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A Multi-Dimensional Study of Cryptocurrency Classification and Capital Rotational Behaviour

Preethi Nanjundan[1], Lijo Thomas[2], Priyadarshi Ghosh[3] and Prachi Gupta[4]
[1]Department of Data Science, Christ University, India
Email: preethi.n@christuniversity.in
[2]Department of Business and Management Christ University, India
Email: lijo.thomas@christuniversity.in
[3]Department of Data Science and Business System SRM Institute of Science and Technology, Chennai, India
Email: pg0145@srmist.edu.in
[4]Department of Business and Management Christ University, India
Email: prachi.gupta@bbabah.christuniversity.in

***Abstract*— Cryptocurrency market movements are complex to understand because they are shaped by market capitalization, systemic influence, and investor capital flows. This study analyses the hierarchy of major cryptocurrencies and the relationship dynamics between them. Eleven crypto-assets observed from 1 January 2021 to 31 December 2025 are classified into four tiers based on market relevance and systemic importance. Weekly smoothed price data are transformed into simple, logarithmic and cumulative returns, and are examined through Pearson correlation, Spearman rank correlation, rolling correlation, ANOVA, DCC-GARCH dynamic correlation modelling, and Hidden Markov Model (HMM)-based regime classification. The findings indicate strong systemic influence from Bitcoin and Ethereum, high interdependence across cryptocurrencies, and evidence of capital rotation from dominant assets to alternative cryptocurrencies during expansionary phases. DCC-GARCH results show that correlation is time-varying, while HMM-DCC results show that correlations are regime-dependent, strengthening around Bitcoin during contraction and shifting toward altcoin-benchmark relationships during alt- rotation phases.**

***Index Terms*— Cryptocurrency markets, Bitcoin, correlation analysis, capital rotation, DCC-GARCH, HMM, market hierarchy, digital assets.**

I. INTRODUCTION

The cryptocurrency market has grown and is considered as a key part of the world financial market today. Although thousands of cryptocurrencies are traded, market capitalization and liquidity remain concentrated in major assets such as Bitcoin and Ethereum, which act as systemic anchors influencing smaller cryptocurrencies. Previous studies highlight that cryptocurrency returns are driven by volatility, investor sentiment, market uncertainty, and speculative behaviour [1], [10], [16]. Cryptocurrencies also exhibit high volatility, market inefficiency, and regime-dependent behaviour [2], [3], [4], [6], [7], [14].This study examines the hierarchical structure, correlation dynamics, and regime-dependent capital rotation of eleven major cryptocurrencies from 2021–2025 using Pearson and Spearman correlations, rolling correlation, ANOVA, DCC-GARCH modelling, and Hidden Markov Models (HMM).

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The objective is to analyse how cryptocurrency relationships change across different market regimes.

II. LITERATURE REVIEW

Existing literature identifies cryptocurrencies as a unique financial asset class with distinct return, volatility, and correlation characteristics [1], [10], [14], [15], [16]. Studies show that cryptocurrency prices are influenced by supply-demand dynamics, investor attention, and market inefficiencies, highlighting the need for specialized modelling approaches [10], [14], [15]. Another stream of research examines the hedging and diversification role of cryptocurrencies. Findings suggest that Bitcoin functions more as a diversifier than a stable safe haven and behaves differently across varying market conditions, particularly during periods of high volatility [2], [6], [7].Research on interconnectedness and co-movement demonstrates that cryptocurrencies are highly interrelated through return and volatility spillovers [5], [9], [11], [12]. GARCH-based studies also confirm the presence of volatility clustering in cryptocurrency returns [8]. Recent studies further emphasize that correlations among cryptocurrencies are dynamic and time-varying, supporting the importance of regime-based analytical frameworks [17].

III. RESEARCH GAP AND CONTRIBUTION

Existing studies examine cryptocurrency correlations and volatility separately, with limited research integrating hierarchical classification, DCC-GARCH, and regime-based analysis. Therefore, this study proposes a combined DCC-GARCH and HMM framework to analyse hierarchical interdependence and regime-dependent capital flows in cryptocurrency markets.

IV. DATA DESCRIPTION AND PREPARATION

A. Asset Selection and Tier Construction

The study uses daily closing price data of eleven cryptocurrencies from January 2021 to December 2025, which is converted into weekly data using a seven-day moving average. Cryptocurrencies are classified into four tiers based on market capitalization, liquidity, and systemic importance. This classification enables comparison between dominant cryptocurrencies, large altcoins, mid-cap assets, and highly volatile digital assets.

$$7DMA_t = (P_t + P_{t-1} + P_{t-2} + P_{t-3} + P_{t-4} + P_{t-5} + P_{t-6}) / 7$$

Simple, logarithmic and cumulative returns are calculated as:

$$R_t = (W_t - W_{t-1})/W_{t-1}; \quad r_t = \ln(W_t/W_{t-1}); \quad C_t = \Pi_{i=1}^{t}(1+R_i)-1$$

B. Tier Indices and Benchmarks

Weighted tier indices are constructed to reduce idiosyncratic noise and capture group-level market behaviour. The tier indices are defined as:

$T_1 = 0.8BTC + 0.2ETH$

$T_2 = 0.4XRP + 0.4BNB + 0.2SOL$

$T_3 = 0.5TRX + 0.3DOGE + 0.2ADA$

$T_4 = 0.35LINK + 0.40XMR + 0.25HBAR$

Three synthetic benchmarks are constructed to represent systemic, equal-weighted, and tier-weighted market exposure. These benchmarks help compare concentrated and hierarchical capital distribution across cryptocurrency markets.

V. METHODOLOGY

The methodology of this paper will depend on analysis of how different cryptocurrencies relation with each other and how they work together in crypto market. Different statistical and quantitative techniques such as correlation analysis, rolling correlation, ANOVA, DCC-GARCH modelling, and Hidden Markov Models (HMM) are used to achive the objective of the study.

A. Correlation and Statistical Testing

ANOVA is used to examine differences in mean returns across cryptocurrency tiers and benchmark assets. Pearson and Spearman correlation methods are applied to analyse dependency structures and financial co-movements, with Iqbal and Efendi [2] confirming their usefulness in identifying relationships between cryptocurrencies and traditional financial assets.

$$\rho_{xy} = \mathrm{Cov}(X,Y)/(\sigma_x \sigma_y),$$

$$\rho_s = 1 - 6\Sigma d_i^2/[n(n^2 - 1)]$$

$$\mathrm{Corr}_t = \mathrm{Corr}(r_{t-w+1}, ..., r_t),$$

$$F = MS_{between}/MS_{within}$$

B. DCC-GARCH Dynamic Correlation

DCC-GARCH is used to estimate time-varying conditional correlations. The conditional covariance matrix is represented as:

$$H_t = D_t R_t D_t$$

where H_t is the conditional covariance matrix, D_t is the diagonal matrix of conditional standard deviations and R_t is the dynamic correlation matrix. Two DCC-GARCH models are estimated: Model A includes BTC, ETH and Weighted Tier 2, while Model B includes BTC, Weighted Tier 3 and the Market Cap Weighted benchmark.

C. HMM Regime Classification and Integration

A four-state Gaussian Hidden Markov Model (HMM) is used to classify market regimes into Accumulation, BTC-led Expansion, Alt Rotation, and Contraction using market and liquidity indicators. The study then combines HMM regime labels with DCC-GARCH dynamic correlations to examine correlation behaviour across different market phases. Here, HMM identifies market regimes, while DCC-GARCH measures correlations within each regime.

VI. Empirical Results and Analysis

A. Cumulative Market Dynamics

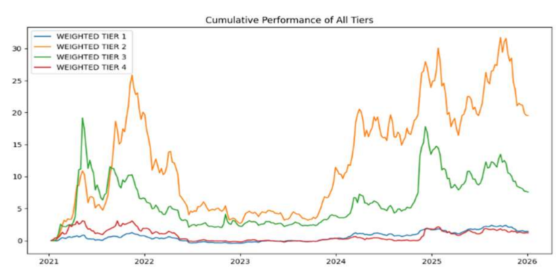

Fig. 1. Cumulative performance across cryptocurrency tiers

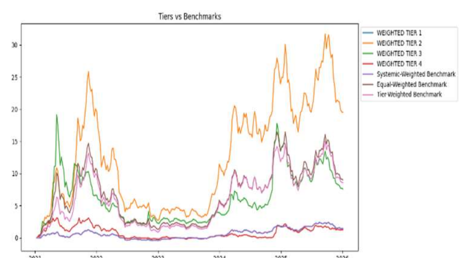

Fig. 2. Comparison of tier indices with synthetic market

Figures 1–3 demonstrate a hierarchical cryptocurrency market structure where Tier 1 provides stability, Tier 2 drives growth during bullish phases, and lower tiers exhibit higher volatility. The analysis also shows evidence of capital rotation, with funds gradually shifting from BTC and ETH toward higher-risk altcoins over time.

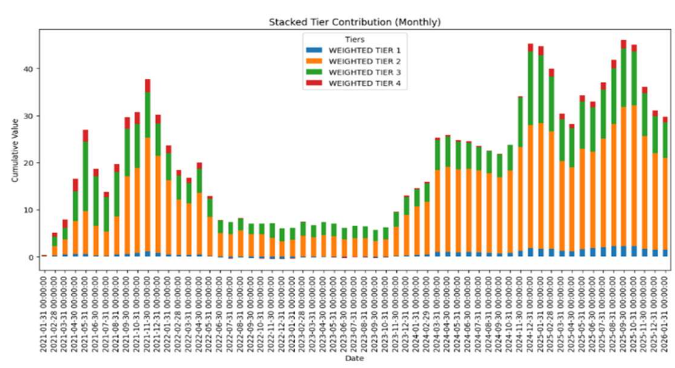

Fig. 3. Monthly tier contribution to total market growth

B. Static and Rolling Correlation Structure

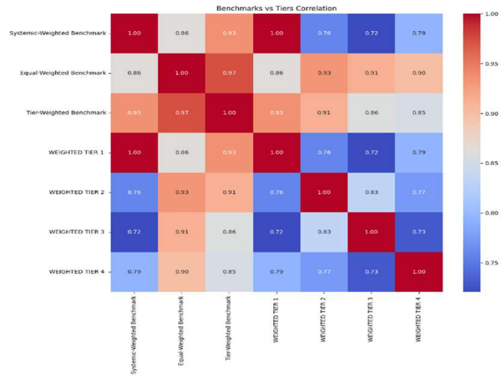

Fig. 4. Pearson correlation between benchmarks and tier indices

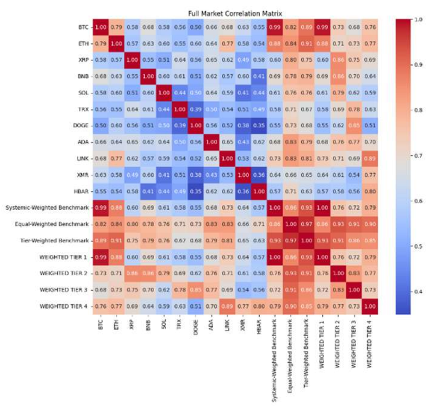

Fig. 5. Full-market Pearson correlation matrix.

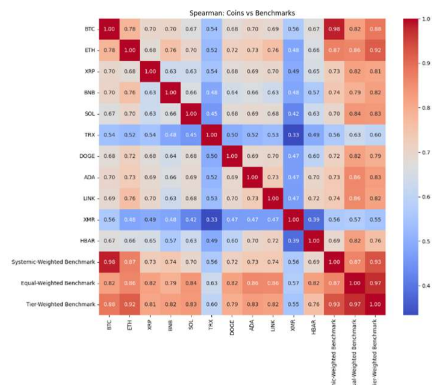

Fig. 6. Spearman rank correlation matrix.

In Fig 4, The Pearson heatmap between benchmarks and tier indices shows strong positive relationships, indicating that all tiers are integrated into the broader cryptocurrency market. The systemic benchmark is almost perfectly related to Tier 1, while the equal-weighted and tier-weighted benchmarks capture broader altcoin participation. Pearson and Spearman correlations show that BTC and ETH act as central market assets, while large altcoins form a connected cluster. ANOVA results indicate no significant differences in mean returns across tiers, suggesting that cryptocurrency hierarchy is driven more by volatility and regime behaviour than returns alone . ANOVA results show no significant differences in mean returns across cryptocurrency tiers, indicating that market hierarchy is influenced more by volatility and regime behaviour than average returns. DCC-GARCH results further reveal that cryptocurrency correlations are dynamic and time-varying, with changing relationships between Bitcoin, Tier 3 assets, and benchmark indices over time.

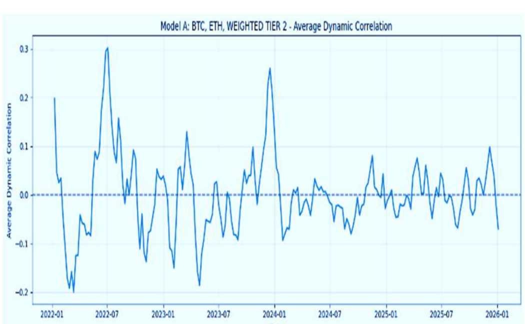

Fig. 7. Average dynamic correlation for Model A.

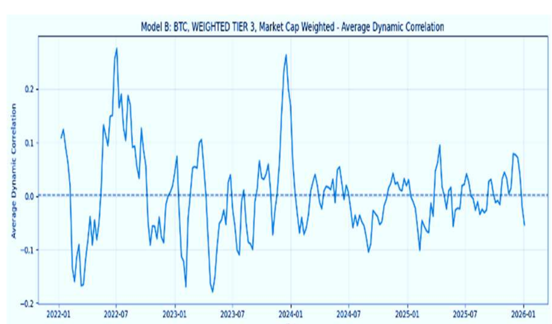

Fig. 8. Average dynamic correlation for Model B.

TABLE I. MEAN DCC-GARCH DYNAMIC CORRELATIONS

Model	Pair	Mean DCC
A	BTC-ETH	0.0040
A	BTC-Tier 2	0.0015
A	ETH-Tier 2	-0.0052
B	BTC-Tier 3	0.0015
B	BTC-MCW	0.0045
B	Tier 3-MCW	0.0014

The HMM identifies four market regimes: Accumulation, BTC-led Expansion, Alt Rotation, and Contraction, with BTC-led Expansion being the most dominant phase. These findings show that cryptocurrency market behaviour changes across regimes, supporting the importance of regime-sensitive models.

Fig. 9. HMM-based cryptocurrency regime classification.

TABLE II. HMM REGIME COUNTS

Regime	Observations
BTC-led Expansion	94
Accumulation	68
Contraction	64
Alt Rotation	28

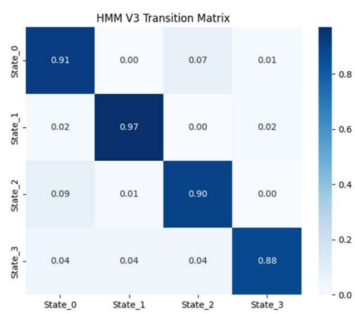

Fig. 10. HMM Transition Matrix

C. Extended Static Correlation and ANOVA Evidence

The correlation matrix shows that BTC and ETH act as systemic market nodes with strong correlations across major cryptocurrencies, while smaller assets such as XMR and HBAR display weaker and more idiosyncratic relationships. Spearman correlations confirm that these relationships are both linear and directionally consistent ANOVA results indicate that mean return differences across tiers and benchmarks are not statistically significant at the 5% level, suggesting that cryptocurrency hierarchy is reflected more through volatility, capital rotation, and regime behaviour than average returns.

D. DCC-GARCH Dynamic Correlation Results

DCC-GARCH results demonstrate that cryptocurrency correlations are dynamic and time-varying. In Model A, average BTC-ETH, BTC-Weighted Tier 2, and ETH-Weighted Tier 2 correlations were 0.0040, 0.0015, and -0.0052 respectively, showing alternating periods of co-movement and divergence. In Model B, BTC-Weighted Tier 3, BTC-Market Cap Weighted, and Weighted Tier 3-Market Cap Weighted correlations averaged 0.0015, 0.0045, and 0.0014 respectively, confirming dynamic rather than static relationships [20].

E. HMM Regime Classification Results

The HMM identifies four market regimes: Accumulation, BTC-led Expansion, Alt Rotation, and Contraction. BTC-led Expansion is the most dominant regime with 94 observations, followed by Accumulation (68), Contraction (64), and Alt Rotation (28), indicating that altcoin rotations are relatively short and concentrated. These findings support the importance of regime-sensitive cryptocurrency modelling [21].

F. Regime-Based Dynamic Correlation

The integrated HMM-DCC analysis shows that correlations vary significantly across market regimes. In Model A, BTC-ETH correlation is highest during Contraction (0.0892), while ETH-Weighted Tier 2 correlation rises to 0.1261 during Alt Rotation, indicating stronger Ethereum-altcoin integration. In Model B, BTC-Weighted Tier 3 correlation peaks during Contraction (0.0909), whereas Weighted Tier 3-Market Cap Weighted correlation increases to 0.1345 during Alt Rotation, highlighting stronger benchmark integration of Tier 3 assets during speculative phases.

TABLE III. SELECTED REGIME-WISE DYNAMIC CORRELATIONS

Regime	BTC-ETH	ETH-T2	BTC-T3	T3-MCW
Accumulation	-0.0080	0.0205	-0.0137	0.0095
Alt Rotation	-0.1228	0.1261	-0.1003	0.1345
BTC-led Exp.	-0.0317	0.0106	-0.0359	0.0131
Contraction	0.0892	-0.0746	0.0909	-0.0403

TABLE IV. DCC-HMM OVERLAY FOR MODEL A

Regime	BTC-ETH	BTC-Tier 2	ETH-Tier 2
Accumulation	-0.0080	0.0063	0.0205
Alt Rotation	-0.1228	0.0028	0.1261
BTC-led Expansion	-0.0317	0.0121	0.0106
Contraction	0.0892	-0.0219	-0.0746

BTC-Weighted Tier 3 correlation is greatest during the Contraction (0.0909). During the Alt Rotation, BTC-Weighted Tier 3 - Market Cap Weighted correlation reaches 0.1345 as Tier 3 now begins to be highly related to broad market movement as the capital shifts into altcoins as shown in Fig 13.

TABLE V. DCC-HMM OVERLAY FOR MODEL B

Regime	BTC-Tier 3	BTC-MCW	Tier 3-MCW
Accumulation	-0.0137	0.0104	0.0095
Alt Rotation	-0.1003	0.0084	0.1345
BTC-led Expansion	-0.0359	0.0179	0.0131
Contraction	0.0909	-0.0249	-0.0403

These overlay results in table 4 and 5 complement the regime-wise correlation table. They show that the same pair of assets can behave differently across phases, which explains why full-sample correlation may appear weak even when short regime-specific correlations are economically meaningful.

VII. DISCUSSION

The findings indicate that the cryptocurrency market functions as a hierarchical financial system, where Tier 1 leads market movements, Tier 2 supports expansion, and lower tiers drive speculative activity. While Pearson and Spearman correlations show overall co-movement, rolling correlation and DCC-GARCH reveal time-varying dependencies. The HMM model identifies market phases such as Accumulation, BTC-led Expansion, Alt Rotation, and Contraction, demonstrating that the integrated HMM-DCC framework captures dynamic market behaviour more effectively than static models.

VIII. CONCLUSION

In conclusion, cryptocurrency correlations are dynamic and regime-dependent. During contraction, assets become more connected with Bitcoin, increasing systemic risk, while during alt rotation, lower-tier assets align more with overall market movements and less with Bitcoin. The findings show that diversification benefits in cryptocurrency markets are conditional rather than constant, as dependence strengthens during stress periods.

The HMM-DCC framework provides a practical way to identify market expansion and risk compression, helping investors and researchers better understand regime-sensitive diversification and concentration risk. Future research may extend this framework using higher-frequency data, broader asset universes, and network-based measures.

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