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Dynamic Connectedness Between FinTech and Energy Markets: Evidence from Fat Tails, Serial Dependence, and Bayesian Approach

Abstract

In a complex global environment, modeling the relationships among several markets and asset classes has become more challenging. Literature strives to provide conclusive evidence due to system complexities. Therefore, we investigate the dynamic relationship between Fintech and energy sectors using fat tails, serial dependence, and the Bayesian approach from May 1, 2019, to October 28, 2022. Results unveil significant temporal variations in network interconnections, with an evident increase in interlinkages across short, medium, and long durations due to transient market events. The COVID-19 pandemic and the onset of the Russia-Ukraine conflict have substantially altered the long-term relational dynamics within these networks. An analysis of net directional linkages reveals a pivotal shift in market roles—from being predominantly shock recipients to becoming shock transmitters—highlighted during the COVID-19 pandemic and the initial phase of the Russia-Ukraine War. Initial observations indicate that, amid the global impact of COVID-19, Fintech markets absorbed shocks through investments in green bonds and renewable energy sources like wind, solar, and clean energy. These findings suggest that while Fintech consistently acts as a shock absorber in long-term scenarios, it assumes the role of a shock transmitter during adverse economic states.

Keywords: Bayesian vector heterogeneous autoregressions; FinTech innovation development; energy dynamics; COVID-19, Russia-Ukraine conflict.

JEL classification: F3, G12, Q43.

1. Introduction

In the face of persisting global uncertainties, the necessity for portfolio diversification has intensified, emphasizing the critical need for safe-haven assets during market turbulence (Elsayed et al., 2020). Such times have not only heightened the demand for secure investment instruments but also revealed a marked increase in investors' herding behavior, thereby amplifying correlations among financial assets amidst crises (Sharma et al., 2022). The financial turmoil ensuing from the global financial crisis, coupled with the advent of COVID-19 and the recent escalation of the Russia-Ukraine conflict, has required a reevaluation of diversification strategies and the identification of efficacious hedging mechanisms (Bouri et al., 2019; Chakrabarti et al., 2021; Ha, 2022; Tiwari et al., 2021). The attraction to alternative asset allocations, especially within the domain of digital assets, has notably captured the interest of Industry 4.0 investors. Studies focused on digital assets have identified Bitcoin as a resilient investment amidst instability, offering a contrasted perspective on cryptocurrencies as an asset class due to their inherent volatility and distinctive behavioral patterns (Disli et al., 2021; Goodell & Goutte, 2021; Guo et al., 2021; Gronwald, 2019).

The confluence of technology and financial services, characterized by FinTech, encompasses innovations such as Blockchain, cognitive computing (AI), and big data analytics, which have been instrumental in reshaping the competitive landscape of the banking industry, enhancing payment technologies, broadening the scope of lending institutions, and refining corporate governance structures since the Global Financial Crisis (GFC) of 2008. By mitigating information asymmetry, streamlining operational efficiencies, and facilitating regulatory compliance, FinTech firms have distinctly contributed to the financial sector, in stark contrast to the conventional banking system characterized by informational opaqueness, operational risks, and sluggish innovation (Sharma et al., 2022).

The birth of Bitcoin in 2009 signaled the evolution of blockchain technology, initially conceived for peer-to-peer transactions but now widely recognized for its consensus mechanisms, which leverage balanced connectivity and public-key encryption to mitigate trust issues (Efanov & Roschin, 2018). This blockchain consensus model has revolutionized traditional manufacturing systems and bolstered sectoral trust (Ahram et al., 2017), finding applications across diverse industries, including the green energy sector. The era of Industry 4.0 has seen exponential growth in AI, robotics, and FinTech, with robotic and AI technologies driving significant transformations in manufacturing processes and beyond, thereby enhancing predictive analytics and strategic decision-making across various sectors (Furman & Seamans, 2019).

This paper posits that digital technologies and FinTech also play a transformative role in the energy sector, particularly in integrating green energy solutions with conventional power grids, a challenge imposing technological innovation (Ahram et al., 2017; Jackman and Moore, 2021). Advanced technologies such as big data, machine learning, deep learning, and the Internet of Things (IoT) are reshaping the energy landscape, enabling more effective control, efficiency, and forecasting of power system operations (Kow et al., 2016; Youssef, El-Telbany, and Zekry, 2017; Seyedmahmoudian et al., 2015; Yang, Wang, and Hu, 2020).

Despite the recognized potential of digital technologies and FinTech in enhancing economic resilience, the literature remains scant on their interconnected dynamics with the green energy sector, especially in the context of global crises such as COVID-19 and the Russia-Ukraine conflict. This study aims to fill this gap by examining the spillover effects and interconnectedness between FinTech and green energy dynamics during these turbulent times, employing Bayesian vector heterogeneous autoregressive (BVHAR) models. Our investigation uniquely contributes to the current debate by providing a comprehensive analysis of the volatility interlinkages between FinTech and the renewable energy market, utilizing a dataset spanning from May 1, 2019, to October 28, 2022, and focusing on specific ETFs, green bonds, and energy indexes to illustrate the level of Fintech implementation and its impact on the energy sector's volatility amidst global uncertainties.

The remainder of the paper is as follows: Section 2 contains a detailed overview of FinTech and its impacts on the green energy market. The empirical approaches used in the study are described in Section 3. Section 4 reports the critical findings. Conclusions and policy recommendations are provided in Section 5.

2. Literature reviews

2.1. The role of AI and Fintech development

Decentralization and consensus mechanisms are pivotal attributes of blockchain technologies, heralding transformative impacts on supply and demand dynamics by inherently bypassing financial intermediaries, diminishing entry barriers, and fostering accessibility. However, critiques highlight the paradox of decentralization in contemporary blockchain frameworks, arguing that the dominance of specific mining algorithms undermines the true decentralization ethos and, consequently, the envisaged benefits of blockchain technology Shah & Parveen (2021).

In parallel, artificial intelligence (AI) presents a paradigm shift in financial services by utilizing novel data to construct alternative client profiles, challenging conventional paradigms. AI's capability to extend lower-cost financial services, including loans to individuals with subprime scores, exemplifies its potential to bridge market gaps, particularly in emerging economies where traditional banking services are less accessible (Yermack, 2015). AI's data-driven strategies starkly contrast human investors' emotion-driven tendencies, indicating a shift towards more efficient and rationalized investment decisions.

Despite their apparent advantages, blockchain and AI technologies encounter inherent challenges. The pseudonymity and anonymity features of cryptocurrency transactions have inadvertently facilitated illicit financial activities, eroding public trust. The inevitability of forks within blockchain systems due to game-theoretic dilemmas and the environmental concerns associated with energy-intensive mining practices underscore blockchain technology's limitations and unintended consequences (Böhme et al., 2015). Additionally, the fear of centralized control via a 51% stake poses a significant threat to blockchain networks' foundational principle of decentralization.

Moreover, the integration of AI in the financial sector has been met with resistance, attributed to regulatory constraints, a deficiency in skilled IT professionals, inflexibilities in existing IT infrastructures, and an inherent aversion to risk within banking institutions (Biais et al., 2019). The disparity in the ability to harness big data further accentuates the digital divide, enabling only market leaders and innovators to extract valuable insights from unique data sets, thereby marginalizing the majority of market participants.

The debate on FinTech is enriched by exploring its dualistic nature. Sustainable FinTech, as discussed by Chen et al. (2020), fosters a competitive environment within the financial ecosystem, enabling FinTech firms to drive innovation, enhance customer experiences, and expedite the development of new financial products. This dynamism threatens to disrupt traditional banking models, potentially leading to job displacement within established financial institutions. In contrast, historical perspectives warn of FinTech's destabilizing potential, urging banks to adapt by prioritizing customer satisfaction and loyalty to mitigate disintermediation (Lee & Choi, 2019).

Addressing the broader implications for monetary policy, EU central bankers argue that while FinTech innovations offer solutions to technological challenges within the financial sector, they cannot replace the foundational roles of the monetary system. Trust establishment, community needs assessment, and the facilitation of effective peer engagement remain critical for advocating policy transformations in this domain, emphasizing the complementary rather than substitutive relationship between FinTech and traditional monetary frameworks An et al. (2021).

2.2. AI, Fintech development, and the green energy market

Energy is vital in the global economy, with AI and FinTech technologies poised to profoundly influence a broad spectrum of industries within the energy sector. The impending impacts of climate change are anticipated to pose greater challenges for entities leveraging information technology (IT) across various domains, including energy industries, manufacturing operations, supply chains, and customer-facing activities (Ahmad et al., 2021; Hamid and Wang, 2023).

Bose (2017) advocated for a thorough exploration of AI and FinTech platforms within the intelligent energy sector, noting the substantial advancements in these technologies and their potential to address various technical challenges in energy systems. Artificial intelligence and Fintech, through the application of neural networks and fuzzy logic based on Artificial Neural Networks (ANNs), present promising solutions for a range of issues including energy price forecasting (Ghoddusi, Creamer, and Rafizadeh, 2019), energy demand projection (Macedo et al., 2015), and overall energy prediction (Johannesen, Kolhe, and Goodwin, 2019), alongside enhancements in smart grids and blockchain security, optimization of hybrid systems, and big data's role in renewable energy management (Zahraee, Khalaji Assadi, and Saidur, 2016; Salah et al., 2019; Ford, Siraj, and Eberle, 2014). The deployment of deep learning models for forecasting, particularly amid intraday network constraints, underscores the evolution of predictive methodologies. Furthermore, the integration of smart grid technology is set to revolutionize energy generation, distribution, and transmission, although it faces significant challenges, notably in security and privacy.

The pursuit of affordable, reliable, and clean energy sources is of utmost importance, with AI and FinTech set to play crucial roles in addressing these requirements (Hamid and Wang, 2023; Jebli and Gam, 2023; Setu et al., 2023). The application of AI and FinTech in energy-related innovations promises significant advancements in green, low-carbon electricity generation. The utilization of AI in the energy sector, from deep learning and machine learning to advanced neural networks, holds substantial promise for enhancing utility operations and transforming the industry.

Energy companies and independent power producers are increasingly leveraging AI to navigate the challenges of decentralization, decarbonization, and the integration of emerging technologies to ensure supply-demand equilibrium, especially as renewable energy sources gain prevalence. The broad application of AI and FinTech across various sectors, including energy storage and stand-alone grids, underlines their potential in optimizing peak load planning, grid stability, real-time metering, intuitive operations, voltage regulation, and power outage predictions.

Despite historical skepticism regarding FinTech adoption due to concerns about labor displacement and market polarization, recent advancements in AI and FinTech are acknowledged for their potential to enhance worker safety and productivity within the energy sector. However, the adoption process remains complex amidst ongoing debates over the benefits and drawbacks of these technologies. Moreover, foreign investment interest continues to grow, driven by the market's combination of high growth potential and low efficiency (Jena et al., 2020). Nevertheless, research on technology-based, non-traditional assets as diversification options remains scant within financial economies.

Generally, there is scant evidence regarding the impact of digital technology and FinTech adoption on the overall economy. In this study, we particularly highlight the resilience of specific assets before, during, and after the COVID-19 pandemic and the Russia-Ukraine conflict. Despite existing research on digital versus conventional assets (Huynh et al., 2020; Le et al., 2021), there is a notable gap regarding the effects of technology-based commodities such as FinTech, AI, robots, or Blockchain within the green and environmental energy markets. Furthermore, prior studies have largely focused on the unilateral effects of renewable energy and FinTech development, overlooking the potential for an interconnected network system between these spheres.

Building on this theoretical foundation and identified literature gaps, our research explores the transmission of tail risk, serial dependence, and interlinkages among AI, FinTech, and the green energy market, assessing the impact of uncertainty on this contagion process. Contributing to financial and energy economics, this study utilizes a mixed heterogeneous autoregressive (HAR) model with Bayesian estimation to account for both positive and negative shocks within extreme distributions. We hypothesize significant variations in tail risk contagion and spillover within AI, FinTech, and green energy sectors across different events, with a marked increase in spillover during crises such as the COVID-19 pandemic and the Russia-Ukraine conflict. Expanding upon prior findings that geopolitical risk primarily drives tail risk transmission during periods of uncertainty, our research explores the dissemination of tail risk among AI, FinTech, and green energy markets, emphasizing the importance of incorporating uncertainty factors in systemic risk assessment.

3. Data and Modeling Techniques

3.1. Data

In our study, we employ two financial innovation proxies, ARK Fintech Innovation ETF (ARKF) and Global X FinTech ETF (FINX), to gauge the evolution and impact of financial technology dynamics. Concurrently, we explore the volatility within the energy sector through various indices, including Green Bonds (SPGB), Clean Energy (SPGTCLEN), Wind Energy (GWE), Solar Energy (SUNIDX), Natural Gas (NGF), and the Crude Oil Volatility Index (OVX). The dataset spans from May 1, 2019, to October 28, 2022. Specifically, we analyze the S&P Green Bond Index (SPGB), which serves as a market-weighted indicator of the global green bond market within the energy sector. Additionally, the Macerich Company Global Solar Energy Index Net Total Return (SUNIDX) is utilized to assess the performance of global solar energy companies. The International Securities Exchange (ISE) Global Wind Energy Index (GWE) measures the activity of firms engaged in the wind energy sector based on their offerings and services. The Natural Gas Futures contract (NGF) stipulates the obligatory purchase quantities for natural gas, reflecting the operation of international natural gas firms. The Crude Oil Volatility Index (OVX) provides insights into the expected volatility of crude oil prices over a forthcoming 30-day period. Our analysis involves the computation of the first logarithmic differences of these series.

Ellington (2021) suggested that it is necessary to consider serial dependence and heavy tails when we model linkages of diverse markets. Table 1 provides the first insights into correlations between *FINX* and five green energy volatility indicators. Moreover, these variables display a high level of persistency kurtosis values.

The descriptive statistics and contemporaneous correlations between the implied volatility of FinTech and green energy dynamics are delineated in Panels A and B of Table 1, respectively. Panel A reveals a consistent alignment between the average and median values across all indices, indicating general stability in the central tendencies of these markets. The standard deviations, ranging from 1.570 to 385.67, suggest a wide variance in market volatility, with NGF presenting the least volatility and SPGTCLEN being markedly the most volatile. In terms of distribution, SPGB and GWE are characterized by negative skewness, diverging from the other markets' patterns. GWE and NGF register the minimal and maximal values for skewness and kurtosis, highlighting divergent distributional characteristics among the indices.

Panel B uncovers strong contemporaneous correlations across the series, barring NGF, which is negatively correlated with the SPGB market. Notably, a significant correlation is observed between FINX and the green energy markets, with FINX and SPGTCLEN showcasing the highest correlation. Additionally, SPGTCLEN, SUNIDX, and GWE exhibit the strongest correlations, underscoring a pronounced interconnectivity among these energy markets. This analysis underpins the intricate relationship between financial technology innovations and the volatility of energy markets, revealing significant insights into the dynamics at play within these interconnected sectors.

Table 1: Descriptive statistics and correlations of Fintech and Energies.

Panel A: Statistical description

	FINX	SPGB	SPGTCLEN	GWE	SUNIDX	NGF
Mean	86.156	146.052	1119.511	286.8417	286.237	3.224
Median	84.299	145.600	1183.560	299.720	304.150	2.637
Standard deviation	19.681	7.7919	385.677	65.548	132.485	1.570
Skewness	0.941	-0.377	0.252	-0.029	0.200	1.711
Kurtosis	4.016	2.409	2.006	1.550	1.761	5.778

Panel B: Correlations

	FINX	SPGB	SPGTCLEN	GWE	SUNIDX	NGF
FINX	1.000	0.293	0.368	0.312	0.377	0.002
SPGB	0.293	1.000	0.674	0.674	0.676	-0.239
SPGTCLEN	0.368	0.674	1.000	0.983	0.996	0.429
GWE	0.312	0.674	0.983	1.000	0.981	0.468
SUNIDX	0.377	0.676	0.996	0.981	1.000	0.440
NGF	0.002	-0.239	0.429	0.468	0.440	1.000

3.2. Estimations from Bayesian vector heterogeneous autoregressions

In our analysis, we adopt a methodology inspired by Ellington (2021), integrating the heterogeneous autoregressive (HAR) framework as initially formulated by Corsi (2009) with the

Bayesian estimation techniques advanced by Chan (2020). This combined approach is particularly advantageous for our study for several reasons. Firstly, it substantially reduces computational demand while effectively capturing the persistence characteristics observed in price levels. This aspect is crucial for analyzing financial data, where long-term dependencies are often significant. Secondly, the methodology facilitates the incorporation of Kronecker structures, allowing for the modeling of serially correlated error terms alongside non-Gaussian heteroscedasticity. This capability enhances the model's robustness by providing a more nuanced representation of the parameters and uncertainties derived from the empirical data. By leveraging this mixed HAR-Bayesian framework, our analysis benefits from both computational efficiency and an improved ability to model complex dynamics within financial markets, thereby aligning with the empirical realities observed in our dataset.

Specifically, X_s(an $n \times 1$ vector) is monitored over $s = 1, \ldots,$ S time scales. The VHAR description can be expressed as follows:

$$X_s = a_0 + \mathbf{A}_1 X_{s-1} + \mathbf{A}_5 X_{(s-1|t-5)} + \mathbf{A}_{22} X_{(s-1|t-22)} + v_s$$

where a_0 contains n constants, **A**'s matrices contain n coefficients, which illustrate autocorrelated relationships daily, every week, and every month. The lagged vectors of X_s are $X_{(s-1|t-k)} = \frac{1}{k}\sum_{i=1}^{k} X_{s-j}$ that consists of three food prices and GPR in the short, medium, and long runs.

For simplicity, the VHAR model can be written as a VAR(22) with no constraints imposed on any autoregressive matrix. Hence, the VAR(3) structure can be presented as follows:

$$X_t = c_0 + \sum_{t=1}^{3} \mathbf{C}_i X_{s-i} + v_s$$

where a vectorc_0 is a vector of constant values. This paper refers to the first, fifth, and twenty-second lags of X_s by assigning the value of *i* to be 1, 5 and 22, respectively. We define $Z_s' = (1, X_{s-1}', X_{s-5}', X_{s-22}')$as a $k \times 1$ vector where$k = 1 + np$. The reduced form is given as:

$$\mathbf{X} = \mathbf{ZC} + \boldsymbol{V} \qquad (1)$$

with $\mathbf{C}(C_0, \mathbf{C}_1, \mathbf{C}_5, \mathbf{C}_{22})'$ is a$k \times n$matrice. More specifically, **V** is vec(**V**) ~ N(0, $\boldsymbol{\Sigma} \otimes \mathbf{I_T}$) where vec(**V**) includes the columns of **V** and $\mathbf{I_T}$ are the T-dimensional identity matrix, and the Kronecker product is captured by $\otimes$.

It is worth noting that we can obtain the covariance structures at cross-sections and serials of **X** individually by replacing $\mathbf{I_T}$ with a $T \times T$ covariance matrix Φ. Specifically, **Σ** captures the cross-sectional analysis of covariance, and Φ reflects the sequential variance structure. Therefore, we write:

$$vec(\mathbf{V}) \sim N(0, \boldsymbol{\Sigma} \otimes \Phi) \qquad (2)$$

We can select distinct covariance structures for Φ in models (1) and (2). In this regard, seven fashions with various covariance structures are employed in our paper, as in Chan (2020) and Ellington (2021). We also follow Chan (2020) and Ellington (2021)in employing model priors for all parameters. We utilize a 252-day rolling window to estimate these seven model fashions.

3.2.1. Network interlinkages

We develop network measures from VAR models by determining the variance of the forecast error variance decomposition matrix. Then, Pesaran & Shin (1998) developed these measures using generalized forecast error variance decompositions (GFEVDs). Time series are assumed to be uncorrelated, meaning that $\Phi = I_T$. Rather than that, these measures are modified for a more general structure on Φ in this paper. For a matrix A, $(A)_{j,k}$, presents the *j*th row and *k*th column. $(B)_j$ presents the full *j*th row of *B*, and Σ*B* presents all elements added together in *A*. Since we can write $X_s$as *C(L)*$X_s = v_s$with *C(L)*= $[\mathbf{I}_n - \mathbf{C}_1 L_1 - \cdots - \mathbf{C}_p L_p]$being an $n \times n$ matrix lag-polynomial. We also assume that the base of the VAR polynomial does not lie inside the unit circle to achieve the MA(∞) representation, $X_s = \Theta(L) v_s$,where *C(L)* = $[\Theta(L)]^{-1}$.

In some exercises, we assume that the errors have an MA(1) representation with $v_s = \epsilon_t + \psi\, \epsilon_{t-1}, \epsilon_t \sim N\,(0, \boldsymbol{\Sigma})$[1]. Therefore, we can indicate that$var\,(v_s) = (1 + \Theta^2)\boldsymbol{\Sigma}$, where we define $\widetilde{\boldsymbol{\Sigma}}$= $c\boldsymbol{\Sigma}$, with $c = (1 + \Theta^2)$.With our setup, the covariance matrix of the forecast error conditional on information at time $s - 1$ can be presented as follows:

$$\Gamma_H = \sum_{q=0}^{Q} \Theta_h \widetilde{\boldsymbol{\Sigma}} \Theta_h'.$$

The forecast error covariance matrix based on shocks occurring now and in the future to the *jth* equations can be defined by using the conditional forecast error, which can be written as follows:

$$\varsigma_v^k(Q) = \sum_{q=0}^{Q} \Theta_h \left[v_{s+Q-q} - \mathbb{E}(v_{s+Q-q} | v_{k,s+Q-q}\right].$$

And if we assume a normal distribution, we have:

$$\varsigma_v^k(Q) = \sum_{q=0}^{Q} \Theta_h \left[v_{s+Q-q} - \tilde{\sigma}_{kk}^{-1} \left(\widetilde{\boldsymbol{\Sigma}}\right)_k v_{k,s+Q-q}\right].$$

The covariance matrix is written as:

$$\Gamma_Q = \sum_{q=0}^{Q} \Theta_q \widetilde{\boldsymbol{\Sigma}} \Theta_q' - \tilde{\sigma}_{kk}^{-1} \sum_{q=0}^{Q} \Theta_q \left(\widetilde{\boldsymbol{\Sigma}}\right)_k \left(\widetilde{\boldsymbol{\Sigma}}\right)_k' \Theta_q'.$$

The unscaled *Q*-step ahead prediction error variance of the jth variable in relation to the change in the kth variable is:

$$\Delta_{(j)kQ} = \left(\Gamma_Q - \Gamma_Q^k\right) = \tilde{\sigma}_{kk}^{-1} \sum_{q=0}^{Q} ((\Theta_q \widetilde{\boldsymbol{\Sigma}})_{j,k})^2.$$

We can obtain a way of expressing the GFEVD as in Pesaran & Shin (1998):

$$(\boldsymbol{\Psi}_Q)_{j,k} = \frac{\tilde{\sigma}_{kk}^{-1} \sum_{q=0}^{Q} ((\Theta_q \widetilde{\boldsymbol{\Sigma}})_{j,k})^2}{\sum_{q=0}^{Q} (\Theta_q \widetilde{\boldsymbol{\Sigma}} \Theta_q')_{j,j}}$$

where $\tilde{\sigma}_{kk} = (\widetilde{\boldsymbol{\Sigma}})_{k,k}, \boldsymbol{\Theta}_q$ denotes the MA coefficients (*n* × *n* matrix) at lag *q*. $(\boldsymbol{\Psi}_Q)_{j,k}$ represents a variable *k's* contribution to *j's* the forecast error variance. The power spectrum, $\mathbf{S}_y(\omega)$, is incorporated to investigate systems that diverse horizons form. We denote ω as the frequency component, and we represent the spectral density that captures the Fourier transform of the infinite MA specification as follows:

$$S_x(\omega) = \sum_{q=-\infty}^{\infty} \mathbb{E}[X_s X_{s-q}] e^{-i\omega q} = \boldsymbol{\Theta}\left(e^{-i\omega}\right) \widetilde{\boldsymbol{\Sigma}} \boldsymbol{\Theta}'(e^{+i\omega})$$

We can write the generalized spectrum of causation over frequency components using the above representation $\omega \in [-\pi, \pi]$ and function of weighting to have a spectral specification of variance decompositions from variable j to k in X_s. We can prove the presence of measures specific to horizons. We then present the generalized causation spectrum and weighting function as follows:

$$(f(\omega))_{j,k} = \frac{\tilde{\sigma}_{kk}^{-1} |(\boldsymbol{\Theta}(e^{-i\omega}))_{j,k}|^2}{(\boldsymbol{\Theta}(e^{-i\omega})\tilde{\boldsymbol{\Sigma}}\boldsymbol{\Theta}'(e^{-i\omega}))_{j,j}}$$

$$\Gamma_j(\omega) = \frac{(\boldsymbol{\Theta}(e^{-i\omega})\tilde{\boldsymbol{\Sigma}}\boldsymbol{\Theta}'(e^{-i\omega}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\boldsymbol{\Theta}(e^{-i\lambda})\tilde{\boldsymbol{\Sigma}}\boldsymbol{\Theta}'(e^{-i\lambda}))_{j,j}\, d\lambda}$$

and we define the variance decomposition matrix in terms of its spectral representation given as:

$$(\boldsymbol{\Psi}_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)\,(f(\omega))_{j,k} d\omega$$

If we sum all horizons, we can obtain $(\boldsymbol{\Psi}_Q)_{j,k}$.

Afterward, scaling $\boldsymbol{\Psi}_d$such that $(\tilde{\boldsymbol{\Psi}}_d)_{j,k} = (\boldsymbol{\Psi}_d)_{j,k} / \sum_{\boldsymbol{k}}(\boldsymbol{\Psi}_H)_{j,k}$ delivers the adjacency matrix, $\tilde{\boldsymbol{\Psi}}_d$ over horizon band *d*, which can be written as:

$$D_d = 100\ \times (\frac{\sum \tilde{\Psi}_d}{\sum \tilde{\Psi}_Q} - \frac{Tr\,\{\tilde{\Psi}_d\}}{\sum \tilde{\Psi}_Q}) \tag{3}$$

Equation (3) allows us to capture the forecast error variance's contribution stemming from all shocks within the designed structure but excluding our own shocks. It implies a horizon of interest that considers system-wide connectivity.

$\tilde{\boldsymbol{\Psi}}_d$ also helps us to derive the direction of interconnections across horizons. Typically, to and from interlinkages are presented as follows:

$$D_{d,j\,\rightarrow\bullet} = 100\ \times \frac{\sum_{k=1\,,k\neq j}^{n}(\tilde{\Psi}_d)_{k,j}}{\sum_{k=1\,,k=j}^{n}(\tilde{\Psi}_H)_{k,j}} \tag{4}$$

$$D_{d,j\,\leftarrow\bullet} = 100\ \times \frac{\sum_{k=1\,,k\neq j}^{n}(\tilde{\Psi}_d)_{k,j}}{\sum_{k=1\,,k=j}^{n}(\tilde{\Psi}_H)_{k,j}} \tag{5}$$

Equation (4) captures the contribution of variable *j* to other variables' dynamics at horizon *d*. We use Equation (5) to represent out-degrees. It is clear that the asset *j*'s variance results from shocks arising in other variables at horizon *d*. We take their differentiation to calculate the net directional linkages at horizon *d* as follows:

$$D_{d,j}^{NET} = D_{d,j\,\rightarrow\bullet} - D_{d,j\,\leftarrow\bullet} \tag{6}$$

Hence, the positive values mean that variables exchange shocks, while negative values indicate the variable is the shock receiver if they have sufficient shock transmission capacity[2].

4. Results

4.1. Model selection

In the context of model evaluation, our methodology aligns with Chan's (2020) approach, where the effectiveness of six distinct models is assessed through the aggregation of their marginal log-likelihoods, as detailed in Table 2. This method of analysis gains support from Ellington (2021), who posits that higher values of these statistics signify a superior model fit. A critical aspect of our analysis involves the consideration of serial correlation, stochastic

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[2] We can control$\tilde{\Theta}_d$further to define pairwise interlinkage in Equations (4) to (6).

volatility, and heavy tails in the data, ensuring a comprehensive evaluation of model performance.

Our empirical findings indicate that the network measures extracted from the Bayesian Hierarchical Vector Autoregression with t-distributed errors and Conditional Stochastic Volatility (BHVAR-t-CSV) and its Moving Average counterpart (BHVAR-t-CSV-MA(1)) models exhibit the most pronounced log marginal likelihood values. Such results underscore the significance of these models in capturing the complexities of the data effectively.

Furthermore, it is imperative to undertake a comparative analysis of the network structures emanating from both the BHVAR-CSV and BHVAR-CSV-MA(1)[3]frameworks. By doing so, we can discern the nuanced impacts of incorporating moving average components into the model structure, thereby offering insights into their respective abilities to accommodate the underlying data characteristics.

Table 2: Average and median log marginal likelihoods of seven BVHAR models

	Average log marginal likelihood	**Median log marginal likelihood**
BHVAR-t	802.883	816.235
BHVAR-CSV	1811.079	**1880.297**
BHVAR-MA(1)	1102.183	1216.235
BHVAR-t-CSV	1946.983	**1935.779**
BHVAR-t-MA(1)	1254.490	1286.274
BHVAR-CSV-MA(1)	1764.482	**1807.727**
BHVAR-t-CSV-MA(1)	1929.812	**1943.471**

***Notes**: BVHAR denotes the Bayesian Heterogeneous Autoregressive model. We refer to t- as errors resulting from a t distribution, CSV as an informal term for common volatility, and MA(1) as the remaining value resulting from an MA(1) process. We employ a rolling window of 252 days from May 01, 2019, to October 28, 2022.*

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[3] The results from these models can be provided by authors upon the request.

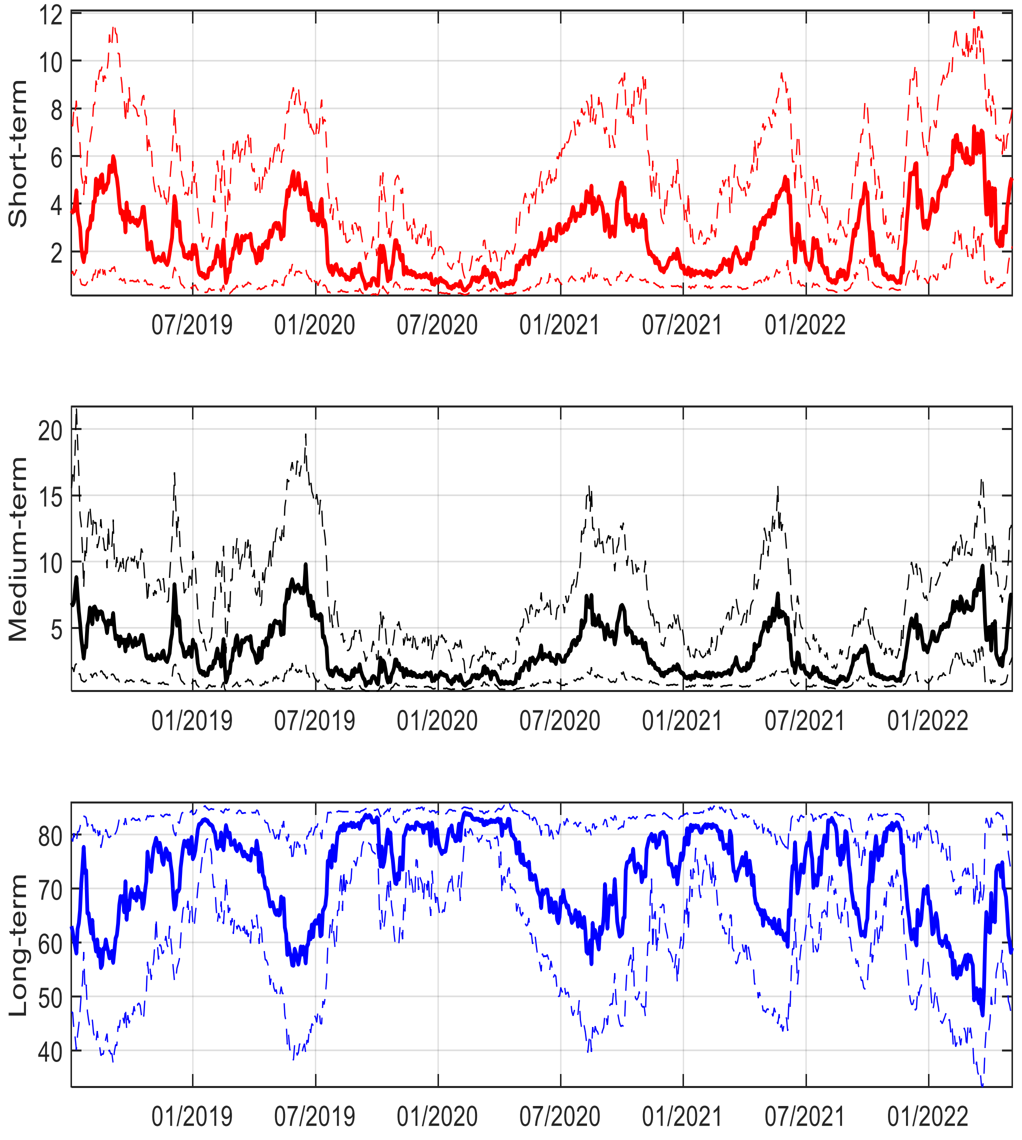


Figure 1: Time horizons network interlinkage measures

4.2. Network linkages

4.2.1. Time Horizon Linkages

In our subsequent analysis, we delineate the dynamics of network interconnections as derived from Equation (3), categorizing time horizons into short-run (spanning 1 day to 1 week), medium-run (extending from 1 week to 1 month), and long-term (exceeding 1 month). The degree of these interlinkages, measured through a one-standard deviation and the posterior median percentile of specific network metrics, is illustrated in Figure 1, where the network's temporal interconnections across short-, medium-, and long-term durations are shown in the top, middle, and bottom panels, respectively.

Three principal insights emerge from our investigation. First, we observe that long-term interconnections exhibit the most pronounced strength, particularly during periods of heightened uncertainty, such as the initial surge of the COVID-19 pandemic in July 2019 and the escalation of the Russia-Ukraine conflict in February 2022. During these times, fluctuations in network interlinkages were persistently elevated, subsequently diminishing as the pandemic evolved with the emergence of new virus strains and as the geopolitical landscape shifted.

Second, the analysis reveals that the interlinkage disparities across different durations are most notable in the long-run, as evidenced by the width of the error bands. This distinction underscores a divergent trend, especially pronounced at the onset of the COVID-19 pandemic and the commencement of the Russia-Ukraine conflict. Such findings indicate that long-term interconnections undergo significant shifts during these periods, contrasting sharply with the more stable patterns observed in short- and medium-term interlinkages.

Third, a peak in short- and medium-term interconnections was identified in July 2019, followed by a general decline towards the end of 2021. This period witnessed fluctuations due to surges of COVID-19 cases globally in late 2020 and mid-2021. However, the start of the Russia-Ukraine conflict marked a resurgence in both short- and medium-term interconnections, reflecting the heightened volatility in the global economy during such crises. As the pandemic's immediate impact waned in 2021, these connections slightly attenuated, only to intensify again with the emergence of geopolitical tensions.

This analysis underscores the variability of network interconnections across different temporal scales, affirming that market linkages intensify in response to transient events. Aligning with the findings of Baumeister et al. (2020), our study corroborates the prominence of long-run interlinkages amidst the COVID-19 health crisis. Further, echoing the research by Balcilar et al. (2021) and Zhang & Broadstock (2020), that the interconnectedness among various commodity markets amplifies during periods of uncertainty, including the global financial crisis and the COVID-19 pandemic. Consequently, our results contribute to the burgeoning literature on the dynamic evolution of the Total Connectedness Index (TCI) in the face of global shocks, highlighting the differential impacts of COVID-19 on network dynamics.

4.2.2. Net-directional linkages

In our subsequent analysis, we delve into the net-directional linkages between the FinTech and energy sectors across varying temporal horizons, initially focusing on short-run and medium-run dynamics. Figures 2 and 3 demonstrate these net-directional interconnections, presenting posterior medians alongside one-standard deviation percentiles to depict short-run interlinkages. Within this framework, positive (negative) values for series j, encompassing {ARKF, FINX, SPGB, SPGTCLEN, GWE, SUNIDX, NGF, OVX}, denote the series' role as a shock transmitter (receiver), a crucial distinction for understanding the directional flow of shocks within the market.

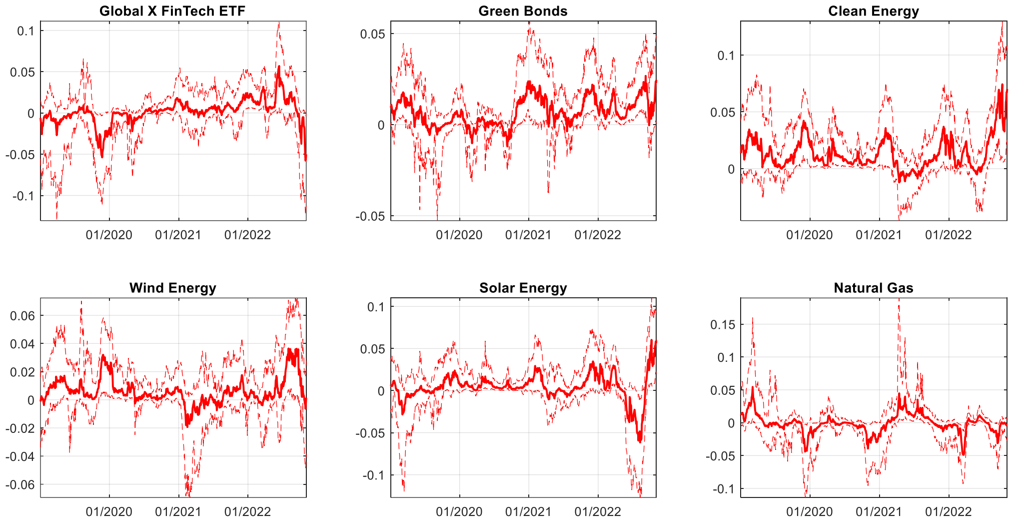
Key observations from Panels A and B of Figures 2 and 3 indicate that both ARKF and FINX exhibit parallel trends with the energy sector partitioned into two distinct phases. The inception of the COVID-19 pandemic towards the end of 2019 marks the first phase, during which ARKF and FINX predominantly assumed the role of shock receivers from the broader market. The second phase, commencing in early 2021 amidst the pandemic and extending to the start of the Russia-Ukraine conflict in early 2022, sees a transformation in FinTech variables as they become shock transmitters. This role reversal is particularly pronounced during periods of uncertainty, where the volatility of indicator values significantly increases.

Conversely, the energy markets, for the most part, functioned as shock transmitters throughout the study period, with the exception of the natural gas and solar energy sectors. The solar energy market, in particular, shifted to a shock receiver role with the advent of the Russia-Ukraine conflict, as indicated by a negative mean value for SUNIDX. Additionally, clean energy and wind energy sectors transitioned to shock receivers during the peak of the COVID-19 crisis (from early to mid-2021), only to revert to shock transmitters, alongside the green bonds market, in transmitting shocks during the Russia-Ukraine conflict.

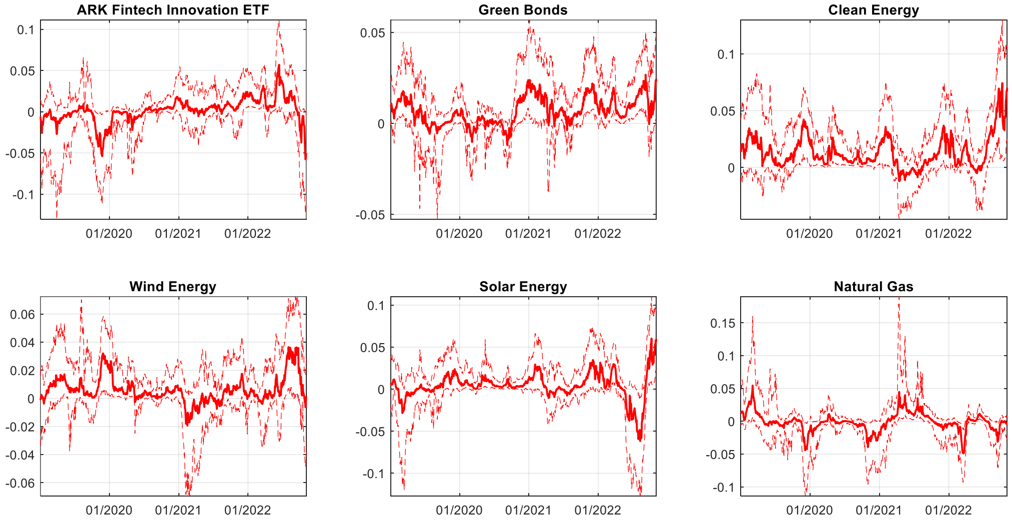
The interplay between FinTech Innovation Development and energy market dynamics becomes increasingly pronounced amidst uncertain times. The COVID-19 crisis heralded a period during which shocks from the wind energy, clean energy, and green bonds markets significantly impacted FinTech Innovation Development. Throughout the Russia-Ukraine conflict, FinTech, alongside the solar energy and natural gas markets, emerged as the dominant shock transmitter. This shift highlights the pivotal role of FinTech Innovation Development in mediating market responses to global crises, highlighting its dual capacity as both a receiver and transmitter of shocks, which is accentuated during periods of heightened uncertainty.

Figure 2: Short horizon (1-day to 1-week) net-directional linkages

Panel A: Global X FinTech ETF



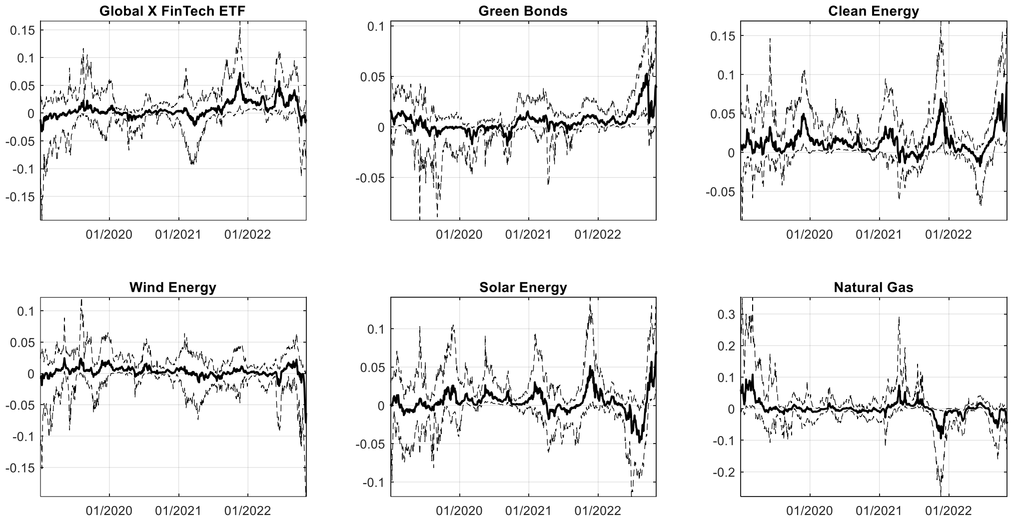
Panel B: ARK Fintech Innovation ETF



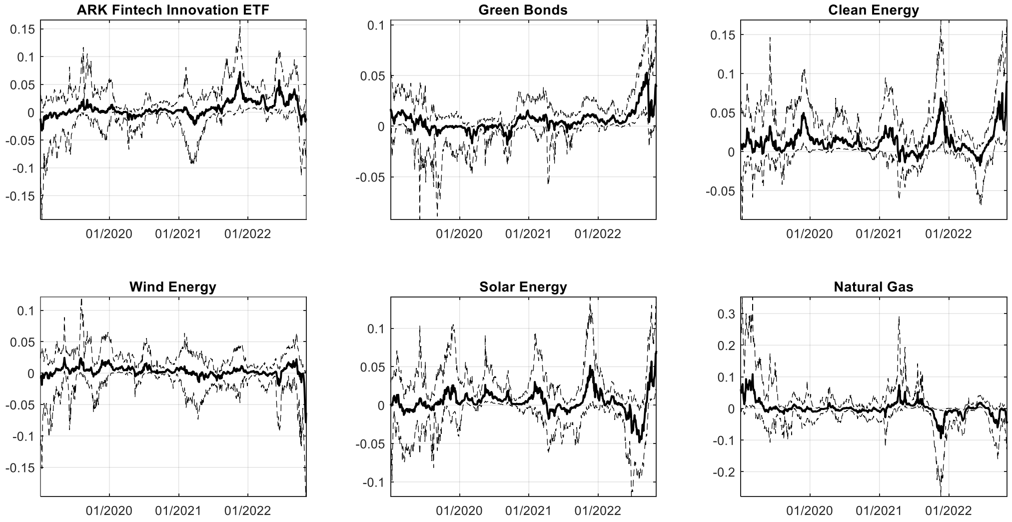
Notes: Positive (negative) values mean that the considered market plays the role of a transmitter (receiver) of shock.

Figure 3: Medium-horizon (1-week to 1-month) net-directional linkages

Panel A: Global X FinTech ETF



Panel B: ARK Fintech Innovation ETF



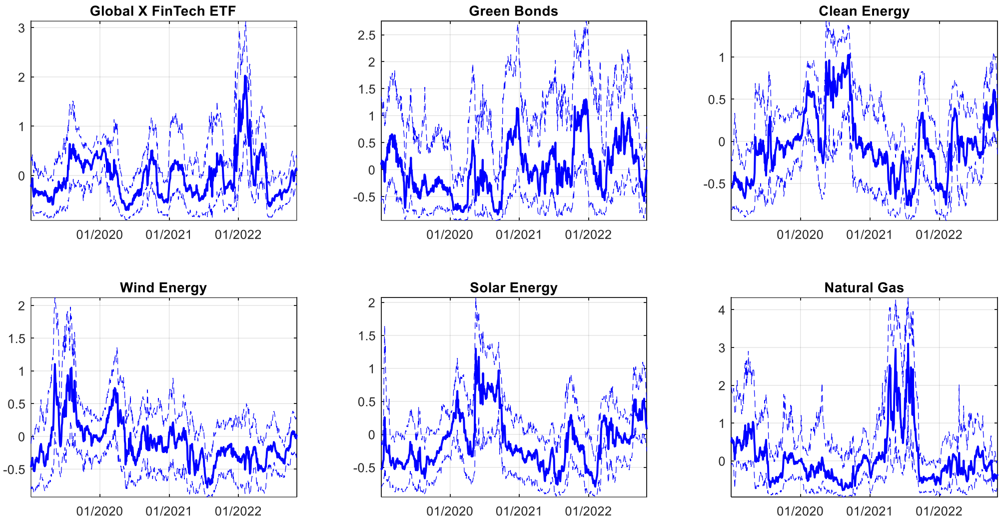
Notes: Positive (negative) values mean that the considered market plays the role of a transmitter (receiver) of shock.

Afterward, we examine the long-horizon net-directional linkages shown in Figure 4. Notably, the mean values of variables in our system fluctuated during the period we studied, suggesting that the role of Fintech Innovation Development and energy dynamics is inconsistent in the long term. Their roles are exchanged constantly. Furthermore, the importance of the Fintech Innovation development and energy market became more critical when severe crises hit the global economy. Specifically, the sample (from January 2019 to January 2022) was divided into three main stages: during the period of the COVID-19 pandemic (to January 2021), before the Russia-Ukraine conflict (from January 2021 to January 2022) and in the time of war (from January 2022). The solar, clean, and wind energy markets throughout the sample demonstrate relatively similar time dynamics. In the first and third stages, they act as a conventional transmission. They have become a shock receiver in the second stage, while the green bonds and natural gas markets operate in contrast to transmit shock.

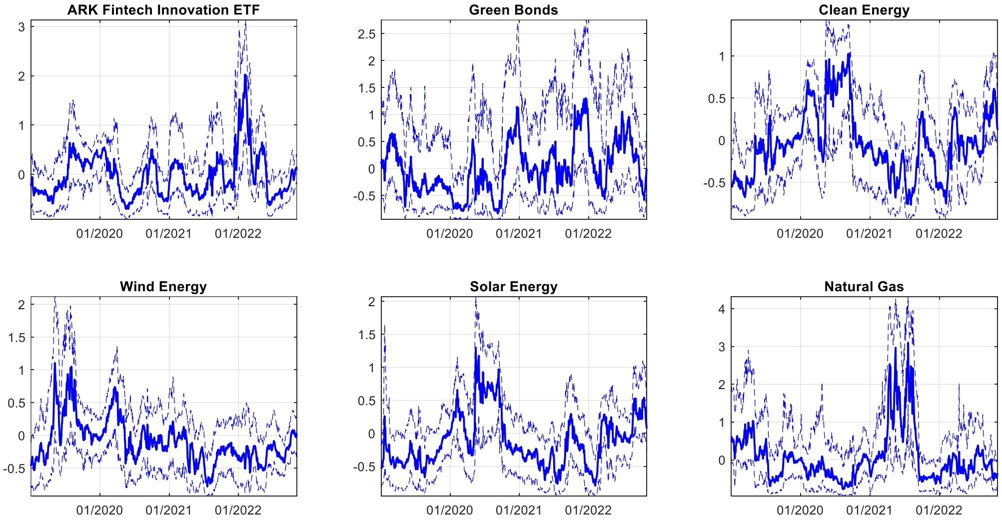
In contrast, Fintech Innovation Development variables served as vital shock receivers in the first and second stages. Suddenly, they became shock transmitters in the third stage (during the Russia-Ukraine conflict). Pranita et al. (2023) indicate that islands with limited connectivity and accessibility require the development of Blockchain and technological innovation. Integrating resources from all stakeholders will enable blue economies to develop more effectively and efficiently while simultaneously achieving sustainability and being more successful and efficient.

Figure 4: Long-horizon (greater than 1-month) net-directional linkages

Panel A: Global X FinTech ETF



Panel B: ARK Fintech Innovation ETF



Notes: Positive (negative) values mean that the considered market plays the role of a transmitter (receiver) of shock.

4.2.3. Robustness check

To enhance the rigor of our investigation and substantiate the previously outlined findings, we conducted a comprehensive log transformation analysis of all series, adhering to the methodology delineated in Section 4.2.2. Furthering our exploration, we extended our analysis to encompass an additional five green energy markets. In parallel, we broadened our scope of uncertainty indices to include various indicators: the cryptocurrency volatility index, geopolitical risk index, developments in artificial intelligence, and the global volatility index, offering a more nuanced understanding of market dynamics. Comprehensive data and additional findings are available upon request.

Our extended analysis consistently supports the initial conclusions, underscoring the validity and robustness of our assertions regarding the dynamic interlinkages within the network. This consistency across diverse datasets and under varying analytical conditions reinforces the reliability of our conclusions, confirming the significant impact of these interlinkages on the studied markets.

5. Conclusion and policy implications

This research explores the complex dynamics between FinTech innovation development and energy markets, employing an analytical framework based on ARK Fintech Innovation ETF, Global X FinTech ETF, and various indicators of the green energy market (namely green bonds, clean energy, wind energy, solar energy, natural gas, and crude oil). Utilizing seven Bayesian vector heterogeneous autoregression models, our study methodically delineates the nature of network interlinkages across different time horizons: short, medium, and long-term. The temporal scope of our analysis spans from May 01, 2019, to October 28, 2022, a period marked by significant global disruptions, including the COVID-19 pandemic and the Russia-Ukraine conflict.

Our findings reveal two critical insights. Firstly, the interconnectedness between FinTech innovation and energy markets intensifies significantly in the long term, suggesting a deep-seated, enduring relationship that transcends temporal fluctuations. Moreover, this long-term interlinkage exhibits distinct patterns from those observed in short to medium terms, especially in the backdrop of major global crises such as the COVID-19 pandemic and the geopolitical tensions stemming from the Russia-Ukraine conflict. These observations highlight the heightened susceptibility of these interconnections to external shocks and uncertainties.

Secondly, the directional dynamics of market influences undergo a notable transformation in response to these crises. Before the Russia-Ukraine conflict, a shift in roles from shock receivers to shock transmitters was observed, a trend that persisted throughout the pandemic. The analysis further reveals that during the initial stages of COVID-19, the FinTech Innovation Development markets were significantly influenced by the wind energy, clean energy, and green bonds markets. Conversely, in the wake of the Russia-Ukraine conflict, FinTech Innovation Development emerged as a predominant force, exerting substantial influence on the solar energy and natural gas markets, thereby indicating a reversal in the flow of shocks between these sectors.

The implications of our study are far-reaching, bearing significant relevance for financial institutions, policymakers, and market practitioners. Understanding the nuanced interplay between FinTech innovation and energy dynamics is paramount for devising strategies to mitigate vulnerabilities and preempt the propagation of risk and instability across markets. This knowledge is particularly crucial for formulating policies that address the foundations of market contagions, encompassing a broad spectrum of assets, including oil, gold, commodities, and cryptocurrencies. Moreover, our findings shed light on the heightened risks associated with investment diversification strategies in the context of unpredictable events, underscoring the need for a cautious and informed approach to portfolio management and proper temporal balancing.

In conclusion, this research contributes valuable insights into the complex interdependencies between the FinTech and energy sectors, offering a comprehensive understanding that can enhance public welfare and financial stability. By identifying the mechanisms through which uncertainties and risks in the energy sector can influence financial markets—and vice versa—our study provides a solid foundation for developing robust policies that safeguard against market volatility and enhance the resilience of vulnerable economic sectors.

References

Abakah, E.J.A., Adeabah, D., Tiwari, A.K., Abdullah, M., (2023a). Effect of Russia–Ukraine war sentiment on blockchain and FinTech stocks. International Review of Financial Analysis. 90, 102948. https://doi.org/10.1016/j.irfa.2023.102948.

Abakah, EJA, Tiwari, AK, Alagidede, IP, Gil-Alana, LA., (2022). Re-examination of risk-return dynamics in international equity markets and the role of policy uncertainty, geopolitical risk and VIX: Evidence using Markov-switching copulas. Finance Research Letters, 47, 102535.

Abakah, EJA, Tiwari, AK, Alagidede, IP, Hammoudeh, S, (2023b). Nonlinearity in the causality and systemic risk spillover between the OPEC oil and GCC equity markets: a pre-and post-financial crisis analysis. Empirical. Economics. pp. 1–77.

Ahram, T., Sargolzaei, A., Sargolzaei, S., Daniels, J., & Amaba, B. (2017). Blockchain technology innovations. *2017 IEEE Technology & Engineering Management Conference (TEMSCON)*, 137–141. https://doi.org/10.1109/TEMSCON.2017.7998367

An, Y. J., Choi, P. M. S., & Huang, S. H. (2021). Blockchain, Cryptocurrency, and Artificial Intelligence in Finance. In P. M. S. Choi & S. H. Huang (Eds.), *Fintech with Artificial Intelligence, Big Data, and Blockchain* (pp. 1–34). Springer. https://doi.org/10.1007/978-981-33-6137-9_1

Arner, D. W., Buckley, R. P., Zetzsche, D. A., & Veidt, R. (2020). Sustainability, FinTech and Financial Inclusion. *European Business Organization Law Review*, *21*(1), 7–35. https://doi.org/10.1007/s40804-020-00183-y

Baumeister, C., Korobilis, D., & Lee, T. K. (2020). Energy Markets and Global Economic Conditions. *The Review of Economics and Statistics*, 1–45. https://doi.org/10.1162/rest_a_00977

Biais, B., Bisière, C., Bouvard, M., & Casamatta, C. (2019). Blockchains, Coordination, and Forks. *AEA Papers and Proceedings*, *109*, 88–92. https://doi.org/10.1257/pandp.20191018

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, Technology, and Governance. *Journal of Economic Perspectives*, *29*(2), 213–238. https://doi.org/10.1257/jep.29.2.213

Bouri, E., Gil-Alana, L. A., Gupta, R., & Roubaud, D. (2019). Modelling long memory volatility in the Bitcoin market: Evidence of persistence and structural breaks. *International Journal of Finance & Economics*, *24*(1), 412–426. https://doi.org/10.1002/ijfe.1670

Chakrabarti, P., Jawed, M. S., & Sarkhel, M. (2021). COVID-19 pandemic and global financial market interlinkages: A dynamic temporal network analysis. *Applied Economics*, *53*(25), 2930–2945. https://doi.org/10.1080/00036846.2020.1870654

Chan, J. C. C. (2020). Large Bayesian VARs: A Flexible Kronecker Error Covariance Structure. *Journal of Business & Economic Statistics*, *38*(1), 68–79. https://doi.org/10.1080/07350015.2018.1451336

Chatziantoniou, I., Gabauer, D., Perez de Gracia, F., (2022). Tail risk connectedness in the refined petroleum market: a first look at the impact of the COVID-19 pandemic. Energy Economics, 111, 106051. https://doi.org/10.1016/j.eneco.2022.106051.

Chen, L., Cong, L. W., & Xiao, Y. (2020). A Brief Introduction to Blockchain Economics. In *Information for Efficient Decision Making* (pp. 1–40). WORLD SCIENTIFIC. https://doi.org/10.1142/9789811220470_0001

Chueca Vergara, C., & Ferruz Agudo, L. (2021). Fintech and Sustainability: Do They Affect Each Other? *Sustainability*, *13*(13), Art. 13. https://doi.org/10.3390/su13137012

Corsi, F. (2009). A Simple Approximate Long-Memory Model of Realized Volatility. *Journal of Financial Econometrics*, *7*(2), 174–196. https://doi.org/10.1093/jjfinec/nbp001

Disli, M., Nagayev, R., Salim, K., Rizkiah, S. K., & Aysan, A. F. (2021). In search of safe haven assets during COVID-19 pandemic: An empirical analysis of different investor types. *Research in International Business and Finance*, *58*, 101461. https://doi.org/10.1016/j.ribaf.2021.101461

Efanov, D., & Roschin, P. (2018). The All-Pervasiveness of the Blockchain Technology. *Procedia Computer Science*, *123*, 116–121. https://doi.org/10.1016/j.procs.2018.01.019

Ellington, M. (2021). Fat tails, serial dependence, and implied volatility index connections. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2021.09.038

Elsayed, A. H., Nasreen, S., & Tiwari, A. K. (2020). Time-varying co-movements between energy market and global financial markets: Implication for portfolio diversification and hedging strategies. *Energy Economics*, *90*, 104847. https://doi.org/10.1016/j.eneco.2020.104847

Furman, J., & Seamans, R. (2019). AI and the Economy. *Innovation Policy and the Economy*, *19*, 161–191. https://doi.org/10.1086/699936

Goodell, J. W., & Goutte, S. (2021). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters*, *38*, 101625. https://doi.org/10.1016/j.frl.2020.101625

Gronwald, M. (2019). Is Bitcoin a Commodity? On price jumps, demand shocks, and certainty of supply. *Journal of International Money and Finance*, *97*, 86–92. https://doi.org/10.1016/j.jimonfin.2019.06.006

Guo, X., Lu, F., & Wei, Y. (2021). Capture the contagion network of bitcoin – Evidence from pre and mid COVID-19. *Research in International Business and Finance*, *58*, 101484. https://doi.org/10.1016/j.ribaf.2021.101484

Ha, L. T. (2022). Dynamic interlinkages between the crude oil and gold and stock during Russia-Ukraine War: Evidence from an extended TVP-VAR analysis. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-022-23456-0

Huynh, T. L. D., Hille, E., & Nasir, M. A. (2020). Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies. *Technological Forecasting and Social Change*, *159*, 120188. https://doi.org/10.1016/j.techfore.2020.120188

Jena, S. K., Tiwari, A. K., Hammoudeh, S., & Shahbaz, M. (2020). Dynamics of FII flows and stock market returns in a major developing country: How does economic uncertainty matter? *The World Economy*, *43*(8), 2263–2284. https://doi.org/10.1111/twec.12830

Le, L.-T., Yarovaya, L., & Nasir, M. A. (2021). Did COVID-19 change spillover patterns between Fintech and other asset classes? *Research in International Business and Finance*, *58*, 101441. https://doi.org/10.1016/j.ribaf.2021.101441

Le, T.-L., Abakah, E. J. A., & Tiwari, A. K. (2021). Time and frequency domain connectedness and spillover among Fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change*, *162*, 120382. https://doi.org/10.1016/j.techfore.2020.120382

Lee, J., & Choi, P. M. S. (2019). *Chain of Antichains: An Efficient and Secure Distributed Ledger Technology and Its Applications* (arXiv:1810.11871). arXiv. https://doi.org/10.48550/arXiv.1810.11871

Ly, S., Sriboonchitta, S., Tang, J., Wong, W.-K., 2022. Exploring dependence structures among European electricity markets: static and dynamic copula-GARCH and dynamic state-space approaches. Energy Reports, 8, pp. 3827–3846. https://dx.doi.org/10.1016/j.egyr.2022.02.308

Naifar, N., Hammoudeh, S., Tiwari, AK., (2019). Do Energy and Banking CDS Sector Spreads Reflect Financial Risks and Economic Policy Uncertainty? A Time-Scale Decomposition Approach. Computational Economics, 54 (2), pp. 507–534.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0

Shah, J., & Parveen, S. (2021). Understanding the Blockchain Technology Beyond Bitcoin. In R. K. Phanden, K. Mathiyazhagan, R. Kumar, & J. Paulo Davim (Eds.), *Advances in Industrial and Production Engineering* (pp. 499–516). Springer. https://doi.org/10.1007/978-981-33-4320-7_45

Sharma, S., Tiwari, A. K., & Nasreen, S. (2022). Are FinTech, Robotics, and Blockchain index funds providing diversification opportunities with emerging markets?Lessons from pre and post-outbreak of COVID-19. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-022-09611-2

Stetco, A., Dinmohammadi, F., Zhao, X., Robu, V., Flynn, D., Barnes, M., Keane, J., Nenadic, G., (2019). Machine learning methods for wind turbine condition monitoring: A review. Renewable Energy, 133, pp. 620–635.https://doi.org/10.1016/j.renene.2018.10.047

Tiwari, A. K., Abakah, E. J. A., Le, T.-L., & Leyva-de la Hiz, D. I. (2021). Markov-switching dependence between artificial intelligence and carbon price: The role of policy uncertainty in the era of the 4th industrial revolution and the effect of COVID-19 pandemic. *Technological Forecasting and Social Change*, *163*, 120434. https://doi.org/10.1016/j.techfore.2020.120434

Tiwari, AK., Adewuyi, AO, Albulescu, CT, Wohar, ME., (2020a). Empirical evidence of extreme dependence and contagion risk between main cryptocurrencies. North-American Journal of Economics and Finance, 51, 101083.

Tiwari, AK., Aye, CC, Gupta, R, Gkillas, K., (2020b). Gold-oil dependence dynamics and the role of geopolitical risks: Evidence from a Markov-switching time-varying copula model. Energy Economics. 88, 104748.

Tiwari, AK, Jena, SK., Kumar, S., Hille, E., (2022). Is oil price risk systemic to sectoral equity markets of an oil importing country? Evidence from a dependence-switching copula delta CoVaR approach. Annals of Operation Research, 315 (1), pp. 429–461.

Tiwari, AK, Pathak, R, DasGupta, R., Sadorsky, P., (2021a). Modelling dependence and systemic risk between oil prices and BSE sectoral indices using stochastic copula and CoVar, ΔCoVar and MES approaches. Applied Economics, 53 (58), pp. 6770–6788.

Yermack, D. (2015). Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal. In D. Lee Kuo Chuen (Ed.), *Handbook of Digital Currency* (pp. 31–43). Academic Press. https://doi.org/10.1016/B978-0-12-802117-0.00002-3