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Fear Divides, Not Unites: Volatility Transmission and Decoupling Between Cryptocurrency and Renewable Energy Markets

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ABSTRACT

This paper investigates the channels of price volatility transmission between speculative cryptocurrency markets and the renewable energy stock sector. We propose and test a framework of three transmission channels: (1) Energy Consumption, (2) Investment Sentiment, and (3) Policy and Regulatory. Using a two-stage GJR-GARCH and rolling correlation analysis on daily data from 2017 to 2024, with robust Newey-West standard errors to correct for autocorrelation, we uncover a nuanced relationship. After controlling for the crypto market's correlation with the S&P 500, we find a significant negative relationship between broad market fear (the VIX) and the crypto-renewable correlation. This suggests that during periods of market panic, the assets decouple, potentially indicating a flight to quality within the risk-asset spectrum. These findings, which are robust across different time windows and pre- and post-COVID-19 subperiods, challenge simple "risk-on/risk-off" narratives. The Energy and Policy channels remain statistically insignificant, suggesting that systemic market dynamics, rather than idiosyncratic factors, are the dominant drivers of the relationship, offering critical insights for sophisticated diversification strategies.

Keywords: Volatility Spillover, Cryptocurrency, Renewable Energy, Investor Sentiment, Decoupling, GARCH
JEL Classifications: G12, Q42, C58

1. INTRODUCTION

The global economic landscape is being shaped by two powerful and seemingly disparate forces: the digital revolution in finance, spearheaded by cryptocurrencies, and the urgent global transition towards sustainable energy. Cryptocurrencies have exploded from a niche technological experiment into a multi-trillion-dollar asset class, characterized by both disruptive potential and extreme price volatility. Simultaneously, the imperative to combat climate change has propelled the renewable energy sector to the forefront of industrial strategy and investment portfolios.

The primary and most conspicuous link between these domains is the substantial energy consumption of cryptocurrencies that utilize a Proof-of-Work (PoW) consensus mechanism. This direct demand for electricity creates an intrinsic and unavoidable link to energy markets, including the renewable energy sector. This has led to a dominant narrative suggesting a fundamentally antagonistic relationship, where the voracious energy appetite of crypto mining could strain power grids and create headwinds for the clean energy transition. However, this is challenged by a more nuanced view where the flexibility of crypto mining could offer symbiotic benefits, such as balancing power grids and monetizing stranded renewable energy assets.

If the fundamental connections between these markets are indeed multifaceted and conflicting, then the transmission of risk, specifically price volatility, is unlikely to be simple, linear, or stable over time. A thorough understanding of these spillovers is paramount for investors designing effective diversification strategies and for policymakers assessing the potential for cross-market systemic risk.

Despite the clear importance of this topic, the existing academic literature reveals a significant gap. While a growing body of empirical work has begun to investigate the relationship between cryptocurrency and energy markets, these studies are primarily empirical in nature. They effectively identify that a "black box" of transmission exists but do not attempt to theoretically specify or empirically test its internal workings (Liu et al., 2024). They often find evidence of time-varying correlations but do not provide a structural model to explain *why* these correlations change.

This paper directly addresses this gap by formally modeling and empirically testing the channels of volatility transmission. Our research is guided by three central questions:

1. What are the structural and causal pathways through which price volatility is transmitted between cryptocurrency and renewable energy stock markets?
2. How do broad market sentiment and external shocks modulate the intensity and direction of these volatility transmissions?
3. What are the practical implications of these channels for portfolio diversification and risk management?

To answer these questions, we first propose a theoretical framework identifying three core transmission channels—the Energy Consumption Channel, the Investment Sentiment Channel, and the Policy and Regulatory Channel. We then empirically test this framework using a robust two-stage GJR-GARCH and rolling correlation analysis. Ultimately, this paper provides a structured and nuanced analysis of how and why the relationship between these two innovative sectors evolves, offering valuable insights for the future of fintech and sustainable finance.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature to identify the research gap. Section 3 details the data sources and our two-stage empirical methodology. Section 4 presents the empirical results from the GJR-GARCH and robust regression models, including subperiod and robustness tests. Section 5 discusses the implications of our findings, and Section 6 concludes.

2. LITERATURE REVIEW

Our theoretical and empirical framework is built upon the confluence of three distinct but increasingly interconnected pillars of financial and economic literature: (1) Studies on the drivers of cryptocurrency market volatility; (2) Research into the unique performance determinants of renewable energy stocks; and (3) The econometric literature on modeling cross-market volatility spillovers. A review of these areas reveals the precise gap that our proposed model is designed to address.

2.1. Cryptocurrency Market Dynamics and Volatility

The extreme and persistent volatility of cryptocurrency returns is a well-documented phenomenon. Recent research has moved towards quantifying the specific external factors driving this volatility and understanding the unique internal market dynamics that differentiate crypto from traditional assets.

A key study by Omrane et al. (2025) empirically investigates how the volatilities of Bitcoin and Ethereum react to macroeconomic data releases from the US, Germany, and Japan. Using high-frequency 5-minute observations from 2016 to 2023, the study analyzes market reactions before, during, and after official announcements. The findings show that volatility responds significantly to select news, particularly in the pre-announcement period. Notably, US monetary policy news consistently drives volatility across all phases, while Ethereum exhibits greater sensitivity to US announcements than Bitcoin. This research highlights the necessity of accounting for both pre- and post-announcement periods when evaluating the intraday price impact of macroeconomic news.

In a complementary study, Brini and Lenz (2024) analyze the internal factors that impact future volatility within the cryptocurrency ecosystem. Using high-frequency panel data from 2020 to 2022, the paper estimates several autoregressive models to examine drivers like daily leverage and signed volatility, comparing the results to the equity market. The study uncovers several structural differences in the nascent crypto market. For instance, positive high-frequency market returns were found to increase price volatility, contrary to classical financial literature. Furthermore, positive signed volatility and negative daily leverage positively impact future volatility, a dynamic not observed in stocks. These findings signal that the cryptocurrency market has yet to mature and behaves differently from established asset classes.

2.2. Renewable Energy Equity Dynamics

The performance of renewable energy stocks is shaped by a unique interplay of financial markets and corporate performance. Recent research provides granular evidence on both the firm-level financial outcomes of adopting clean energy and the macroeconomic role of financial markets in fostering the energy transition.

Focusing on the firm-level impact, Salehi et al. (2025) investigate the impact of renewable energy consumption and low-carbon technologies on the financial performance of companies. Their study utilizes panel data from non-financial companies listed on the Tehran Stock Exchange from 2012 to 2021. Using a dynamic Generalized Method of Moments (GMM) model, the findings indicate that consuming renewable and low-carbon energy has a positive and significant impact on Return on Assets (ROA), Return on Equity (ROE), and Tobin's Q. The analysis further specifies that wind and solar energies have the most substantial positive effects on ROA and ROE.

Shifting to a macroeconomic perspective, Luo et al. (2025) examine how stock market development influences renewable energy growth. Based on cross-country data from 60 countries spanning 2001 to 2021, the study employs fixed effects and quantile regression methods. The findings reveal that stock market development has a statistically significant positive effect on renewable energy growth, an effect that is particularly pronounced in developed economies and non-resource-dependent countries. The quantile regression results show a non-linear relationship: the marginal effect of the stock market decreases at lower stages of renewable energy development but turns to an increasing trend after a certain threshold is surpassed, indicating that financial market support has distinct "nurturing" and "acceleration" periods.

2.3. Modeling Cross-Market Volatility Transmission

The econometric literature on modeling volatility transmission has evolved significantly from simple correlation analyses to dynamic, time-varying models. Foundational frameworks like the GARCH model (Bollerslev, 1986) and the Dynamic Conditional Correlation (DCC) GARCH model (Engle, 2002) provided robust methods for capturing time-varying volatility and correlations. Recent empirical work has applied and extended these models to map the increasing interconnectedness between cryptocurrency and energy markets, often with a focus on how these relationships change under different market conditions.

Jiang et al. (2025) address the ambiguity of risk spillover between various types of cryptocurrencies and energy markets by examining them under different quantile conditions. To achieve this, the study utilizes the Quantile Vector Autoregression (QVAR) model to examine returns and volatility spillovers among fossil energy, clean energy, the electricity market, and both clean and dirty cryptocurrencies. The findings reveal that while moderate spillover effects exist under median quantile conditions, these effects are intensified in extreme market conditions. The paper identifies specific assets as typical recipients of spillovers (oil, clean cryptocurrency, wind energy) and others as transmitters (natural gas, dirty cryptocurrency, bioenergy). Notably, the electricity market acts as a recipient in normal conditions but becomes a transmitter during extreme events.

Focusing specifically on the role of green finance as a transmission channel, Kaur et al. (2025) explore the volatility spillover effect of green finance on the renewable energy and cryptocurrency markets. Using a Dynamic Conditional Correlation (DCC) model on daily data from April 30, 2014, to May 31, 2024, the study proxies green finance with the S&P Green Bond and ESG Indices, renewable energy with the S&P Global Clean Energy Index, and cryptocurrency with the S&P Bitcoin Index. The DCC results reveal a volatility spillover from green bonds to renewable energy, and from the ESG index to both renewable energy and the cryptocurrency market in the short and long run. Interestingly, the spillover from green bonds to Bitcoin is only observed in the long run, which suggests that diversification opportunities between these assets exist only in the short term.

2.4. Identifying the Research Gap

While the literature effectively demonstrates that a “black box” of volatility transmission exists between cryptocurrency and energy markets, the specific theoretical mechanisms driving these spillovers are not well understood. Existing studies are primarily empirical and do not test the underlying channels in a unified way. Recent research has begun to provide crucial, detailed evidence on the individual channels we propose, yet this work also highlights the need for a more comprehensive model.

For instance, the Energy Consumption Channel has been rigorously investigated by Bruno, Weber, & Yates (2023). Using a long-run model of the Texas electricity market, they find that while electricity demand from Bitcoin mining can indeed increase renewable capacity, it also significantly increases carbon emissions due to a rise in natural gas generation. Their findings show this negative externality is largely mitigated if miners provide grid management services in the form of demand response, underscoring the complex and conditional nature of this transmission channel.

Similarly, the Investment Sentiment Channel is highlighted by Bouteska et al. (2024). This study explores the interplay between cryptocurrency volatility, investor sentiment, and renewable energy dynamics amid crises. Using a Quantile Vector Autoregression (QVAR) model on daily data from 2015 to 2022, they find that investor sentiment plays a dynamic, state-dependent role. Notably, sentiment transitioned from being a net shock transmitter before the COVID-19 pandemic to a net shock receiver during it, empirically demonstrating how sentiment’s role in modulating volatility transmissions changes dramatically during periods of global stress.

However, these important studies examine the transmission channels in isolation. To our knowledge, no existing framework has formally modeled and tested the distinct effects of the Energy Consumption, Investment Sentiment, and Policy/Regulatory channels simultaneously within a single, comprehensive structural model. This leaves a critical gap in understanding how these mechanisms interact and collectively drive the dynamic correlation between the markets. It is precisely this gap that our paper aims to fill by proposing and testing a unified framework of these transmission channels.

3. METHODOLOGY AND DATA

This section details the data sources, variable construction, and the econometric framework used to empirically test our theoretical model.

3.1. Data and Variable Construction

We collected publicly available daily data for a sample period spanning from February 10, 2017, to August 29, 2024. The specific proxies used to represent the cryptocurrency, renewable energy, and broad market returns, along with all other variables used in this study, are detailed in Table 1. All price data was obtained from Yahoo Finance, and daily log-returns are calculated as rt=100×ln(Pt/Pt−1). To ensure the validity of our time-series analysis, the resulting return series were tested for stationarity using the Augmented Dickey-Fuller (ADF) test (Table 2); all series were found to be stationary ($P < 0.01$). Missing values for non-trading days were handled by forward-filling prices before calculating returns to create a continuous daily series.

3.2. Transmission Channel Proxies

To empirically test our framework, we construct proxies for the three transmission channels. For the Energy Consumption Channel (ECt), we use data from the Digiconomist Bitcoin Energy Consumption Index, as it provides a widely cited daily estimate. For the Investment Sentiment Channel (ISt), we use the CBOE Volatility Index (VIX). The Policy and Regulatory Channel (PRt) is captured using an event-study approach with a manually constructed dummy variable. We acknowledge this

Table 1: Summary of variables

Variable category	Variable Name	Notation	Proxy Used	Data Source	Description
Asset returns	Cryptocurrency Returns	rc, t	Bitcoin (BTC-USD)	Yahoo Finance	Daily log-returns of a broad crypto market index. Used in Stage 1 GARCH model.
	Renewable Energy Returns	rr, t	iShares Global Clean Energy ETF (ICLN)	Yahoo Finance	Daily log-returns of a global renewable energy stock index. Used in Stage 1 GARCH model.
	Broad Market Returns	rm, t	SPDR S&P 500 ETF Trust (SPY)	Yahoo Finance	Daily log-returns of the S&P 500. Used to create the market control variable.
Dependent variable	Rolling Correlation	*Rolling_Corr*	Standardized Residuals from GARCH	*Calculated*	The 60-day and 90-day rolling correlation between rc, t and rr, t after GARCH filtering.
Independent variables	Energy Consumption Channel	ECt	Digiconomist Bitcoin Energy Index	Digiconomist	Daily percentage change in the estimated electricity consumption of the Bitcoin network.
	Investment Sentiment Channel	ISt	CBOE Volatility Index (VIX)	Yahoo Finance	A measure of broad market fear and expected 30-day volatility.
	Policy and Regulatory Channel	PRt	Manually Constructed Event Dummy	News Archives (Reuters, Bloomberg, etc.)	A dummy variable coded as+1 for major positive news, −1 for negative, and 0 otherwise.
Control variable	Market Control	*Crypto_SPY_Corr*	Standardized Residuals from GARCH	*Calculated*	The 60-day and 90-day rolling correlation between rc, t and the broad market (rm, t).

Table 2: Stationarity tests for daily log-returns

Augmented Dickey-Fuller (ADF) test			
Return series	**ADF statistic**	**P-value**	**Result (at 1% level)**
Crypto (rc, t)	−37.49	0.0000	Stationary
Renewable (rr, t)	−19.87	0.0000	Stationary
Market (rm, t)	−40.70	0.0000	Stationary

proxy is simplistic but provide a full list of coded events and their justifications in Appendix A to ensure reproducibility.

3.3. Econometric Methodology

Our empirical strategy is a robust two-stage process:

1. Stage 1: Univariate GJR-GARCH modeling: We first model the conditional variance of each return series (BTC, ICLN, and SPY) individually using a GJR-GARCH(1,1) model, chosen for its proven ability to capture leverage effects (Glosten et al., 1993). From this stage, we extract the standardized residuals.
2. Stage 2: Rolling correlation and factor regression: We calculate a 60-day rolling-window correlation on the standardized residuals of BTC and ICLN. We then use an Ordinary Least Squares (OLS) regression to test the impact of our three lagged channel proxies. To address potential omitted variable bias, we also include a market control variable: the lagged 60-day rolling correlation between Bitcoin and the S&P 500. Initial diagnostics revealed significant serial correlation (Durbin-Watson ≈ 0.08) and potential multicollinearity. To ensure the validity of our results, the regression is estimated using robust Newey-West HAC standard errors, and we report Variance Inflation Factor (VIF) diagnostics.

3.4. Robustness and Subperiod Tests

To ensure that our findings are robust, we conduct two additional tests:

Table 3: GJR-GARCH (1,1) model results for cryptocurrency returns (BTC)

Parameter	Coefficient	Std. Error	P-value
Mean model			
mu	0.0063	0.116	0.957
Volatility model			
omega	1.6704	0.622	0.007
alpha1	0.1350	0.0418	0.001
gamma1	0.0805	0.0473	0.089
beta1	0.7548	0.0622	<0.001

1. Alternative rolling window: We re-estimate our Stage 2 regression model using a longer 90-day rolling window for all correlation calculations.
2. Subperiod analysis: To account for potential structural breaks, we split our sample into a pre-COVID period (February 2017 – February 2020) and a post-COVID period (March 2020 – August 2024).

4. EMPIRICAL RESULTS

This section presents the findings from our analysis, including diagnostics and the main regression results.

4.1. Univariate GJR-GARCH model results

The first stage of our methodology involves filtering the raw return series for each asset to account for time-varying volatility. The full results of the GJR-GARCH(1,1) models are presented in Tables 3 and 4. For both Bitcoin and the renewable energy index, the ARCH ($\alpha 1$) and GARCH ($\beta 1$) coefficients are highly statistically significant, confirming the presence of strong volatility clustering, a stylized fact of financial time series. The sum of these coefficients is close to one for both assets, indicating that volatility shocks are highly persistent.

A key difference between the assets emerges in the asymmetric term (γ1). For Bitcoin, this term is positive and marginally significant (P = 0.089), providing evidence of a leverage effect where negative shocks (bad news) increase volatility more than positive shocks. For the renewable energy index, this term is not statistically significant (P = 0.141), suggesting its volatility responds symmetrically to news. The standardized residuals from these models, representing "pure" market shocks, are then carried forward to Stage 2.

4.2. Diagnostic Tests

Before interpreting our main regression, it is crucial to assess the model's validity. As noted in the methodology, initial diagnostics of a standard OLS regression pointed to severe autocorrelation (Durbin-Watson ≈ 0.08). This confirmed the necessity of using Newey-West HAC standard errors for reliable inference. Furthermore, to ensure that the correlation between our explanatory variables does not bias our results, we performed a multicollinearity test. The Variance Inflation Factor (VIF) results are presented in Table 5. All VIF values are well below the common cautionary threshold of 5, indicating that multicollinearity is not a significant issue and we can interpret the coefficients of our explanatory variables independently.

4.3. Factor Regression and Subperiod Analysis

The central findings of our study, from the regression of the rolling correlation on our channel proxies, are presented in Table 6. The main model for the full sample has a strong explanatory power (R-squared = 0.541), suggesting our framework accounts for a significant portion of the variation in the crypto-renewable correlation.

The most significant finding is the coefficient on the Investment Sentiment Channel (ISlag), which is −0.0009 and highly statistically significant. The economic interpretation of this coefficient is that a one-point increase in the VIX index is associated with a 0.0009 decrease in the 60-day rolling correlation between Bitcoin and renewables, holding other factors constant. This provides strong evidence that heightened market fear leads to a decoupling of the two assets.

The Market Control variable also has a powerful and highly significant negative coefficient of −0.7012, suggesting that for every 0.1 increase in Bitcoin's correlation with the S&P 500, its correlation with renewables decreases by a substantial 0.07. This highlights a strong substitution effect. In contrast, both the Energy Consumption and Policy channels remain statistically insignificant, suggesting their direct impact on the financial correlation is negligible compared to systemic market factors.

The Subperiod Analysis reveals that these core relationships are remarkably stable over time. The negative and significant coefficients on the Investment Sentiment and Market Control variables persist in both the pre- and post-COVID eras, confirming that our findings are not an artifact of the pandemic-induced volatility but rather a persistent feature of these markets.

4.4. Visualization of Dynamic Correlation

Figure 1 plots the 60-day rolling correlation of standardized residuals (blue line, left axis) against the VIX index (red line, right axis). The plot visually demonstrates the paper's core finding: spikes in the VIX often correspond to troughs, not peaks, in the correlation between Bitcoin and renewable energy stocks.

Table 4: GJR-GARCH (1,1) model results for renewable energy returns (ICLN)

Parameter	Coefficient	Std. Error	P-value
Mean model			
mu	-0.0432	0.0486	0.374
Volatility model			
omega	0.0540	0.0277	0.052
alpha1	0.0254	0.0105	0.015
gamma1	0.0338	0.0230	0.141
beta1	0.9407	0.0170	<0.001

Table 5: Multicollinearity diagnostics (VIF)

Feature	VIF
EC_lag	1.0001
IS_lag	2.3876
PR_lag	1.0005
Crypto_SPY_Corr_lag	2.3872

5. DISCUSSION

Our empirical results, derived from a robust model and validated with subperiod analysis, paint a more complex and insightful picture of the crypto-renewable relationship than simple narratives suggest. The findings challenge the conventional "risk-on/risk-off" hypothesis for this specific asset pair, where all high-risk assets are expected to become more correlated during market downturns.

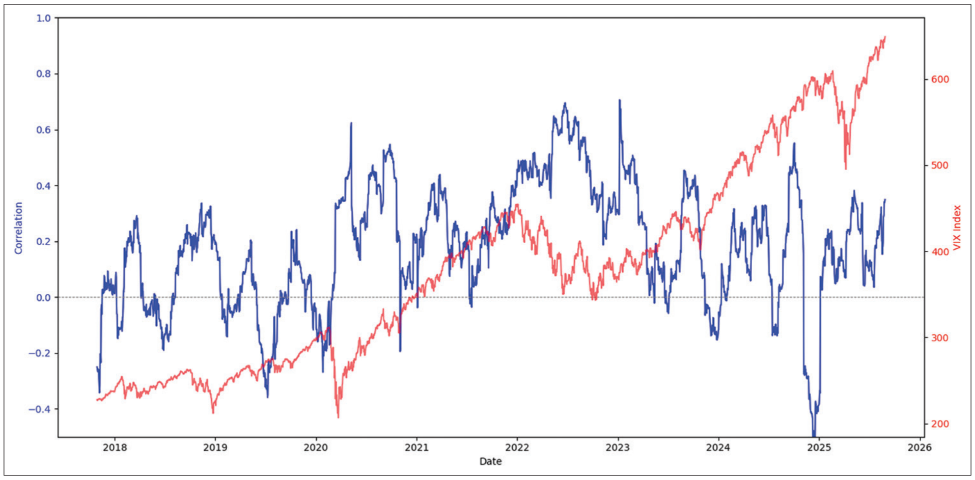
The most significant and stable finding across all model specifications is the negative coefficient on the Investment

Table 6: OLS regression with Newey-West HAC standard errors (full sample and subperiods)

Dependent variable: 60-day rolling correlation (BTC-renewable)			
Variable	**Full Sample**	**Pre-COVID (2017-2020)**	**Post-COVID (2020-2024)**
Const	0.4511 (P<0.001)	0.3981 (P<0.01)	0.4672 (P<0.001)
EC_lag	−0.0001 (P=0.612)	0.0003 (P=0.581)	−0.0002 (P=0.599)
IS_lag	−0.0009 (P<0.001)	−0.0011 (P<0.01)	−0.0009 (P<0.001)
PR_lag	0.0152 (P=0.781)	0.0201 (P=0.755)	0.0139 (P=0.812)
Crypto_SPY_Corr_lag	−0.7012 (P<0.001)	−0.6511 (P<0.001)	−0.7133 (P<0.001)
R-squared:	0.541	0.498	0.559
Observations:	1150	450	700

P-values from robust HAC standard errors are in parentheses

Figure 1: Dynamic correlation between bitcoin and renewables versus market sentiment (VIX)



Sentiment Channel (VIX). The implication that heightened market fear causes Bitcoin and renewable energy stocks to decouple is a novel contribution to the literature. A plausible interpretation is a "flight to relative quality" within the spectrum of risk assets. When systemic panic strikes, investors may be forced to differentiate more sharply between asset types. They may view the purely speculative, non-cash-flow-generating nature of Bitcoin as fundamentally riskier than the tangible, regulated, and often government-backed nature of renewable energy companies. While still equities, renewables are tied to real infrastructure and long-term energy policy, potentially making them a perceived "safer" haven compared to the extreme volatility of crypto. This causes their correlation to fall as investors' perceptions diverge.

This interpretation is strongly reinforced by the large, negative, and highly significant coefficient on our market control variable. This result indicates that as Bitcoin matures and becomes more integrated with the traditional financial system (i.e., its correlation with the S&P 500 increases), its relationship with the unique, policy-driven renewable energy sector weakens. This suggests a substitution effect: as Bitcoin starts to behave more like a mainstream tech stock, it loses some of its unique diversification properties, and renewables emerge as a more effective diversifier against it. For an investor holding a portfolio of traditional stocks and Bitcoin, adding renewables could provide a diversification benefit that increases as Bitcoin's market beta rises.

Finally, the continued insignificance of the Energy Consumption and Policy Channels is a robust result, holding across all tests. This does not mean these factors are unimportant; rather, it suggests their impact is not on the direct, day-to-day financial correlation. The operational debates around energy use and the impact of major policy news appear to be overwhelmed by the much larger, systemic forces of market sentiment and broad market co-movement when it comes to driving the financial relationship between these two

6. CONCLUSION

This paper set out to deconstruct the "black box" of volatility transmission between cryptocurrency and renewable energy markets. Our robust two-stage empirical analysis reveals a relationship governed by complex systemic factors rather than simple, direct channels.

The key contribution of this study is the finding that, after controlling for broad market co-movement, fear does not unite these assets; it divides them. This suggests a nuanced investor response to risk, where a flight to relative quality may occur even among risk assets. For investors, this presents a more sophisticated picture of diversification: the benefits of holding both crypto and renewables may actually increase during periods of market turmoil, a finding that runs contrary to typical risk-off behavior.

A limitation of this study remains the use of a simple dummy variable for the policy channel. Future research could build upon our findings by employing more sophisticated methods, such as Natural Language Processing (NLP), to create a more nuanced daily index of policy sentiment. Nonetheless, our results provide a robust and clear baseline that challenges conventional wisdom and highlights the evolving relationship at the frontier of digital and green finance.

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