A Theoretical Model of Price Volatility Transmission between Cryptocurrency Markets and Renewable Energy Stock Indices

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Abstract: This paper proposes a theoretical framework to model the price volatility transmission between cryptocurrency markets and the renewable energy stock sector. We develop a novel Factor-Augmented Dynamic Conditional Correlation GARCH (FA-DCC-GARCH) model, which extends the standard multivariate GARCH approach by incorporating observable, time-varying factors that represent core transmission mechanisms. This provides a structural blueprint for future empirical investigation. The model posits that volatility transmission is driven by three primary channels: (1) the Energy Consumption link from crypto mining; (2) a shared Investment Sentiment and Diversification channel reflecting investor risk appetite; and (3) a Policy and Regulatory channel for exogenous shocks. Our framework predicts asymmetric volatility transmission, with stronger spillovers from crypto to renewables during periods of high uncertainty.By deconstructing the spillover effects, the model offers a nuanced understanding beyond purely empirical studies and provides a robust set of testable hypotheses for assessing the time-varying risks and diversification benefits between these critical markets.

Keywords: Cryptocurrency, Renewable Energy, Volatility Spillover, GARCH, Theoretical Model, Energy Economics, Financial Econometrics.

1. INTRODUCTION

The global economic landscape of the 21st century 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, emerging from a niche technological experiment, have exploded into a multi-trillion dollar asset class, characterized by both disruptive potential and extreme price volatility (Fang *et al*., 2022). Simultaneously, the imperative to combat climate change has propelled the renewable energy sector to the forefront of industrial strategy and investment portfolios (Kumar *et al*., 2012). These two sectors, once viewed as occupying separate ecosystems, are now demonstrating increasing interdependence.

The primary and most conspicuous link between these domains is the substantial and controversial energy consumption of cryptocurrencies that utilize a Proof-of-Work (PoW) consensus mechanism (de Vries, 2018). Bitcoin mining alone is estimated to consume around 121 Terawatt-hours (TWh) per year, an energy footprint comparable to that of entire nations like Argentina (Cambridge Centre for Alternative Finance, 2025). This direct demand for electricity creates an intrinsic and unavoidable link to energy markets, including the rapidly growing 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, increase energy costs, and create significant headwinds for the clean energy transition (de Vries, 2018).

However, this perspective is increasingly being challenged by a more nuanced and complex picture. Proponents of the crypto-energy nexus argue that the unique characteristics of crypto mining operations can offer symbiotic benefits to the renewable energy sector (Makarov and Deryugin, 2021). For instance, the geographical and operational flexibility of miners allows them to act as a flexible load, helping to balance power grids that are often destabilized by the intermittent nature of renewable sources like wind and solar. Furthermore, it is argued that crypto mining can monetize stranded renewable energy assets—power generated in remote locations without access to sufficient transmission infrastructure—and, in doing so, could even spur further innovation and investment in green energy technologies (Makarov and Deryugin, 2021). This sharp dichotomy between the parasitic and symbiotic narratives presents a compelling puzzle for financial economists, energy analysts, and policymakers alike.

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. Volatility spillover, the phenomenon where price fluctuations and uncertainty in one market trigger subsequent price fluctuations and uncertainty in another, serves as a critical measure of market interconnectedness. A thorough understanding of these spillovers is paramount for a number of reasons. For investors and portfolio managers, it is essential for designing effective diversification strategies and implementing robust risk management frameworks. For

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regulators and policymakers, it is crucial for assessing the potential for cross-market systemic risk and ensuring financial stability during the dual transitions towards digitalization and sustainability.

Despite the clear importance of this topic, the existing academic literature reveals a significant theoretical gap. While a growing body of empirical work has begun to investigate the relationship between cryptocurrency and energy markets (Fang *et al*., 2022), these studies often suffer from two key limitations. First, they have predominantly focused on the linkage between cryptocurrencies and traditional energy commodities like oil, with renewable energy equities remaining relatively underexplored (Umar *et al*., 2021). Second, and more critically, these studies are primarily empirical, focusing on detecting the presence, direction, and timing of spillovers without deeply theorizing the underlying mechanisms that drive them (Le *et al*., 2021; Salisu and Ogbonna, 2022). They often find evidence of time-varying correlations but do not provide a structural model to explain *why* these correlations change, effectively treating the transmission process as an impenetrable "black box". This gap impedes effective risk management and the design of informed policy in the critical nexus of energy and digital finance.

This paper directly addresses this theoretical void by formally modeling 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 index (REI) markets?

2. How do market asymmetries, investor sentiment, and regime shifts—such as those induced by regulatory changes—modulate the intensity and direction of these volatility transmissions?

3. What potential policy levers can be identified to mitigate destabilizing spillovers and foster a stable relationship between these two innovative sectors?

To answer these questions, we develop a novel theoretical framework: the Factor-Augmented Dynamic Conditional Correlation (FA-DCC-GARCH) model. Our primary contribution is not to test a model with empirical data, but to construct the theoretical architecture for such a test. We move beyond a black-box approach by identifying and formalizing three core transmission channels—the Energy Consumption Channel, the Investment Sentiment and Diversification Channel, and the Policy and Regulatory Channel—and integrating them as explicit, time-varying factors within a state-of-the-art multivariate GARCH framework. This approach allows for the generation of specific, testable hypotheses regarding the nature, dynamics, and drivers of volatility spillovers. Ultimately, the proposed model offers a structured and nuanced way to analyze how and why the diversification benefits of holding both crypto assets and renewable energy stocks might appear, disappear, or even reverse over time, providing valuable insights for the future of fintech and sustainable finance.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive review of the relevant literature, establishing the theoretical gap our model aims to fill. Section 3 details the construction of our theoretical FA-DCC-GARCH model, from its foundational equations to the detailed specification of the transmission channels. Section 4 discusses the model's theoretical implications and derives a set of testable hypotheses for future empirical analysis, along with key considerations for investors and policymakers. Section 5 concludes with a summary of our contributions, an acknowledgment of the model's limitations, and concrete suggestions for future research.

2. LITERATURE REVIEW

Our theoretical 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 thorough review of these areas reveals the precise theoretical gap that our proposed model is designed to address.

2.1. Cryptocurrency Market Volatility

The extreme volatility of cryptocurrency returns is one of the most well-documented and researched phenomena in modern finance. Compared to traditional financial assets, cryptocurrencies exhibit dramatic price swings and persistent volatility clustering, where periods of high volatility are followed by more high volatility, and vice versa (Katsiampa, 2017). Early research in this area often focused on identifying speculative bubble characteristics in markets like Bitcoin (Cheah and Fry, 2015), exploring whether price movements were divorced from any fundamental value.

More recent and comprehensive work has identified a wide range of drivers behind this volatility (Fang *et al*., 2022). These can be broadly categorized as internal and external factors. Internal factors include technological developments, such as significant protocol upgrades or changes in the mining algorithm, which can create uncertainty and trigger price adjustments (Charfeddine *et al*., 2020). External factors are numerous and powerful. Regulatory announcements from major economies have been shown to be a primary driver (Catania and Grassi, 2021), with news of potential crackdowns or, conversely, regulatory approvals, leading to significant structural breaks and amplified price fluctuations. Macroeconomic news and changes in broad financial market conditions also play a role.

Furthermore, behavioral finance theories have proven particularly insightful in explaining cryptocurrency price dynamics. The market is heavily influenced by investor sentiment, which can be proxied by social media activity, search engine trends, and news analytics (Fang *et al*., 2022). The highly speculative nature of many crypto investments amplifies the impact of these psychological factors, often creating powerful feedback loops that generate and sustain high levels of volatility. A key finding across this body of literature is that cryptocurrency volatility is exceptionally reactive to information shocks, making it a potent potential source of spillover to other markets. While some studies have noted that cryptocurrency markets have historically been largely isolated from traditional financial markets, this isolation has been steadily decreasing over time as institutional adoption grows (Corbet *et al*., 2019).

2.2. Renewable Energy Equity Dynamics

The financial performance and volatility of renewable energy stocks are governed by a unique and diverse set of factors that distinguish them from both the broader equity market and traditional energy firms. Unlike oil and gas companies, which are intrinsically tied to the prices of fossil fuels, renewable energy companies are highly sensitive to government policy and regulatory frameworks (Henriques and Sadorsky, 2008). National and international policies such as subsidies, feed-in tariffs, carbon pricing schemes, and tax credits are fundamental determinants of their profitability and, consequently, their stock prices and volatility. Changes or uncertainty surrounding these policies can induce significant volatility persistence patterns unique to the sector (Reboredo *et al*., 2017).

Technological advancement is another critical driver. The costs of key technologies, such as solar panels and wind turbines, have fallen dramatically over the past decade, improving the economic viability of renewable projects (Kumar *et al*., 2012). Innovations that enhance efficiency or energy storage capabilities can have a profound impact on company valuations. Furthermore, as renewable energy projects are typically capital-intensive, their financing is sensitive to changes in interest rates, which affect the cost of capital and project feasibility. Competition from conventional energy sources, influenced by fluctuating fossil fuel prices, also plays a role in their performance (Henriques and Sadorsky, 2008).

More recently, the integration of Environmental, Social, and Governance (ESG) considerations into investment decision-making has become a major force. The massive inflow of capital into ESG-focused funds has created a significant and dedicated source of demand for renewable energy stocks, establishing new dynamics in their price formation and volatility patterns (Al Mamun *et al*., 2023). This unique combination of policy dependence, technological sensitivity, and exposure to sustainable investment trends suggests that the correlation of renewable energy stocks with other asset classes, including cryptocurrencies, is unlikely to be straightforward or stable.

2.3. Cross-Market Volatility Transmission and Modeling

The econometric literature on modeling volatility transmission has undergone significant evolution. Early studies in this field often relied on relatively simple tools like correlation analysis or Vector Autoregression (VAR) models to assess market interconnectedness. While useful, these methods typically assume that the relationships are constant over time, a limitation that is particularly problematic when analyzing volatile and rapidly evolving markets.

A paradigm shift occurred with the seminal work of Engle (1982) on Autoregressive Conditional Heteroskedasticity (ARCH) models and the subsequent generalization by Bollerslev (1986) to GARCH models. These models provided, for the first time, a robust framework for modeling time-varying variance (volatility), capturing the pervasive phenomenon of volatility clustering observed in financial time series. This laid the foundation for more sophisticated multivariate analysis capable of modeling not just the volatility of individual assets but also the dynamic nature of their co-movements.

For multivariate analysis, several models have become standard in the field. The BEKK-GARCH model (Engle and Kroner, 1995) is one such example, allowing for rich spillover dynamics but can be computationally intensive. A particularly influential and widely used framework is the Dynamic Conditional Correlation (DCC) GARCH model, developed by Engle (2002). The DCC model offers a significant practical advantage by adopting a two-stage estimation process: first, univariate GARCH models are fitted to each individual asset return series, and second, the dynamic conditional correlations are modeled. This separation makes the model computationally feasible even for larger systems of assets and provides an intuitive way to analyze how correlations evolve over time. Our proposed theoretical model builds directly upon this powerful DCC framework.

2.4. Identifying the Theoretical Gap

When applying these modeling techniques to the crypto-energy nexus, the existing literature, while growing, remains nascent and demonstrates a clear theoretical deficiency. Most studies have focused on the linkage between Bitcoin and traditional energy prices like crude oil, finding mixed and often unstable evidence of spillovers (Umar *et al*., 2021; Bouri *et al*., 2021). The direct link with renewable energy stocks has received far less attention. The few studies that do exist, such as Le *et al*. (2021), have found evidence of significant volatility spillovers from policy uncertainty to green energy and crypto markets, particularly during periods of broad market stress.

However, a unifying limitation across these studies is their primarily empirical nature. They effectively identify that a "black box" of transmission exists but do not attempt to theoretically specify its internal workings. They analyze outputs without modeling the process (Salisu and Ogbonna, 2022). Specifically, no existing framework formally models the bidirectional transmission mechanisms that are unique to the crypto-renewable nexus. Crucially, no work models the feedback loop where the volatility in renewable energy markets affects the operational cost of crypto mining (Hayes, 2017), which in turn feeds back into cryptocurrency price formation and volatility. Existing financial models have largely neglected to incorporate the sector-specific technological and operational constraints—namely, the energy cost of production—that form the physical basis of this relationship (Rezitis and Stropan, 2022). It is precisely this theoretical void that our paper aims to fill by proposing a structural model that endogenizes these transmission channels.

3. THE THEORETICAL MODEL FRAMEWORK

To address the identified gap in the literature, we propose a theoretical model designed to formally deconstruct the volatility transmission mechanism between cryptocurrency and renewable energy markets into distinct, identifiable, and conceptually grounded channels. Our framework is an extension of the well-established DCC-GARCH model, which we augment with exogenous, time-varying factors that represent our theorized transmission channels. The resulting Factor-Augmented DCC-GARCH (FA-DCC-GARCH) model provides a structural blueprint for understanding the complex and dynamic interplay between these two sectors.

3.1. The Foundational DCC-GARCH Model

We begin by specifying the standard DCC-GARCH framework (Engle, 2002), which will serve as the foundation for our augmented model. Let (r_t = [r_{c,t}, r_{r,t}]') be the (2 times 1) vector of log-returns at time (t) for the cryptocurrency index (subscript c) and the renewable energy stock index (subscript r). The return process for each asset is defined as:

[r_t = mu_t + epsilon_t]

where (mu_t) is the (2 times 1) vector of conditional means, and (epsilon_t) is the (2 times 1) vector of mean-corrected residuals, or shocks, at time (t). It is assumed that these residuals follow a process with a time-varying conditional covariance matrix, (H_t), such that (epsilon_t = H_t^{1/2} z_t), where (z_t) is a (2 times 1) vector of independent and identically distributed (i.i.d.) random variables with a zero mean and an identity covariance matrix.

The key feature of the DCC model lies in the decomposition of the conditional covariance matrix (H_t):

[H_t = D_tR_tD_t]

This equation elegantly separates the conditional covariance into two distinct components:

1. (D_t): This is a (2 times 2) diagonal matrix containing the time-varying conditional standard deviations of each asset's returns, (sqrt{h_{i,t}}), on its diagonal. Each conditional variance, (h_{i,t}), is modeled independently using a standard univariate GARCH(p,q) process (Bollerslev, 1986): [h_{i,t} = omega_i + sum_{j=1}^{q} alpha_{ij} epsilon_{i,t-j}^2 + sum_{j=1}^{p} beta_{ij} h_{i,t-j} quad text{for } i in {c, r}] In this equation, (omega_i) is the constant (long-run average variance), the ARCH terms ((alpha_{ij})) measure the reaction of volatility to past shocks ((epsilon_{i,t-j}^2)) (Engle, 1982), and the GARCH terms ((beta_{ij})) measure the persistence of volatility based on its own past values ((h_{i,t-j})).
2. (R_t): This is the (2 times 2) time-varying conditional correlation matrix, which captures the dynamic co-movement between the assets. It is this component that is of primary interest for studying volatility transmission.

In the standard DCC model proposed by Engle (2002), (R_t) is derived from a quasi-correlation matrix, (Q_t), which is specified to follow a GARCH-like mean-reverting process:

$$Q_t=(1-a-b)\bar{Q} + a u_{t-1}u_{t-1}' + b Q_{t-1}$$

Here, $(u_t = D_t^{-1} \epsilon_t)$ are the standardized residuals (i.e., shocks scaled by their conditional standard deviation). $(\bar{Q})$ is the long-run, unconditional correlation matrix of these standardized residuals. The scalar parameters (a) and (b) are non-negative, with the constraint that $(a+b<1)$ to ensure the process is stationary and mean-reverting. These parameters govern the dynamics of the correlation, with (a) representing the impact of recent shocks on correlation and (b) representing the persistence of the correlation.

The conditional correlation matrix (R_t) is then obtained by simply rescaling (Q_t) to ensure its diagonal elements are equal to 1:

$$R_t = \text{diag}(Q_t)^{-1/2} \; Q_t \; \text{diag}(Q_t)^{-1/2}$$

The crucial element in this standard model is that the dynamics of the conditional correlation, $(\rho_{cr,t})$, are driven solely by the internal dynamics of past shocks. This formulation, while powerful, is insufficient for our purposes because it treats the transmission mechanism as a black box and does not allow for external, structural factors to directly influence the correlation process.

3.2. The Factor-Augmented (FA-DCC-GARCH) Innovation

Our core theoretical contribution is to augment the DCC model to explicitly incorporate the theorized transmission channels. We propose that the transmission mechanism is not merely an artifact of past financial returns but is actively and directly driven by observable, structural factors that represent the real-world linkages between the cryptocurrency and renewable energy sectors.

We achieve this by making the long-run correlation component, $(\bar{Q})$, time-varying and functionally dependent on a vector of exogenous theoretical channel variables, (X_t). The key innovation of our FA-DCC-GARCH model is therefore in the respecification of the (Q_t) process:

$$Q_t = (1 - a - b)\bar{Q}_t + a u_{t-1}u_{t-1}' + b Q_{t-1}$$

The critical difference is that the long-run target correlation matrix, $(\bar{Q}_t)$, is now a time-varying function of the lagged exogenous factors that represent our specified transmission channels:

$$\bar{Q}_t = f(X_{t-1})$$

This specification is conceptually profound. It implies that the "baseline" or "gravitational center" around which the daily conditional correlation fluctuates is not constant over time. Instead, it shifts dynamically according to the state of these fundamental, structural channels. For example, a major policy announcement or a significant change in crypto mining energy consumption can directly alter the long-run equilibrium relationship between the two markets, which is a feature the standard DCC model cannot capture.

3.3. Detailed Specification of the Transmission Channels $((X_t))$

We theorize that the vector (X_t) contains proxies for three primary transmission channels. In an empirical application, each of these channels would be represented by an observable variable.

3.3.1 The Energy Consumption Channel $((EC_t))$

This channel represents the most direct, physical link between the Proof-of-Work (PoW) cryptocurrency ecosystem and the energy sector (Truby, 2018). The mechanism is fundamentally rooted in the energy demand of crypto mining operations, which are highly sensitive to fluctuations in cryptocurrency prices and mining profitability. A surge in mining activity, typically driven by rising crypto prices, leads to a significant increase in electricity demand. This can influence the renewable energy market in two conflicting ways. On one hand, it may be beneficial for renewable energy producers if they can monetize excess or stranded capacity by supplying power to energy-flexible miners, thereby securing stable revenue streams and potentially accelerating investment in new green infrastructure (Makarov and Deryugin, 2021). On the other hand, it may be detrimental if the increased load contributes to grid instability, drives up wholesale electricity prices, or attracts negative regulatory scrutiny, thereby increasing operational and financial risks for renewable energy firms (de Vries, 2018).

This channel is inherently bidirectional, forming a dynamic feedback loop. Volatility in the renewable energy index ($\sigma_{REI,t}^2$) can affect the price and stability of electricity ($P_{elec,t}$), which in turn alters the marginal cost of Bitcoin production ($C_{BTC,t}$) (Hayes, 2017). The profitability of mining, which can be modeled as $\pi_{mining,t} = P_{BTC,t} - \lambda C_{BTC,t}$ (where λ is energy intensity), is therefore directly impacted. A decline in profitability can trigger large-scale sell-offs by miners, amplifying Bitcoin's own volatility ($\sigma_{BTC,t}^2$).

Conversely, a sharp drop in the Bitcoin price can reduce mining profitability, leading to a reduction in electricity demand and, consequently, a decline in contracted revenues for renewable energy providers, thereby introducing volatility into the renewable energy equity market.

To capture the *shock* or *change* in energy demand—rather than just its level, which is less likely to drive price volatility—we propose that the theoretical proxy for this channel be defined as the volatility or first difference (rate of change) of the estimated electricity consumption of major PoW cryptocurrencies. This refinement ensures that the factor *ECt* reflects the dynamic stress imposed on energy markets by mining activity. A suitable empirical proxy could be derived from the Cambridge Bitcoin Electricity Consumption Index (CBECI) (Cambridge Centre for Alternative Finance, 2025), such as the rolling standard deviation or the month-on-month change in consumption estimates.

While *ECt* is treated as an exogenous factor within the correlation dynamics of the FA-DCC-GARCH model, the full bidirectional feedback loop is embedded in the model's overall structure. Specifically, the energy cost of mining (*C*BTC,*t*), which is a function of electricity prices (*P*elec,*t*), is a key determinant of the conditional mean (*μt*) and variance (*hi*,*t*) for cryptocurrency returns. Thus, volatility in the renewable energy market feeds back into the crypto return process through this cost channel, ensuring the model captures the endogenous nature of the relationship.

3.3.2. The Investment Sentiment and Diversification Channel ((IS_t))

This channel captures the behavioral and psychological linkages that arise from common exposure to broader financial market sentiment and shifting risk appetite. Both cryptocurrencies and renewable energy stocks can be perceived by certain investor segments as high-growth, high-risk, or "tech-like" assets. This shared perception can lead their prices to move in tandem, especially during periods of extreme market sentiment (Baur and Dimpfl, 2021).

During "risk-on" periods, when investor optimism is high, capital may flow indiscriminately into both asset classes as investors chase high returns, thereby increasing their correlation. Conversely, during "risk-off" periods or flights to safety, panicked investors may pull capital out of both asset classes simultaneously, also causing their correlation to increase. This herding behavior can be modeled explicitly, where high levels of sentiment can lead to increased cross-asset volatility persistence.

A further nuance within this channel is the role of ESG-focused sentiment. A major ESG controversy surrounding cryptocurrency could trigger a specific capital reallocation, with investors moving funds from crypto markets directly into "green" assets like renewable energy stocks (Al Mamun *et al.*, 2023). This would act as a powerful force, potentially suppressing volatility in energy stocks while increasing it in crypto, and thus altering their correlation.

- Theoretical Proxy: A broad market-wide fear index, such as the CBOE Volatility Index (VIX), or a more targeted technology-focused sentiment index derived from news or social media analytics.

3.3.3. The Policy and Regulatory Channel ((PR_t))

This channel accounts for the significant impact of exogenous shocks stemming from policy decisions and regulatory announcements made by governments and administrative bodies. Given that both markets are relatively new and operate in contested or evolving regulatory spaces, they are highly sensitive to such news (Le *et al.*, 2021).

Policy shocks can affect the markets individually or jointly. For example, a government crackdown on or outright ban of crypto mining in a major jurisdiction would directly impact the Energy Consumption Channel and crater sentiment towards crypto, with potential knock-on effects for renewables if miners were significant energy customers. Conversely, a major green energy subsidy program, such as the US Inflation Reduction Act, could attract a massive wave of investment into the renewables sector, potentially pulling capital away from more speculative assets like cryptocurrencies and thus weakening their correlation. Joint policies, such as those designed to promote "green digital assets" or regulate the energy sources for mining, could create a strong positive or negative linkage. These regulatory announcements are known to cause structural breaks in volatility patterns (Catania and Grassi, 2021).

The impact of these shocks can be modeled using regime-switching dynamics. We can define a state variable (Z_t in {0,1}) to indicate low or high regulatory intervention regimes. The spillover coefficients in the model could then be scaled by a factor like ((1 + eta Z_t)), where (eta>0), to capture the heightened market sensitivity during phases of intense regulatory scrutiny.

- Theoretical Proxy: A quantitative policy uncertainty index constructed from the textual analysis of policy papers and news reports related to either cryptocurrency or renewable energy regulation.

3.4. Functional Form and Asymmetric Dynamics

To operationalize the model, the functional form f(·) relating the channel variables to the long-run correlation must be specified. To ensure that the estimated correlations remain within their logical [-1, 1] bounds, a logistic or hyperbolic tangent transformation is appropriate. Furthermore, to capture the potentially conflicting narratives within the Energy Consumption channel, we propose a more flexible functional form that allows for non-linear effects. A simple linear specification may fail to distinguish whether the channel is truly symbiotic or parasitic, or if both effects are present and offsetting. Therefore, the off-diagonal element of the long-run correlation matrix, ¥bar{q}_{cr,t}, can be modeled with the inclusion of a quadratic term:

$$\bar{q}_{cr,t}=\Lambda(\delta_0+\delta_{1a}EC_{t-1}+\delta_{1b}EC_{t-1}^2+\delta_2 IS_{t-1}+\delta_3 PR_{t-1})$$

where ¥Lambda(·) is a logistic function. The coefficients ¥delta_{1a} and ¥delta_{1b} now jointly represent the impact of the Energy Consumption channel. This quadratic specification allows for a U-shaped or inverted U-shaped relationship, where the effect of increasing energy consumption on the crypto-renewable correlation could change direction after reaching a certain threshold. For instance, a small increase in mining activity could foster a symbiotic relationship (positive correlation), while a large increase could lead to grid strain and regulatory backlash, creating a parasitic dynamic (negative correlation). The coefficients ¥delta_2 and ¥delta_3 represent the magnitude and direction of the impact of the other channels.

Finally, our framework explicitly incorporates the well-documented phenomenon of asymmetric effects, where negative shocks often have a greater impact on volatility than positive shocks of the same magnitude (Conrad *et al.*, 2018). Weexpect spillovers from cryptocurrency to renewable energy to be stronger during periods of market stress and negative returns. This can be formalized by introducing a sign-dependent component into the model's spillover parameters. A spillover coefficient matrix (A) could be defined as:

$$A=A^{+}+A^{-}\cdot I\{r_{c,t-1}<0\}$$

where (I) is an indicator function that equals 1 if the cryptocurrency market return was negative in the previous period, and 0 otherwise. Empirical evidence suggests that the elements of $(|A^{-}|)$ would be greater than those of (A^{+}), signifying stronger spillovers during crises.

We can formalize this with a proposition: Proposition 1: If the profitability of cryptocurrency mining, $(\pi_{mining,t})$, falls below a critical threshold (τ) (indicating that mining operations are becoming unprofitable), then the spillover coefficients from crypto to renewables and vice versa will be amplified relative to their baseline levels. Proof: When $(\pi_{mining,t}<\tau)$, miners are incentivized to liquidate their crypto holdings to cover operational costs, increasing the downward pressure on crypto prices and amplifying $(|r_{BTC,t}|)$. Per the Sentiment Channel, this sudden spike in crypto volatility elevates the overall market sentiment index (S_t), leading to contagion and an increase in renewable energy index volatility, $(\sigma^2_{REI,t})$. Simultaneously, distressed mining operations reduce their electricity consumption, which can negatively impact the revenues of renewable energy providers who were supplying them, thereby lowering REI prices and further increasing $(\sigma^2_{REI,t})$. This creates a powerful volatility amplification loop during market downturns, where $(\frac{\partial|r_{BTC,t}|}{\partial\sigma^2_{REI,t}}>0)$ and $(\frac{\partial\sigma^2_{REI,t}}{\partial\sigma^2_{BTC,t}}>0)$ completing the feedback cycle.

3.5. Model Identification and Empirical Considerations

A critical challenge in empirically implementing the FA-DCC-GARCH model is the potential for endogeneity and multicollinearity among the proposed channel factors (EC_t, IS_t, PR_t). A significant policy announcement, for instance, could simultaneously influence investor sentiment and the economic calculations of crypto miners. To disentangle the unique impact of each channel, a robust identification strategy is essential. We propose a multi-pronged approach combining temporal logic, instrumental variables, and structural identification.

- Temporal Ordering and High-Frequency Data: The use of high-frequency (daily) data can help establish a plausible causal sequence. We posit that certain shocks logically precede others. For instance, a regulatory announcement (PR_t) can be treated as an initial, exogenous event. The market's reaction, captured by a change in a broad sentiment index (IS_t), would be a secondary effect observable at time t or t+1. Changes in the estimated aggregate energy consumption of miners (EC_t), which result from operational decisions based on profitability, may occur with a further lag. This temporal ordering, while not definitive, helps to structure the causal analysis.

- Instrumental Variables (IV): To more formally address endogeneity, particularly between policy and the other channels, instrumental variables can be employed. For example, to isolate the exogenous component of the global Policy and

Regulatory Channel (PR_t), one could use a policy announcement in a country with a significant regulatory framework but a very small domestic cryptocurrency market or mining industry. Such an event is likely to influence global investor sentiment and policy discussions (the instrument is relevant) without having a direct, immediate impact on global energy consumption patterns (the exclusion restriction is met). This would allow for the identification of the causal effect of policy shocks on market correlation, independent of the energy consumption channel.

- Structural Identification in a VAR Framework: We recommend that future empirical work embed the channel analysis within a Structural Vector Autoregression (SVAR) framework prior to estimating the GARCH model. By imposing theory-driven restrictions, the independent contributions of each channel's shocks can be disentangled. Based on our theoretical framework, a plausible set of zero restrictions could be imposed:

  1. A shock to the Investment Sentiment channel (IS_t) does not contemporaneously affect the Policy and Regulatory channel (PR_t), assuming that policy decisions are not made in immediate response to daily market fear.

  2. A shock to the Energy Consumption channel (EC_t) does not contemporaneously affect PR_t or IS_t, assuming that changes in mining energy use do not trigger same-day policy changes or shifts in broad market sentiment.

This set of restrictions would identify the independent impact of policy shocks, which are then allowed to contemporaneously affect all other variables. The orthogonalized impulse response functions from this SVAR can then provide clear insights into the dynamic impact of a shock to each specific channel.

- Robustness Checks: Finally, we emphasize the critical importance of conducting extensive robustness checks. Any empirical implementation should re-estimate the model using alternative proxy variables for each channel to ensure that the findings are not contingent on a single data source or index construction methodology.

3.6 .Illustrative Example of Model Operation

To demonstrate the structural mechanism of the Factor-Augmented DCC-GARCH (FA-DCC-GARCH) model, we provide a stylized numerical simulation illustrating how an exogenous shock to a theoretical channel factor immediately shifts the volatility transmission dynamics, a feature impossible in the standard DCC framework.

Scenario: Policy-Induced Decoupling

We isolated the effect of the policy and regulation channel (PR_t) on the condition correlation ($\rho_{cr,t}$) between the Cryptocurrency (c) and Renewable Energy (r) markets. We assume a scenario where a significant green subsidy policy is introduced, which we hypothesize will cause the two asset classes to decouple (i.e., correlation should decrease).

Assumed Parameters and Coefficients:

Parameter	Value	Description
α	0.05	Impact of last period's shock (reactiveness).
β	0.9	Persistence of correlation (inertia).
δ_0	0.2	Baseline coefficient for $\bar{Q}_t$.
δ_3	-0.5	Coefficient for PR_{t-1} (negative impact: policy shock reduces correlation).
Other δ's	0	For simplicity, we set all other factor impacts to zero.

The long-run correlation target is thus simplified to:.$\bar{q}_{cr,t}$= tanh $(0.2-0.5.PR_{t-1})$

Core Mechanism Demonstrated

This simulation highlights the FA-DCC-GARCH model's crucial innovation:

1. Structural Intervention: At$t = 2$, the dynamic conditional correlation ($\rho_{cr,t}$) shifts solely because of the exogenous Policy Shock **(**PR_{t-1}**)**, not because of abnormal past asset price movements ($u_{t-1}u'_{t-1}$), which were kept constant.

2. Time-Varying Equilibrium: The policy change forces the baseline equilibrium ($\bar{\mathbf{Q}}_t$) to immediately become negative. This demonstrates the model's ability to move the system away from a static equilibrium and capture structural breaks induced by policy or operational factors.

3. Anchoring Dynamics: The calculated conditional correlation ($\rho_{cr,t}$) at $t = 2$ and $t = 3$ is now anchored and pulled toward-0.050. This precisely quantifies how a fundamental policy shift can erode diversification benefits (or increase them) over time, moving beyond the "black box" detection of spillovers.

Step-by-Step Simulation Results

Time	PRt−1 (Policy Factor)	q̄cr,t (Long-Run Target)	qcr,t (Quasi-Correlation)	ρcr,t (Conditional Correlation)	Interpretation
t=1	0.0 (Neutral)	+0.197	0.19	+0.190	Baseline: Correlation is low and positive, mean-reverting towards +0.197.
t=2	+0.5 (Policy Shock)	-0.05	0.169	+0.169	Immediate Shift: The policy shock immediately drags the long-run target from +0.197 to −0.050. The correlation begins to fall in the direction of the new equilibrium.
t=3	+0.5 (Sustained)	-0.05	0.15	+0.150	Adjustment: With no new shocks, the correlation continues its trajectory, decaying rapidly from +0.169 towards the new negative target of −0.050.

3.7 .Model Identification and Empirical Considerations

A critical aspect of transitioning the FA-DCC-GARCH from a theoretical blueprint to an empirically testable model involves detailing theestimation strategy and addressing practical challenges like endogeneity and computational feasibility.

Estimation Strategy and Feasibility

The FA-DCC-GARCH model is estimated using a standardtwo-stage Quasi-Maximum Likelihood (QML) approach, similar to the original DCC model:

1. Stage 1: Univariate GARCH Estimation: Independent GARCH(p,q) models are fitted to the log-returns of the cryptocurrency and renewable energy indices to obtain the conditional variances (H_t) and the standardized residuals (u_t).

2. Stage 2: Conditional Correlation Estimation: The standardized residuals (u_t) from Stage 1 are used to estimate the parameters of the conditional correlation matrix (R_t). Crucially, the coefficients on the factor variables (δ_0, δ_{1a}, $\delta_{1\beta}$, δ_2, δ_3)are estimated in this stage by incorporating the time-varying long-run target, $\bar{Q}_t$= f(Xt−1), directly into the correlation log-likelihood function.

By leveraging the two-stage process of the DCC framework, the FA-DCC-GARCH remains computationally feasible even with the inclusion of multiple exogenous factors, as it avoids the numerical intensity associated with simultaneously estimating the numerous parameters required by models like the BEKK-GARCH.

4. MODEL IMPLICATIONS AND TESTABLE HYPOTHESES

The primary purpose of our theoretical FA-DCC-GARCH model is not to provide definitive empirical answers but rather to structure the inquiry into the crypto-renewable nexus in a rigorous and testable manner. The framework yields a rich set of specific hypotheses and has significant implications for both investors and policymakers.

4.1. Testable Hypotheses

The coefficients in our proposed long-run correlation equation provide the basis for direct empirical testing.

Hypothesis 1 (The Non-Linear Energy Consumption Channel):The effect of the EC_t factor is best tested through its linear (¥delta_{1a}) and quadratic (¥delta_{1b}) coefficients, which allows for a direct test of the conflicting "symbiotic" versus "parasitic" narratives.

- A statistically significant and positive ¥delta_{1a} with an insignificant ¥delta_{1b} would support a purely symbiotic narrative, where higher energy demand from miners consistently aligns the business cycles of the two sectors.

- A statistically significant and negative ¥delta_{1a} with an insignificant ¥delta_{1b} would support a purely parasitic narrative, where the energy burden creates a persistent conflict.

- A statistically significant ¥delta_{1b} < 0 would support a more nuanced, inverted U-shaped relationship. This would imply that at lower levels of energy consumption, the relationship is symbiotic (¥delta_{1a} > 0), but after a certain point, increasing energy demand becomes detrimental, leading to a negative correlation as

Potential Pitfalls and Identification Challenges

Challenge		Proposed Solution		
Multicollinearity	High correlation between the factors (e.g.,IS_t andPR_t) can inflate standard errors and make individual factor effects (δ_i) difficult to distinguish.	IS_t and PR_tcan inflate standard errors and make individual factor effects (δ_i) difficult to distinguish.	Employ Structural Vector Autoregression (SVAR) techniques for initial decomposition. By imposing theory-driven zero restrictions (e.g., a pure sentiment shock does not immediately affect policy or energy consumption), the independent shock components can be cleanly identified.	
Endogeneity	While the factors are lagged (i.e., PR_{t-1}), high market volatility could itself trigger a regulatory response or a shift in sentiment. This feedback loop violates the assumption of strict exogeneity in $\bar{Q}_t$'s dynamics.		Use Instrumental Variables (IV). To isolate the exogenous component of the global	PR_t, an event like a policy announcement in a small-market jurisdiction (e.g., one with a negligible domestic mining industry) could serve as a valid instrument.

grid strain and regulatory risks mount. This would be powerful evidence of a threshold effect in the crypto-renewable nexus. Conversely, ¥delta_{1b} > 0 would imply a U-shaped relationship. The empirical estimation of these coefficients is therefore particularly insightful for policymakers managing the growth of both sectors.

- Hypothesis 2 (The Investment Sentiment and Diversification Channel): We hypothesize that the coefficient (delta_2) on the (IS_t) factor will be positive ((delta_2 > 0)). This hypothesis is rooted in the idea that both asset classes are treated as "risk-on" investments by a significant portion of the market. A positive (delta_2) would imply that during periods of high market fear or risk aversion (e.g., a high VIX), the correlation between crypto and renewables decreases. This would enhance the diversification benefits of holding both assets precisely when such benefits are most needed by investors. Conversely, during calm or euphoric "risk-on" market environments, their correlation would increase as they attract similar speculative investment flows, thus diminishing their diversification potential. Testing this hypothesis is crucial for understanding the state-contingent hedging properties of these assets.

- Hypothesis 3 (The Policy and Regulatory Channel): The coefficient (delta_3) on the (PR_t) factor is expected to be highly event-dependent and potentially asymmetric. A simple test of a single coefficient would be insufficient. A more sophisticated empirical test would require the careful construction of the (PR_t) index to distinguish between different types of policy shocks: (a) those negative for crypto only (e.g., mining bans), (b) those positive for renewables only (e.g., green subsidies), (c) those that jointly and positively affect both (e.g., frameworks for "green bitcoin"), and (d) those that jointly and negatively affect both (e.g., broad restrictions on speculative assets). The model provides a robust framework for testing the statistical significance, direction, and magnitude of these distinct policy event categories on the co-movement between the two markets.

4.2. Implications for Investors and Portfolio Managers

The theoretical framework carries significant practical implications for investment strategy and risk management.

- Dynamic Diversification: The model's central tenet is that the diversification benefit of combining cryptocurrencies and renewable energy stocks is not a static property but a highly dynamic state. An investor cannot simply calculate a historical correlation and assume it will hold in the future. The effectiveness of adding crypto to a green-focused portfolio depends critically on the prevailing regime across the three transmission channels. For instance, during a crypto bull market driven purely by speculation (high (IS_t)) and accompanied by rapidly increasing mining activity (high (EC_t)), the model predicts that the correlation with renewables may become strongly positive, completely eroding any diversification benefits.

- Advanced Risk Management: Risk managers should recognize that traditional risk measurement tools that assume constant correlations may severely underestimate portfolio risk, particularly during market downturns. The asymmetric nature of volatility transmission predicted by our model suggests that portfolios are most vulnerable during crises. This calls for the implementation of more sophisticated risk management techniques, such as dynamic hedging strategies that actively adjust portfolio weights in response to changes in the underlying channel factors and time-varying correlations. The model implies that REIs may offer diminishing hedging benefits against crypto downturns precisely when they are most needed. Therefore, optimal portfolios would require dynamic rebalancing strategies that are triggered when, for example, cryptocurrency volatility exceeds a certain threshold ((sigma_{BTC,t}^2 > bar{sigma}^2)).

4.3. Implications for Policymakers and Regulators

The model also offers crucial insights for policymakers tasked with ensuring financial stability while fostering innovation in both the digital finance and energy sectors.

- Unintended Consequences and Systemic Risk: The framework explicitly highlights the potential for unintended policy consequences. A policy designed in a silo to regulate the cryptocurrency market could have significant and unforeseen spillover effects on the financial stability and investment landscape of the renewable energy sector, and vice versa. For instance, a poorly designed crypto mining restriction could inadvertently bankrupt renewable energy providers who had come to rely on miners as anchor customers in certain regions. By understanding the strength and direction of the transmission channels, policymakers can better anticipate these cross-market impacts and design more holistic and robust regulations that account for systemic risk.

- Targeted Policy Levers for Stability: The model provides a pathway for designing targeted interventions to promote stability. A formal stability condition for the system can be derived, which depends on the magnitude of the spillover coefficients: The system's mean-reverting property, necessary for stability, depends on the general condition that the persistence of volatility is not explosive. For the dynamic correlation process, this is ensured when the scalar coefficients governing its evolution satisfy $a + b < 1$. More broadly, the condition that systemic risk is minimized is often expressed as the spectral radius being less than one, which depends on the magnitude of the spillover matrices. This condition implies that systemic risk is minimized when the feedback effects of volatility are contained. Policymakers could aim to design regulations that specifically target the most destabilizing spillover parameters. For example, policies that promote or mandate the use of renewable energy for mining operations could reduce the volatility spillover from crypto to renewables (parameter (a_{12})), helping to satisfy the stability condition. Other potential levers include stabilizing long-term renewable procurement contracts for crypto miners or implementing green subsidies ((Z_t< 0)) that weaken spillover intensity during turbulent periods. Such policies would align with broader goals like the UN's Sustainable Development Goals, specifically SDG 7 (Affordable and Clean Energy) and SDG 9 (Industry, Innovation, and Infrastructure).

4.4. Concrete Policy Applications

The FA-DCC-GARCH framework translates abstract systemic risk into actionable policy insights by allowing regulators to quantify the cross-market impact of specific interventions.

Targeted Policy Examples

1. Mitigating Unintended Consequences (China Mining Ban, 2021):

   i. Action: The sudden, near-complete ban on cryptocurrency mining in China in 2021 was an extreme, negative shock to the Policy and Regulatory Channel (PR_t for crypto).

   ii. FA-DCC-GARCH Implication: The model predicts that this localized, negative PR_t shock not only crashed crypto prices but also created an unintended, adverse spillover onto renewable energy stocks. This happens if renewable energy producers had invested capital based on long-term contracts with miners for stable demand or stranded power monetization. The framework quantifies the magnitude of this spillover, allowing regulators to anticipate how a policy targeting one sector could inadvertently bankrupt companies in the other.

2. Fostering Stable Integration (U.S. Inflation Reduction Act - IRA):

   i. Action: The U.S. IRA provides massive subsidies and tax credits for green energy projects. This is a significant positive shock to the Policy and Regulatory Channel (PR_t for renewables).

ii. FA-DCC-GARCH Implication: If the δ_3 coefficient is negative (as in the simulation), this policy shock would actively reduce the correlation between renewable energy stocks and speculative crypto assets ($\rho_{cr,t}$), thereby enhancing the diversification benefits of the markets and fostering stability. The model supports the design of policies—like stabilizing long-term renewable power contracts for miners—that specifically target the δ coefficients to promote systemic stability.

3. Managing the Symbiotic-Parasitic Threshold (CBECI Data):

i. Action: Using data like the Cambridge Bitcoin Electricity Consumption Index (CBECI) to proxyEC_t , policymakers can estimate the non-linear coefficients (δ_{1a} ,δ_{1b}).

ii. FA-DCC-GARCH Implication: If the model confirms an inverted U-shaped relationship (Hypothesis 1), it identifies a critical threshold: at low levels of , the relationship is symbiotic (positive correlation) because miners consume stranded power; however, above a certain level, the relationship becomes parasitic (negative correlation) as grid strain and regulatory risks become dominant. This insight allows energy regulators to manage the *rate* of crypto mining growth to keep the system in the beneficial, stable, symbiotic regime.

5. CONCLUSION

The rapid and concurrent growth of digital finance and the green energy transition has created a complex web of interdependencies that traditional financial models are ill-equipped to explain. The increasing intertwining of these sectors necessitates more sophisticated frameworks for understanding and managing cross-market risk transmission. This paper has put forth such a framework, the Factor-Augmented DCC-GARCH model, to formally structure the analysis of price volatility spillovers between cryptocurrency markets and renewable energy stock indices.

Our primary contribution is the theoretical architecture itself. By moving beyond the prevailing "black box" empirical approaches, our model deconstructs the complex transmission mechanism into three core, conceptually distinct, and measurable channels: the Energy Consumption Channel, the Investment Sentiment and Diversification Channel, and the Policy and Regulatory Channel. This decomposition allows for a more granular and nuanced understanding of why the relationship between these two critical and innovative sectors fluctuates so dramatically over time. The model's key theoretical findings include the prediction of asymmetric spillovers that intensify during periods of market stress and the demonstration of how the entire system's stability is dependent on policy choices. The framework provides a clear roadmap for future empirical research by generating a series of specific, testable hypotheses about the nature of the crypto-renewable nexus.

This study is, by design, subject to limitations, the most significant of which is the empirical challenge of accurately measuring the theoretical transmission channels. The validity of any empirical test of this framework hinges on the quality and representativeness of the proxy variables used. The Energy Consumption Channel (EC_t), for instance, relies on estimates like the CBECI which are themselves models subject to significant underlying assumptions and estimation uncertainty. Furthermore, the Investment Sentiment (IS_t) and Policy (PR_t) channels are inherently difficult to quantify and are vulnerable to measurement error, as they are often derived from textual analysis of news or policy documents, a process that can be affected by algorithmic bias, linguistic ambiguity, and incomplete data.

Noise or mis-specification in these proxy variables could bias the estimated coefficients (¥delta_1, ¥delta_2, ¥delta_3) and lead to incorrect inferences about the importance or direction of each transmission channel. A poorly constructed sentiment index, for example, might fail to distinguish between general market fear and crypto-specific panic, thereby conflating two distinct economic mechanisms.

Addressing this limitation should be a primary focus of future research. We strongly recommend that future work prioritize the development and validation of more robust, multi-source proxies for each channel. This could involve:

1. Constructing ensemble indices that combine multiple data sources to smooth out idiosyncratic noise (e.g., combining the VIX with crypto-specific fear-and-greed indices derived from social media and blockchain data).

2. Employing advanced natural language processing techniques with carefully validated training sets to improve the accuracy and objectivity of policy and sentiment indices.

3. Applying econometric models designed to account for measurement error in explanatory variables, providing more reliable coefficient estimates.

Researchers must be transparent in the methodology used to construct each factor and conduct rigorous robustness checks using alternative proxy definitions to ensure the reliability of their findings. These limitations naturally point toward a rich agenda for future research, at the forefront of which is the empirical implementation and testing of the proposed FA-DCC-GARCH model using such improved proxies.

Further extensions to the model could also be explored. For instance, future work could incorporate network models to analyze multi-asset spillovers between cryptocurrencies, renewables, and other related sectors like technology stocks and commodity markets. The framework could also be extended to examine intradayvolatility transmission patterns using high-frequency data, which may reveal additional transmission mechanisms related to algorithmic trading and market microstructure effects. In conclusion, as institutional investment continues to flow into both the cryptocurrency and renewable energy sectors, understanding their interconnectedness is no longer an academic curiosity but a matter of central importance for global financial stability and the success of sustainable investment strategies. The theoretical model presented here provides a foundational step towards this understanding, offering a structured framework for analyzing the risks and opportunities at the evolving frontier of digital and green finance.

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