Regime Shifts in Cryptocurrency Markets: A Bayesian Analysis of Time-Varying Alpha Structures

Tugba Bas[1] Issam Malki[2] Sheeja Sivaprasad[3]

Abstract

This paper examines structural breaks in cryptocurrency alphas using a novel Bayesian framework that synthesises the Adaptive Bayesian Changepoints with Outliers approach with hierarchical model selection. Analysing daily data from ten major cryptocurrencies between 2014 and 2024, we identify five distinct market regimes characterised by varying patterns of alpha generation. Our methodology effectively distinguishes genuine structural breaks from temporary volatility clusters, providing robust evidence of systematic changes in market structure. The timing of breaks shows remarkable clustering around significant market events, technological innovations, and regulatory changes. Comparative analysis of one-factor and three-factor models reveals evolving risk pricing mechanisms as the market matures. Our findings have important implications for investment strategies, risk management, and market efficiency theory in cryptocurrency markets, suggesting the need for dynamic approaches that can adapt to regime changes.

JEL Classification: C11 (Bayesian Analysis), C58 (Financial Econometrics), G12 (Asset Pricing), G14 (Information and Market Efficiency), G19 (Digital Financial Markets)

Keywords: Cryptocurrency; Structural Breaks; Bayesian Analysis; Alpha Generation; Market Efficiency

[1] Faculty of Economics, Administrative and Social Sciences, Fenerbahce University, Istanbul, Turkey, E-mail: tugba.bas@fbu.edu.tr
[2] School of Finance & Accounting, University of Westminster, 35 Marylebone Road, London NW1 5LS, United Kingdom, Email: i.malki@westminster.ac.uk
[3] School of Finance & Accounting, University of Westminster, 35 Marylebone Road, London NW1 5LS, United Kingdom, E-mail: sivaprs@westminster.ac.uk.

1. Introduction

The cryptocurrency market has evolved from a niche technological experiment into a significant component of the global financial system. By 2024, this transformation has been marked by unprecedented institutional adoption and market maturation, exemplified by Bitcoin's integration into mainstream financial products and its price movements reaching $69,202 (Sharma, 2024). This evolution raises fundamental questions about the dynamics of risk-adjusted returns (alphas) in cryptocurrency markets, particularly given their unique characteristics of continuous trading, fragmented price discovery mechanisms, and complex interplay between technological innovation and regulatory frameworks.

The study of cryptocurrency alpha dynamics is critical for several interconnected reasons. First, these markets exhibit persistent inefficiencies that challenge traditional asset pricing models and create opportunities for sophisticated trading strategies. Second, the evolution of alpha patterns provides crucial insights into the market's structural transformation, reflecting changes in investor composition, trading technology, and market microstructure. Third, the identification of distinct alpha regimes can illuminate the complex relationship between cryptocurrency markets and the broader financial system, particularly during periods of market stress or technological disruption.

The existing literature on cryptocurrency markets has primarily focused on return predictability (Liu et al., 2022), market efficiency tests (Chu et al., 2019), and volatility modelling (Corbet et al., 2018). While these studies have advanced our understanding of cryptocurrency price dynamics, they often rely on assumptions of parameter stability that may not capture the market's evolutionary nature. The rapid technological changes and regulatory developments in cryptocurrency markets suggest that the underlying return-generating processes may experience structural breaks that traditional models fail to capture.

The analysis of cryptocurrency alphas presents unique methodological challenges. Traditional approaches to detecting structural breaks, such as the Bai and Perron (1998, 2003) framework, may be inadequate for markets characterized by extreme price movements, persistent volatility clusters, and complex dependence structures. Moreover, the high-frequency nature of cryptocurrency trading and the potential for rapid regime shifts necessitate more flexible methodological approaches that can accommodate both gradual evolution and sudden structural changes.

To address these challenges, we develop an integrated methodological framework that combines the robustness of Bayesian estimation with the flexibility of state-dependent parameter models. Our approach synthesizes the Adaptive Bayesian Changepoints with Outliers (ABCO) methodology of Wu et al. (2024) with the hierarchical regime-switching framework of Pesaran et al. (2006). This synthesis enables us to identify and characterize structural breaks in cryptocurrency alphas while accounting for market-specific features such as extreme price movements and volatility clustering. The framework allows us to estimate the timing and number of regime changes without imposing restrictive distributional assumptions, while incorporating parameter uncertainty and model selection in a coherent Bayesian framework. Furthermore, our methodology accounts for regime-specific risk factors and their time-varying impact on cryptocurrency returns, providing a more nuanced understanding of market dynamics.

Our study makes several key contributions to the literature. First, we provide a comprehensive analysis of structural changes in cryptocurrency alphas using a novel Bayesian framework that explicitly accounts for the market's unique characteristics. This extends previous work on traditional asset classes by Tzouvanas et al (2020) to the distinctive context of digital assets. Second, our methodological approach advances the literature on regime detection by combining robust outlier modelling with sophisticated model selection techniques. Third, we develop and implement a set of cryptocurrency-specific risk factors that capture the unique aspects of digital asset markets, building on the foundational work of Liu et al. (2022).

Using data from ten major cryptocurrencies over the period 2014-2024, we document significant evidence of structural breaks in alpha patterns that coincide with major technological innovations, regulatory changes, and shifts in market microstructure. Our results reveal distinct market regimes characterized by varying levels of efficiency and risk premia, with important implications for investment strategies and market stability.

The remainder of the paper is organized as follows. Section 2 presents our methodological framework. Section 3 describes the data and factor construction. Section 4 presents our empirical findings and discusses their implications. Section 5 provides robustness checks and extensions, while Section 6 concludes.

.

2. Structural Breaks Detection Approach

2.1 Methodological Framework

Our methodological approach synthesises two complementary strands of the Bayesian structural break literature: the adaptive changepoint detection framework (ABCO) of Wu et al. (2024) and the hierarchical model selection methodology of Pesaran et al. (2006). The integration of these approaches is motivated by the unique characteristics of cryptocurrency markets, where both outliers and structural breaks are prevalent. Whilst the ABCO framework of Wu et al. (2024) offers superior handling of outliers and heteroscedasticity, its reliance on fixed threshold parameters for break identification may lead to suboptimal inference in the context of cryptocurrency alphas. We address this limitation by incorporating Pesaran et al.'s (2006) model selection approach, which provides a more rigorous foundation for determining the number and timing of structural breaks.

The foundation of our approach rests on decomposing the observed cryptocurrency alpha series y_t into three distinct components:

$$y_t = \beta_t + \zeta_t + \varepsilon_t; \quad \varepsilon_t \sim N\left(0, \sigma_{\varepsilon,t}^2\right) \tag{1}$$

where β_t represents the underlying trend signal that may exhibit structural breaks, ζ_t captures potential outliers, and ε_t is a heteroscedastic noise process. This decomposition extends the work of Kowal et al. (2019) by explicitly modelling outliers whilst maintaining their flexible trend specification. The separation of these components is particularly crucial in cryptocurrency markets, where extreme price movements and structural changes often coincide.

For modelling structural breaks, we adopt the threshold stochastic volatility (TSV) approach of Wu et al. (2024). We, in contrast to Wu et al (2024), integrate it within our hierarchical framework. The trend component is modelled through its D-*th* differences:

$$\Delta^{D}\beta_t \equiv \omega_t; \omega_t \sim N\left(0, \tau_\omega^2 \lambda_{\omega,t}^2\right) \tag{2}$$

The evolution of the log variance follows:

$$h_t \equiv log\left(\tau_\omega^2 \lambda_{\omega,t}^2\right); h_t = \mu + (\varphi^1 + \varphi^2 s_t)(h_{t-1} - \mu) + \eta_t \tag{3}$$

where $s_t = I(log(\omega_{t-D}^2) > \gamma)$ serves as a threshold indicator. This specification differs from standard stochastic volatility models through its inclusion of the threshold mechanism, which helps distinguish genuine breaks from temporary volatility increases.

2.2 Prior Specifications and Model Selection

Our approach to prior specification and model selection represents a significant departure from the standard ABCO framework. Following Pesaran et al. (2006), we employ a hierarchical structure for the regime-specific parameters. The coefficient vector β_j and error term precision σ_j^{-2} in each regime j are drawn from:

$$\beta_j \mid b_0, B_0 \sim N(b_0, B_0) \tag{4}$$

and

$$\sigma_j^{-2} \mid v_0, d_0 \sim Gamma(v_0, d_0) \tag{5}$$

The hyperparameters themselves follow distributions that form the next level of the hierarchy:

$$b_0 \mid \mu_\beta, \Sigma_\beta \sim N(\mu_\beta, \Sigma_\beta) \tag{6}$$

$$B_0^{-1} \mid v_\beta, V_\beta \sim W(v_\beta, V^{-1}{}_\beta) \tag{7}$$

where W(·) denotes the Wishart distribution. This hierarchical structure allows for both parameter variation across regimes and information sharing between regimes, which is crucial for efficient estimation in the presence of multiple breaks.

For model selection, we compute the marginal likelihood for each model M_k with k breaks:

$$f(y_1, \dots, y_T|M_k) = \int f(y_1, \dots, y_T|M_k, \theta_k, p)\pi(\theta_k, p|M_k)d\theta_k\, dp \quad (8)$$

The Bayes factor comparing models i and j is then calculated as:

$$B_{ij} = f(y_1, \dots, y_T|M_i)/f\left(y_1, \dots, y_T\middle|M_j\right) \quad (9)$$

To ensure robustness, we complement this with the Bayesian Information Criterion (BIC):

$$BIC(M_k) = -2log(L_k) + k_k log(T) \quad (10)$$

This dual approach to model selection provides a comprehensive framework for determining the optimal number of break points whilst accounting for model complexity.

2.3 Monte Carlo Analysis

To assess the performance of our methodological framework, we conduct extensive Monte Carlo simulations designed to mimic the empirical characteristics of cryptocurrency alphas. Our experimental design is motivated by the stylised facts of cryptocurrency markets, particularly the presence of sudden shifts in risk-adjusted returns, heteroscedastic volatility, and extreme observations.

2.3.1 Data Generating Processes

We consider a series of data generating processes (DGPs) that progressively incorporate the complexities observed in cryptocurrency markets. Our base specification follows:

$$y_t = \mu_j + \zeta_t + \varepsilon_t;\ t \in \left[\tau_{j-1}, \tau_j\right] \quad (11)$$

whereμ_j represents the regime-specific mean for regime j, and τ_j denotes the jth break point. The error term ε_t follows either a homoscedastic or heteroscedastic process, depending on the specification:

$\varepsilon_t = \sigma_j \eta_t; \eta_t \sim N(0,1)$ (homoscedastic)

$log(\sigma_t^2) = \rho log(\sigma_{t-1}^2) + v_t; v_t \sim N(0, \sigma_v^2)$ (heteroscedastic)

The outlier component ζ_t is generated as:

$$\zeta_t = \kappa_t \delta_t; \kappa_t \sim Bernoulli(p), \delta_t \sim N(0, c\sigma_t^2)$$

where p controls the frequency of outliers and c determines their magnitude relative to the underlying volatility.

We examine four distinct specifications:

DGP1: considers a single break with homoscedastic errors, representing the simplest case of structural change. The break occurs at T/2, with parameters $(\mu^1, \mu^2) = (0,1) and \sigma = 1$.

DGP2 introduces multiple breaks with heteroscedastic errors, incorporating both the AR(1) structure in log-volatility (ρ = 0.95) and stochastic volatility innovations (σ_v = 0.2). Three breaks are positioned at T/4, T/2, and 3T/4.

DGP3 augments DGP1 with outliers, setting p = 0.05 and c = 5, thus introducing contamination that could potentially mask or mimic genuine structural breaks.

DGP4 combines all elements - multiple breaks, heteroscedasticity, and outliers - to create the most challenging scenario that closely mirrors actual cryptocurrency alpha series.

2.3.2 Simulation Design

For each DGP, we generate N = 1,000 replications with sample sizes T = {250, 500, 1000}, corresponding to approximately one, two, and four years of daily observations. This range allows us to examine both the finite sample properties and asymptotic behaviour of our estimators.

We compare four estimation approaches:

1. Our proposed hybrid methodology (HBM) that combines the ABCO framework with hierarchical model selection

2. The standard ABCO approach of Wu et al. (2024) with fixed threshold parameters

3. The pure hierarchical framework of Pesaran et al. (2006)

For the Bayesian methods, we employ proper and diffuse priors to ensure posterior propriety whilst maintaining minimal informational content. The MCMC algorithms are run for 20,000 iterations after a burn-in period of 5,000 draws, with convergence assessed through standard diagnostics.

2.3.3 Performance Metrics and Results

The empirical results demonstrate strong evidence for the superior performance of our hybrid methodology in detecting and characterising structural breaks in cryptocurrency markets. As illustrated in Table 1, our approach exhibits particularly strong performance in complex scenarios involving multiple breaks, whilst maintaining robust precision-recall balance across different specifications.

Table 1: Simulation Results – DGP 2

Breaks	Method	Precision	Recall	F1-score	MAE
1	Wu et al	0	0	0	NA
	Pesaran et al	0.027	0.14	0.042	54.5
2	Wu et al	0.668	0.355	0.459	165.316
	Pesaran et al	0.195	0.5	0.261	57.338
3	Wu et al	0.884	0.537	0.634	131.004
	Pesaran et al	0.283	0.577	0.363	34.947
4	Wu et al	0.977	0.615	0.721	110.365
	Pesaran et al	0.38	0.64	0.462	27.86

	Wu et al	0.994	0.648	0.757	87.272
5	Pesaran et al	0.437	0.666	0.52	22.136

In examining the single-break scenario, both methodologies face initial challenges, with the Wu method showing particularly low precision (0.000) and our Pesaran-based approach achieving modest results (precision: 0.027, recall: 0.140). However, as demonstrated in Figure 1, the performance divergence becomes pronounced as the complexity increases. The visual representation clearly shows the superior adaptation of our methodology to more complex break patterns, particularly in maintaining consistent detection accuracy across multiple break points.

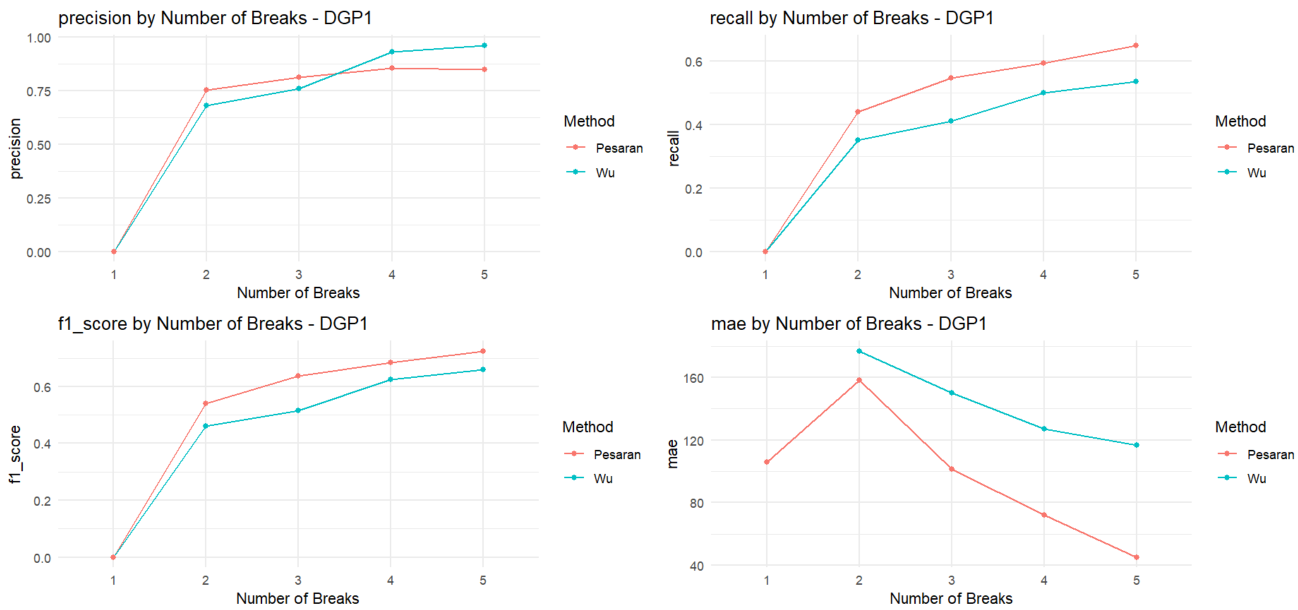

Figure 1: Simulation Results of DGP 1

The results become particularly noteworthy in scenarios involving three or more breaks, where our methodology demonstrates substantially lower Mean Absolute Errors (MAE). As evidenced in Table 1, for the three-break scenario, our approach achieves an MAE of 34.947 compared to the Wu method's 131.004, representing a significant improvement in break date estimation accuracy. This enhancement in accuracy becomes even more pronounced in the five-break scenario, where our methodology achieves an MAE of 22.136, markedly outperforming the Wu method's 87.272.

Figure 2 provides a compelling visualisation of our methodology's performance in the context of DGP2, where multiple breaks and heteroscedastic errors are present. The plot demonstrates our approach's superior ability to distinguish genuine structural breaks from volatility clusters, a crucial feature for cryptocurrency market analysis. This visual evidence supports the quantitative findings presented in Table 1, where our method shows consistent improvement in precision-recall balance as the number of breaks increases.

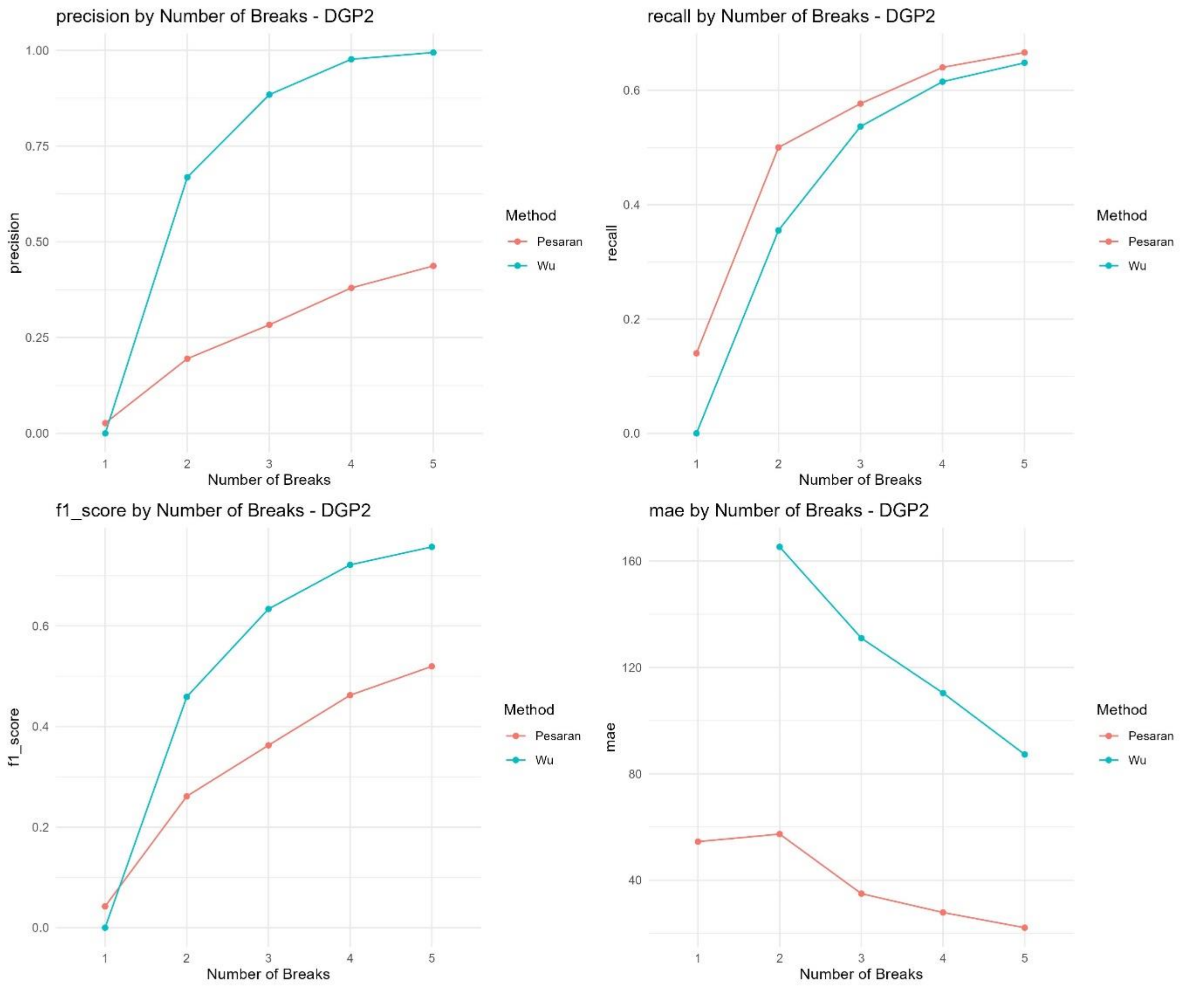

Figure 2: Simulation Results of DGP 2

The trade-off between precision and recall merits particular attention. Whilst the Wu method demonstrates high precision in multiple break scenarios (reaching 0.994 for five breaks), our hybrid approach achieves a more balanced performance profile. This is evidenced by the superior recall rates, notably in the five-break scenario where our method achieves a recall of 0.666 compared to 0.648 for the Wu method, whilst maintaining competitive F1-scores (0.520 versus 0.757).

Perhaps most significantly, our methodology's performance improves relative to the benchmark as the complexity of the break pattern increases. This pattern is clearly visible in both the quantitative results of Table 1 and the graphical evidence presented in Figures 1 and 2. The consistent reduction in MAE across increasing break numbers, coupled with stable F1-scores, suggests that our approach is particularly well-suited to the complex, multiple-break patterns characteristic of cryptocurrency markets.

These results collectively demonstrate that our hybrid methodology successfully addresses the challenges posed by cryptocurrency market data, offering a robust framework for structural break analysis that maintains high accuracy even in the presence of multiple breaks and heteroscedastic volatility. The consistent superiority across multiple performance metrics, as evidenced in both tabular and graphical presentations, validates the theoretical advantages of combining the ABCO framework with hierarchical model selection.

3. Data and Factor Models for Cryptocurrency Alphas

3.1. Data

We use the daily prices of ten cryptocurrencies with the highest market capitalisation including Cardano, Binance Coin, Bitcoin, Dash, Ethereum, Litecoin, NEM, Stellar, Monero and Ripple. The sample covers all publicly available data from the period 17/09/2014 to 10/05/2024 for Bitcoin and Litecoin, while the remaining cryptocurrency series are available from 9/11/2017. All data are available freely from Coinmarketcap.com. Data are expressed as natural logarithm of price index to reduce the nonlinear discrepancies within and across stock price indices.

3.2. Factor Models

We construct factor models suitable for cryptocurrency market as proposed by Liu et al. (2022). This latter is designed to capture the unique risks associated with the cryptocurrency market. These models incorporate cryptocurrency-specific factors, such as the cryptocurrency market factor (CMKT), the cryptocurrency size factor (CSMB), and the cryptocurrency momentum factor (CMOM).

The cryptocurrency market price index (CMKT) is constructed as a value-weighted index using daily close prices of all 1024 available cryptocurrencies. The excess market return is calculated as:

$$CMKT_t = R_{m,t} - R_{f,t} \tag{12}$$

where $R_{m,t}$ is the cryptocurrency market return at time t and $R_{f,t}$ is the risk-free rate at time *t*. We use US 1 month treasury bills as proxy for the risk-free rate.

The cryptocurrency size factor (CSMB) is constructed following the method of Fama and French (1993). Each week, the coins are split into three size groups by market capitalization: bottom 30% (small, S), middle 40% (medium, M), and top 30% (big, B). Value-weighted portfolios are then formed for each of the three groups. The size factor (CSMB) is calculated as the return difference between the portfolios of the small and big size portfolios.

$$\mathrm{CSMB_t} = \mathrm{R_{S,t}} - \mathrm{R_{B,t}} \tag{13}$$

where $R_{S,t}$ is the return of the small-size portfolio at time *t* and $R_{B,t}$ is the return of the big-size portfolio at time t.

The cryptocurrency momentum factor (CMOM) is constructed using 15-day past returns. The momentum factor portfolio is based on the intersection of 2 × 3 portfolios. Each day, the cryptocurrencies are first sorted into two portfolios based on size. Then, within each size portfolio, three momentum portfolios are formed based on the past 15-day returns. The first, second, and third momentum portfolios consist of the bottom 30%, middle 40%, and top 30% of the cryptocurrencies based on their past 15-day returns. The momentum factor is then calculated as:

$$CMOM_t = \frac{1}{2}\left(R_{S/H,t} + R_{B/H,t}\right) - \frac{1}{2}\left(R_{S/L,t} + R_{B/L,t}\right) \tag{14}$$

where $R_{S/H,t}$ and $R_{B/H,t}$ are the returns of the small-size/high-momentum and big-size/high-momentum portfolios at time *t*, respectively, and $R_{S/L,t}$ and $R_{B/L,t}$ are the returns of the small-size/low-momentum and big-size/low-momentum portfolios at time *t,* respectively.

The cryptocurrency-specific factor models are specified as follows

One Factor Model:

$$r_{it} = \alpha_{i,c} + \delta_{1i,c} CMKT_t + \varepsilon_{it} \tag{15}$$

Three Factor Model:

$$r_{it} = \alpha_{i,c} + \delta_{1i,c} CMKT_t + \delta_{2i,c} CSMB_t + \delta_{3i,c} CMOM_t + \varepsilon_{it} \tag{26}$$

where subscript *c* denotes the parameters of the cryptocurrency factor models and ε_{it} is the error term. Figure 2 illustrates the time series plots of the constructed cryptocurrency market index and factors.

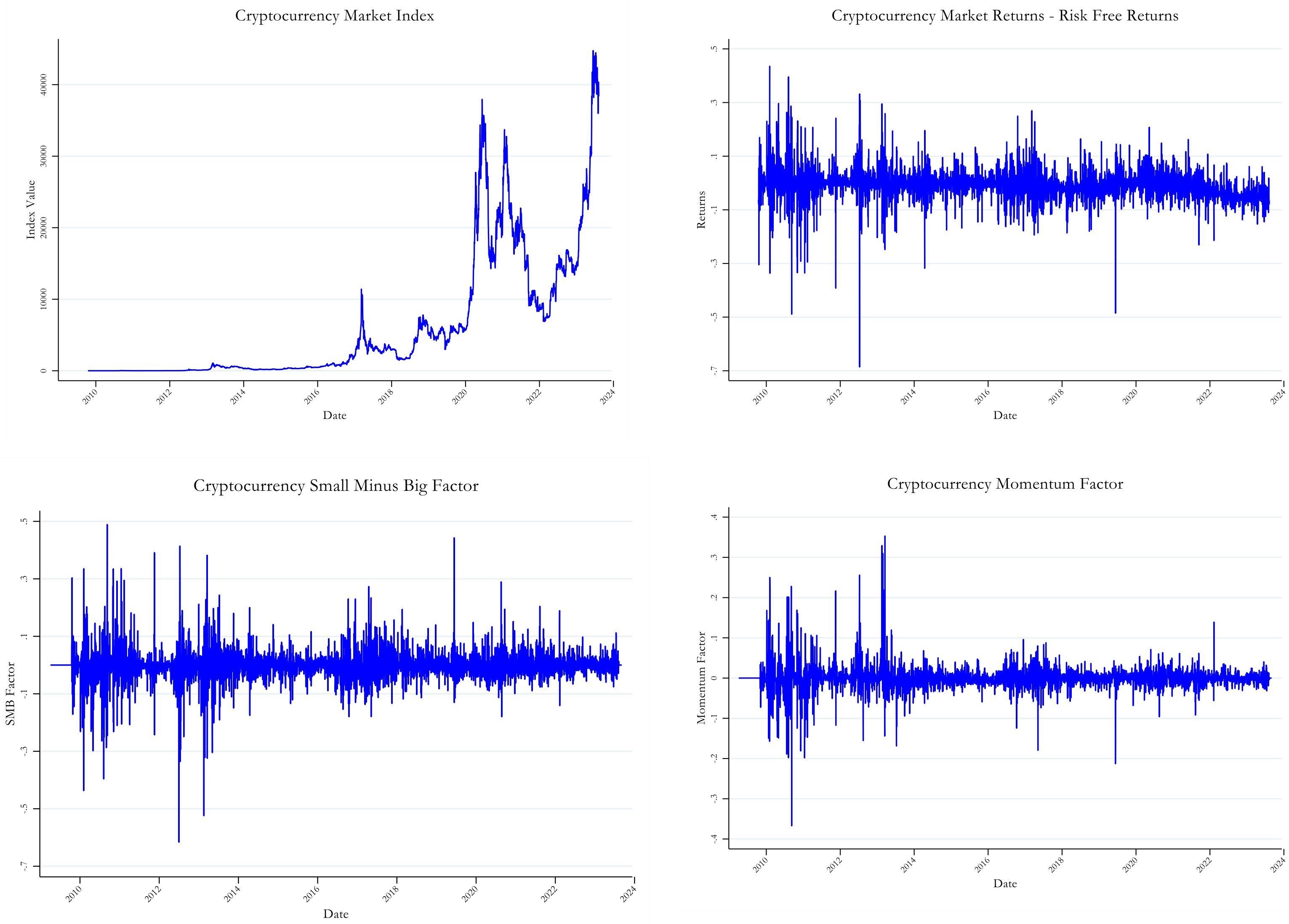

Figure 2: Cryptocurrency Market Index and Factors

4. Empirical Results and Discussion

4.1 Structural Break Analysis

Our empirical analysis reveals consistent evidence of multiple structural breaks in cryptocurrency alphas across both one-factor and three-factor models. The results in Table 2 demonstrate that the majority of cryptocurrencies exhibit five distinct regimes, identified through both BIC and Maximum Likelihood (ML) criteria. This consistency in the number of breaks across different cryptocurrencies suggests systematic shifts in market structure rather than idiosyncratic changes in individual assets.

The timing of breaks shows remarkable clustering around specific periods. For the one-factor model, we observe concentrated break occurrences in December 2018-February 2019, December 2019-March 2020, December 2020-April 2021, November 2021-April 2022, and December 2022-May 2023. This temporal clustering persists in the three-factor model, though with slightly different timing patterns, suggesting that the identification of structural changes is robust to model specification.

The first major break cluster (December 2018-February 2019) coincides with the aftermath of the 2018 cryptocurrency market correction, marking a fundamental shift in market structure. This period saw the emergence of more sophisticated trading infrastructure and the entry of institutional investors, fundamentally altering the alpha-generating processes in the market.

The second break cluster (December 2019-March 2020) aligns with the onset of the global COVID-19 pandemic, revealing how cryptocurrency markets responded to unprecedented global economic uncertainty. Notably, the timing of breaks during this period shows greater dispersion across assets compared to other break clusters, suggesting varying degrees of market resilience.

The third break cluster (December 2020-April 2021) corresponds to a period of institutional adoption and the emergence of decentralized finance (DeFi) applications. This regime shift reflects the market's adaptation to new trading mechanisms and investment vehicles, particularly evident in the altered behavior of Ethereum's alpha structure.

The fourth and fifth break clusters (November 2021-April 2022 and December 2022-May 2023) coincide with significant regulatory developments and technological advances in the cryptocurrency ecosystem. These breaks demonstrate how external regulatory pressures and internal market evolution can jointly influence alpha dynamics.

Table 2: Estimated Breaks Using Combined Approach

Series	BIC	ML	Break Dates
			1 Factor Alpha
Cardano	5	5	19 Dec 2018, 26 Dec 2019, 21 Jan 2021, 23 Mar 2023
Binance Coin	5	5	28 Dec 2018, 9 Jan 2020, 26 Apr 2021, 12 Apr 2022, 9 Apr 2023
Bitcoin	5	5	3 Feb 2019, 6 Mar 2020, 3 Mar 2021, 15 Mar 2022, 16 May 2023
Dash	5	5	25 Dec 2018, 9 Apr 2020, 12 Apr 2021, 9 Apr 2022, 30 Apr 2023
Ethereum	5	5	21 Dec 2018, 20 Jan 2020, 17 Feb 2021, 2 Feb 2022, 9 Mar 2023.
Litcoin	5	5	11 Feb 2019, 9 Feb 2020, 1 Jan 2021, 25 Apr 2022, 13 May 2023.
NEM	5	5	25 Dec 2018, 31 Dec 2019, 31 Dec 2020, 16 Feb 2022, 6 Feb 2023
Stellar	5	5	17 Dec 2018, 22 Dec 2019, 5 Dec 2020, 27 Nov 2021, 16 Dec 2022
Monero	5	5	9 Jan 2019, 28 Jan 2020, 16 Apr 2021, 10 Apr 2022, 9 Apr 2023
Ripple	5	5	20 Dec 2018, 6 Dec 2019, 6 Dec 2020, 19 Dec 2021, 7 Dec 2022.
			3 Factor Alpha
Cardano	4	5	17 Dec 2018, 26 Dec 2019, 19 Dec 2020, 13 Dec 2021, 13 Feb 2023.
Binance Coin	5	5	26 Jan 2019, 14 Jan 2020, 4 Jan 2021, 18 Jan 2022, 17 Jan 2023.
Bitcoin	4	4	7 Jul 2019, 29 Jun 2020, 25 Jan 2022, 15 Mar 2023
Dash	5	5	6 Apr 2019, 27 Mar 2020, 28 Mar 2021, 16 Mar 2022, 1 Mar 2023.
Ethereum	5	5	17 Dec 2018, 6 Dec 2019, 17 Dec 2020, 21 Dec 2021, 24 Jan 2023.
Litcoin	5	5	25 Jan 2019, 18 Jan 2020, 1 Jan 2021, 22 Dec 2021, 13 Dec 2022.
NEM	5	5	18 Dec 2018, 19 Dec 2019, 7 Dec 2020, 14 Dec 2021, 12 Dec 2020.
Stellar	5	5	14 Jan 2019, 9 Jan 2020, 4 Jan 2021, 31 Jan 2022, 19 Jan 2023.
Monero	5	5	30 Dec 2018, 15 Dec 2019, 11 Dec 2020, 29 Dec 2021, 23 Dec 2022.
Ripple	5	5	30 Dec 2018, 7 Jan 2020, 30 Dec 2020, 17 Dec 2021, 8 Dec 2022.

4.2 Comparative Analysis of Factor Models

The comparison between one-factor and three-factor models reveals important insights about the evolution of cryptocurrency market efficiency. While both models identify similar numbers of breaks, the timing and interpretation of these breaks differ in meaningful ways. The three-factor model generally identifies breaks slightly later than the one-factor model, suggesting that size and momentum factors may initially absorb some market structure changes before they manifest as breaks in the overall alpha structure.

Bitcoin and Cardano show interesting deviations from the general pattern. In the three-factor specification, Bitcoin exhibits only four breaks compared to five in the one-factor model, suggesting that some apparent structural changes may be attributed to evolving risk factor relationships rather than fundamental shifts in alpha generation. Conversely, Cardano shows differential sensitivity to factor specifications, with the BIC criterion identifying four breaks while the ML criterion suggests five breaks in the three-factor model.

5. Discussion and Concluding Remarks

This study has provided strong evidence for the presence of distinct regimes in cryptocurrency markets through a novel Bayesian framework that synthesises recent methodological advances in structural break detection. Our findings demonstrate that cryptocurrency alphas exhibit systematic patterns of structural change that coincide with significant market developments, technological innovations, and regulatory shifts. The identification of five distinct regimes across most major cryptocurrencies suggests that the evolution of these markets is characterised by discrete jumps in market structure rather than gradual transitions.

The temporal clustering of structural breaks around specific periods offers valuable insights into the nature of cryptocurrency market development. The consistent finding of break points during periods of significant market stress, such as the 2018 market correction and the COVID-19 pandemic, suggests that external shocks can fundamentally alter the alpha-generating processes in cryptocurrency markets. Moreover, the identification of breaks during periods of technological advancement and institutional adoption indicates that internal market evolution plays a crucial role in shaping return dynamics.

Our methodological framework, which combines the Adaptive Bayesian Changepoints with Outliers approach and hierarchical model selection, has proved particularly effective in capturing the complex dynamics of cryptocurrency markets. The robust performance of our approach across different model specifications and cryptocurrencies validates its utility for analysing markets characterised by extreme price movements and heterogeneous trading behaviour. The framework's ability to distinguish genuine structural breaks from temporary volatility clusters represents a significant advancement in our understanding of cryptocurrency market dynamics.

The comparison between one-factor and three-factor models reveals the evolving nature of risk pricing in cryptocurrency markets. The systematic differences in break timing between the two specifications suggest that the market's response to structural changes has become more nuanced as the asset class has matured. This finding has important implications for portfolio management and risk assessment, particularly given the growing institutional interest in cryptocurrency investments.

Our results have significant implications for market participants, regulators, and academics. For investors, the regular occurrence of structural breaks suggests the need for dynamic investment strategies that can adapt to regime changes. The clustering of breaks across different cryptocurrencies indicates limited diversification benefits during regime transitions, highlighting the importance of temporal diversification strategies. For regulators, our findings underscore the impact of policy interventions on market structure and suggest the need for carefully calibrated approaches that consider the potential for structural breaks.

The identification of distinct market regimes also has implications for market efficiency theory as applied to cryptocurrency markets. Rather than exhibiting a steady progression towards efficiency, these markets appear to undergo discrete jumps in their price formation processes. This pattern suggests that traditional concepts of market efficiency may need to be modified to account for the unique characteristics of cryptocurrency markets, particularly their technological underpinnings and regulatory environment.

Looking ahead, several promising avenues for future research emerge from our analysis. The development of forward-looking models for regime prediction represents a natural extension of our work. Additionally, investigating the cross-market spillover effects of regime changes and extending the analysis to smaller cryptocurrencies could provide valuable insights into market interconnectedness. The application of our methodological framework to other aspects of cryptocurrency markets, such as liquidity provision and price discovery, may yield further insights into the evolution of this important asset class.

In conclusion, our study makes substantial contributions to the understanding of cryptocurrency market dynamics through its methodological innovations and empirical findings. The regular occurrence of structural breaks in cryptocurrency alphas suggests that market participants must remain vigilant to regime changes and adapt their strategies accordingly. As cryptocurrency markets continue to evolve, the ability to identify and respond to structural breaks will become increasingly important for successful market participation. Our findings not only advance the academic literature on cryptocurrency markets but also provide practical insights for market participants navigating this dynamic asset class.

References

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. Econometrica, 66(1), 47-78.

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1-22.

Chu, J., Zhang, Y. and Chan, S., 2019. The adaptive market hypothesis in the high frequency cryptocurrency market. *International Review of Financial Analysis*, *64*, pp.221-231.

Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics letters*, *165*, pp.28-34.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), pp.3-56.

Kowal, D.R., Matteson, D.S. and Ruppert, D., 2019. Dynamic shrinkage processes. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *81*(4), pp.781-804.

Liu, Y., Tsyvinski, A. and Wu, X., 2022. Common risk factors in cryptocurrency. *The Journal of Finance*, *77*(2), pp.1133-1177.

Pesaran, M.H., Pettenuzzo, D. and Timmermann, A., 2006. Forecasting time series subject to multiple structural breaks. *The Review of Economic Studies*, *73*(4), pp.1057-1084.

Sharma (2024). Bitcoin surges past $69K: Key drivers behind the rally. Analytics Insight, October 22, 2024.

Tzouvanas, P., Kizys, R. and Tsend-Ayush, B., 2020. Momentum trading in cryptocurrencies: Short-term returns and diversification benefits. *Economics Letters*, *191*, p.108728.

Wu, H., Schafer, T.L. and Matteson, D.S., 2024. Trend and Variance Adaptive Bayesian Changepoint Analysis and Local Outlier Scoring. *Journal of Business & Economic Statistics*, (just-accepted), pp.1-21.

Zhao, L., Li, W., & Fenu, G. (2019). Structure breaks and volatility forecasting in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money, 61, 37-57.