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# Are cleaner energy and financial technologies needed? Contagion and causality evidence between global fintech markets, energy consumption, and environmental pollution

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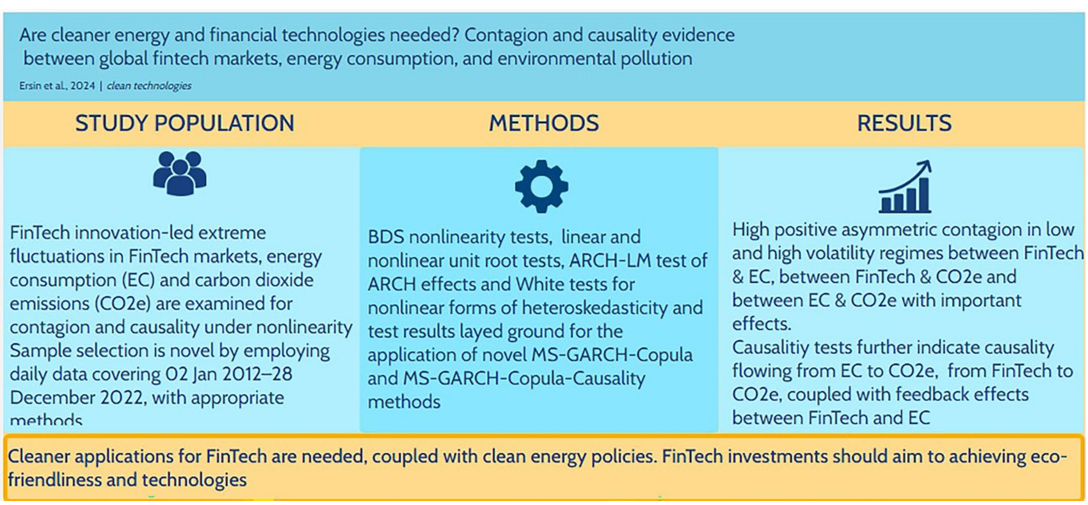
## Abstract
Financial technology (FinTech) depends on high amounts of energy with an upward trend, possibly affecting emissions due to energy consumption (EC). The study investigates tail dependence, contagion, and nonlinear between FinTech, EC, and carbon dioxide emissions ($CO_2e$) with MS-GARCH-copula and MS-GARCH-copula-causality with a daily sample covering 02 Jan 2012–28 December 2022. The method is a generalized version of single-regime GARCH-copula and causality tests to Markov-switching. Empirical results indicated that FinTech, EC, and $CO_2e$ series follow nonlinear processes in addition to unit roots as determined by BDS nonlinearity tests and a set of linear and nonlinear unit root tests. Further, for all series, heteroskedasticity and nonlinear forms of heteroskedasticity cannot be rejected by ARCH–LM and White heteroskedasticity tests, leading to the estimation of the series and their joint dynamics by MS-GARCH-copula and a new MS-GARCH-copula based nonlinear Granger-causality test, the RSGCC test, under two distinct regimes characterized with the low and high volatility for extreme tails of data. Positivity and significance of copula parameters under both regimes indicate a high degree of positive but asymmetric tail dependence and contagion between FinTech & EC, in addition to contagion between FinTech & $CO_2e$ and EC & $CO_2e$. RSGCC results determine unidirectional causalities from EC to $CO_2e$ and from FinTech to $CO_2e$, coupled with bidirectional causality between FinTech and EC, which enhance the dynamics due to feedback effects. The findings of this paper are of importance for two central Sustainable Development Goals. Results could also be used to bring the FinTech markets and EC to the attention of policymakers, researchers, and eco-friendliness-focused portfolio managers.

### Graphical Abstract




**Keywords** Energy consumption · Environmental pollution · Financial technology (FinTech) · Cleaner technologies · Copula · Markov-switching · Contagion · Causality · Tail inference

Extended author information available on the last page of the article

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**Abbreviations**

| | |
|---|---|
| GHG | Greenhouse gases |
| ARCH–LM | Autoregressive Conditional Heteroskedasticity–Lagrange Multiplier |
| BDS | Brock, Dechert, and Scheinkman |
| $CO_2e$ | Carbon dioxide emissions |
| COP27 & COP28 | 27$^{Th}$ and 28th meetings of the Conference of the Parties (COP) to the UNFCCC |
| EC | Energy consumption |
| FinTech | Financial technology |
| GARCH | Generalized autoregressive conditional heteroskedasticity |
| IPCC | Intergovernmental Panel on Climate Change |
| KWh | Kilowatt-hour |
| MAE | Mean absolute error |
| MAPE | Mean absolute percentage error |
| MS | Markov-switching |
| MS-GARCH-Copula | Markov switching-GARCH-copula |
| PoW | Proof of work |
| RMSE | Root-mean-squared error |
| RSGCC | Regime-switching Granger copula causality |
| SDG, SDG7, SDG12 | Sustainable Development Goals, SDG No. 7, SDG No. 12 |
| STAR | Smooth transition autoregressive |
| TWh | Terawatt hour |
| UNFCCC | United Nations Framework Convention on Climate Change |

## Introduction

Global environmental challenges are intensifying as the incline in global temperature and unexpected weather alterations become more and more evident. As a foremost GHG, $CO_2e$ is considered to be central in triggering climate change. In a new report from IPCC in 2023, $CO_2e$ was noted to have reached the highest levels over a two million years period and the 1.1 °C increase in global surface temperature in the last decades is alarming the nations to adopt cleaner technologies and to commit green innovation (IPCC 2023).

Conversely, the available carbon budgets aligned with meeting the temperature target outlined in the Paris Agreement were dwindling rapidly. As a result, the recent COP28 agreement in December 2023 announced "the end of the era of fossil fuel" (UNFCCC 2023). The COP28 agreement puts forth the fundamental targets: (i) engaging in strategies to cap the global temperature increases at 1.5 degrees Celsius, (ii) to support communities vulnerable to climate change impacts, (iii) they are attaining net zero emissions by 2050, in addition to, (iv) urging governments to accelerate the shift from fossil fuels to renewable energy sources such wind and solar, (v) providing financial and technological assistance to nations to achieve the upcoming climate commitments (UNFCCC 2023).

FinTech, an interdisciplinary field merging finance and technology, is increasingly relevant to environmental and energy concerns. As it becomes integral to daily life, there's a pressing need for clean technology to reduce its ecological footprint. The expanding user base of FinTech amplifies energy demands and the necessity for cleaner energies. FinTech is characterized as technology-driven financial innovation, which has given rise to new business models, applications, processes, or products that hold the potential to significantly improve financial services (FSB 2023). Blockchain, cryptocurrencies, crowdfunding, and digital currency stand as the foundational pillars of FinTech tools. The FinTech industry is transforming various sectors, including online shopping, payment systems, insurance, cryptocurrency trading, and the credit market, particularly through the utilization of blockchain technology (Thakor 2020). Recent studies show that the founding pillars of FinTech are blockchain and cryptocurrencies, crowdfunding, and digital currencies, (Cai 2018; Muhammad et al. 2022). Almost all of the most popular FinTech means are generated through high levels of complex mathematical calculations done by computers that necessitate high levels of EC. Among these pillars, Bitcoin, the major cryptocurrency has a yearly EC predicted to be between 135 and 177 TWh due to PoW, the algorithm used in the cryptocurrency mining for Bitcoin (de Vries 2020) with complex calculations creating an EC equal to those from countries such as Thailand or Sweden (Kohli et al. 2023). Each cryptocurrency transaction as a FinTech demands 619 kWh of electricity, equal to the EC of an average US family for 21 days (Badea and Mungiu-Pupazan 2021). As the yearly EC for FinTech is more than many countries, the total energy needed for all FinTech leads to tremendous amounts. Further, the EC of total FinTech technologies is predicted to result in more carbon emissions than the annual carbon emission output of the Czech Republic and Qatar (Jiang et al. 2021). It can be accepted that FinTech is one of the many factors influencing the path that environmental pollution will follow.

It is of crucial importance to study the relationships between FinTech and energy in addition to their links to the environment. With this focus, this study centers on the FinTech markets by utilizing the FinTech stock market index. The FinTech stock index is designed to capture the performance of the FinTech companies in time and the inclines in the index are under the influence of firm performances and expectations for future firm performances. the fluctuations in the FinTech market also affect the energy markets. As the new technologies are fostered, energy demand will be positively affected, leading to upward shifts in energy prices. Further, the shifts in both energy and FinTech are expected to influence the environment through more $CO_2e$ due to the acceleration of EC in economies. However, it is natural to expect that the inclines or declines in FinTech would not have radical effects on normal to moderate levels measured with the quantiles of the data, but instead, the increases in FinTech and energy prices are expected to have influences at extreme levels, in the upper and lower directions. Such relations could be effectively captured with contagion models that focus on modeling the tail behavior between variables.

The data unavailability limit the empirical analyses in examining these complex dynamics. In this paper, we argue that the effects of FinTech development, coupled with the advancement of financial technologies, could influence the overall market capitalization and radical fluctuations of the stocks of FinTech companies and FinTech markets also affect the energy markets in various ways. Further, we argue that the extreme levels of FinTech markets lead to inclinations in the consumption of energy, which could only be sustainable as long as the incline in the EC would not lead to increased $CO_2e$.[1]

To overcome the data issues, we employ recent global FinTech market data that covers daily observations for over a decade in addition to EC and global $CO_2e$ to achieve a global perspective. The modeling of FinTech development-led extreme FinTech stock market fluctuations, in addition to oscillations in EC and $CO_2e$ is challenging due to its distributional characteristics of nonlinearity and heteroskedasticity, especially for the daily data employed in this study. The study employs two novel methods that help in measuring the tail behavior of FinTech development measured with FinTech stock market capitalization and size and their relations with EC and $CO_2e$. At the first stage, the MS-GARCH-copula approach (Bildirici et al. 2022), allows capturing nonlinearity and heteroskedasticity simultaneously in marginal distributions of each series, and afterward, their joint distributions are effectively modeled to measure tail dependence and contagion relations at the upper and lower tails, or extreme levels of data. The second stage in this paper consists of the RSGCC tests, which incorporate the above-mentioned characteristics of data to measure nonlinear causal links under heteroskedasticity at the lower and upper tails at distinct regimes. The method is a generalization of a novel causality analysis proposed by Kim et al. (2020) for Granger causality testing under GARCH-copula. in the RSGCC method, the copula-based Granger causality testing is generalized to regime switching to examine causality dynamics under Markov-switching and heteroskedasticity (Bildirici et al. 2022).

The paper contributes both theoretical and empirical aspects. For the former, the paper is the first to examine FinTech, EC, and $CO_2e$ in terms of volatility contagion and causality dynamics. For the empirical aspect, the paper utilizes two novel techniques to control the nonlinear and volatile characteristics of the data and to produce insights into the relations at the tails of data. Further, with this modeling strategy, the paper also aims to overcome the data unavailability issue for FinTech and to provide the basis for future studies. In the last section, the findings of the novel methods will also be compared with the linear approach to causality modeling to point out the effects of omitting the nonlinearity and its possible translation into inefficient policy recommendations.

This study comprises five sections. Sect. "Literature" encompasses the literature review. Sect. "Methodology" introduces the econometric methodology. Sect. "Empirical results" provides the data and findings. The final section encompasses policy recommendations and conclusions.

## Literature

The literature review will be conducted in three parts. The first focuses on the recent advancements in the literature in applying econometric models with a focus on daily data utilization for environmental implications of financial market fluctuations. Sharif et al. (2023) explore financial markets and their effects on environmental degradation and their findings underline the necessity of steps that should be taken towards greening of financial markets and towards achieving the environmental goals. A set of recent studies examine financial assets and ecological innovations. Among these, Sadiq et al. (2023) stress the need for greening of financial assets and the requirement of urgent eco-innovation. As a pillar of FinTech, Bitcoin has been central in terms of technology and innovation leading to EC and a high ecological footprint (de Vries et al. 2022). Bildirici et al. (2024) questioned the sustainability of metaverse by showing chaos, entropy, fractionality, and complexity in metaverse stock markets, EC from Bitcoin's cryptocurrency mining and CO2e and they exposed contagion spillover and causality from metaverse to EC and environmental pollution. Gharbi et al. (2023) showed spillovers and risk connectedness amid the FinTech industry and macroeconomic dynamics that also inclined in the Covid-19 period.

Greening of FinTech technologies becomes an emerging factor to contribute to the environment. However, to our knowledge, there is no research on FinTech particularly

[1] For sharp and prolonged periods of incline or decline trends in the FinTech market triggered by financial technology advancements, tail dependence and contagion relations are expected. The upper and lower tails, or the extremes of the data are tested for the existence of significant connections between FinTech, EC, and $CO_2e$ characterized as tail-dependence. Such relations could be effectively captured with novel contagion models in this study.

with a focus on the nexus between FinTech stock markets, EC, and $CO_2$e with emphasis on contagion and causality dynamics under nonlinearity and volatility. From a business perspective, the need for commitment to transforming FinTech companies into environmentally and socially responsible companies is highlighted (Carè et al. 2023). While FinTech markets are a relatively unexplored field in this respect, cryptocurrency markets are not due to their energy-hunger. Cryptocurrencies are considered among the three pillars of FinTech. They are criticized for their energy use and environmental effects, especially for those that adopt energy-hungry mining technologies such as the major cryptocurrency, Bitcoin. Bitcoin is predicted to demand yearly energy reaching those from countries, leading to a significant carbon footprint (de Vries et al. 2022). The technology behind plays a crucial role. The PoW algorithm and the Bitcoin transactions require high amounts of EC occurring due to complex calculations, and their yearly EC reaches the EC of countries such as Thailand (Kohli et al. 2023). In another study, each cryptocurrency transaction is predicted to demand 619 kWh of electricity, equal to the 3-week EC of a typical household in the USA (Badea and Mungiu-Pupazan 2021).

The EC of FinTech is also predicted to result in significant levels of annual carbon emissions (Jiang et al. 2021). These findings put FinTech at the center of research and FinTech should be considered to influence the path that environmental pollution will follow in the future. In addition to the challenges to achieve greener financial technology coupled with green energy and energy efficiency, the energy transition commitment of nations and relevant policies appear as a second factor in shaping the carbon footprint of FinTech and its environmental impact.

As a second strand of literature, the cryptocurrency markets have been examined for their energy demand and environmental friendliness and as noted in Sect. "Introduction", cryptocurrencies are among the main pillars of FinTech. The examination is given in Table 1. The connection between Bitcoin and environmental damage has been strengthened by certain research. O'Dwyert and Malone (2014) proposed a method to calculate the energy footprint of Bitcoin mining for the Bitcoin network in Ireland. Their estimated results emphasize that EC measured with the electricity demand of Bitcoin mining is unexpectedly high, on par with that of Ireland (O'Dwyert and Malone 2014). More recently, Wimbush (2018) showed that cryptocurrency mining and its technology could create more value than its costs; however, it has been uneconomic so far due to high level of energy and environmental costs, while Kamran et al. (2022) showed that Bitcoin as a FinTech could be used as a safe-haven with certain limits, in addition to its function to diversify the investment portfolios.

A third strand of literature focuses on FinTech technologies, their innovation, and their effects on the environment. However, the focus is so far limited due to the availability of data. Further, the overlook suggests two different points, negative or positive, for the effects of FinTech on the energy and environment. Further, the studies are generally restricted to yearly datasets or questionnaire-based secondary data without time dimensions. Croutzet and Dabbous (2021) question whether FinTech encourages renewable energy in the total energy mix of 21 OECD countries with a balanced panel covering 2005–2018 and they conclude that the benefits of financial technology advancements in promoting renewable energy in the overall energy mix. Muganyi et al. (2022) examined how commerce, industrialization, green finance, and the FinTech sector affect pollution in the environment. Their empirical findings underscore the vital role of the FinTech industry and green finance in enhancing environmental quality and curbing pollution (Muganyi et al. 2022). Zhou et al. (2020) looked into how environmental pollution in China is affected by green funding. Elheddad et al. (2021) examined data from 29 selected OECD countries and demonstrated that electronic finance technologies contribute to a reduction in carbon emissions. Muhammad et al. (2022) investigated how 23 EU nations' environmental efficiency was affected by the FinTech sector.

The overall investigation of the literature above suggests excessive ecological effects of cryptocurrencies as a pillar to FinTech and also to financial technologies through their effects on the EC to the environment. An overlook of policy recommendations is the need to focus on the greening of financial technologies and relevant innovation for environmental sustainability targets.

## Methodology

### MS-GARCH processes for marginal distributions

In an MS-GARCH model, a time series $r_t$ follows the following dynamics (Haas 2004),

$$r_t = \theta_{0,(st)} + \sum_{i=1}^{f} \theta_{i,(st)} r_{t-i,(st)} + \sum_{n=1}^{m} \lambda_{n,(st)} \varepsilon_{t-n,(st)} + \varepsilon_{t,(st)} \tag{1}$$

$$\sigma^2_{t,(st)} = \alpha_{0,(st)} + \sum_{n=1}^{q} \alpha_{i,(st)} \sigma_{t-n,(st)} + \sum_{n=1}^{p} \beta_{i,(st)} \varepsilon^2_{t-n,(st)} \tag{2}$$

here, Eq. (1) assumes that $r_t$ is a time series, which follows Markov-switching in its conditional mean with regime-dependent ARMA processes combined with Eq. (2), a regime-dependent conditional variance process (Bildirici and Ersin 2014). The model given in Eqs. (1) and (2)

**Table 1** Empirical literature review on cryptocurrencies as a pillar of FinTech

| Study | Year | Consensus algorithm | Cryptocurrency | Highlights |
|---|---|---|---|---|
| Sedlmeir et al (2020) | 2020 | PoW | Bitcoin | EC due to increased competition in mining |
| Sedlmeir et al. (2020) | 2020 | PoW, non-PoW | Bitcoin, ethereum, litecoin, bitcoin cash and SV | EC in line with the number of transactions, the possibility of environmental effects |
| de Vries (2020) | 2020 | PoW | Bitcoin | Underestimated high EC of bitcoin |
| de Vries et al. (2022) | 2022 | PoW, PoS | Bitcoin, ethereum | Bitcoin's carbon footprint (CF) decomposed into different energy sources. The declining share of renewable EC contributes to the CF of bitcoin. PoW produces 2/3 of the total EC in all cryptocurrencies |
| Gallersdörfer et al. (2020) | 2020 | PoW, PoS | Top 20 coins including bitcoin, ethereum, litecoin, monero, dash | Even excluding Bitcoin, EC of cryptocurrencies results in enormous amounts of EC and environmental damages |
| Li et al. (2019) | 2019 | PoW, PoS | Monero and the other 8 currencies, monero is central | Role of hashing algorithm on energy efficiency. Environmental and EC impacts. Effects on sustainable economic development should be further studied |
| Sarkodie et al. (2022) | 2022 | PoW | Effects bitcoin trade volume | Estimates and puts forth long-run effects of bitcoin trade volume on EC and CF |
| (Stoll et al. 2019) | 2019 | PoW | Bitcoin | PoW-based bitcoin generates a significant ecological footprint |
| Qin et al. (2020) | | PoW | Bitcoin | Long-term CF of bitcoin predictions, inclining trend, to 400 from 60 TWh, from 2020 to 2100. CF is dependent on the path of the electricity sector in the future |
| Snytnikov and Potemkin (2022) | 2022 | PoW | Cryptocurrencies (general) | On oil extraction site mining of cryptocurrencies + flare gas + greener hydrogen production and carbon capture to reduce EC and $CO_2$ emission impacts |
| Kabaklarlı (2022) | 2022 | PoW, PoS | Bitcoin | Greening of bitcoin is necessary to achieve sustainability in FinTech |
| Wang et al. (2022) | 2022 | PoW | Bitcoin | An index, of cryptocurrency environmental attention, is developed. Implications on the economy and financial markets of environmental attention are evaluated |
| Wendl et al. (2023) | 2023 | PoW, PoS | Mainly bitcoin | After a systematic literature review, the study emphasizes environmental impacts |

assumes ARMA terms in addition to the intercept (I) and the heteroskedasticity (H) to be governed with MS, therefore, the model above is annotated as an (MSIARMAH-GARCH) model. To ensure positivity of the variance process, the parameters $\phi,\ \alpha,\ \kappa,\ \beta > 0$ are restricted for non-negativity. Similarly, if no moving average terms are included, model reduces to a MSIARH-GARCH. A more tractable model is the MSIH-GARCH, in which the dynamics that $r_t$ follows assumes no autoregressive nor moving average terms in the mean. The MSIH-GARCH model,

$$r_t = \theta_{0,(st)} + \varepsilon_{t,(st)} \tag{3}$$

$$\sigma^2_{t,(st)} = \alpha_{0,(st)} + \sum_{n=1}^{q} \alpha_{i,(st)}\sigma_{t-n,(st)} + \sum_{n=1}^{p} \beta_{i,(st)}\varepsilon^2_{t-n,(st)} \tag{4}$$

Further, in case of insignificance of the intercept terms, the model reduces to a MS-GARCH process,

$$r_t = \varepsilon_{t,(st)} \tag{5}$$

$$\sigma^2_{t,(st)} = \alpha_{0,(st)} + \sum_{n=1}^{q} \alpha_{i,(st)}\sigma_{t-n,(st)} + \sum_{n=1}^{p} \beta_{i,(st)}\varepsilon^2_{t-n,(st)} \tag{6}$$

In all variants of the MS-GARCH models above, we assume that the switching standard error mechanism is conditional on the past,

$$\sigma_{t-i-1,(st-i)} = E\left(\varepsilon_{t-i-1,(st-i-1)}|s_{t-i}, r_{t-i-1}\right) \tag{7}$$

where $s_t$ is a Markovian process governing the switches among the regimes,

$$\pi_{nt} = \Pr\left[s_t = j|r_{t-1}\right] = \sum\nolimits_{i=0}^{1} \Pr\left[s_t = j|s_{t-1} = i\right] \Pr\left[s_t = j|r_{t-1}\right] \sum\nolimits_{i=0}^{1} \psi_{ni}\pi^*_{it-1} \tag{8}$$

with Log-likelihood (L) defined as,

$$\mathrm{L} = \prod_{t=1}^{T} f\left(r_t|s_{t=i}, r_{t-1}\right) \Pr\left[s_{t=i}|r_{t-1}\right]. \tag{9}$$

There are different approaches to define $\sigma_{t,(st)}$. and $\varepsilon^2_{t-1,(st)}$ and the necessary stability conditions (Francq and Zakoïan 2001; Henneke et al. 2009) and the model in this paper assumes Francq and Zakoian's approach similar to a set of studies (Bildirici et al. 2022; Bildirici and Sonustun 2021).

## MS-GARCH-Copula for joint distributions

The joint distribution is measured with Clayton, Student's $t$, and Gumble copula functions. Following Sklar's extended theorem, the method assumes time-varying copulae, which leads to time-variation in the dependence structures (Bildirici et al. 2022). The following function defines copula as,

$$C_\tau(u_1, u_2|\theta, v) = \int_{-\infty}^{\tau_u-1(u_1)} \int_{-\infty}^{\tau_u-1(u_2)} \frac{1}{2\pi\sqrt{(1-\theta^2)}} \exp\left(1 + \frac{s^2 - 2\theta st + t^2}{v(1-\theta^2)}\right)^{-\frac{-v+2}{2}} \mathrm{dsdt} \tag{10}$$

named as a Student's $t$ copula, which assumes symmetric tails,

$$\lambda_{\mathrm{LT}} = \lambda_{\mathrm{UT}} = -2\tau_{v+1}\left(\sqrt{v+1}\frac{\sqrt{1-\theta}}{\sqrt{1+\theta}}\right) > 0 \tag{11}$$

where $\lambda_{\mathrm{LT}}$ and $\lambda_{\mathrm{UT}}$ are lower and upper tail copulae. Asymmetric copula functions are suggested. For the following copula function,

$$C\left(\hat{u}_{1t,}\hat{u}_{2t}|\theta\right) = \exp\left(-\left[(-\ln(u_1))^\theta + (-\ln(u_2))^\theta\right]^{\frac{1}{\theta}}\right) \tag{12}$$

Gumble copula is accomplished by,

$$\lambda_{\mathrm{U}} = 2 - 2^{-\frac{1}{\theta}}, \lambda_L = 0 \tag{13}$$

where the power coefficient $\theta \in ]1, +\infty[$.

The Clayton copula is given as,

$$C(u_1, u_2|\theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}} \text{ and } \theta \in ]0, +\infty[\ \lambda_U = 0 \tag{14}$$

here, $\lambda_{\mathrm{U}} = 0$, $\lambda_{\mathrm{L}} = 2^{-\theta^{-1}}$ are the upper and lower tail copula parameters. The estimation necessitates the maximization of the log-likelihood (LL),

$$\mathrm{LL} = \sum_{t=1}^{T} \ln\left[\sum_{j=1}^{n}\left(\hat{u}_{1t,}\hat{u}_{2t}|s_{t=j}, \Upsilon_{t-1},\right) \Pr\left(s_{t=j}|\Upsilon_{t-1}\right)\right] \tag{15}$$

where the regime-switching probabilities are conditional on $\Upsilon_{t-1}$, noted as $\mathrm{P}(s_t = j|\Upsilon_{t-1})$ and $\mathrm{P}\left(s_{t=j}|\Upsilon_t\right)$, the information set available at the period $t$-1 and $t$. By utilizing Kim's filter (Kim 1994), the conditional probability is,

$$\mathrm{P}(s_t = j|\Upsilon_{t-1}) = \sum_{i=1}^{n} \mathrm{P}_{ij}^{t-1} \Pr(s_t = i|\Upsilon_{t-1}) \tag{16}$$

for the former. For the latter,

$$\mathrm{P}\left(s_{t=j}|\Upsilon_t\right) = \frac{C\left(\hat{u}_{1t,}\hat{u}_{2t}|s_{t=j}, \Upsilon_{t-1}\right)\mathrm{P}\left(s_{t=j}|\Upsilon_{t-1}\right)}{\sum_{j=1}^{n} C\left(\hat{u}_{1t,}\hat{u}_{2t}|s_{t=j}, \Upsilon_{t-1}\right)\mathrm{P}\left(s_{t=j}|\Upsilon_{t-1}\right)} \tag{17}$$

Transition followed by smoothed transition probabilities are,

$$\mathrm{P}_{ij} = \mathrm{P}\left(s_{t=j}|s_{t-1=\mathrm{i}}, \Upsilon_{t-1}\right)\mathrm{and}\mathrm{P}\left(s_{t=j}|\Upsilon_t\right) = \mathrm{P}\left(s_{t=j}|\Upsilon_t\right)\sum_{i=1}^{n}\frac{\mathrm{P}_{ij}\,\mathrm{P}\left(s_{t+1=i}|\Upsilon_t\right)}{\Pr\left(s_{t+1=i}|\Upsilon_t\right)} \tag{18}$$

further, the dependence parameter follows a time-varying structure completed by,

$$\hat{\Upsilon}_t = \underset{\Upsilon}{\operatorname{argmax}} \sum_{t=1}^{T} \ln(C(\hat{u}_{1t}, \hat{u}_{2t}; \Upsilon_t)) \tag{19}$$

### Granger causality (GC) testing with MS-GARCH-Copula

Kim et al. (2020) proposed a method to test GCs with the copula-based methods. The method generalizes GC (Granger 1969) to copulae. Relevant literature on the effectiveness of copulae in causality modeling exists (Nalatore et al. 2014; Zhu et al. 2016). The method is generalized to nonlinear and high-order causality modeling (Bildirici et al. 2022).

Let $A = a_t$, $B = b_t$, $A \nrightarrow B$ stating no-causality from $A$ to $B$; $A \mapsto B$ denotes a causal link from $A$ to $B$ and the null hypothesis of no GC from $A$ to $B$ is in fact an equality of explanatory power of two functions,

$$f\left(b_{t+1}|b_t^n a_t^m\right) = f\left(b_{t+1}|b_t^n\right) \tag{20}$$

$b_t^n = \left(b_t, \dots, b_{t-n+1}\right)$ and $a_t^m = \left(a_t, \dots, a_{t-m+1}\right)$ are the available information for $B$ and $A$, $n$ and $m$ are orders, $f$ defines conditional probability for density function. $f\left(b_{t+1}|b_t^n a_t^m\right)$ shows prediction of $B$ at the next period $t+1$, with available information from previous period $t$. The right-hand-side function, $f\left(b_{t+1}|b_t^n\right)$, excludes $A$ at $t+1$ in modeling and predicting $B$ and utilizes $B$ at $t$ only for this purpose. $H_0$: $A \nrightarrow B$ tests no GC against $H_1$: $A \mapsto B$ and the likelihood ratio test statistic is calculated as,

$$GC_{A \to B} = E\left[\log \frac{f\left(b_{t+1}|b_t^n, a_t^m\right)}{f\left(b_{t+1}|b_t^n\right)}\right] \tag{21}$$

Copulae at high dimensions could be recursively reduced toward low dimensions. The resulting representation ease implementation in addition to efficiency. GC representation becomes,

$$GC_{A \to B} = E\left[\log \frac{f\left(b_{t+1}|b_t^n, a_t^m\right)}{f\left(b_{t+1}|b_t^n\right)}\right] = E\left[\log \frac{h\left(b_{t+1}, a_t^m|b_t^n\right)}{f\left(b_{t+1}|b_t^n\right) \times \mathrm{g}(\mathrm{a}_t^m|\mathrm{b}_t^n)}\right] \tag{22}$$

where marginal density of $A$ and $B$ are given with $g$ and $f$, conditional joint density of $(A, B)$ with $h$. The conditional joint density becomes,

$$h\left(b_{t+1}, a_t^m|b_t^n\right) = f\left(b_{t+1}|b_t^n\right) \times g\left(a_t^m|b_t^n\right) \times c(u, v|b_t^n) \tag{23}$$

here $u = F(b_{t+1}|b_t^n)$ is the conditional marginal distribution of B, $v = G(a_t^m|b_t^n)$ is for $A$, and $c$ is the copula density function. After substitution of Eqs. 20 and 21, copula-based $GC$ causality from $A$ to $B$ ($CGC_{A\to B}$) is calculated as,

$$CGC_{A \to B} = E\left[\log c\left(F\left(b_{t+1}|b_t^n\right), G\left(a_t^m|b_t^n\right)|b_t^n\right)\right] \tag{24}$$

The approach allows testing GC under regime dependence with copulae. In cases that deviate from Gaussian distributions, copula-based GC leads to better properties without assuming normality (Lee & Yang 2014). The MS-GARCH-copula-causality method above provides regime-dependent testing of GC under different tails and regimes (Bildirici et al. 2022).

## Empirical results

### Data

The dataset in this study consists of three variables for FinTech, EC, and $CO_2$e variables and our daily sample covers 02 Jan. 2012–28 December 2022. The data source for the FinTech and EC is the Refinitiv Eikon database. For the FinTech, the STOXX Global FinTech index is selected due to being the longest dataset available with the largest coverage. The index includes companies leveraging FinTech to revolutionize how financial services reach consumers and enhance the competitiveness of traditional providers. With ongoing FinTech development and increased support from governments and regulators, these companies are well-placed to capitalize on the persistent FinTech trend, potentially significantly impacting their future revenues. The FinTech index in the analysis is denoted as FIN. To achieve daily EC data, we utilized daily EC in TWh, which is annotated as EC, and the data are obtained from Datastream. Atmospheric $CO_2$e is obtained from the $CO_2$ Earth Database, and these data measure $CO_2$e in ppm and are considered as a measure of $CO_2$e concentrations in the global atmosphere. Throughout the analysis, the $CO_2$e concentration series is annotated as $CO_2$e.

Basic statistics for the distributional properties of the dataset are represented in Table 2. Series in levels are subject to natural logarithms to remove the effects of units and to reduce factors such as excess skewness. The dataset is further first-differenced. Due to logarithm rules, after first differencing, differenced series represent daily percentage changes. The first-differencing is a result of the unit roots in the series in levels as will be seen in Table 3 and is conducted to attain stationarity of data.

In Table 2, variables, especially those in first differences, are subject to excess kurtosis, combined with skewness, signs of heavy-tailed and leptokurtic distributions for FIN

**Table 2** Descriptive statistics

| | Level | | | First-differenced (Δ) | | |
|---|---|---|---|---|---|---|
| | EC | $CO_2e$ | FIN | ΔEC | $\Delta CO_2e$ | ΔFIN |
| Mean | 5.888523 | 6.008042 | 5.672512 | 0.000109 | 1.66E − 05 | 0.000557 |
| Median | 5.739596 | 6.008887 | 5.632196 | 0.000304 | 2.52E − 05 | 0.000702 |
| Max | 6.761613 | 6.041468 | 6.520695 | 0.107252 | 0.000202 | 0.110671 |
| Min | 5.458577 | 5.972791 | 4.591274 | − 0.146014 | − 0.00024 | − 0.13898 |
| SD | 0.382271 | 0.018371 | 0.549881 | 0.015812 | 0.000104 | 0.012453 |
| Skew | 0.260471 | − 0.04784 | − 0.25133 | − 0.474832 | − 0.66634 | − 0.59147 |
| Kur | 3.442038 | 1.867187 | 1.923908 | 54.92025 | 2.709892 | 15.03791 |
| JB | 60.86548 | 201.2941 | 161.2831 | 24,269.53 | 289.6509 | 16,722.07 |

JB is the Jarque–Bera test of normality Chi-square test statistic and the critical value is 5.99 for large samples at 5% significance level and JB test results indicate non-normality of all series. SD is standard deviation, Skew. is skewness, Kur. is kurtosis test statistics

**Table 3** Tests for unit roots and homoskedasticity

| | Variables in levels | | | Variables in first-differences | | |
|---|---|---|---|---|---|---|
| Tests | EC | $CO_2e$ | FIN | ΔEC | $\Delta CO_2e$ | ΔFIN |
| ADF | − 3.060 | − 0.492 | 1.946 | − 15.233** | − 14.733** | 17.080** |
| KSS | − 3.182 | 1.459 | − 2.031 | − 24.803** | − 8.989** | − 7.815** |
| Results | Level series are I (1) processes, i.e., stationary after first differencing | | | | | |
| ARCH–LM (1) | 3993.6** | 973.9** | 2737.8** | 189.6** | 312.4** | 368.6** |
| ARCH–LM (1–5) | 3990.4** | 1694.9** | 2733.9** | 189.9** | 821.14** | 686.2** |
| White Test (ct) | 1407.7** | 3736.0** | 92.6** | 1324.6** | 1159.6** | 501.8** |
| White Test (noct) | 453.21** | 3598.6** | 88.5** | 458.8** | 3733.4** | 471.3** |
| Results | ARCH effects and Heteroskedasticity of nonlinear forms in all series | | | | | |

ARCH–LM(p) is the ARCH–LM test at order p. For the White test, *ct* and *noct* are the White test with and without cross-terms. ADF test critical values are − 3.41 and − 3.96 (McKinnon, 1996, Case 3), KSS test critical values are -3.40 at 5%, − 3.93 at 1% significance levels (Kapetanios et al. 2003, Table 1, Case 3). * and ** indicate 5% and 1% levels of significance

and EC, and $CO_2e$ series. These also translate into JB tests, which indicate non-normality for all series.

Table 3 displays the outcomes of unit root tests and two tests were conducted: the conventional linear augmented Dickey–Fuller (ADF) test and the KSS nonlinear unit root test (Kapetanios et al. 2003). Unlike ADF, KSS is a unit root test under nonlinearity since it tests the unit root against a smooth transition autoregressive (STAR) alternative. Both linear and nonlinear test results indicate I (1) processes for all level series and in the next section, analyses are maintained with the first differenced variables.

The second part of Table 3 also reports ARCH–LM and White homoskedasticity tests. The former test points at ARCH-type heteroskedasticity and the latter confirms heteroskedasticity with nonlinear forms. Both tests point to the requirement of modeling FIN, EC, and $CO_2e$ series with models considering heteroskedasticity.

Further, we tested these series with BDS nonlinearity tests in Table 4, which indicate dependence and nonlinearity. Overall results are given in Tables 3 and 4 lead to the modeling of FIN, EC, and $CO_2e$ with models that utilize nonlinear and heteroskedastic characteristics of the dataset, and the results provide the basis for modeling with MS-GARCH-copula modeling.

## Model estimation results

The models in this section benefit from regime-switching copula for contagion and tail dependence followed by regime-switching GARCH-copula-based GC tests. In the first stage, the model estimations are presented and the results are given in Table 5, consisting of two sections, parameter estimates for the models with regime transition results followed by regime-dependent copula parameter estimates for tail-dependence and contagion modelling. Diagnostic tests are given in the last column.

For all marginal distributions modeled with MS-GARCH processes, parameter estimates of ARCH and GARCH terms provide information on volatility dynamics. Further, each model distinguishes between regime-specific

**Table 4** BDS test

| Dimension | Level series | | | First-differenced series | | |
|---|---|---|---|---|---|---|
| | EC | $CO_2e$ | FIN | ΔEC | $\Delta CO_2e$ | ΔFIN |
| 2 | 678.256 | 230.3748 | 248.2414 | 53.486 | 145.9526 | 13.20918 |
| 3 | 658.173 | 247.8116 | 267.6503 | 49.724 | 160.0889 | 16.82364 |
| 4 | 637.239 | 269.6958 | 291.7511 | 46.366 | 175.3275 | 19.32517 |
| 5 | 616.182 | 301.0875 | 326.1589 | 43.967 | 195.8336 | 21.14344 |
| 6 | 596.437 | 343.8434 | 372.9576 | 42.292 | 223.0756 | 23.12266 |

parameters, confirming asymmetry. Overall, the parameter estimates for FIN, EC, and $CO_2e$ are statistically significant in both regimes at 5% significance level. The stability condition entails ARCH + GARCH < 1, which is achieved for each regime of each model. However, the sum is close to 1. Accordingly, external shocks will have long-lasting effects on each series in each regime. Lastly, the remaining ARCH-type heteroskedasticity tests confirm the capability of all models in capturing the volatility dynamics, since no remaining ARCH effects are present in the residuals. The RMSE, MAE, MAPE, and LogL statistics confirm the effectiveness of the models estimated in terms of goodness of fit and one-step-ahead predictions.

The transition probability, $P(s_t|s_{t-1})$, denotes the probability of the regime at *t* conditional on the regime at *t*-1. As a typical, P(1|1) indicates the probability of regime 1 at period *t* conditional on the previous state being also regime 1. P(1|1) and P(2|2) provide vital information for regime persistence. Considering relatively lower standard error estimates in regime 1 relative to regime 2, regimes 1 and 2 are low and high volatility regimes, respectively. For $CO_2e$, EC, and FIN, regime-switching probability estimates are $p(1|1) < p(2|2)$, suggesting relatively higher persistence and duration in the second regimes characterized by high volatility. However, all regimes are long-lasting since $p(1|1) > 0.7$. Therefore, first regimes are also persistent. For $CO_2e$, the average duration is 11.1 days (8.3 days) in regimes 1 and 2. For FIN, for the high and low variance regimes, the duration is 16.67 days and 3.7 days. For EC, the duration of the two regimes is close to those obtained for FIN. Hence, results clearly show distinct characteristics of each regime in terms of persistence and regime duration.

In the final part of Table 5, estimation results for copula parameters are reported. The copula results are significant tools for determining the co-movements between the variables. The copula parameters are significant at 5% and 1% levels of significance. The positivity and the size of copula

**Table 5** MS-GARCH-copula model results

| Parameter estimates for marginal distributions | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent | $\Delta CO_2e$ | | | | ΔEC | | | | ΔFIN | | | |
| Regimes | 1 | | 2 | | 1 | | 2 | | 1 | | 2 | |
| ARCH | 0.103*** | (−4.61) | 0.011*** | (−5.4) | 0.143*** | (−2.81) | 0.171** | (−2.32) | 0.130** | (−2.45) | 0. 081** | (−2.33) |
| GARCH | 0.770*** | (−3.4) | 0.824* | (−1.89) | 0.833*** | (−2.72) | 0.811*** | (−2.09) | 0.711*** | (−2.66) | 0.869* | (−1.93) |
| constant | 0.148** | (−2.49) | 0.231** | (−1.96) | 0.669** | (−2.55) | 0.229*** | (−2.46) | 0.0008* | (−1.86) | 0.0095** | (−2.118) |
| P(1\|1) | 0.88*** | | 0.91*** | | 0.73*** | | | | | | | |
| P(2\|2) | 0.91*** | | 0.92*** | | 0.94*** | | | | | | | |
| *Model fit and diagnostics* | | | | | | | | | | | | |
| LogL | 2480.11 | | | | 16,654 | | | | 2287.44 | | | |
| RMSE | 0.938 | | | | 1.087 | | | | 0.700 | | | |
| MAE | 0.782 | | | | 0.909 | | | | 0.4932 | | | |
| MAPE | 29.98 | | | | 48.11 | | | | 15.38 | | | |
| ARCH–LM | 0.03 [0.89] | | | | 0.03 [0.88] | | | | 0.11 [0.69] | | | |
| *Copula parameter estimates for joint distributions* | | | | | | | | | | | | |
| Regime 1 | | | | | Regime 2 | | | | | | | |
| $\Delta CO_2e$ and ΔEC | | | 0.91*** | | $\Delta CO_2e$ and ΔEC | | | | 0.86*** | | | |
| $\Delta CO_2e$ and ΔFIN | | | 0.85*** | | $\Delta CO_2e$ and ΔFIN | | | | 0.88*** | | | |
| ΔEC and ΔFIN | | | 0.81*** | | ΔEC and ΔFIN | | | | 0.93*** | | | |

*t* statistics in (). ***, **, * signify significance at 1%, 5%, and 10%. ARCH–LM is the ARCH LM test statistic at orders 1–5, p-value in [].

**Table 6** MS-GARCH-copula-causality test results

| Regimes | 1 | | 2 | |
|---|---|---|---|---|
| GC tested | $t$ | Outcome | $t$ | Result |
| $\Delta CO_2e \rightarrow \Delta EC$ $EC \rightarrow \Delta CO_2e$ | 1.38<br>4.73*** | $\Delta EC \rightarrow \Delta CO_2e$ Unidirectional | 0.98<br>5.46*** | $\Delta EC \rightarrow \Delta CO_2e$ Unidirectional |
| $\Delta FIN \rightarrow \Delta CO_2e$ $\Delta CO_2e \rightarrow \Delta FIN$ | 4.84***<br>1.072 | $\Delta FIN \rightarrow \Delta CO_2e$ Unidirectional | 4.17***<br>0.93 | $\Delta FIN \rightarrow \Delta CO_2e$ Unidirectional |
| $\Delta EC \rightarrow \Delta FIN$ $\Delta FIN \rightarrow \Delta EC$ | 3.36***<br>2.95*** | $\Delta EC \rightarrow \Delta FIN$ and $\Delta FIN \rightarrow \Delta EC$ Bidirectional | 3.76***<br>2.88*** | $\Delta EC \rightarrow \Delta FIN$ and $\Delta FIN \rightarrow \Delta EC$ Bidirectional |

*** indicate 1% level of statistical significance

**Table 7** Single regime GARCH-copula-causality test results

| GC tested: | Regime | $t$ | Outcome |
|---|---|---|---|
| $\Delta CO_2e \rightarrow \Delta EC$ | Single | 2.980*** | $\Delta CO_2e \rightarrow \Delta EC$ and $\Delta EC \rightarrow \Delta CO_2e$ Bidirectional |
| $\Delta EC \rightarrow \Delta CO_2e$ | Single | 10.731*** | |
| $\Delta CO_2e \rightarrow \Delta FIN$ | Single | 110.9114*** | $\Delta CO_2e \rightarrow \Delta FIN$ and $\Delta FIN \rightarrow \Delta CO_2e$ Bidirectional |
| $\Delta FIN \rightarrow \Delta CO_2e$ | Single | 12.7665*** | |
| $\Delta FIN \rightarrow \Delta EC$ | Single | 3.021*** | $\Delta FIN \rightarrow \Delta EC$ and $\Delta EC \rightarrow \Delta FIN$ Bidirectional |
| $\Delta EC \rightarrow \Delta FIN$ | Single | 4.176*** | |

**Table 8** Comparison of causality results

| | MS-GARCH copula causality | | GARCH copula causality | Are results different? |
|---|---|---|---|---|
| Regime | 1 | 2 | – | |
| Direction of causality | | | | |
| $\Delta CO_2e \rightarrow \Delta EC$<br>$\Delta EC \rightarrow \Delta CO_2e$ | Unidirectional $\Delta EC \rightarrow \Delta CO_2e$ | Unidirectional $\Delta EC \rightarrow \Delta CO_2e$ | Bidirectional | Different |
| $\Delta CO_2e \rightarrow \Delta FIN$<br>$\Delta FIN \rightarrow \Delta CO_2e$ | Unidirectional $\Delta FIN \rightarrow \Delta CO_2e$ | Unidirectional $\Delta FIN \rightarrow \Delta CO_2e$ | Bidirectional | Different |
| $\Delta FIN \rightarrow \Delta EC$<br>$\Delta EC \rightarrow \Delta FIN$ | Bidirectional: $\Delta FIN \rightarrow \Delta EC$ and $\Delta EC \rightarrow \Delta FIN$ | Bidirectional: $\Delta FIN \rightarrow \Delta EC$ and $\Delta EC \rightarrow \Delta FIN$ | Bidirectional | Same |

estimates confirm strong and positive tail dependence among the series analyzed in each regime with varying magnitudes, confirming contagion in all cases. Accordingly, findings approve strong and positive tail dependence between EC and $CO_2e$ in each regime, while the size of tail dependence varies between regimes. The results point at contagion between EC and FIN and between $CO_2e$ and FIN and EC and $CO_2e$ in all regimes and highlight asymmetric and regime-dependent contagion dynamics.

## Nonlinear causality results

Following the estimation of the marginal distributions of the series with MS-GARCH-copula, regime-switching GC tests are performed. The results are given in Table 6.

GC test method allows evaluation of regime-dependent GC relations and their directions. Application of causality tests is necessary to determine the direction of causality, which provides vital information for policy applications. Further, results are compared with the linear counterpart approach. In the first row, the results signify evidence of unidirectional causality from EC to $CO_2e$ in both regimes. The causal links between FIN and $CO_2e$ are unidirectional, from FIN to $CO_2e$ in both regimes. Therefore, indistinct from the type of regime, unidirectional causality cannot be rejected from FIN to emissions. Regime-specific causality test results between EC and FIN are in the last section. The findings indicate causality from FIN to EC and also from EC to FIN at conventional significance levels. As a result, bidirectional causality amid two series cannot be rejected.

For comparative purposes, Table 7 reports the GARCH-copula-causality test results. In contrast to the results in Table 6, GARCH-Copula-Causality results omit regime switching type nonlinearity, and given the nonlinear structure in the series and their volatility, these single-regime results are produced to point to possible deviations due to omitting such factors. Under this deficiency, the overall look results in a tendency to accept bidirectional causality amid the series at conventional significance levels for all tested pairs of variables.

Table 8 summarizes the GC test results and possible deviations under two different approaches. While the MS-GARCH-copula-causality results point to the univariate direction of causality in two out of three tests, the single-regime causality results indicate bidirectional causal links in all three. Given the nonlinearity of data, omitting nonlinear regime-switching dynamics would likely affect the causality test results. Under such conditions, MS-GARCH-copula-causality results provide more efficient findings for the connections among FinTech markets, EC, and $CO_2$e.

## Discussion

The findings provide vital information for policymakers in terms of the association of FinTech, EC, and $CO_2$e. According to our results, the tail dependence between EC, FinTech, and $CO_2$e was determined to be strong and positive for both low-volatility and high-volatility regimes. The results exhibited deviations from the findings that ignore nonlinearity in the conditional variance processes of the series analyzed. Considering the BDS and ARCH–LM tests, nonlinearity and volatility cannot be rejected for the EC, FinTech, and $CO_2$e series. MS-GARCH-Copula and RSGCC methods allowed regime-specific modeling and testing of the co-movements and causality under different regimes governing Markov-switching type nonlinearity. Though this was the case, the GARCH-copula-causality results given above omitted the regime-switching type nonlinearity, which led to evidence of deviations in the results. The results from this single regime variant could be characterized as over-acceptance of causality due to bidirectional causalities this method determines in all cases. Considering the nonlinear structure in the series and their volatility, the relationship between FinTech and $CO_2$e is unidirectional in both regimes from FinTech to $CO_2$e confirming that FinTech influences $CO_2$e under all scenarios, i.e., low or high volatility regimes. The research also suggests causality from FinTech to EC and from EC to FinTech at statistically significant levels, in a bidirectional setting, which is also known as the feedback effect—the EC and FIN causality relations tend to lead to self-fulfilling cycles.

Market dynamics and transaction processes in FinTech also have significant negative effects on environmental sustainability. The coefficient estimates of copulae specify that FinTech is associated positively with $CO_2$e, and the opposite is not true. Combined with the unidirectional causality links under distinct regimes, the results designate no feedback effects between FinTech and $CO_2$e. Regarding the discussion above, the technology behind FinTech and the serious electricity-use and irreversible waste of e-waste problems require attention on mining and transaction policies.

Then again, the financial technologies and FinTech development relate to two of the central SDG goals, SDG12 and SDG7, in addition to being related to COP27 and COP28. For SDG, the first is, SDG12, which concentrates on clean technology and green innovation, and SDG7, a goal specifically focusing on clean energy technology and investments towards green energies to achieve the mitigation of $CO_2$e. During COP27, stakeholders stressed the pressing need to pursue a low-carbon economy, which is estimated to necessitate an annual investment of nearly \$6 trillion (UNFCCC 2022). COP28 served as a platform where global consensus is sought to tackle the climate crisis, aiming to cap the global temperature rise at 1.5 degrees Celsius, support vulnerable communities in adapting to climate change impacts, and attain net-zero emissions by 2050.

With a primary focus on increasing the proportion of renewable energy, some countries are adopting supportive policies to encourage innovation. For instance, the United States allocates an annual investment of \$1.3 trillion in the green economy, resulting in the creation of 9.5 million full-time jobs (Georgeson and Maslin 2019). In 2020, the European Union set a determined target of achieving carbon neutrality by 2050 with the "Green Deal" policy initiative and progress has been achieved over the last years. China, the top polluter of CO2e compared to the USA and the EU, also shined in COP28, in addition China's double carbon and low-carbon-city intervention policies are among the policies to reduce EC particularly from fossil-fuels (Jiang et al. 2022; Yang et al. 2023).

As the commitment to cleaner energies is not adequate, combined with the EC of FinTech, it is natural to expect that this new technology will hinder the efforts made on environmental sustainability. A recent empirical projection study stressed that the commitment to clean energy technology is far from being adequate to achieve the SDGs in 2050, even if all countries were to be fully committed (Fekete et al. 2021). However, it is also argued that the technological advancements in FinTech could also help make the world a better place if the greening of FinTech is achieved (Kabaklarlı 2022; Lagna and Ravishankar 2022). Our findings confirm the negative effects of FinTech stock market size on the environment coupled with positive associations with EC. Similar to FinTech, recent literature questioned the sustainability of Metaverse

(Pekow 2023) and recent evidence confirmed the influence of Metaverse on the $CO_2e$ concentrations at the global level (Bildirici et al. 2024). The results of our study highlight strong commitment needed to reverse the negative effects of FinTech, that occurs through its extensive EC. The reversal of the effect of FinTech had been shown to require cleaner energy policies, at which, FinTech could be used to encourage the energy transition (Croutzet and Dabbous 2021). Given the achievement of the reduction of EC of FinTech is not feasible as the sector continues to grow, policies should aim to include specific targets for financial technologies and markets in line with SDG and COP28. Furthermore, the shift of industries to industry 4.0 also inclined the demand for FinTech and technologies including artificial intelligence, robotics, and blockchain (Bildirici et al. 2023). Energy policies favoring renewable energy and energy efficiency are expected to help in the achievement of the specific SDG goals for cleaner energy and cleaner industrial production within the Industry 4.0 revolution (Bildirici and Ersin 2023). Eco-innovation, green energy and energy efficiency as well as reduction of dependence to fossil-fuels-based EC are among policy recommendations at the national level (Adebayo 2022; Liu et al. 2023). Policies with these aspects could help support the reduction of the environmental effects of FinTech only partially, unless steps were not taken particularly focusing on FinTech.

The discussion and the findings of our study suggests that FinTech has not been successful in promoting environmental sustainability so far in the context of FinTech markets. A set of literature suggests that FinTech could help cope with environmental degradation by increasing energy efficiency, green investments to reduce GHG including $CO_2e$ (Tao et al. 2022). However, unless green algorithms and methods were not developed, it would not be possible to reverse the environmental degradation from cryptocurrencies, another pillar of FinTech (Gundaboina et al. 2022).

The relative size if FinTech industry could be criticized as being small, compared to major industries, with major contributions to environmental degradation. By focusing predominantly on the effects of FinTech in this paper, the findings suggest FinTech to be included among the policies focusing on cleaner technologies and environmental sustainability. The small industry critique is easily refutable, given the great size of the finance sector at the global economy, at which, FinTech plays a particular role. Further, the paramount role of the finance sector will continue in the future and the inclining trend of FinTech will continue with newer innovations for FinTech. The findings advocate policies to focus on the greening of FinTech to mitigate the EC of FinTech and to reverse the adverse effects on the environment.

## Conclusion

The article aimed to investigate the connections among FinTech, EC, and $CO_2e$, focusing on tail reliance, contagion, and causality using daily data spanning from June 18, 2012, to December 22, 2022. Given the ongoing upward trajectory of FinTech markets, the exploration of the nexus between FinTech, EC and $CO_2e$ is of crucial importance. The empirical findings of the study revealed compelling evidence with the associations among the variables and the examination requires the nonlinear and heteroskedastic features of the series analyzed. After confirming nonlinearity and nonlinear unit root processes with BDS and KSS tests, variables are modeled effectively with nonlinear MS-GARCH-copula and RSGCC causality approaches with Markov-switching type nonlinear forms and tail dependence at extreme levels of the dataset for contagion and causality modeling.

The findings showed that there are two distinct regimes, one with low volatility and the other with high volatility, both regimes being subject to strong levels of contagion at tails of data. This finding holds for both regimes, and at the second regime, a relatively more persistent regime with high volatility, the contagion parameters are estimated with relatively higher values. However, the low variance regime also is subject to very high persistence, also pointing to very high levels of contagion, which closely follow those obtained for the high volatility regime. Copula parameters defining the tail dependency are asymmetric and statistically significant, estimated at a range that exceeds 0.70 and 0.80 in both regimes confirming the strong level of tail dependence and contagion. Following the contagion analysis with MS-GARCH-Copula, RSGCC tests are employed to examine nonlinear Granger-causality under each regime. The RSGCC method produces robust results under nonlinearity and heteroskedasticity, in addition to tail dependence captured with copula, the three features of the data analyzed. Novel nonlinear causality tests confirmed unidirectional causal links from FinTech to EC and from EC to $CO_2e$ in both regimes in addition to bidirectional causality between EC and FinTech indicating feedback effects that particularly amplify the association between FinTech and EC in both regimes. These findings and the directions were compared to the results obtained from a single-regime GARCH-Copula causality test, for deviations of the results and in the end, the policy recommendation, if one ignores the nonlinearity in the volatility dynamics. The comparison yielded noteworthy differences and the single-regime approach has been observed to over accept causality by pointing at bidirectional causality in all tested variable pairs. The discussion section provided detailed discussion of such results if nonlinearity was to be ignored.

The empirical results led to important outcomes for the policymakers and decision makers, Accordingly, policymakers should not ignore the significant contagion and causal relationships between FinTech, EC, and environmental pollution, FinTech markets impact EC, which in turn, influences $CO_2e$ and these relationships persist across different regimes, becoming particularly evident at extreme market levels at the tails of data. Such levels are under the influence of major changes in the market driven by the major spikes due to chief FinTech innovation, which amplifies the energy demand for FinTech. While acknowledging central variables such as the renewable EC or energy efficiency in important sectors, the study shows that a comprehensive framework is necessary to include specific factors such as the FinTech markets and its technologies in addition to cryptocurrencies as they appear as another pillar of FinTech. In sum, the study emphasizes the need for future policies to address these issues for effective pollution mitigation strategies.

Policy recommendations based on the findings suggest governments regulate the FinTech market to address environmental pollution. Key proposals include:

(i) Prioritizing efficient payment systems with a focus on greening and clean technologies to reduce EC.
(ii) Utilizing blockchain and smart contracts to facilitate investments in renewable energy and eco-friendly initiatives.
(iii) Promoting awareness among customers about their carbon footprint during the transition to FinTech.
(iv) Providing loans and incentives to investors in energy efficiency and clean energy to decrease EC and $CO_2e$.
(v) Enhancing Risk Assessment and Insurance (RAI) models through FinTech for better management of climate-related risks.

FinTech could also have many positive sides such as fostering financial inclusion in underserved areas and such areas should also cover its extensive energy use and the effects on the environmental degradation. Finance sector has a significant size among all sectors in the globe and the commitment to green FinTech will be influential on its environmental effects. Therefore, if environmentally concerned policies were to be developed, FinTech could play a vital role in promoting cleaner energy through many channels including energy efficiency, facilitation of sustainable investments, generation of data-driven insights for awareness regarding the ecological footprint of FinTech, and supporting green initiatives across all sectors. These policies could contribute to the global fight against climate change and the quest for sustainable development in the future.

The study has provided pivotal findings regarding the contagion and causality dynamics among FinTech, energy consumption and carbon dioxide emissions. The study also has certain limitations. The data availability is a central issue for FinTech. To solve it, the paper proposes a consensus of methods that capture tail dynamics for data from FinTech stock markets. The FinTech index used is argued to have a global coverage of FinTech companies. However, it consists of Fintech companies, whose stocks are publicly traded. The selected FinTech index includes major players throughout the World, which influence the fluctuations and the major shifts in the FinTech and new FinTech innovation and such fluctuations cannot be captured adequately with yearly data at global level. As more datasets on FinTech become available, future studies are encouraged to extend the analysis with the new data. Further, future studies are advised to focus specifically on the environmental effects of the different pillars of FinTech including blockchain and cryptocurrencies, crowdfunding, and digital currencies with the proposed methods put forth in this study.

**Author contributions** Author Contributions: All authors contributed equally at all steps to the study including the conception and design, material preparation, data collection and analysis, writing of the first draft of the manuscript, commenting on the previous versions, supervision and revisions, and writing of the final manuscript. All authors read and approved the final manuscript.

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**Data availability** The dataset used in this study are publicly available from the following databases. Daily global STOXX FinTech stock index is from Refinitiv Eikon database and also available from STOXX (https://qontigo.com/index/stxftgr/). Daily global atmospheric carbon dioxide emissions in ppm is available from CO2 Earth Database (https://www.co2.earth/). Energy consumption (in TWh) is available from Datastream.

## Declarations

**Conflict of interest** The authors declare no competing interests.

## References


Adebayo TS (2022) Environmental consequences of fossil fuel in Spain amidst renewable energy consumption: a new insights from the wavelet-based granger causality approach. Int J Sust Dev World 29(7):579–592. https://doi.org/10.1080/13504509.2022.2054877

Badea L, Mungiu-Pupazan MC (2021) The economic and environmental impact of bitcoin. IEEE Access 9:48091–48104. https://doi.org/10.1109/ACCESS.2021.3068636

Bildirici M, Ersin Ö (2014) Modeling Markov switching ARMA-GARCH neural networks models and an application to forecasting stock returns. Sci World J. https://doi.org/10.1155/2014/497941

Bildirici M, Ersin ÖÖ (2023) Nexus between industry 4.0 and environmental sustainability: a fourier panel bootstrap cointegration and causality analysis. J Clean Prod 386:135786. https://doi.org/10.1016/j.jclepro.2022.135786

Bildirici ME, Sonustun B (2021) Chaotic behavior in gold, silver, copper and bitcoin prices. Resour Policy 74:102386. https://doi.org/10.1016/J.RESOURPOL.2021.102386

Bildirici ME, Salman M, Ersin ÖÖ (2022) Nonlinear contagion and causality nexus between oil, gold, VIX investor sentiment, exchange rate and stock market returns: the MS-GARCH copula causality method. Mathematics 10(21):4035. https://doi.org/10.3390/MATH10214035

Bildirici M, Kayıkçı F, Ersin ÖÖ (2023) Industry 4.0 and renewable energy production nexus: an empirical investigation of G20 countries with panel quantile method. Sustainability 15(18):14020. https://doi.org/10.3390/su151814020

Bildirici M, Ersin ÖÖ, Ibrahim B (2024) Chaos, fractionality, nonlinear contagion, and causality dynamics of the metaverse, energy consumption, and environmental pollution: markov-switching generalized autoregressive conditional heteroskedasticity copula and causality methods. Fractal Fr 8(2):114. https://doi.org/10.3390/fractalfract8020114

Cai CW (2018) Disruption of financial intermediation by FinTech: a review on crowdfunding and blockchain. Account Finance 58(4):965–992. https://doi.org/10.1111/acfi.12405

Carè R, Boitan IA, Fatima R (2023) How do FinTech companies contribute to the achievement of SDGs? Insights from case studies. Res Int Bus Finance 66:102072. https://doi.org/10.1016/J.RIBAF.2023.102072

Croutzet A, Dabbous A (2021) Do FinTech trigger renewable energy use? Evidence from OECD countries. Renew Energy 179:1608–1617. https://doi.org/10.1016/J.RENENE.2021.07.144

de Vries A (2020) Bitcoin's energy consumption is underestimated: a market dynamics approach. Energy Res Soc Sci 70:101721. https://doi.org/10.1016/J.ERSS.2020.101721

de Vries A, Gallersdörfer U, Klaaßen L, Stoll C (2022) Revisiting bitcoin's carbon footprint. Joule 6(3):498–502. https://doi.org/10.1016/j.joule.2022.02.005

Elheddad M, Benjasak C, Deljavan R, Alharthi M, Almabrok JM (2021) The effect of the fourth industrial revolution on the environment: the relationship between electronic finance and pollution in OECD countries. Technol Forecasting Soc Change. https://doi.org/10.1016/j.techfore.2020.120485

Fekete H, Kuramochi T, Roelfsema M, Den Elzen M, Forsell N, Höhne N, Luna L, Hans F, Sterl S, Olivier J, Van Soest H, Frank S, Gusti M (2021) A review of successful climate change mitigation policies in major emitting economies and the potential of global replication. Renew Sustain Energy Rev 137(110602):1–18. https://doi.org/10.1016/j.rser.2020.110602

Francq C, Zakoïan JM (2001) Stationarity of multivariate Markov-switching ARMA models. J Econom 102(2):339–364. https://doi.org/10.1016/S0304-4076(01)00057-4

FSB. (2023). FinTech. Financial Stability Board. https://www.fsb.org/work-of-the-fsb/financial-innovation-and-structural-change/fintech/

Gallersdörfer U, Klaaßen L, Stoll C (2020) Energy consumption of cryptocurrencies beyond bitcoin. Joule 4(9):1843–1846. https://doi.org/10.1016/J.JOULE.2020.07.013

Georgeson L, Maslin M (2019) Estimating the scale of the US green economy within the global context. Palgrave Commun 5(1):1–12. https://doi.org/10.1057/s41599-019-0329-3

Gharbi O, Trichilli Y, Boujelbéne M (2023) Risk spillovers connectedness between the US FinTech industry VaR, behavioral biases and macroeconomic instability factors: COVID-19 implications. China Finance Rev Int 13(3):410–443. https://doi.org/10.1108/CFRI-12-2022-0277/FULL/PDF

Granger CWJ (1969) Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37(3):424. https://doi.org/10.2307/1912791

Gundaboina L, Badotra S, Tanwar S, Manik (2022) Reducing resource and energy consumption in cryptocurrency mining by using both proof-of-stake algorithm and renewable energy. 2022 Int Mob Embed Technol Conf MECON 2022:605–610. https://doi.org/10.1109/MECON53876.2022.9752365

Haas M (2004) A new approach to markov-switching GARCH models. J Financ Economet 2(4):493–530. https://doi.org/10.1093/jjfinec/nbh020

Henneke JS, Rachev ST, Fabozzi FJ, Nikolove M (2009) MCMC-based estimation of Markov switching ARMA–GARCH models. Appl Econ 43(3):259–271. https://doi.org/10.1080/00036840802552379

IPCC. (2023). Contribution of working groups I, II and III to the sixth assessment report of the intergovernmental panel on climate change. In: H Lee, J Romero (Eds) IPCC Climate Change Synthesis Report. IPCC. https://doi.org/10.59327/IPCC/AR6-9789291691647

Jiang S, Li Y, Lu Q, Hong Y, Guan D, Xiong Y, Wang S (2021) Policy assessments for the carbon emission flows and sustainability of bitcoin blockchain operation in China. Nat Commun 12(1):1–10. https://doi.org/10.1038/s41467-021-22256-3

Jiang T, Yu Y, Jahanger A, Balsalobre-Lorente D (2022) Structural emissions reduction of China's power and heating industry under the goal of "double carbon": a perspective from input-output analysis. Sustain Prod Consum 31:346–356. https://doi.org/10.1016/J.SPC.2022.03.003

Kabaklarlı E (2022) Green FinTech: sustainability of bitcoin. Digit Finance 4:265–273. https://doi.org/10.1007/s42521-022-00053-x

Kamran M, Butt P, Abdel-Razzaq A, Djajadikerta HG (2022) Is bitcoin a safe haven? Application of FinTech to safeguard Australian stock markets. Stud Econ Finance 39(3):386–402. https://doi.org/10.1108/SEF-05-2021-0201/FULL/PDF

Kapetanios G, Shin Y, Snell A (2003) Testing for a unit root in the nonlinear STAR framework. J Econom 112:359–379

Kim CJ (1994) Dynamic linear models with Markov-switching. J Econom 60(1–2):1–22. https://doi.org/10.1016/0304-4076(94)90036-1

Kim JM, Lee N, Hwang SY (2020) A copula nonlinear granger causality. Econ Model 88:420–430. https://doi.org/10.1016/J.ECONMOD.2019.09.052

Kohli V, Chakravarty S, Chamola V, Sangwan KS, Zeadally S (2023) An analysis of energy consumption and carbon footprints of cryptocurrencies and possible solutions. Digit Commun Netw 9(1):79–89. https://doi.org/10.1016/J.DCAN.2022.06.017

Lagna A, Ravishankar MN (2022) Making the world a better place with FinTech research. Inf Syst J 32(1):61–102. https://doi.org/10.1111/isj.12333
Lee TH, Yang W (2014) Granger-causality in quantiles between financial markets: using copula approach. Int Rev Financ Anal 33:70–78. https://doi.org/10.1016/J.IRFA.2013.08.008
Li J, Li N, Peng J, Cui H, Wu Z (2019) Energy consumption of cryptocurrency mining: a study of electricity consumption in mining cryptocurrencies. Energy 168:160–168. https://doi.org/10.1016/J.ENERGY.2018.11.046
Liu X, Adebayo TS, Ramzan M, Ullah S, Abbas S, Olanrewaju VO (2023) Do coal efficiency, climate policy uncertainty and green energy consumption promote environmental sustainability in the United States? An application of novel wavelet tools. J Clean Prod 417:137851. https://doi.org/10.1016/J.JCLEPRO.2023.137851
Muganyi T, Yan L, Yin Y, Sun H, Gong X, Taghizadeh-Hesary F (2022) FinTech, RegTech, and financial development: evidence from China. Financ Innov. https://doi.org/10.1186/s40854-021-00313-6
Muhammad S, Pan Y, Magazzino C, Luo Y, Waqas M (2022) The fourth industrial revolution and environmental efficiency: the role of FinTech industry. J Clean Prod. https://doi.org/10.1016/j.jclepro.2022.135196
Nalatore H, Sasikumar N, Rangarajan G (2014) Effect of measurement noise on Granger causality. Phys Rev E Stat Nonlinear Soft Matter Phys 90(6):062127. https://doi.org/10.1103/PHYSREVE.90.062127/FIGURES/4/MEDIUM
O'Dwyert KJ, Malone D (2014) Bitcoin mining and its energy footprint. IET Conf Publ 2014(CP639):280–285. https://doi.org/10.1049/CP.2014.0699
Pekow M (2023) A Sustainable Metaverse? Virtual reality and the environment. Metaverse Marketing. https://www.linkedin.com/pulse/sustainable-metaverse-virtual-reality-environment-martin-petkov/
Qin S, Klaaßen L, Gallersdörfer U, Stoll C, Zhang D (2020) Bitcoin's future carbon footprint. https://doi.org/10.48550/arxiv.2011.02612
Sadiq M, Le-Dinh T, Tran TK, Chien FS, Phan TTH, Quang Huy P (2023) The role of green finance, eco-innovation, and creativity in the sustainable development goals of ASEAN countries. Econ Res Ekonomska Istraživanja. https://doi.org/10.1080/1331677X.2023.2175010
Sarkodie SA, Ahmed MY, Leirvik T (2022) Trade volume affects bitcoin energy consumption and carbon footprint. Finance Res Lett. https://doi.org/10.1016/J.FRL.2022.102977
Sedlmeir J, Ulrich Buhl H, Fridgen G, Keller R (2020) The energy consumption of blockchain technology: beyond myth. Bus Inf Syst Eng 62(6):509–608. https://doi.org/10.1007/s12599-020-00656-x
SedlmeirBuhl FridgenKeller JHUGR (2020) Ein Blick auf aktuelle Entwicklungen bei blockchains und deren Auswirkungen auf den Energieverbrauch. Inform Spektrum 43:391–404. https://doi.org/10.1007/s00287-020-01321-z
Sharif A, Brahim M, Dogan E, Tzeremes P (2023) Analysis of the spillover effects between green economy, clean and dirty cryptocurrencies. Energ Econ. https://doi.org/10.1016/j.eneco.2023.106594
Snytnikov P, Potemkin D (2022) Flare gas monetization and greener hydrogen production via combination with cryptocurrency mining and carbon dioxide capture. Iscience 25(2):103769. https://doi.org/10.1016/J.ISCI.2022.103769
Stoll C, Klaaßen L, Gallersdörfer U (2019) The carbon footprint of bitcoin. Joule 3(7):1647–1661. https://doi.org/10.1016/J.JOULE.2019.05.012
Tao R, Su CW, Naqvi B, Rizvi SKA (2022) Can FinTech development pave the way for a transition towards low-carbon economy: a global perspective. Technol Forecast Soc Chang 174:121278. https://doi.org/10.1016/J.TECHFORE.2021.121278
Thakor AV (2020) FinTech and banking: What do we know? J Financ Intermed 41:100833. https://doi.org/10.1016/J.JFI.2019.100833
UNFCCC (2022) Sharm el-Sheikh Climate Change Conference. https://unfccc.int/cop27
UNFCCC (2023) COP28 Agreement Signals "Beginning of the End" of the Fossil Fuel Era. United Nations Climate Change. https://unfccc.int/news/cop28-agreement-signals-beginning-of-the-end-of-the-fossil-fuel-era
Wang Y, Lucey B, Vigne SA, Yarovaya L (2022) An index of cryptocurrency environmental attention (ICEA). China Finance Rev Int 12(3):378–414. https://doi.org/10.1108/CFRI-09-2021-0191/FULL/PDF
Wendl M, Doan MH, Sassen R (2023) The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: a systematic review. J Environ Manage 326:116530. https://doi.org/10.1016/J.JENVMAN.2022.116530
Wimbush S (2018) Cryptocurrency mining is neither wasteful nor uneconomic. Nature 555(7697):443
Yang S, Jahanger A, Hossain MR (2023) Does China's low-carbon city pilot intervention limit electricity consumption? An analysis of industrial energy efficiency using time-varying DID model. Energy Econ 121:106636. https://doi.org/10.1016/J.ENECO.2023.106636
Zhou X, Tang X, Zhang R (2020) Impact of green finance on economic development and environmental quality: a study based on provincial panel data from China. Environ Sci Pollut Res 27(16):19915–19932. https://doi.org/10.1007/s11356-020-08383-2
Zhu K, Yamaka W, Sriboonchitta S (2016) Multi-asset portfolio returns: a Markov switching copula-based approach. Thai J Math 183–200. https://scholar.google.com/scholar_lookup?title=Multi-asset+portfolio+returns:+A+Markov+switching+copulabased+approach&author=Zhu,+K.&author=Yamaka,+W.&author=Sriboonchitta,+S.&publication_year=2016&journal=Thai+J.+Math.&pages=183%E2%80%93200



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