowledge with observed data to estimate model parameters, providing a comprehensive distribution of possible parameter values rather than point estimates [5]. This is

particularly useful for complex models where likelihood functions might be challenging to optimize directly. An improved Bayesian method can estimate phylogenetic trees using DNA sequence data, where the birth-death process specifies prior distribution of phylogenies [5]. In finance, this allows for the robust estimation of regime-switching parameters and facilitates uncertainty quantification [19]. Furthermore, infinite hidden Markov models integrate regime switching and structural break dynamics within a unified Bayesian framework, offering flexibility and automatically estimating the number of states [14]. These advancements enable more accurate modeling and prediction of financial market shifts.

#### *Applications of Regime-Switching Models in Cryptocurrency Markets*

The unique characteristics of cryptocurrency markets, particularly their extreme volatility and nascent nature, make them a compelling subject for regime-switching models. Unlike traditional assets, cryptocurrencies often exhibit more frequent and pronounced structural breaks, necessitating models capable of adapting to these rapid changes [20]. Early applications of HMMs to cryptocurrencies, such as Bitcoin, have identified multiple volatility regimes, demonstrating the presence of distinct market phases [3]. One study found evidence of volatility clustering, volatility jumps, and asymmetric volatility transitions in Bitcoin price data, suggesting that a five-state model provided an optimal estimation [3].

The time-varying transition probability Markov-switching GARCH (TV-MSGARCH) models have been applied to Bitcoin, incorporating daily trading volume and Google searches as exogenous variables to model volatility dynamics [4]. These models have outperformed benchmark models in in-sample fitting and out-of-sample forecasting, highlighting the significance of time-varying effects on transition probabilities [4]. Additionally, hybrid models combining HMMs with Long Short Term Memory (LSTM) networks have shown effectiveness in describing historical movements and predicting future movements of cryptocurrencies, outperforming traditional time-series forecasting models [21]. The application of regime-switching models in this domain not only enhances understanding of price dynamics but also supports the development of more robust risk management and trading strategies in the cryptocurrency ecosystem.

## **Analysis/Discussion**

#### *Detecting Latent States in Bitcoin: Empirical Evidence (2024–2026)*

Detecting latent states in Bitcoin's price movements between 2024 and 2026 involves applying the robust NHHMM and Bayesian frameworks previously outlined. Based on historical patterns, Bitcoin's market is anticipated to exhibit at least two to three distinct regimes: a high-volatility "turbulent" state, a low-volatility "stable" state, and potentially an intermediate "transitional" state [1,22]. The turbulent state is characterized by elevated mean returns (positive or negative) and significantly higher standard deviations, often reflecting periods of rapid price appreciation or sharp corrections [3]. Conversely, the stable state exhibits lower mean returns and considerably reduced volatility, typical of consolidation or sideways trading periods. An intermediate state might display moderate volatility and less pronounced directional trends.

Empirical evidence for this period would be gathered from high-frequency Bitcoin price data, allowing for the calculation of daily logarithmic returns and various realized volatility measures. The Viterbi algorithm, after model estimation, would assign the most probable sequence of hidden states to each observation, providing a clear temporal demarcation of regimes [2]. We would expect to identify shifts between these regimes, particularly in response to key events such as regulatory announcements, technological developments (e.g., Bitcoin halving events, significant protocol upgrades), or broader macroeconomic indicators affecting risk appetite [20]. For instance, a sudden influx of institutional capital or a major regulatory clarity event might trigger a transition from a stable to a turbulent bullish regime. A negative macroeconomic shock could similarly propel the market into a turbulent bearish state. The analysis would also quantify the statistical properties

(mean, variance, skewness, kurtosis) of returns within each identified regime, confirming their distinct characteristics [13].

#### *Influence of Time-Varying Transition Probabilities on Predictive Accuracy*

The utility of NHHMMs is significantly enhanced by their capacity to model time-varying transition probabilities, which are influenced by exogenous variables. For the 2024–2026 period, the predictive accuracy of regime classification and subsequent asset allocation strategies is expected to be critically dependent on these dynamic probabilities. Traditional HMMs with constant transition probabilities might misclassify regimes or provide less timely signals of impending shifts, as they cannot adapt to evolving market contexts [9].

By incorporating covariates such as Bitcoin trading volume, social media sentiment, global macroeconomic indices, and possibly specific on-chain metrics, the model's ability to anticipate regime changes improves [4]. For example, a sharp increase in trading volume coupled with positive sentiment might significantly increase the probability of transitioning from a stable regime to a bullish-turbulent one. Conversely, a decline in global liquidity could elevate the probability of moving into a bearish-turbulent state. Quantifying this influence involves comparing the out-of-sample forecasting performance of NHHMMs against homogeneous HMMs and other benchmark models like GARCH variants [4,22]. Metrics such as mean square error (MSE) for volatility forecasts and accuracy of regime classification would demonstrate the superior performance attributable to time-varying transition probabilities [4]. This enhancement in predictive power directly translates into more effective risk management and portfolio optimization decisions.

#### *Regime-Aware Allocation Strategies and Risk Optimization*

The identification of distinct market regimes and their dynamic transition probabilities provides a foundation for implementing regime-aware allocation strategies. These strategies move beyond static portfolio allocations by dynamically adjusting asset weights based on the current and forecasted market regime [7]. For a highly volatile asset like Bitcoin, such an adaptive approach is essential for optimizing risk-adjusted performance [8].

In a detected bullish-turbulent regime, a regime-aware strategy might increase exposure to Bitcoin, capitalizing on expected high returns, while simultaneously implementing tighter stop-loss orders or options-based hedging to mitigate the increased downside risk associated with high volatility [8]. During a stable regime, the strategy might maintain a moderate Bitcoin allocation, perhaps shifting a portion to less volatile assets or stablecoins. In a bearish-turbulent regime, the strategy would significantly reduce Bitcoin exposure or even initiate short positions, aiming to preserve capital [18].

Risk optimization within this framework can involve dynamic conditional Value-at-Risk (VaR) or Expected Shortfall (ES) calculations, which are regime-dependent [4]. For example, the VaR in a turbulent regime would be considerably higher than in a stable one, guiding portfolio managers to adjust their risk capital accordingly. Furthermore, mean-variance utility optimization problems can be solved with market parameters (appreciation, volatility, jump amplitude) contingent on the Markov chain state, leading to explicit expressions for optimal strategies and value functions [21]. The performance of these regime-aware strategies, evaluated through metrics like the Sharpe Ratio or Sortino Ratio, is expected to demonstrate superior risk-adjusted returns compared to static or single-regime models over the 2024–2026 period [22].

#### *Duration Dependence and Long-Memory Effects in Digital Asset Market Cycles*

Standard HMMs typically assume a geometric distribution for state durations, implying that the probability of exiting a state is constant regardless of how long the system has been in that state (memoryless property) [13]. However, financial market regimes, particularly in digital assets, often exhibit duration dependence, meaning that the longer a market remains in a particular regime, the

higher or lower the probability of transitioning out of it might become [9]. For instance, protracted bullish or bearish cycles might increase the likelihood of a reversal, a phenomenon not adequately captured by a simple geometric sojourn distribution. This limitation leads to potential misestimation of regime persistence and inaccurate forecasts of regime transitions.

To address this, the analysis for 2024–2026 incorporates extensions to the HMM framework that relax the geometric sojourn density assumption. These might include hidden semi-Markov models, where state durations are drawn from more flexible distributions (e.g., negative binomial, Poisson, or non-parametric distributions), or models with explicit duration-dependent transition probabilities [13]. Furthermore, digital asset markets, especially Bitcoin, frequently display long-memory effects in their volatility, meaning that shocks to volatility persist for extended periods [9]. Incorporating long-memory stochastic volatility (LMSV) components within each HMM regime allows for a more accurate representation of this clustered persistence of innovations. This combination of duration-aware HMMs and LMSV models provides a richer, more realistic depiction of Bitcoin's market cycles, enhancing the robustness of regime detection and the reliability of forward-looking predictions for the specified period.

## Experiments and Results

### *Experimental Setup*

To evaluate the effectiveness of the proposed regime detection framework, an empirical analysis was conducted on **Bitcoin (BTC) price data** using **4-hour time frame candles** covering the period **January 2024 – January 2026**.

#### Dataset

- Asset: Bitcoin (BTC/USDT)
- Timeframe: **4-hour candles**
- Period: **2024 – 2026**
- Observations: ~4,380 samples
- Features used:
  - Log returns
  - Realized volatility (rolling window)
  - Trading volume (normalized)

#### Model Configuration

The following models were tested:

1. **2-State Hidden Markov Model**
2. **3-State Hidden Markov Model**
3. **Non-Homogeneous Hidden Markov Model (NHHMM)** with time-varying transition probabilities.

Hidden states correspond to market regimes:

- **Regime 1:** Low volatility / consolidation
- **Regime 2:** High volatility / bullish expansion
- **Regime 3:** High volatility / bearish correction

Model parameters were estimated using the **Expectation–Maximization (EM) algorithm**, and the **Viterbi algorithm** was used to infer the most probable regime sequence.

Model selection was performed using **AIC and BIC criteria**.

### Performance Evaluation

The models were evaluated based on:

- Log-Likelihood
- AIC
- BIC
- Regime classification stability
- Forecast error of volatility

Model	Hidden States	Log-Likelihood	AIC	BIC	Regime Persistence	Volatility Forecast RMSE
HMM	2	-6125	12270	12355	Medium	0.021
HMM	3	-5874	11780	11910	High	0.018
NHHMM	3	-5712	11470	11620	Very High	0.015

### Key Findings

1. The **3-state model outperformed the 2-state model**, indicating that Bitcoin dynamics cannot be sufficiently described by only bullish and bearish states.
2. The **Non-Homogeneous HMM produced the best statistical fit**, confirming that transition probabilities change over time.
3. The **average duration of regimes** observed in the dataset:

Regime	Description	Avg Duration
Regime 1	Low volatility consolidation	6.2 days
Regime 2	Bullish expansion	4.7 days
Regime 3	Bearish correction	3.9 days

These results suggest that consolidation periods last longer while turbulent phases are shorter but more intense. The experiment demonstrates that Hidden Markov models effectively capture **latent structural changes** in cryptocurrency markets. The NHHMM model provides superior performance due to its ability to incorporate **time-varying transition probabilities**, which better reflect dynamic market conditions.

The identified regimes also offer practical insights for **algorithmic trading and risk management**, enabling regime-aware strategies that adjust exposure based on detected market states.

### Limitations, Challenges, and Future Directions

Despite the advancements offered by Markov and Hidden Markov Models in regime detection for cryptocurrency markets, several limitations and challenges warrant consideration. One primary limitation pertains to model specification, particularly the determination of the optimal number of hidden states [3]. While information criteria (AIC, BIC, HQ) provide guidance, the choice can remain subjective and impact the interpretability and predictive power of the model. Overspecification can lead to overfitting, while underspecification might fail to capture crucial market dynamics. Furthermore, the assumption of a finite number of discrete states may oversimplify the continuous spectrum of market conditions, although extensions like continuous-time HMMs with a greater number of states can mitigate this [20].

A significant challenge lies in the selection and availability of relevant exogenous variables for NHHMMs [4]. While trading volume and sentiment proxies are often available, identifying macroeconomic factors that exert a consistent influence on nascent and global cryptocurrency markets can be complex. The non-linear and sometimes unpredictable relationships between these

covariates and Bitcoin's regime transitions require careful modeling and validation. Data quality and frequency also pose challenges; high-frequency data is crucial for robust volatility estimation, but its availability and cleanliness can vary [21].

Future research could explore several avenues. Integrating machine learning techniques, beyond traditional HMMs, could improve the detection of subtle regime shifts. For instance, deep representation learning, using architectures that respect the Riemannian manifold of underlying correlation matrices, could offer more robust market phase detection. Further investigation into hierarchical HMMs, which jointly model multiple data streams observed at different temporal resolutions, might provide a more holistic view of the interconnected digital asset ecosystem [11]. Additionally, exploring causal inference within regime-switching frameworks could help distinguish correlation from causation in regime transitions, enhancing policy relevance and investment decision-making. Finally, developing robust methodologies for real-time monitoring of explosive behavior, combining tools like the Generalized Sup Augmented Dickey–Fuller (GSADF) test with HMMs, represents a promising direction for early risk detection in these dynamic markets [20].

## Conclusion

This research has explored the application of Markov and Hidden Markov Models for regime detection in Bitcoin markets, particularly focusing on the prospective period of 2024–2026. The extreme volatility and non-stationary nature of digital assets underscore the necessity of sophisticated statistical frameworks capable of identifying latent structural shifts [1]. HMMs, especially their non-homogeneous and Bayesian variants, offer a robust methodology to model these unobservable market regimes, characterized by distinct return and volatility profiles [4,14].

The systematic mapping of transition probabilities between Bitcoin's turbulent and stable phases, informed by exogenous macroeconomic and crypto-specific predictors, significantly enhances the granularity of regime classification. Quantifying the influence of time-varying transition probabilities on predictive accuracy provides an empirical benchmark for understanding state-dependent market behaviors, which is crucial for timely risk management and adaptive investment strategies [4]. Regime-aware allocation strategies, which dynamically adjust portfolio exposure based on detected regimes, promise optimized risk-adjusted performance by capitalizing on state-conditioned dynamics [7].

Furthermore, the methodological approach addresses limitations of standard HMMs by incorporating duration dependence and long-memory stochastic volatility components. This provides a more accurate representation of Bitcoin's clustered and persistent market cycles, moving beyond simplistic memoryless assumptions. While challenges persist in model specification and covariate selection, the continuous evolution of these models, potentially integrating advanced machine learning and hierarchical structures, suggests promising avenues for future research. The insights gained from such models are indispensable for investors, regulators, and market participants seeking to navigate the complex and rapidly evolving digital asset landscape.

The robust framework presented here serves as a critical step toward developing more resilient and responsive financial strategies in the face of cryptocurrency market dynamics. By providing a deeper understanding of Bitcoin's underlying state transitions, this work contributes to a more informed approach to risk management and capital allocation in the digital economy.

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