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The Elusive Hedge: Crypto Correlation Dynamics in Global Stock/Index Bull/Bear Markets

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Abstract

Background: The integration of cryptocurrencies into regulated investment channels has intensified the need to test whether their diversification value survives market stress.
Objective: This study evaluates regime-dependent cryptocurrency–equity correlations at index and individual-stock levels across seven developed and emerging markets.
Methods: Weekly returns comprise 522 Bitcoin observations, 490 Ethereum observations, seven national indices, and 250 constituent stocks. A 20% directional-change algorithm identifies all bullish and bearish episodes. Pearson correlations are complemented by Spearman coefficients, Fisher r-to-z tests, and 10,000 paired circular-block bootstrap replications.
Results: All 14 index–cryptocurrency and 500 stock–cryptocurrency correlations are below |0.40| in bullish regimes. Robust regime changes occur in 3/14 index pairs and 74/500 stock pairs; 71 stock correlations are higher in bearish regimes and three are lower. The index evidence is concentrated in Bitcoin linkages with Brazil, South Africa, and the United States.
Conclusion: Cryptocurrencies are conditional diversifiers rather than universal hedges. Investors and portfolio managers should monitor regime-specific correlations and stress-test crypto exposure instead of relying on static diversification assumptions.

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INTRODUCTION

Cryptocurrencies have moved from peripheral speculative instruments toward increasingly accessible components of global investment portfolios (Almeida & Gonçalves, 2023; Arnone, 2024; Ma et al., 2020; Zhong, 2025). This transition accelerated when the U.S. Securities and Exchange Commission approved the listing and trading of spot Bitcoin exchange-traded products in January 2024, while the European Union's Markets in Crypto-Assets framework introduced harmonized requirements for issuers and service providers from 2024 (U.S. Securities and Exchange Commission, 2024). Greater accessibility and regulatory clarity can expand institutional participation, but they do not establish that cryptocurrency returns will protect equity portfolios when markets decline (Asif & Unar, 2024; Cumming et al., 2025; Desai, 2025).

Evidence on cryptocurrency diversification remains mixed. Low average correlations with conventional assets may provide diversification during calm conditions, yet connectedness often rises during uncertainty and crisis (Asiri et al., 2023; Kayani et al., 2024; Naeem et al., 2023). This conditionality challenges the use of one full-sample correlation as an all-weather portfolio parameter and motivates direct comparison between bullish and bearish cryptocurrency regimes.

Two gaps remain especially important. First, most cross-market studies use aggregate indices, even though an index is a weighted average that can conceal offsetting constituent-level relationships. Stock-level covariance heterogeneity may therefore reveal defensive pockets that disappear after aggregation. Second, evidence is often limited to one region or a small set of indices, restricting comparison across developed and emerging markets with different structures, liquidity, and investor bases.

This study asks whether Bitcoin and Ethereum maintain weak equity-market correlations across regimes and whether the changes are statistically reliable. It compares seven national indices and 250 constituent stocks in Brazil, Russia, India, China, South Africa, Indonesia, and the United States. Its contribution is a multi-country, dual-level test of the 'elusive hedge': Pearson estimates are checked with Spearman correlations, Fisher r-to-z tests, and paired bootstrap inference, allowing descriptive regime shifts to be separated from robust changes.

Literature Review And Research Position

Diversification, Hedging, and Regime Dependence

Modern Portfolio Theory links diversification to imperfect co-movement: combining assets with low or negative correlations can reduce portfolio variance (Liu & Clarkson, 2025). A diversifier is imperfectly positively correlated with another asset on average; a hedge is uncorrelated or negatively correlated over the relevant horizon; and a safe haven preserves that relation specifically during market stress (Almeida & Gonçalves, 2023). These concepts are conditional definitions, so a cryptocurrency cannot be classified as a reliable hedge from a low full-sample coefficient alone (Belguith, 2026; Kuang, 2025).

Previous studies document low or unstable crypto–equity correlations, time-frequency variation, and greater integration during stress (Bouri et al., 2020). The 'elusive hedge' argument follows diversification may appear in favorable periods but weaken precisely when investors need protection. Exogenous shocks, institutional participation, and market-specific conditions can alter these linkages, making regime and geography central to interpretation rather than secondary controls.

Aggregation, Stock-Level Heterogeneity, and Research Gap

Index aggregation can suppress economically meaningful dispersion. If constituent correlations move in different directions or with different magnitudes, their weighted average may remain close to zero even when several stocks experience material changes. Conversely, a significant index shift need not imply that all constituents behave alike. Individual-stock analysis therefore supplies theoretical information unavailable from index analysis: it identifies cross-sectional heterogeneity, shows whether an aggregate effect is broad or concentrated, and locates the securities responsible for potential hedging or contagion.

Table 1. Comparative synthesis and position of the present study

Study	Scope	Method	Main contribution	Remaining gap/position
Bouri et al. (2020)	Crypto and traditional assets	Asymmetric multivariate GARCH	Dynamic dependence; aggregate assets	No seven-country stock-level comparison
Choi (2026)	Developed and emerging markets	Regime-dependent correlations	Cross-country heterogeneity	Predominantly aggregate markets
Huynh et al. (2022)	Crypto and equity markets	Time-frequency analysis	Horizon-dependent diversification	Limited constituent-level evidence
Jacob et al. (2021)	ASEAN-5 markets	Correlation analysis	Regional market linkages	Single region and index focus
Mo (2025)	Global equity markets	Time-varying correlations	Dynamic global evidence	No granular multi-country stock test
Colombage et al. (2025)	Crypto under market stress	Conditional hedging analysis	Elusive-hedge proposition	Does not map 500 stock–crypto pairs

Present study	7 indices; 250 stocks; BTC and ETH	Pearson, Spearman, Fisher, 10,000 bootstraps	Index–stock and bull–bear comparison	Tests whether shifts are robust and asset-specific

Source: Authors' synthesis

Research Novelty and Conceptual Framework

The novelty is not the claim that correlations vary, but the simultaneous evaluation of where, at what aggregation level, and with what inferential support they vary. The design combines all confirmed bullish and bearish episodes, compares indices with their constituent stocks, and defines a robust change only when Fisher and bootstrap evidence agree. This prevents isolated coefficients or one crisis episode from being generalized as a universal hedge or contagion effect.

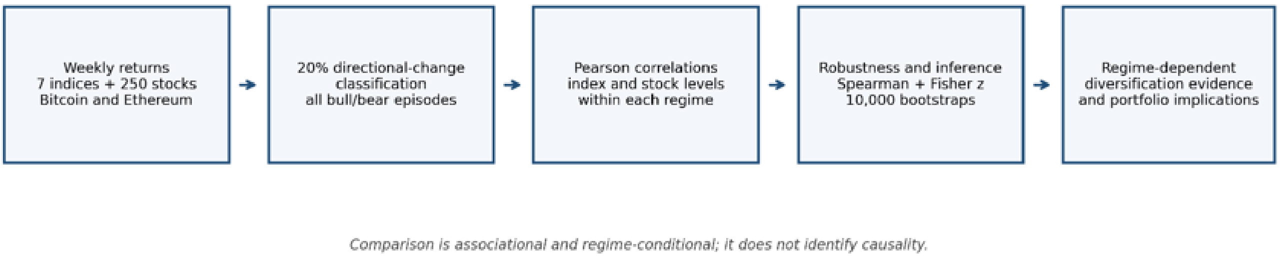

Figure 1. Conceptual framework of the regime-dependent correlation analysis
Source: Authors' design

METHOD

This quantitative, non-experimental study uses descriptive, correlational, and comparative designs. Weekly secondary prices cover Bitcoin from 2 August 2015 to 3 August 2025 (522 returns) and Ethereum from 13 March 2016 to 3 August 2025 (490 returns). The equity sample comprises seven national benchmark indices and 250 constituent stocks: 40 from Brazil, 34 from Russia, 29 from India, 38 from China, 38 from South Africa, 41 from Indonesia, and 30 from the United States. Bitcoin and Ethereum were selected for liquidity, market capitalization, and data history; they are analyzed separately rather than combined.

Weekly closing prices for equities were obtained from the respective market datasets and cryptocurrency prices from CoinDesk. Equity and index returns are retained in local currency to avoid adding exchange-rate variation to the focal association. Dates were standardized to weeks ending on Sunday. Missing prices were neither replaced with zero nor interpolated; returns were computed only from two valid consecutive prices. Assets required at least 80% coverage within the relevant subsample and at least 30 paired returns. Pairwise-complete observations were used for individual correlations.

Return and Market-Regime Classification

Simple weekly returns were calculated as $R_t = (P_t/P_{t-1}) - 1$. Cryptocurrency regimes were identified ex post and separately using a 20% directional-change algorithm. A peak was confirmed after a decline of at least 20%, and the peak-to-subsequent-trough interval was classified as bearish; the complement was bullish until the next confirmed peak. All bearish episodes were pooled for each cryptocurrency, rather than using only the latest decline. Consequently, Bitcoin contributes 379 bullish and 143 bearish returns, while Ethereum contributes 392 bullish and 98 bearish returns before pairwise filtering.

Table 2. Cryptocurrency market-regime episodes

Cryptocurrency	Regime	Start	End	Cumulative change
Bitcoin	Bullish	2 Aug 2015	10 Dec 2017	+7,380.9%
Bitcoin	Bearish	10 Dec 2017	9 Dec 2018	−83.3%
Bitcoin	Bullish	9 Dec 2018	23 Jun 2019	+268.8%
Bitcoin	Bearish	23 Jun 2019	8 Mar 2020	−56.5%
Bitcoin	Bullish	8 Mar 2020	7 Nov 2021	+1,142.6%
Bitcoin	Bearish	7 Nov 2021	20 Nov 2022	−74.4%

Bitcoin	Bullish	20 Nov 2022	3 Aug 2025	+607.8%
Ethereum	Bullish	13 Mar 2016	7 Jan 2018	+13,285.1%
Ethereum	Bearish	7 Jan 2018	9 Dec 2018	−93.9%
Ethereum	Bullish	9 Dec 2018	7 Nov 2021	+5,435.9%
Ethereum	Bearish	7 Nov 2021	12 Jun 2022	−78.6%
Ethereum	Bullish	12 Jun 2022	1 Dec 2024	+301.4%
Ethereum	Bearish	1 Dec 2024	13 Apr 2025	−59.6%
Ethereum	Bullish	13 Apr 2025	3 Aug 2025	+164.2%

Source: Authors' calculations from weekly cryptocurrency prices

Correlation Tests, Robustness, and Software

Pearson's r is the primary measure of linear association between cryptocurrency and equity returns within each regime. Correlations with $|r| < 0.40$ are classified as weak or negligible. Because Jarque–Bera tests reject normality for most series, Spearman's rank coefficient is reported as a robustness check against non-normality and outliers. Pearson and Spearman agreement is interpreted as directional robustness, not proof of causality.

Regime differences are tested with Fisher's r-to-z transformation using non-overlapping bullish and bearish subsamples. Uncertainty is also evaluated through 10,000 paired circular-block bootstrap replications, preserving short-run dependence while resampling the paired returns. The reported difference is $\Delta r = r(\text{bullish}) - r(\text{bearish})$, with a 95% bootstrap confidence interval. A change is labelled robust only when both Fisher and bootstrap p-values are below 0.05 and the bootstrap interval excludes zero. This joint criterion separates the 74 robust stock-level changes from the 97 Fisher-only and 79 bootstrap-only significance counts.

Data preparation, correlation estimation, resampling, and visualizations were implemented in Python 3.11 and reconciled against a formula-driven Microsoft Excel audit workbook. The 20% rule provides a transparent and reproducible economic classification but does not model latent statistical states. Likewise, the within-regime coefficients do not capture continuous time variation or tail dependence; DCC-GARCH, dynamic copulas, wavelet coherence, and Markov-switching models are therefore treated as extensions rather than analyses already performed in this study.

RESULTS AND DISCUSSION

Results

Distributional Characteristics

Cryptocurrency returns are substantially more dispersed than national-index returns. Bitcoin has a weekly mean of 1.66% and standard deviation of 9.91%; Ethereum has a mean of 2.15% and standard deviation of 13.81%. All full-series Jarque–Bera p-values are below 0.001. The combination of skewness, excess kurtosis, and unequal regime sizes justifies reporting rank-based correlations and resampling-based uncertainty rather than relying on Pearson significance alone.

Table 3. Descriptive statistics of weekly index and cryptocurrency returns

Asset	N	Mean	SD	Skewness	Excess kurtosis	JB p-value
Brazil	522	0.24%	3.05%	−0.347	6.265	<0.001
Russia	518	0.15%	3.01%	−1.870	15.244	<0.001
India	522	0.22%	2.21%	−0.192	5.291	<0.001
China	500	0.01%	2.42%	−0.225	3.862	<0.001
South Africa	522	0.17%	2.53%	−0.524	3.921	<0.001
Indonesia	514	0.04%	2.65%	−0.874	8.681	<0.001
United States	522	0.21%	2.42%	−0.751	9.428	<0.001
Bitcoin	522	1.66%	9.91%	0.296	2.286	<0.001
Ethereum	490	2.15%	13.81%	0.734	2.583	<0.001

Source: Authors' calculations

Index-Level Correlations and Regime Changes

The heatmap shows uniformly weak bullish correlations and a localized bearish increase, especially for Bitcoin. All 14 bullish index coefficients remain below |0.40|. Bitcoin correlations rise robustly in Brazil (−0.014 to 0.326), South Africa (−0.011 to 0.333), and the United States (0.019 to 0.389). No Ethereum index change satisfies both Fisher and bootstrap criteria. Thus, market stress does not produce a universal correlation increase across countries or cryptocurrencies.

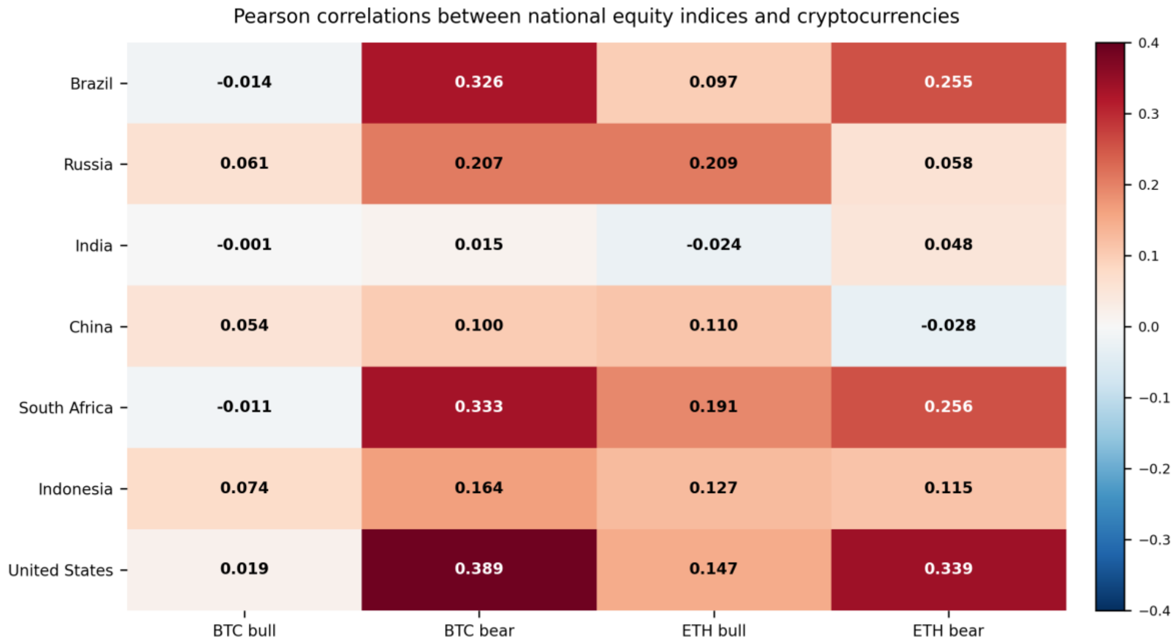

Figure 2. Heatmap of index–cryptocurrency Pearson correlations by regime
Source: Authors' calculations. Values are Pearson correlations.

Table 4. Index-level correlation changes and uncertainty

Crypto	Country	N bull/bear	r bull	r bear	rho bull	rho bear	Δr	95% boot CI	p Fisher/boot	Robust
BTC	Brazil	379/143	-0.014	0.326	0.030	0.214	-0.340	[-0.555; -0.085]	<0.001/0.003	Yes
BTC	Russia	379/139	0.061	0.207	0.067	0.202	-0.147	[-0.358; 0.044]	0.135/0.161	No
BTC	India	379/143	-0.001	0.015	0.005	-0.033	-0.017	[-0.191; 0.165]	0.866/0.857	No
BTC	China	365/135	0.054	0.100	0.026	0.019	-0.046	[-0.239; 0.158]	0.649/0.661	No
BTC	South Africa	379/143	-0.011	0.333	0.009	0.259	-0.344	[-0.569; -0.083]	<0.001/0.004	Yes
BTC	Indonesia	371/143	0.074	0.164	0.117	0.056	-0.090	[-0.337; 0.172]	0.356/0.511	No
BTC	United States	379/143	0.019	0.389	0.070	0.350	-0.370	[-0.570; -0.145]	<0.001/<0.001	Yes
ETH	Brazil	392/98	0.097	0.255	0.074	0.236	-0.157	[-0.390; 0.087]	0.155/0.193	No
ETH	Russia	392/94	0.209	0.058	0.141	0.189	0.152	[-0.082; 0.338]	0.184/0.163	No
ETH	India	392/98	-0.024	0.048	-0.045	-0.000	-0.071	[-0.264; 0.124]	0.533/0.475	No
ETH	China	376/94	0.110	-0.028	0.104	-0.054	0.138	[-0.072; 0.356]	0.236/0.210	No
ETH	South Africa	392/98	0.191	0.256	0.159	0.266	-0.065	[-0.273; 0.138]	0.553/0.547	No
ETH	Indonesia	386/96	0.127	0.115	0.097	0.093	0.013	[-0.209; 0.250]	0.912/0.915	No
ETH	United States	392/98	0.147	0.339	0.168	0.344	-0.192	[-0.396; 0.023]	0.074/0.071	No

Source: Authors' calculations. Δr = r(bullish) − r(bearish); robust requires Fisher and bootstrap $p < 0.05$ and a bootstrap interval excluding zero.

Stock-Level Heterogeneity and Sectoral Evidence

The stock-level sample contains 500 stock–cryptocurrency pairs. Every bullish Pearson coefficient is below |0.40|, but the regime change is heterogeneous. Fisher identifies 97 significant changes and the bootstrap identifies 79; their intersection contains 74 robust changes. Of these, 71 correlations are higher in bearish regimes and only three are lower. Pearson and Spearman changes share the same direction for 429 pairs (85.8%). The evidence therefore supports conditional diversification in bullish periods and a concentrated erosion of that benefit during bearish periods, rather than a uniform global pattern.

Table 5. Stock-level correlation summary by country and cryptocurrency

Crypto	Country	K	Median r bull	Median r bear	Fisher sig.	Boot sig.	Robust	Higher bear	Lower bear
BTC	Brazil	40	0.006	0.180	18	15	15	15	0
BTC	Russia	34	0.027	0.132	5	3	2	2	0
BTC	India	29	0.032	0.195	10	5	5	5	0
BTC	China	38	0.038	0.012	1	2	1	0	1
BTC	South Africa	38	-0.003	0.192	18	15	15	15	0
BTC	Indonesia	41	0.032	0.103	3	0	0	0	0
BTC	United States	30	0.015	0.260	27	22	22	22	0
ETH	Brazil	40	0.066	0.117	2	3	2	2	0
ETH	Russia	34	0.124	0.064	1	2	1	0	1
ETH	India	29	0.106	0.187	2	2	2	2	0
ETH	China	38	0.048	-0.038	2	1	1	0	1
ETH	South Africa	38	0.115	0.137	0	0	0	0	0
ETH	Indonesia	41	0.081	0.059	0	1	0	0	0
ETH	United States	30	0.092	0.211	8	8	8	8	0

Source: Authors' calculations. Robust is the Fisher–bootstrap intersection

The robust-change network confirms that the result is concentrated. Bitcoin accounts for most higher-bearish links, led by the United States (22), Brazil (15), and South Africa (15). Ethereum contributes fewer robust links and the only robust decreases appear in Russia and China. The network therefore visualizes why an average cross-country statement would be misleading: the count, direction, and cryptocurrency differ materially across markets.

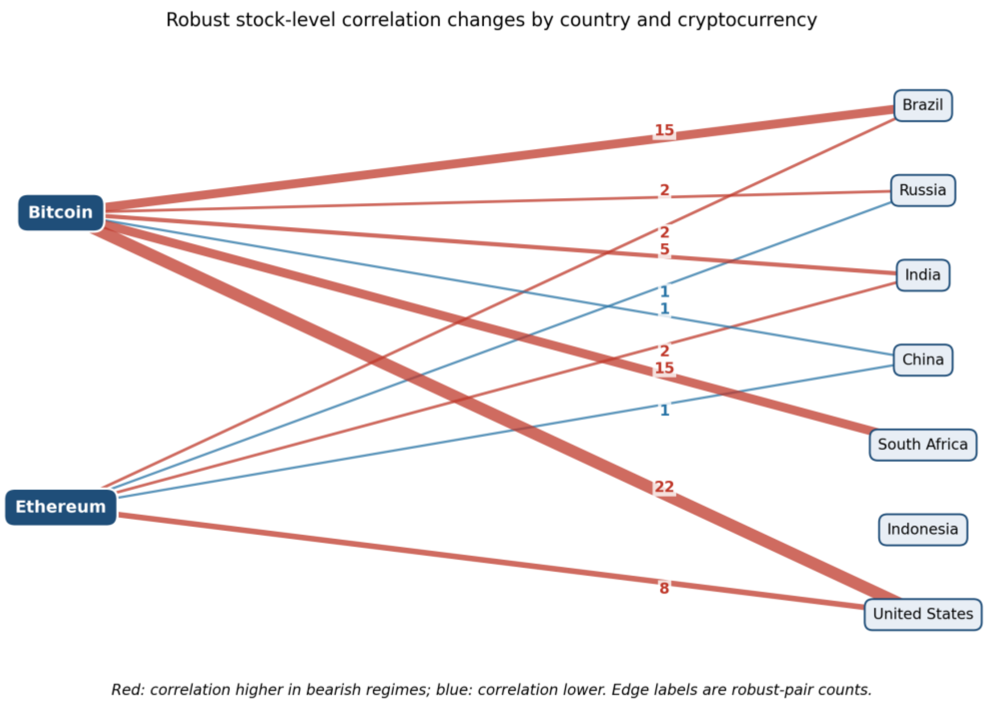

Figure 3. Network of robust stock-level regime changes
Source: Authors' calculations from 74 stock–cryptocurrency pairs meeting both Fisher and bootstrap criteria.

Table 6. Sectoral profile of robust positive-to-negative correlation shifts

Ticker	Company	Country	Crypto	Sector	r bull	r bear	95% boot CI Δr	p Fisher/boot
NVTK	NOVATEK	Russia	Ethereum	Energy—natural gas	0.178	-0.055	[0.022; 0.425]	0.044/0.023
600690	Haier Smart Home	China	Ethereum	Consumer discretionary—home appliances	0.186	-0.051	[0.025; 0.457]	0.040/0.031
601111	Air China	China	Bitcoin	Industrials—airlines	0.128	-0.089	[0.042; 0.392]	0.032/0.016

Source: Authors' calculations. Sector labels are broad economic classifications; Δr = r(bullish) − r(bearish).

Discussion

The three robust positive-to-negative shifts occur in unrelated sectors (natural gas, airlines, and home appliances) so they do not establish a universal defensive sector. They are better interpreted as security-specific exceptions. This is the theoretical value of disaggregation: an index can conceal isolated counter-cyclical relationships, but isolated stocks should not be elevated into a general sector strategy without out-of-sample validation and transaction-cost analysis.

Economic, Managerial, and Policy Implications

For investors and portfolio managers, a low bullish correlation should not be treated as a permanent hedge coefficient. Crypto allocations should be accompanied by regime monitoring, rolling exposure limits, and stress scenarios that impose the higher bearish correlations observed for the relevant country and cryptocurrency. Institutional managers should distinguish broad index exposure from security-level positions: the 74 robust changes are concentrated in specific markets, while only three move toward negative correlation.

For global portfolio management, the findings favor adaptive rather than static allocation. The approval of exchange-traded crypto products can lower access frictions and broaden participation, while harmonized frameworks such as MiCA can strengthen disclosure and service-provider oversight. Neither development guarantees diversification. Greater market access may also increase common investor ownership and synchronized deleveraging, a mechanism consistent with stronger bearish co-movement, although this study does not test a causal ETF or regulatory effect.

For regulators, the evidence supports monitoring cross-market exposure and regime-specific co-movement rather than claiming that cryptocurrencies already create systemic risk. The empirical indicators here are correlations, Fisher tests, and bootstrap intervals, not bank balance-sheet exposures, leverage networks, or contagion losses. Accordingly, proportionate surveillance could track abrupt correlation increases alongside institutional holdings, liquidity, and leverage; capital or macroprudential conclusions require those additional systemic-risk measures.

CONCLUSION

This study provides multi-country evidence that cryptocurrency diversification is conditional on market regime, aggregation level, geography, and the cryptocurrency examined. All 14 index and 500 stock correlations are weak in bullish regimes, but only 3 index pairs and 74 stock pairs show robust regime changes. Seventy-one robust stock correlations are higher in bearish periods and three are lower. The dominant pattern therefore supports the elusive-hedge proposition, while its concentration rejects a universal claim across countries or assets.

The theoretical contribution is to connect regime dependence with aggregation heterogeneity. Index correlations cannot reveal whether a shift is widespread or driven by a small set of constituents; stock-level evidence cannot, by itself, establish a scalable sector hedge. Combining both levels with joint Fisher–bootstrap confirmation clarifies when low correlation represents a broad diversification condition and when it is merely an isolated historical outcome.

The findings remain associational and in-sample. The 20% directional-change rule is transparent but simpler than latent-state models; Pearson and Spearman do not capture continuous time variation, tail dependence, or causality; multiple comparisons may still generate false discoveries; and returns exclude transaction costs, liquidity constraints, and currency translation. Future research should compare directional-change regimes with Markov switching or hidden Markov models and evaluate DCC-GARCH, dynamic copulas, wavelet coherence, quantile dependence, multiple-testing corrections, and out-of-sample portfolio performance.

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AUTHOR CONTRIBUTION STATEMENT

Arief Rachmansyah contributed to conceptualization, methodology, software, validation, formal analysis, investigation, data curation, visualization, and writing of the original draft. Nugraha contributed to conceptualization, supervision, validation, and writing through review and editing. Both authors approved the final version of the manuscript. The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this article. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The study uses secondary weekly price data, and the processed data, regime classifications, correlation outputs, and formula-driven audit workbook are available from the corresponding author upon reasonable request, subject to the terms of the original data providers.

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