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Financial technology and ESG market: A wavelet-DCC GARCH approach

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ABSTRACT

This paper examines the co-movement between FinTech and ESG markets from a time-frequency domain perspective. We use an approach suggested by Vacha and Barunik (2012) and include wavelet coherence analysis and dynamic conditional correlation from a multivariate GARCH model (DCC GARCH). We find a significant bi-directional positive relationship between the FinTech and ESG indices. We also find the DCC GARCH process to be mean reverting. The correlations between FinTech and ESG indices, based on both the wavelet coherence and DCC GARCH models, are found to fluctuate over time with the one based on DCC GARCH being higher on the average compared to the one based on wavelet coherence. Finally, we find that the correlations are significant for almost all frequencies except for the 256-day frequency. For the lower frequencies, such as 512-day (approximately 2-year frequency), the correlation increases.

1. Introduction

In 2015, all UN member states agreed upon 17 sustainable development goals (SDGs) to be achieved by 2030 including poverty reduction, equality, economic and environmental goals. While these SDGs provide a detailed and realistic picture of global complex challenges (Salvia et al., 2019), related research provides evidence that there are challenges toward a full realization of its intended objectives. For example, according to Moyer and Hedden (2020), the overall set of indicators to achieve the SDG target values is projected to increase from 43 percent in 2015 to only 54 percent in 2030 with 15 percent of countries not achieving any of the goals. This was reiterated by Glass and Newig (2019) whose results show that even high- and medium-income OECD and European countries still have considerable room left for improvements that pave the way for realizing SDGs. Similarly, Nicolai et al. (2016) indicated that only a few of the SDGs are moving in the right direction and most of the targets are either progressing at a very slow pace or in some cases the outcomes are getting worse. And finally, in their annual sustainable development report, Sachs et al. (2022) highlighted that “for the second year in a row the world was no longer making progress on SDGs in 2021”. They reported a decline in the SDG index compared to 2020 and concluded that the current pace is too slow to achieve SDGs by 2030. This calls for more scrutiny of the impediments and drivers of sustainable development across the globe.

The finance sector has always been a critical element in propelling socio-economic reforms and addressing its challenges (Ibrahim and Vo, 2021) and in recent years Financial Technology (FinTech) has emerged as a transformative force in the global financial landscape, revolutionizing the way financial services are delivered and consumed. Related literature has witnessed a surge in research

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that studies the implications of FinTech for achieving sustainable development. One stream of research looks into the indirect channels through which FinTech impacts sustainable development and the second stream investigates its direct implications. Amongst the indirect factors, some studies highlight the role of FinTech in advancing financial inclusion by extending access to previously underserved and unbanked populations (Abraham et al., 2019; Ozili, 2018; Salampasis and Mention, 2018; Schwinn and Teo, 2018; Senyo and Osabutey, 2020; Shaban et al., 2019). These studies argue that enhanced financial inclusion fosters economic empowerment, reduces poverty, and promotes social mobility, ultimately contributing to sustainable development goals. Additionally, some literature asserts the role of FinTech in paving the way for innovative solutions in green finance (Guang-Wen and Siddik, 2023; Mirza et al., 2023; Muganyi et al., 2021; Qin et al., 2024; Udeagha and Muchapondwa, 2023b; Zhou et al., 2022). They posit that FinTech platforms facilitate the allocation of capital towards environmentally friendly projects. Furthermore, the convergence of FinTech and the energy sector and its potential to enhance energy efficiency has been the subject of various studies in recent years (Awais et al., 2023; Huo et al., 2022; Jiang, 2023; Liu et al., 2022; Muhammad et al., 2022; Teng and Shen, 2023; Ullah et al., 2023). Some examples of the second stream of research which looks into the direct connection between FinTech and sustainable development include Lisha et al. (2023), Mhlanga (2022), Tay et al. (2022), Udeagha and Muchapondwa (2023b) and Zhang et al. (2021). There are studies that specifically focus on the possibility of FinTech boosting sustainability in healthcare (Meiling et al., 2021), agriculture (Anshari et al., 2019), and supply chain processes for SMEs (Soni et al., 2022).

As far as this research is concerned, the overwhelming majority of the extant literature on the relationship between FinTech and sustainable development employs a panel data analysis approach.[1] While panel data analysis is a valuable tool for researchers to understand the relationships over time and across units, we argue that in this context, considering the data availability and complexity, there are unaddressed issues regarding the quality and comparability of data and constructs used in these studies. For instance, Muganyi et al. (2021); Qin et al. (2024); Udeagha and Muchapondwa (2023a); Zhou et al. (2022) use the FinTech index created by the Institute of Digital Finance at Peking University in China which undermines the comparability of results in a global context. Lisha et al. (2023) and Teng and Shen (2023) consider the number of start-up formations (from Crunchbase database) and Awais et al. (2023) use internet servers per 1 million people and ATMs per 100 thousand adults as a measure of FinTech which may not fully grasp the complexity of the concept of FinTech. Furthermore, Mirza et al. (2023) and Muhammad et al. (2022), take the investment related to technological adoption and FinTech credit, using yearly data which overlooks the frequency and time component of this phenomenon.

Considering the identified gap in the literature the research question which this study aims to address is: what are the directional interactions between FinTech and ESG indices, and how do these interactions vary over time and frequency? In this way we can identify periods in which the FinTech sector leads or lags behind ESG indices, enhancing our understanding of the causality and timing of their interactions and shedding light on how the relationship between FinTech and ESG markets evolve over time. Therefore, we aim to analyze the co-movements between FinTech and ESG markets, addressing the gap in literature on their interconnections from a temporal perspective. For this purpose, we use time series analysis and introduce a wavelet approach to investigate its frequency components without losing the time information. This enables us to uncover the interactions which are harder or even impossible to observe using other methods. We are the first to apply wavelets in the analysis of FinTech and ESG markets; however, we acknowledge recent works employing wavelets in ESG studies such as Umar and Gubareva (2021) who explores the relationship between COVID-19 media coverage and ESG equity market, Kilic et al. (2022) who examine the co-movements between stock market returns and ESG index and Andersson et al. (2022) who analyze the interactions between ESG, currency and commodity markets. Contrary to these studies, we use a novel approach suggested by Vacha and Barunik (2012) to follow a model-free way of estimating time-varying correlations and include dynamic conditional correlation from a multivariate GARCH model. In this way, we contribute to the extant discussions on the implications of FinTech on the ESG market in a way that is easier to interpret.

This study makes several notable contributions to the literature on the nexus between FinTech and ESG investments. We innovate by applying wavelet coherence analysis to explore the relationship between FinTech and ESG indices within the time-frequency domain. This approach allows for a more nuanced examination of their interconnections, uncovering significant correlations across various periods and frequencies. This methodology stands in contrast to traditional econometric techniques, offering a deeper understanding of the temporal and frequency-dependent nature of these relationships. Our research elucidates the complex directional interactions between FinTech and ESG indices, identifying periods during which each sector leads or lags the other. This bidirectional relationship enhances our understanding of the causality and timing of their interactions, providing insights into how technological innovations in finance and sustainability considerations influence each other over time. By employing DCC GARCH models, we contribute to the literature on financial market dynamics through the lens of mean-reverting processes. Our findings on the time-varying correlations and their mean-reverting nature add to the discourse on the predictability and stability of the relationship between FinTech innovations and ESG performance. Our study also extends the analysis of market interconnections by employing a VAR model and Granger causality tests to understand the transmission of shocks and predictive relationships among the indices. This analysis offers insights into the systemic importance of FinTech and ESG sectors within the financial landscape and their roles as transmitters or receivers of market shocks. Our research addresses a notable gap by analyzing the co-movement between FinTech and ESG markets from a time-series perspective, a domain not extensively explored by previous scholars. In doing so, we enrich the academic discourse on the integration of sustainable investment criteria and technological innovations in finance.

Using daily data from June 15, 2015, to August 1, 2023, on three FinTech indices, namely (i) Alternate Finance, (ii) Future

[1] We note that in this context, apart from secondary data, there are studies which employ primary data analysis, such as Guang-Wen and Siddik (2023), who find a positive and significant relationship between fintech adoption and green finance using a survey of 302 banking staff in Bangladesh.

Payments, and (iii) Democratized Banking, and two ESG indices, namely (i) S&P ESG and (ii) MSCI ESG leaders indices, we perform wavelet coherence analysis. We find that the two FinTech indices (Future Payments and Democratized Banking) are positively correlated with both ESG indices for a significantly large number of dates and frequencies. There also exists a positive correlation relation between Alternate Finance and both ESG indices, but to a lesser extent. In terms of the lead/lag relationship, we find a bi-directional relationship between FinTech and ESG indices depending on dates and frequencies without one set of indices dominating the other. For robustness and comparison purposes, we also estimate multivariate dynamic constant correlation generalized autoregressive conditional heteroscedasticity (DCC GARCH) models taking a pair of indices, one from the three FinTech indices and one from the two ESG indices, at a time. We find that all the DCC GARCH processes are mean-reverting. We also find that the unconditional correlation is higher than the average conditional correlations from both wavelet coherence and DCC GARCH model for all pairs considered. The average conditional correlation is higher for DCC GARCH model compared to the wavelet coherence. Both of these conditional correlations vary over time, with the correlation based on the DCC GARCH model being higher than the one based on wavelet coherence on average. Finally, the wavelet coherence analysis allows us to compute the average correlation over different frequencies by averaging the correlation across time. We find the behavior of correlation to be similar when using the S&P ESG index compared to MSCI ESG index. The correlations are significant for almost all frequencies except for the 256-day frequency. For the lower frequencies, e.g., 512-day (approximately 2-year frequency), the correlation increases.

The organization of this paper is as follows: Following an overview of related literature in Section 2, Section 3 covers the methodologies used in the study. Moving forward, Section 4 discusses the empirical results. Finally, in Section 5, we conclude by highlighting our primary findings.

2. Review of related literature

FinTech, the intersection of financial services and technology, has emerged as a catalyst for sustainable development. This literature review critically examines the scholarly works and research studies that highlight the contribution of FinTech to sustainable development across various sectors. With its disruptive potential and transformative capabilities, FinTech offers potential innovative solutions to address economic, environmental, and societal challenges. By leveraging technology, FinTech promotes financial inclusion, green finance, renewable energy, and social welfare. This review aims to provide an in-depth analysis of the ways in which FinTech fosters sustainable development and explores the challenges and future directions in this evolving field. Additionally, we discuss some of the methodological approached in related studies.

2.1. *FinTech and sustainable development*

FinTech advancements have notably improved financial inclusion by offering innovative solutions like mobile money and digital credit scoring, increasing account ownership from 51 % to 69 % from 2011 to 2017 (Shaban et al., 2019). Despite progress, disparities persist, especially in low-income countries and among underprivileged groups. FinTech facilitates greater access to credit for SMEs and marginalized sectors by employing advanced algorithms for more accurate credit assessments (Jagtiani and Lemieux, 2017). However, issues like privacy concerns and potential discrimination remain (Bartlett et al., 2018). In wealth management, FinTech reduces costs and expands service accessibility (Abraham et al., 2019), although challenges in serving the less privileged continue. Crowdfunding and innovative credit models have become crucial in supporting underserved sectors (Jenik et al., 2017).

FinTech significantly bolsters green finance, with studies showing a positive correlation between FinTech adoption and green finance initiatives (Guang-Wen and Siddik, 2023; Mirza et al., 2023). FinTech aids banks in evaluating sustainable business models, thus increasing green lending and investments. Technological advancements support environmental protection by facilitating cost-effective green investments (Muganyi et al., 2021), and impacting green growth and environmental indices positively (Qin et al., 2024). Additionally, there is a bidirectional relationship between FinTech development and green finance, highlighting FinTech's role in environmental sustainability (Udeagha and Muchapondwa, 2023b; Zhou et al., 2022).

The integration of FinTech and the energy sector promotes energy efficiency and sustainability. Research links FinTech to better energy efficiency outcomes in renewable energy enterprises and urban environments (Huo et al., 2022; Jiang, 2023). Green finance, enhanced by FinTech, supports eco-friendly economic activities and the transition to sustainable energy (Awais et al., 2023). FinTech, along with green policies and environmental taxes, facilitates the adoption of energy-efficient solutions and sustainable practices (Muhammad et al., 2022; Teng and Shen, 2023; Ullah et al., 2023).

The recent literature highlights the transformative potential of FinTech in various dimensions of sustainable development,[2] including economic growth, financial inclusion, sustainable investment, and climate change mitigation. Arner et al. (2020) argue that FinTech plays a crucial role in promoting financial inclusion, which is a fundamental component of achieving well-rounded and sustainable development, as outlined in the UN Sustainable Development Goals (SDGs). The complete capacity of FinTech in aiding the SDGs can be achieved by adopting a forward-looking strategy in building the necessary infrastructure that facilitates the transformation toward digital financial services. Lisha et al. (2023) investigate the interconnectedness among sustainability, eco-friendly innovations, FinTech, financial progress, and natural resources within the BRICS economies spanning from 2000 to 2019. Utilizing the Method of Moments Quantile Regression (MMQR), the findings reveal that both FinTech and natural resources have an adverse

[2] It is worth mentioning that literature also highlights the influence of sustainability profile and CSR activities on the performance of fintech firms (Merello et al., 2022).

effect on environmental sustainability across all three quantile ranges (0.10th-0.30th, 0.40th-0.60, and 0.70th-0.90th). On the other hand, green innovations and financial development foster environmental sustainability across a wide range of quantiles (0.10th-0.90th), while economic growth leads to higher emissions at significant quantiles. Utilizing secondary data examined via document analysis, Mhlanga (2022) explores how FinTech contributes to mitigating the obstacles or risks linked with climate change in the context of the Fourth Industrial Revolution. The findings revealed that leveraging FinTech for financial inclusion could enhance the ability of households, individuals, and businesses to withstand the impact of sudden climate-related incidents or the gradual consequences of altered precipitation patterns, increasing sea levels, or the encroachment of saline water. Mechanisms such as insurance, savings, credit facilities, digital money transfers, and novel digital distribution channels all have the potential to support both those affected by climate change and those responsible for managing emerging environmental challenges. Using a systematic literature review Tay et al. (2022) investigate the extent of digital financial inclusion on a global scale. Their study reveals that developing nations, particularly those in Asia, are actively adopting and enhancing digital financial inclusion as a means to alleviate poverty. Nevertheless, the outcomes emphasize the ongoing disparities present within developing countries, manifesting as gender disparities, disparities between affluent and disadvantaged individuals, and discrepancies between urban and rural regions in terms of their accessibility to and utilization of digital financial services. Udeagha and Muchapondwa (2023a) examine the collective impacts of green finance and FinTech in achieving the carbon neutrality objectives spanning the period from 1990 to 2020. The results pertaining to the BRICS economies suggest that the adoption of green finance, coupled with FinTech and advancements in energy-related technologies, contribute to the advancement of environmental sustainability. Additionally, the findings reveal a mutual causal relationship between CO2 emissions and the adoption of green finance and FinTech. And finally, in an interesting study, Zhang et al. (2021) look into a project by one of China's biggest FinTech giants (Alibaba group) called Ant Forest project which created a system to encourage its users to engage in carbon footprint-reducing activities such as planting trees, walking or biking, going paperless, etc., and in turn reward them with energy point and credits on their saving accounts. They found that this project has led to great progress in land restoration, carbon reduction and socio-economic improvements in northern China.[3]

2.2. *Review of methodological approaches*

This section examines three advanced methodologies that have gained prominence for their applicability and effectiveness in dissecting the complexities of the ESG and FinTech markets, namely wavelet analysis, DCC-GARCH models, and connectedness analysis.

Wavelet analysis has emerged as a powerful tool for financial market analysis, offering a granular view of time series data by simultaneously capturing time and frequency information. This dual analysis capability is particularly valuable in the volatile and dynamic environments of ESG and FinTech markets, where it can reveal hidden patterns and correlations. Sanchís and Gubareva (2024) illustrate the utility of wavelet analysis in assessing the impact of ESG criteria on stock performance, demonstrating how wavelet-derived insights can guide investment decisions. Similarly, Rubbaniy et al. (2022) utilized wavelet coherence analysis to investigate the safe-haven properties of ESG investments. In the realm of FinTech, Rafiuddin et al. (2023) apply wavelet coherence to understand growth of FinTech to measure the contribution towards the sustainable development goal, uncovering lead-lag relationships that are invisible to traditional analysis methods. These studies underscore the methodology's benefits such as its ability to capture latent processes with differing cycle trends, the functionality of this technique to handle data with non-linear lead-lag connection and also the fact that this method is not affected by the size of the data.

The DCC-GARCH model stands out for its sophisticated approach to modeling time-varying correlations and volatilities, a feature of critical importance in the intertwined and rapidly changing ESG and FinTech sectors. Engle (2002) introduced the DCC-GARCH model as a framework for estimating varying correlations, which has been extensively applied in financial research, including ESG and FinTech studies. For instance, Shaik and Rehman (2023) employ the DCC-GARCH model to explore the dynamic volatility connectivity of ESG indices. Similarly, Zhang et al. (2022) employ this method to investigate the dynamic connectedness between the ESG stock index, the renewable energy stock index, the green bond stock index, the sustainability stock index, and the carbon emission futures.[4] In the context of FinTech Özdemir (2022) utilizes the model to assess volatility spillover between major cryptocurrencies, highlighting the potential for systemic risks arising from these new financial technologies. These applications illustrate the model's efficacy in capturing the complex volatility and correlation structures characteristic of modern financial markets. When comparing the Wavelet approach with the Dynamic Conditional Correlation (DCC) GARCH model, it is pertinent to highlight that the DCC-GARCH model is particularly equipped to address contagion effects in both returns and variances. Unlike the Wavelet method, which primarily analyzes the time-frequency characteristics of data, the DCC-GARCH framework explicitly models the time-varying correlations between multiple time series. This feature makes it exceptionally useful for capturing the dynamics of contagion during periods of market stress, where both the returns and volatility of financial assets can exhibit significant co-movements and shifts, crucial for understanding complex interactions in financial markets.

Connectedness analysis, based on network theory, offers a novel lens through which to view the financial markets, particularly

[3] Additionally, we note that fintech's utilization of data analytics, artificial intelligence, and machine learning offers unprecedented insights into financial behaviors and trends which can be leveraged to make informed decisions related to economic development, poverty alleviation, and resource allocation (Lv et al., 2018).

[4] For more studies on the application of GARCH models in ESG related investments see Mousa et al. (2022), Setiawan et al. (2022) and Taera et al. (2023).

suited to understanding the intricate relationships in the ESG and FinTech markets. Diebold and Yilmaz (2012) pioneered the use of connectedness analysis in finance, developing measures of network connectedness that have been applied to a wide range of financial market studies. In the context of ESG, Wan et al. (2024) and Iqbal et al. (2024) applied connectedness analysis to information transmission and risk contagion among global ESG stock markets. For FinTech, Alshater et al. (2024) investigated the interconnectedness within several regional FinTech indices and the impact of Russia's invasion of Ukraine on the dynamic spillovers, revealing a high degree of interconnectedness that poses both opportunities and challenges for investors. These studies highlight the utility of connectedness analysis in decoding the complex interdependencies that define the ESG and FinTech sectors.

3. Methodology

3.1. Wavelet analysis

In this subsection, we first briefly describe wavelet coherence analysis (Grinsted et al., 2004; Torrence and Compo, 1998). The continuous wavelet transform (CWT, $W_n^X(s)$) for a discrete time series $x_n, n = 1, \ldots, N$ with uniform time steps δt is defined as:

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{k=1}^{N} x_k \psi_0 \left[\frac{(k-n)\delta t}{s}\right] \tag{1}$$

where $\psi_0()$ represents a particular mother wavelet, $s > 0$ is the scaling factor (that stretches the wavelet) and n is the translation parameter (that represents the location of the wavelet). Then, we can define the cross wavelet transform ($W_n^{XY}(s)$) of two time series x_n and y_n as follows:

$$W_n^{XY}(s) = W_n^X(s) W_n^{Y^*}(s) \tag{2}$$

where the superscript '*' represents the complex conjugate. Now, the wavelet coherence ($R_n^2(s)$) of the two time series can be defined as:

$$R_n^2(s) = \frac{\left|S\left(s^{-1} W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right) S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{3}$$

where $S()$ is a smoothing function. In this case, the phase difference is given by

$$\phi_n^{XY}(s) = \tan^{-1}\left(\frac{\mathrm{Im}(W_n^{XY}(s))}{\mathrm{Re}(W_n^{XY}(s))}\right) \tag{4}$$

Where Re() and Im() represent the real and imaginary parts of the complex cross wavelet transform. In the coherence diagram, the phase is plotted using arrow. When the two series are in phase or positively correlated, the arrow will be pointing to the right and vice versa. When the first series leads the second, the arrow would be pointing right-up or left-down. Similarly, when the second series leads the first, the arrow would be pointing right-down or left-up.

3.2. DCC GARCH analysis

The Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC GARCH) model suggested by Engle (2002) is the extension of the standard GARCH model where Y_t is a $m \times 1$ vector representing m time series.[5] The DCC GARCH model is described by the following system of equations:

$$Y_t = \mu + \varepsilon_t, \quad \varepsilon_t = H_t^{1/2} \eta_t \tag{5}$$

$$H_t = D_t R_t D_t, \quad D_t = diag\left(\sqrt{h_{1t}}, \ldots \sqrt{h_{Nt}}\right) \tag{6}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \quad Q_t^* = diag\left(\sqrt{q_{11t}}, \ldots \sqrt{q_{mmt}}\right) \tag{7}$$

$$Q_t = G(1-\alpha-\beta) + \alpha\left(\varepsilon_{t-1}\varepsilon_{t-1}^{\prime}\right) + \beta Q_{t-1} \tag{8}$$

Q_t and R_t are the covariance and correlation matrices respectively, and G is the unconditional covariance matrix of the $D_t^{-1}\varepsilon_t$. It is required that $\alpha > 0$ and $\beta > 0$ for the covariance matrix to be positive definite. When $\alpha + \beta < 1$, the model is so-called mean reverting.

[5] In this study, $m = 2$ because we are considering two series at a time.

4. Empirical results

4.1. Data description

In order to analyze the stock market performance ESG and FinTech indices, we use the daily price data of two ESG leaders indices: (i) S&P 500 ESG leaders and (ii) MSCI (Morgan Stanley Capital International) world ESG leaders. These indices are free float-adjusted and market capitalization-weighted, tailored to reflect the performance of companies chosen from a parent index according to ESG criteria. This selection process involves excluding companies engaged in certain business activities, as well as considering ESG ratings and exposure to ESG-related controversies. By representing companies that are frontrunners in ESG practices within their respective sectors, these indices serve as optimal tools for assessing the financial outcomes of sustainable business strategies. The choice of both S&P 500 and MSCI World ESG Leaders indices allows for a broader geographic coverage, encompassing companies not only from the United States but also from other parts of the world. As for the FinTech indices, we use the daily price data of three S&P Kensho FinTech indices[6] (recently used by Shrestha et al., 2023): (i) Alternative Finance, (ii) Future Payments, and (iii) Democratized Banking Indices. The S&P Kensho FinTech indices capture the performance of companies at the forefront of this transformation. Analyzing these indices provides insights into how technological innovations impact the financial industry and investor behavior. Both ESG and FinTech indices are from the Refinitiv® Datastream® database. The sample period covers June 15, 2015, to August 1, 2023, yielding a total of 2046 return observations. Utilizing indices from the Refinitiv® Datastream® database ensures access to comprehensive, high-quality data, supporting robust empirical analysis. The extensive sample period further enables the examination of both short-term dynamics and longer-term trends. By selecting indices that represent distinct yet increasingly intersecting sectors, our research can offer valuable insights into the comparative market performance, potential synergies, and divergences between FinTech innovation and sustainable investment practices.

Fig. 1 shows the prices and logarithmic returns for all the series considered in the study. Table 1 shows the summary statistics of the daily logarithmic returns, where S&P ESG and Future Payments have the highest mean return and Alternative Finance has the minimum mean return. They all have negative skewness and significantly higher kurtosis compared to the standard normal distribution. Finally, all Jarque-Bera statistics are significant.[7]

4.2. Evidence from the wavelet coherence

Fig. 2 shows the estimated wavelet coherence and phase for all six pairs with one of the three FinTech indices and one of the two ESG indices. We have some interesting results from the coherence figure. There are more significant regions or areas between the two FinTech (future payments and democratized banking) indices and the two ESG (S&P ESG and MSCI ESG) indices, indicating significant correlation over many periods and at many frequencies. However, when it comes to the significant regions between Democratized Banking index and the two ESG indices, the total area is less compared to the previous two FinTech indices.

Another interesting observation is that the significant regions for FinTech indices are similar regardless of which ESG indices we choose. Furthermore, almost all arrows are pointing to the right, indicating a strong positive correlation between the FinTech indices and the ESG indices. Finally, there are a significant number of arrows pointing upward (indicating FinTech indices leading ESG indices) and a significant number of arrows pointing downward (indicating ESG indices leading FinTech indices). This indicates that, for some dates and some frequencies, the FinTech indices lead the ESG indices. Since all these indices represent the stock market performance and stock markets are supposed to be, in general, efficient, it is reasonable to expect one type of market does not significantly dominate the other for all times and frequencies.

4.3. Evidence from DCC GARCH

The estimates of the parameters for the DCC GARCH model are summarized in Table 2. All the parameters are highly significant. All the estimates of α and β are positive as required by the model because these are the parameters of the model describing the data generating process for the covariance matrices whose diagonal terms cannot be negative. Finally, the estimates of the sum of these parameters (i.e., $\alpha + \beta$) are all less than 1, indicating that the covariance generating process is a mean reverting process. The main reason we estimated DCC GARCH model is to get the time series estimate of the dynamic correlation between the FinTech and ESG indices. We will discuss the behavior of the dynamic correlation in the next subsection.

[6] The S&P Kensho New Economy Indices evaluate the performance of US-listed stocks that are related to several technologically advanced and often disruptive industries that make up the "Fourth Industrial Revolution." The Alternative Finance Index tracks the performance of firms that offer alternative financing and wealth management solutions. The Future Payments Index assesses the performance of businesses that are focused on enabling the next-generation payment infrastructure. Finally, the Democratised Banking Index measures the performance of firms engaged in financial services innovation. We exclude the Distributed Ledger index used by Shrestha et al. (2023) due to lack of data going back to 2015.

[7] In our analysis, the sample period includes the duration of the Covid-19 pandemic. This likely caused significant structural changes across various sectors including ESG and FinTech markets, potentially affecting the trends and patterns in our data. Therefore, it is crucial to recognize the possibility of a structural break within this period. This may impact the estimation of the DCC-GARCH model. However, it will not affect the wavelet coherence analysis as this allows the relationship between series over time and frequency.

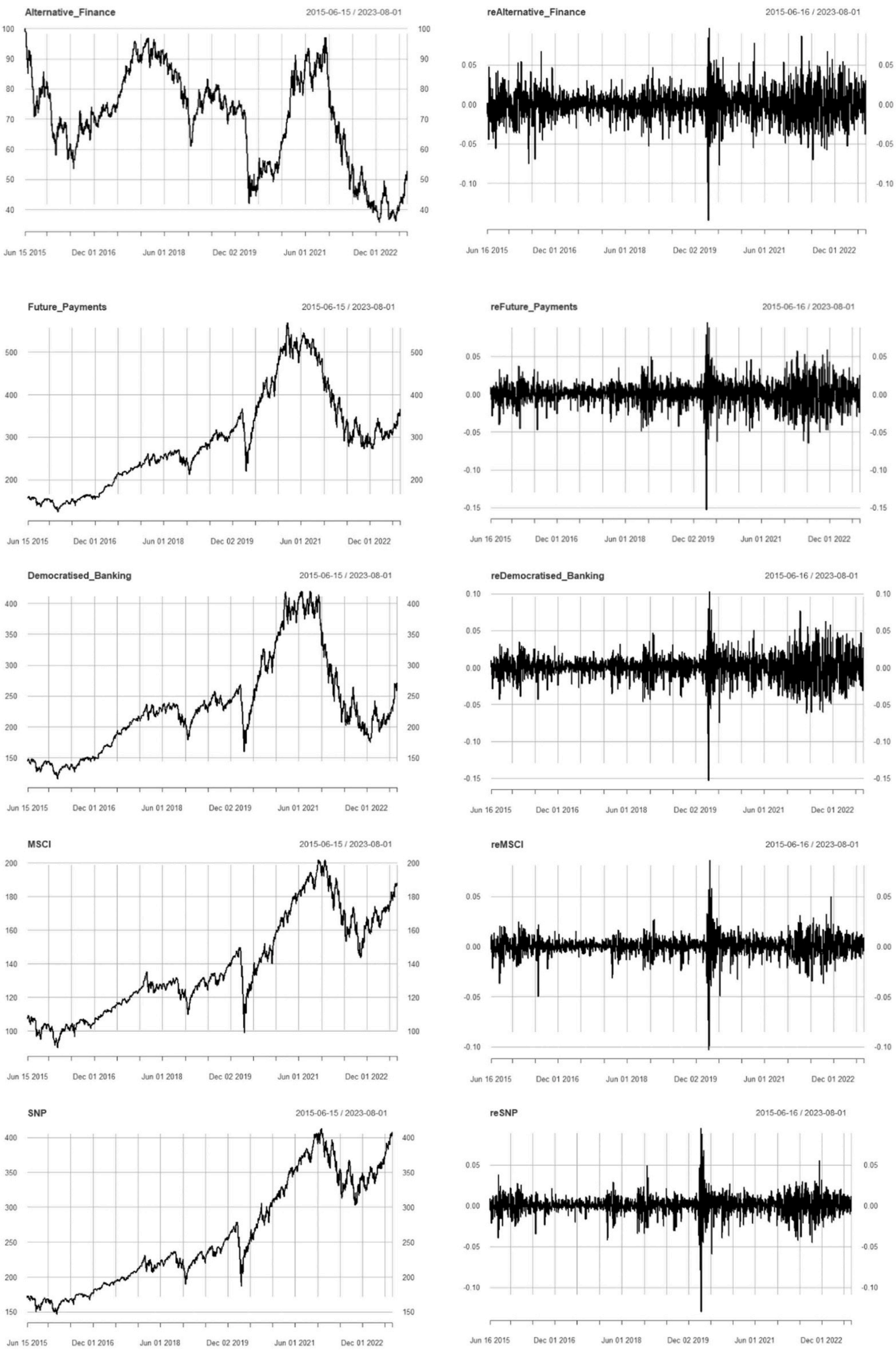

Fig. 1. The price levels (shown on the left) and logarithmic returns (shown on the right).

Table 1
Descriptive statistics of the daily logarithmic returns.

	S&P ESG	MSCI ESG	Alt. Finance	Fut. Payments	Dem. Banking
Observations	2046	2046	2046	2024	2046
Min.	-0.1298	-0.1027	-0.1469	-0.1527	-0.1528
Max.	0.0954	0.0862	0.097	0.0953	0.1031
Mean	0.0004	0.0003	-0.0003	0.0004	0.0003
Std. Dev	0.0121	0.0101	0.0196	0.0167	0.0175
Skewness	-0.76	-1.0044	-0.3083	-0.7805	-0.5896
Kurtosis	17.9646	19.3913	6.6071	10.7512	9.3218
Jarque-Bera	19,288.07***	23,249.14***	1141.65***	5329.93***	3525.77***

Notes: The critical value for the Jarque-Bera statistics is approximately 9.21 at 1 percent level. *** indicate significance at the 1 % level.

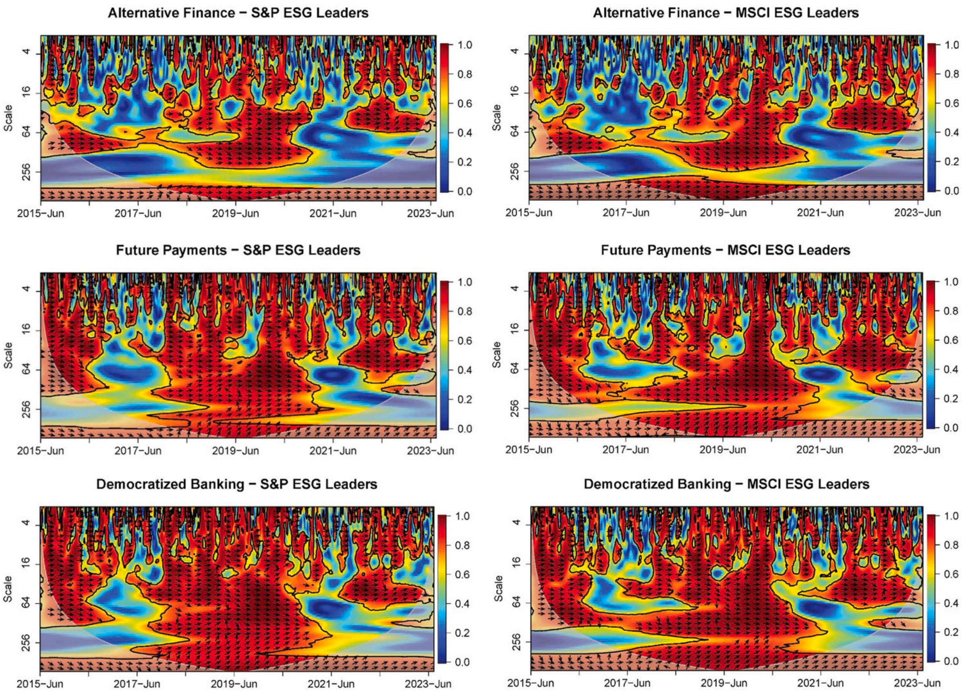

Fig. 2. Wavelet coherence - the horizontal axis shows time, while the vertical axis shows the scales (period) in days. The vertical axes are expressed in logarithmic form with base 2.

Table 2
Coefficient estimates of multivariate DCC GARCH.

		S&P 500 ESG leaders		MSCI world ESG leaders	
		Coefficient	St. Deviation	Coefficient	St. Deviation
Alternative finance					
	α_{DCC}	0.06342***	0.01327	0.05469***	0.013006
	β_{DCC}	0.90245***	0.021842	0.91595***	0.022248
	Log. Likelihood	12,807.45		13,152.88	
Future payments					
	α_{DCC}	0.05966***	0.009769	0.05889***	0.013072
	β_{DCC}	0.90054***	0.018524	0.88613***	0.027612
	Log. Likelihood	13,685.62		13,926.59	
Democratised banking					
	α_{DCC}	0.06529***	0.011474	0.05826***	0.01256
	β_{DCC}	0.91185***	0.018121	0.91317***	0.02191
	Log. Likelihood	13,714.86		13,922.57	

Notes: *** indicate significance at the 1 % level.

4.4. Time series dynamics of the co-movement

Using both the wavelet coherence and DCC GARCH, we can get the time series estimate of the dynamic correlation between one of the FinTech indices and one of ESG indices.[8] The time series of the dynamic correlations are shown in Fig. 3. The unconditional correlations as well as the average value of the dynamic correlation from wavelet coherence and DCC GARCH are summarized in Table 3. The unconditional correlations are higher than the average conditional correlations from both wavelet coherence and DCC GARCH for all pairs considered. Furthermore, the average dynamic (i.e., conditional) correlations are higher for DCC GARCH model compared to the wavelet coherence. This is also clear from Fig. 3 where both dynamic correlation series fluctuate but the one from the DCC GARCH is higher than that from the wavelet coherence on the average.

4.5. Frequency dynamics of the co-movement

The wavelet coherence allows us to compute the average correlation over different frequencies by averaging the correlation across time for a given frequency. The correlations over different frequencies (scales) are plotted in Fig. 4. Again, the behavior of the correlation with respect to S&P ESG index (black lines) is similar to the correlation with respect to MSCI ESG indices (red lines). It is clear from Fig. 4 that the correlation is significant for almost all frequencies except for the frequencies around 256-day. For lower frequencies like 512-day (e.g., approximately two -year frequency), the correlation increases.

4.6. Connectedness analysis

Table 4 provides the output from our connectedness analysis based on Diebold and Yilmaz (2012), which is a method used to measure the interconnectedness or spillover effects among different entities within a network. The analysis is based on a VAR (Vector Auto-regression) model and computes how much of the forecast error variance of each entity can be attributed to shocks from the other entities.

The values in the main section of the table represent the percentage of forecast error variance in each row index attributable to shocks in each column index. For example, the cell at the intersection of the S&P 500 ESG row and the Alternative finance column, the value is 13.14. This means that 13.14 % of the forecast error variance in S&P 500 ESG (row) can be attributed to shocks from Alternative finance (column). Similarly, in the intersection of the Democratised banking row and the Future payments column, the value is 22.82. This means that 22.82 % of the forecast error variance in Democratised banking is due to shocks from Future payments. The diagonal of the matrix shows how much of the index's own forecast error variance is explained by its own shocks. For example, MSCI world ESG leaders have a diagonal value of 26.23, meaning that 26.23 % of the forecast error variance in MSCI world ESG leaders is due to its own shocks.

The "FROM" row shows the total directional connectedness *from* each index to all others. The "TO" column shows the total directional connectedness *to* each index from all others. For example, S&P 500 ESG sends out 74.4 % of its shocks to others, while it receives 68.74 % of its shocks from others. Inc.Own is the proportion of the index's forecast error variance that is explained by its own shocks. The higher this number, the more self-driven the index's movements are, compared to movements driven by shocks from other indices. The values are shown as percentages of the total connectedness index (TCI). NET represents the net directional connectedness. A positive value indicates that an index is a net transmitter (sending more shocks to others than it receives), while a negative value indicates a net receiver (receiving more shocks from others than it sends). For example, S&P 500 ESG has a NET value of −5.66, suggesting it is a net receiver of shocks.(Fig. 5).

Figure shows the percentage of its forecast error variance that is attributable to shocks originating from all the other indices (corresponding to the "TO'' column in Table 4). This can be considered as a measure of how much an index is influenced by others. As can be seen the spillovers from others vary noticeably over time.

Fig. 6 presents the directional volatility spillovers from each of the six indices to others (corresponding to the "FROM'' row in Table 4). They vary greatly over time. Among the six markets, the gross volatility spillovers from the alternative finance to the others are generally smaller than the spillovers from the other five markets.

S&P 500 Index (sp) frequently shows negative NET values, indicating it often acts as a net receiver of spillovers from other indices in your dataset. Being a net receiver suggests that the S&P 500 index's movements could be more influenced by the developments in other markets or indices included in your analysis than it influences them. Alternative finance (af) predominantly has positive NET values, highlighting its role as a net transmitter of spillovers to other indices. As a net transmitter, the Alternative finance seems to exert influence on other markets. The NET values for the Future payments (fp) are more mixed but lean towards positive, indicating it often acts as a transmitter of spillovers, though not as consistently as the Alternative finance. The mixed nature of its NET values suggests that while it can influence other markets, it might also be susceptible to receiving spillovers. The democratized banking shows a tendency towards negative NET values, though not as pronounced as the S&P 500. This suggests it generally acts as a net receiver of spillovers. This receiving nature implies that democratized banking, while possibly stable and influential on their own, are still significantly affected by conditions in other markets. The MSCI Index exhibits a balance between positive and negative NET values,

[8] In fact, the wavelet coherence allows us to estimate the correlation over time as well as over different frequencies (i.e., scales). Therefore, to get the estimate of correlation over time, we average the correlations over different frequencies. This allows us to compare the dynamic correlation from wavelet coherence with that from the DCC GARCH.

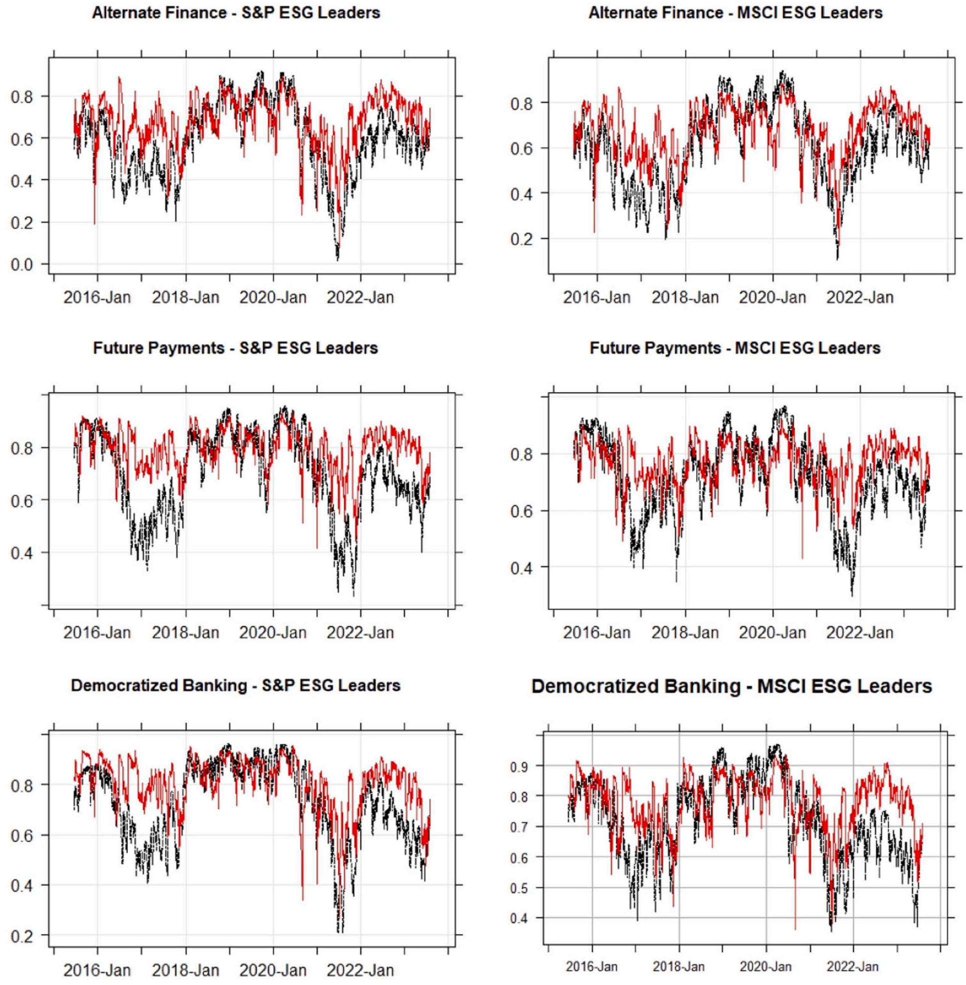

Fig. 3. Comparison of dynamic correlations from the DCC GARCH (red line) and dynamic correlations from the wavelet coherence (black line).

Table 3
Comparison of correlation coefficients by DCC GARCH and mean value of correlations obtained from Wavelet coherence analysis.

		S&P 500 ESG leaders	MSCI world ESG leaders
Alternative finance			
	Unconditional	0.74031	0.75364
	DCC	0.68533	0.67926
	Coherence	0.59337	0.60780
Future payments			
	Unconditional	0.84897	0.83905
	DCC	0.79487	0.77254
	Coherence	0.70350	0.71713
Democratised banking			
	Unconditional	0.83854	0.83140
	DCC	0.80629	0.78037
	Coherence	0.72828	0.72005

indicating a fairly balanced role as both a transmitter and receiver of spillovers.

4.7. Granger causality test

Table 5 summarizes the results from testing different lag lengths for Granger causality analysis. The model with 1 lag is likely the best balance between complexity and fit according to the AIC, HQIC, and SBIC, suggesting it should be used for our analysis.

Table 6 outlines the results of Granger causality tests between pairs of variables in our study, to identify if past values of one

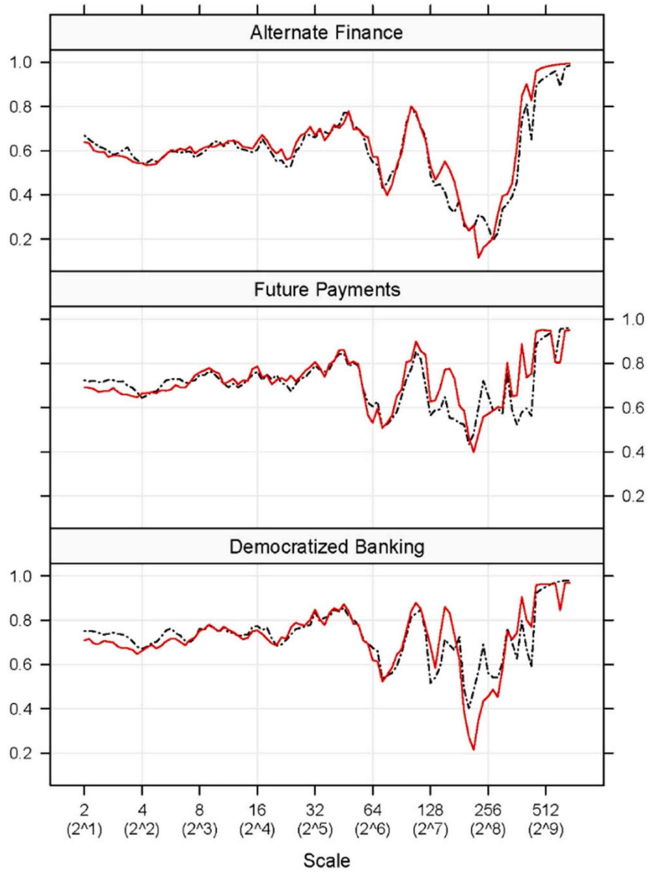

Fig. 4. Correlation between the FinTech and S&P ESG indices over different scales is represented by the black line, and the correlation between FinTech and MSCI ESG indices is represented by the red line. The scale axes are represented in logarithmic form with base 2.

Table 4
Volatility spillover results of connectedness analysis.

	S&P 500 ESG leaders	Alternative finance	Future payments	Democratised banking	MSCI world ESG leaders	FROM
S&P 500 ESG leaders	25.6	13.14	18.2	19.12	23.94	74.4
Alternative finance	13.79	32.56	15.58	23.18	14.89	67.44
Future payments	16.41	13.31	27.68	24.81	17.8	72.32
Democratised banking	15.83	18.03	22.82	26.35	16.97	73.65
MSCI world ESG leaders	22.72	13.48	18.49	19.08	26.23	73.77
TO	68.74	57.96	75.08	86.19	73.6	361.58
Inc.Own	94.34	90.52	102.76	112.54	99.83	cTCI/TCI
NET	-5.66	-9.48	2.76	12.54	-0.17	90.39/ 72.32
NPT	1	0	3	4	2	

variable (first variable in the pair) can predict future values of another variable (second variable in the pair).

For seven variable pairs, the null hypothesis of no Granger causality is rejected (p-value < 0.05). This suggests that past values of the predictor variable have a statistically significant effect on forecasting the future values of the target variable. For example, past values of S&P 500 ESG Leaders significantly predict future values of MSCI World ESG Leaders, indicating a Granger causality from S&P 500 ESG Leaders to MSCI World ESG Leaders.

For the rest of the pairs, the null hypothesis cannot be rejected (p-value ≥ 0.05). This implies that there is insufficient statistical evidence to conclude that past values of the predictor variable have a significant effect on forecasting the future values of the target variable. In other words, for these pairs, one variable does not Granger-cause the other based on the data and significance level used.

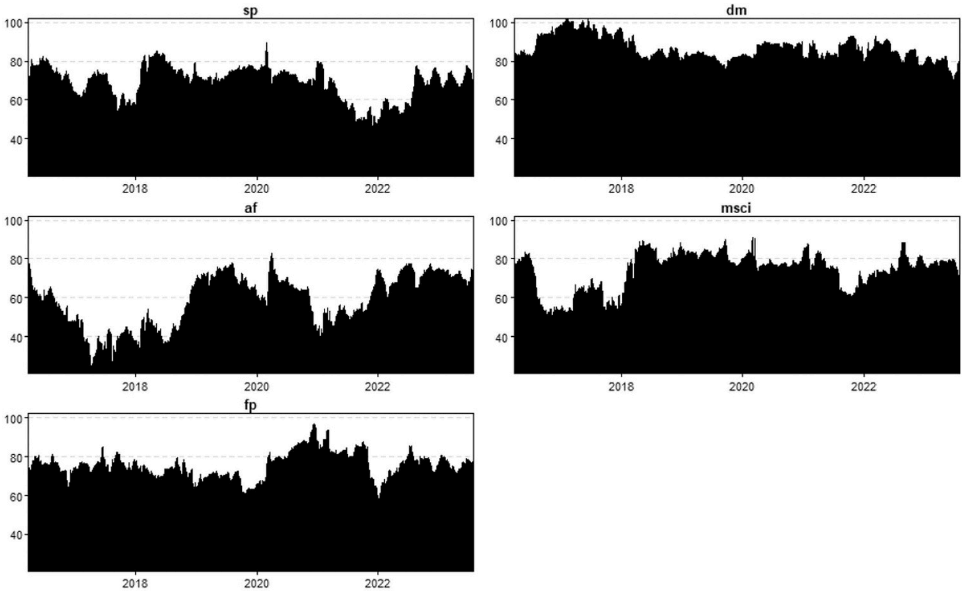

Fig. 5. Directional volatility spillovers, TO indices.

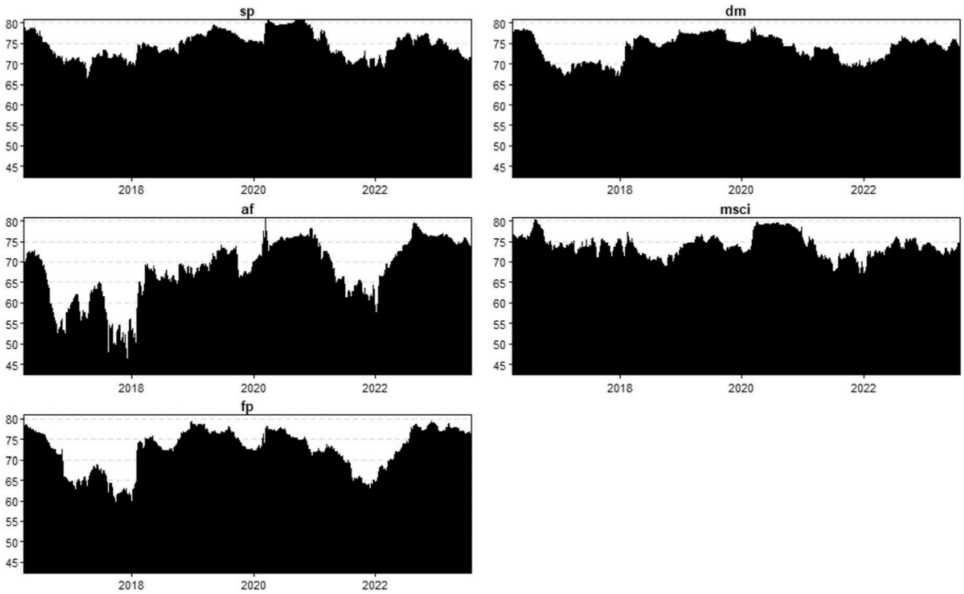

Fig. 6. Directional volatility spillovers, FROM indices.

5. Discussions

The wavelet coherence analysis conducted in this study illuminates the nuanced and dynamic interconnections between ESG and FinTech indices, echoing and extending findings from existing literature on the interplay between technological innovations in finance and sustainable investment trends. The observed periods of heightened correlation between Future Payments, Democratised Banking, and the ESG indices resonate with recent studies that highlight the growing influence of FinTech on sustainable finance. For instance, Wang et al. (2022) have discussed how FinTech development are enabling more efficient allocation of capital towards sustainable investments, thereby enhancing the ESG performance metrics. Our findings of significant coherence between these sectors could reflect this evolving landscape where technological advancements facilitate or amplify sustainable investment flows. Moreover, the directional nature of the phase differences identified in our analysis suggests both synchronous movements and varying lead-lag relationships between the indices. This is particularly relevant in light of research by Bonfanti (2023), who argue that FinTech innovations can precede shifts in investment strategies, including those oriented towards ESG criteria. Similarly, the lead-lag

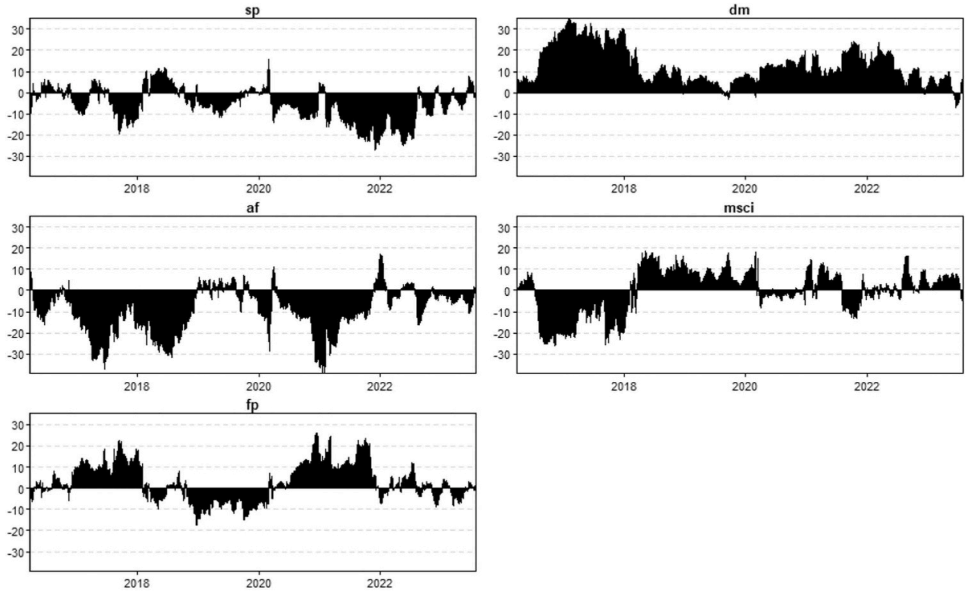

Fig. 7. Net volatility spillovers.

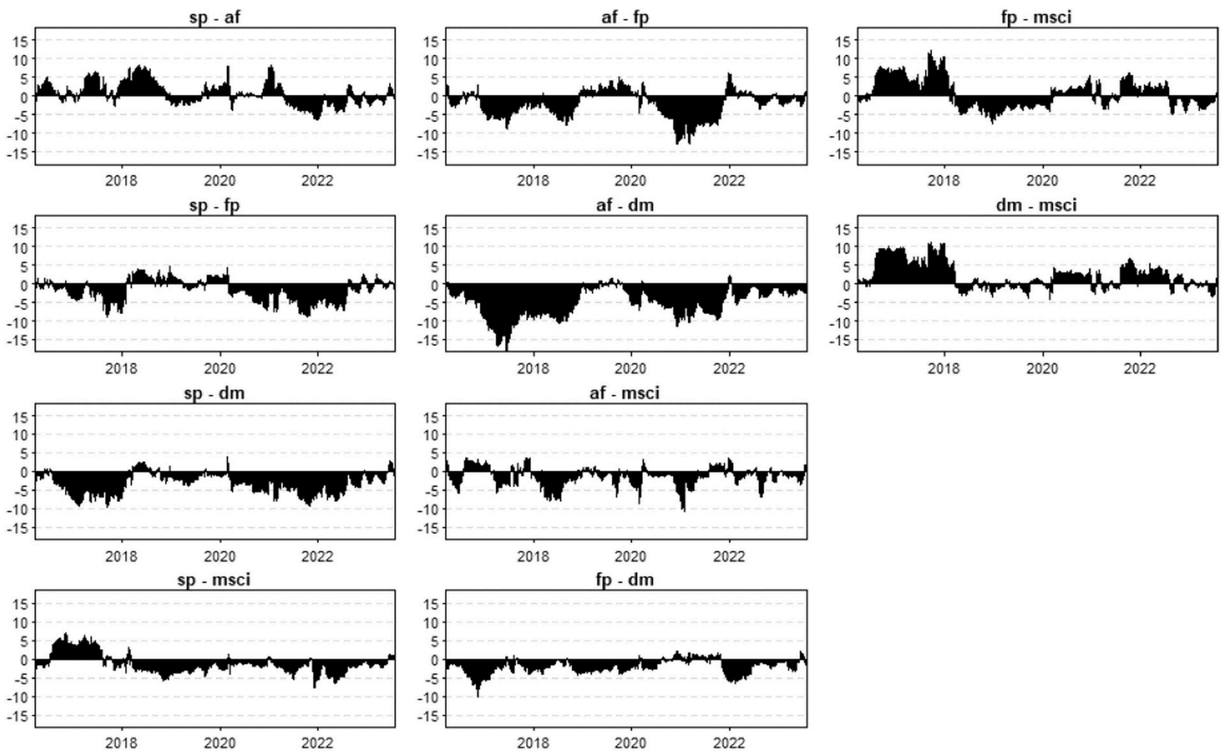

Fig. 8. Net pairwise volatility spillovers.

relationships may corroborate the findings of Galeone et al. (2024), which posit that ESG investments can influence the trajectory of technological innovation within the financial sector, as firms and investors prioritize sustainability-driven FinTech solutions. The complex interplay highlighted by our study also contributes to the discourse on market efficiency and information flow within the financial markets. The presence of both synchronous movements and lead-lag dynamics among ESG and FinTech indices suggests that information is not instantaneously or uniformly integrated into market prices, a notion supported by research on the efficiency of ESG markets (Friede et al., 2015). This could imply that, while markets are generally efficient, the assimilation of information related to

Table 5
Evaluation of optimal lag length.

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-6433.35				17.1723	17.0327	17.0445	17.0633
1	-6304.79	257.13	25	0	13.0569	16.7587	16.8294*	16.9424*
2	-6277.02	55.53*	25	0	12.9618*	16.7514*	16.8811	17.0881

Table 6
Granger causality results.

Variable Pair	Coefficient	z	P>z	Results
SP→AF	-0.31957	-1.26	0.208	Do Not Reject H0
SP→FP	0.154319	1.48	0.139	Do Not Reject H0
SP→DMB	-0.22376	-1.44	0.151	Do Not Reject H0
SP→MSCI	-0.95585	-2.01	0.044	Reject H0
AF→SP	0.03973	0.55	0.579	Do Not Reject H0
AF→FP	0.079021	2.14	0.032	Reject H0
AF→DMB	0.099355	1.95	0.049	Reject H0
AF→MSCI	-0.1266	-0.78	0.433	Do Not Reject H0
FP→SP	0.400309	1.3	0.194	Do Not Reject H0
FP→AF	-0.86538	-2.24	0.025	Reject H0
FP→DMB	-0.41535	-1.75	0.079	Do Not Reject H0
FP→MSCI	-0.95337	-1.37	0.169	Do Not Reject H0
DMB→SP	0.175969	0.72	0.472	Do Not Reject H0
DMB→AF	-0.64386	-2.1	0.035	Reject H0
DMB→FP	0.291885	2.32	0.02	Reject H0
DMB→MSCI	-0.4283	-0.78	0.437	Do Not Reject H0
MSCI→SP	0.221737	2.71	0.007	Reject H0
MSCI→AF	-0.13407	-1.29	0.197	Do Not Reject H0
MSCI→FP	0.07126	1.67	0.095	Do Not Reject H0
MSCI→DMB	-0.08968	-1.41	0.16	Do Not Reject H0

sustainability and technological innovations may occur at different rates, offering potential opportunities for informed investment decisions. Our findings underscore the importance of considering the temporal and frequency-dependent nature of correlations when analyzing the relationship between technological innovation in finance and sustainable investments. This aligns with the call by Bouri et al. (2020) for more nuanced analyses that account for the evolving dynamics between FinTech and other market indices.

The dynamic correlation analysis utilizing the DCC GARCH model, as presented in our study, significantly contributes to the literature on the evolving relationship between FinTech and ESG investment strategies. The evidence of time-varying correlations and the mean-reverting nature of these correlations between ESG and FinTech indices echo the findings of prior research while offering new insights into the stability and predictability of these relationships over time. The observation that these correlations revert to a long-term average over time contributes to the literature on financial market stability and mean-reversion processes, as discussed by Bollerslev (1986) and Engle and Kroner (1995). This mean-reverting behavior suggests an inherent stability in the relationship between ESG performance and FinTech innovations, despite the presence of short-term fluctuations. This aspect of our findings resonates with the conclusions of Adcock et al. (2012), who highlight the mean-reverting tendencies in financial markets as indicative of long-term equilibrium relationships among financial variables. Our study also dialogues with recent scholarship examining the interconnections between sustainability criteria and FinTech. For instance, Lins et al. (2017) found that firms with strong ESG profiles tend to have higher valuations and better financial performance, a dynamic that could be increasingly influenced by FinTech innovations that enhance the transparency and efficiency of ESG investing. Moreover, the mean-reverting nature of the dynamic correlations identified in our study could have implications for portfolio management and risk assessment strategies, aligning with the research agenda proposed by Hoepner et al. (2016). They advocate for more nuanced analyses of ESG criteria's role in financial decision-making, suggesting that the integration of technological innovations could significantly affect these analyses.

The results from our connectedness analysis, employing a VAR model to uncover the intricate web of interactions among ESG and FinTech indices, resonate with and extend the current body of literature on financial markets' interconnectedness and the transmission of shocks. Diebold and Yilmaz (2012) laid foundational work on measuring connectedness in financial markets, demonstrating how shocks can propagate through networks of financial assets. Our findings align with their methodological framework, offering a nuanced application to the specific context of ESG and FinTech indices. By identifying indices that serve as net transmitters or receivers of shocks, our study contributes to an understanding of the role that sustainable investment criteria and technological innovations in finance play in the broader market dynamics. Furthermore, our results echo the implications of contagion and spillover effects discussed by Forbes and Rigobon (2002), who investigated how crises and major economic events could lead to increased co-movements among international financial markets. The identification of net transmitters and receivers in our study suggests potential pathways for the propagation of financial shocks within the nexus of ESG and FinTech sectors, highlighting the importance of these sectors in financial stability and risk management strategies. Bekaert et al. (2014) explored the global financial network's architecture, emphasizing the roles of different entities in spreading or absorbing shocks. Our analysis, in a similar vein, illustrates how ESG and

FinTech indices are embedded within a network where shocks can be transmitted or buffered, further underlining the systemic importance of these emerging sectors in the financial landscape. Moreover, the dynamic nature of the connectedness among indices uncovered in our study has important implications for portfolio diversification and risk management, themes explored by Aït-Sahalia et al. (2015). The fluctuating roles of indices as shock transmitters or receivers could inform investors and policymakers about changing risk profiles and the need for adaptive strategies in response to evolving market conditions.

6. Conclusion

Given the remarkable increase in ESG investment as documented in the literature and overwhelming evidence on the implication of factors such as financial inclusion, green finance, energy efficiency, etc., for sustainable development, a potential co-movement analysis between FinTech and ESG markets from a time-series perspective has not been explored by scholars in the field. In this study, we enhance the existing body of knowledge concerning the co-movement between FinTech and ESG markets. Our contribution involves investigating how their elements are interconnected within the time-frequency domain. What sets our methodology apart is the examination of their correlation within the time-frequency domain, a novel approach that contrasts with traditional econometric techniques used to analyze market relationships.

Using daily data from June 15, 2015, to August 1, 2023, on three FinTech indices, namely (i) Alternate Finance, (ii) Future Payments and (iii) Democratized Banking, and two ESG indices, namely (i) S&P ESG and (ii) MSCI ESG leaders indices, we perform wavelet coherence analysis. We find that the two FinTech indices (Future Payments and Democratized Banking) are positively correlated with both ESG indices for a significantly large number of dates and frequencies. There also exists a positive correlation relation between Alternate Finance and both ESG indices but to a lesser extent. In terms of the lead/lag relationship, we find a bi-directional relationship between FinTech and ESG indices depending on dates and frequencies without one set of indices dominating the other.

For robustness and comparison purposes, we also estimate multivariate dynamic constant correlation generalized autoregressive conditional heteroscedasticity (DCC GARCH) models taking a pair of indices, one from the three FinTech indices and one from the two ESG indices, at a time. We find that all the DCC GARCH processes are mean-reverting. We also find that the unconditional correlation is higher than the average conditional correlations from both wavelet coherence and DCC GARCH model for all pairs considered. The average conditional correlations are higher for DCC GARCH model compared to the wavelet coherence. Both of these conditional correlations vary over time, with the correlation based on the DCC GARCH model being higher than the one based on wavelet coherence on average.

Finally, the wavelet coherence analysis allows us to compute the average correlation over different frequencies by averaging the correlation across time. We find the behavior of correlation to be similar when using the S&P ESG index compared to MSCI ESG index. The correlations are significant for almost all frequencies except for the 256-day frequency. For the lower frequencies, e.g., 512-day (approximately 2-year frequency), the correlation increases.

We expand the existing body of research on several fronts. We investigate the non-linear relationship across different timeframes, which act as proxies for distinct investment periods. This examination unveils whether the intensity of interconnectedness varies over different frequencies. Additionally, we employ a wavelet coherence decomposition to separate the return patterns into various investment periods. Furthermore, we utilize DCC-GARCH returns to offer a comprehensive overview of causality while considering the influence of volatility and heteroscedasticity in the two-way connections. These findings will significantly impact the formulation of portfolio and hedging strategies for investors. Moreover, for regulatory bodies, it emphasizes the necessity of effective interventions in FinTech policies to support the growth of ESG initiatives. Subsequent studies could expand upon our findings by employing different methodologies and assessing how incorporating these investments in a portfolio selection context could affect the framework. Future research can also look into the implications of the Covid-19 pandemic on the dynamic between these two markets.

CRediT authorship contribution statement

Keshab Shrestha: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Babak Naysary:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

References

Abraham, F., Schmukler, S.L., Tessada, J., 2019. Robo-Advisors: Investing through Machines.

Adcock, C.J., Cortez, M.C., Armada, M.J.R., Silva, F., 2012. Time varying betas and the unconditional distribution of asset returns. Quant. Financ. *12* (6), 951–967. https://doi.org/10.1080/14697688.2010.544667.

Aït-Sahalia, Y., Cacho-Diaz, J., Laeven, R.J.A., 2015. Modeling financial contagion using mutually exciting jump processes. J. Financ. Econ. *117* (3), 585–606. https://doi.org/10.1016/j.jfineco.2015.03.002.

Alshater, M.M., Polat, O., El Khoury, R., Yoon, S.M., 2024. Dynamic connectedness among regional FinTech indices in times of turbulences. Appl. Econ. Lett. *31* (7), 670–675. https://doi.org/10.1080/13504851.2022.2141443.

Andersson, E., Hoque, M., Rahman, M.L., Uddin, G.S., Jayasekera, R., 2022. ESG investment: what do we learn from its interaction with stock, currency and commodity markets? Int. J. Financ. Econ. *27* (3), 3623–3639. https://doi.org/10.1002/ijfe.2341.

Anshari, M., Almunawar, M.N., Masri, M., Hamdan, M., 2019. Digital marketplace and FinTech to support agriculture sustainability. Energy Procedia *156* (2018), 234–238. https://doi.org/10.1016/j.egypro.2018.11.134.

Arner, D.W., Buckley, R.P., Zetzsche, D.A., Veidt, R., 2020. Sustainability, FinTech and financial inclusion. Eur. Bus. Organ. Law Rev. *21* (1), 7–35. https://doi.org/10.1007/s40804-020-00183-y.

Awais, M., Afzal, A., Firdousi, S., Hasnaoui, A., 2023. Is FinTech the new path to sustainable resource utilisation and economic development? Resour. Policy *81* (2022), 103309. https://doi.org/10.1016/j.resourpol.2023.103309.

Bartlett, R., Morse, A., Stanton, R., Wallace, N., 2018. Consumer-Lending Discrimination in the Era of FinTech.

Bekaert, G., Ehrmann, M., Fratzscher, M., Mehl, A., 2014. The global crisis and equity market contagion. J. Financ. *69* (6), 2597–2649. https://doi.org/10.1111/jofi.12203.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econ. *31* (3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1.

Bonfanti, N. (2023). Esg-Driven Innovation in the Fintech Industry. (August). ⟨https://doi.org/10.13140/RG.2.2.26951.47525⟩.

Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L., Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. Q. Rev. Econ. Financ. *77*, 156–164. https://doi.org/10.1016/j.qref.2020.03.004.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. *28* (1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econ. Stat. *20* (3), 339–350. https://doi.org/10.1198/073500102288618487.

Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econom. Theory *11* (1), 122–150. https://doi.org/10.1017/S0266466600009063.

Forbes, K.J., Rigobon, R., 2002. No contagion, only interdependence: measuring stock market comovements. J. Financ. *57* (5), 2223–2261. https://doi.org/10.1111/0022-1082.00494.

Friede, G., Busch, T., Bassen, A., 2015. ESG and financial performance: aggregated evidence from more than 2000 empirical studies. J. Sustain. Financ. Invest. *5* (4), 210–233. https://doi.org/10.1080/20430795.2015.1118917.

Galeone, G., Ranaldo, S., Fusco, A., 2024. ESG and FinTech: are they connected? Res. Int. Bus. Financ. *69* (December 2023), 102225 https://doi.org/10.1016/j.ribaf.2024.102225.

Glass, L.-M., Newig, J., 2019. Governance for achieving the sustainable development goals: how important are participation, policy coherence, reflexivity, adaptation and democratic institutions? Earth Syst. Gov. *2*, 100031 https://doi.org/10.1016/j.esg.2019.100031.

Grinsted, A., Moore, J., Jevrejeva, S., 2004. Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Process. Geophys. *11* (4), 515–533. https://doi.org/10.5194/npg-11-515-2004.

Guang-Wen, Z., Siddik, A.B., 2023. The effect of Fintech adoption on green finance and environmental performance of banking institutions during the COVID-19 pandemic: the role of green innovation. Environ. Sci. Pollut. Res. *30* (10), 25959–25971. https://doi.org/10.1007/s11356-022-23956-z.

Hoepner, A., Oikonomou, I., Scholtens, B., Schröder, M., 2016. The effects of corporate and country sustainability characteristics on the cost of debt: an international investigation. J. Bus. Financ. Account. *43* (1-2), 158–190. https://doi.org/10.1111/jbfa.12183.

Huo, D., Zhang, X., Meng, S., Wu, G., Li, J., Di, R., 2022. Green finance and energy efficiency: dynamic study of the spatial externality of institutional support in a digital economy by using hidden Markov chain. Energy Econ. *116* (October), 106431 https://doi.org/10.1016/j.eneco.2022.106431.

Ibrahim, M., Vo, X.V., 2021. Exploring the relationships among innovation, financial sector development and environmental pollution in selected industrialized countries. J. Environ. Manag. *284* (February)), 112057 https://doi.org/10.1016/j.jenvman.2021.112057.

Iqbal, N., Umar, Z., Ruman, A.M., Jiang, S., 2024. The term structure of yield curve and connectedness among ESG investments. Res. Int. Bus. Financ. *67* (PA)), 102145 https://doi.org/10.1016/j.ribaf.2023.102145.

Jagtiani, J., & Lemieux, C. (2017). Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information. ⟨https://www.fdic.gov/bank/analytical/cfr/bank-research-conference/annual-17th/papers/14-jagtiani.pdf⟩.

Jenik, I., Timothy, L., & Nava, A. (2017). Crowdfunding and Financial Inclusion. *Cgap (Working Paper)(March)*.

Jiang, B., 2023. Does fintech promote the sustainable development of renewable energy enterprises? Environ. Sci. Pollut. Res. *30* (24), 65141–65148. https://doi.org/10.1007/s11356-023-27030-0.

Kilic, Y., Destek, M.A., Cevik, E.I., Bugan, M.F., Korkmaz, O., Dibooglu, S., 2022. Return and risk spillovers between the ESG global index and stock markets: evidence from time and frequency analysis. Borsa Istanb. Rev. *22*, S141–S156. https://doi.org/10.1016/j.bir.2022.11.015.

Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. J. Financ. *72* (4), 1785–1824. https://doi.org/10.1111/jofi.12505.

Lisha, L., Mousa, S., Arnone, G., Muda, I., Huerta-Soto, R., Shiming, Z., 2023. Natural resources, green innovation, fintech, and sustainability: a fresh insight from BRICS. Resour. Policy *80* (October 2022), 103119. https://doi.org/10.1016/j.resourpol.2022.103119.

Liu, H., Yao, P., Latif, S., Aslam, S., Iqbal, N., 2022. Impact of green financing, FinTech, and financial inclusion on energy efficiency. Environ. Sci. Pollut. Res. *29* (13), 18955–18966. https://doi.org/10.1007/s11356-021-16949-x.

Lv, Z., Iqbal, R., Chang, V., 2018. Big data analytics for sustainability. Future Gener. Comput. Syst. *86*, 1238–1241. https://doi.org/10.1016/j.future.2018.05.020.

Meiling, L., Yahya, F., Waqas, M., Shaohua, Z., Ali, S.A., Hania, A., 2021. Boosting sustainability in healthcare sector through fintech: analyzing the moderating role of financial and ICT development. Inq. (U. S. *58* https://doi.org/10.1177/00469580211028174.

Merello, P., Barberá, A., la Poza, E.D., 2022. Is the sustainability profile of FinTech companies a key driver of their value? Technol. Forecast. Soc. Change *174* (May 2021). https://doi.org/10.1016/j.techfore.2021.121290.

Mhlanga, D., 2022. The role of financial inclusion and FinTech in addressing climate-related challenges in the industry 4.0: Lessons for sustainable development goals. Front. Clim. 1–18.

Mirza, N., Umar, M., Afzal, A., Firdousi, S.F., 2023. The role of fintech in promoting green finance, and profitability: evidence from the banking sector in the euro zone. Econ. Anal. Policy *78*, 33–40. https://doi.org/10.1016/j.eap.2023.02.001.

Mousa, M., Saleem, A., Sági, J., 2022. Are esg shares a safe haven during covid-19? Evidence from the arab region. Sustain. (Switz.) *14* (1). https://doi.org/10.3390/su14010208.

Moyer, J.D., Hedden, S., 2020. Are we on the right path to achieve the sustainable development goals? World Dev. *127* https://doi.org/10.1016/j.worlddev.2019.104749.

Muganyi, T., Yan, L., Sun, H. p, 2021. Green finance, FinTech and environmental protection: Evidence from China. Environ. Sci. Ecotechnology *7*, 100107. https://doi.org/10.1016/j.ese.2021.100107.

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. *381* (P1)), 135196 https://doi.org/10.1016/j.jclepro.2022.135196.

Nicolai, S., Hoy, C., Bhatkal, T., Aedy, T.(2016). Projecting progress: The SDGs in sub-Saharan Africa⟨https://www.odi.org/sites/odi.org.uk/files/resource-documents/10486.pdf⟩.
Özdemir, O., 2022. Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. Financ. Innov. *8* (1) https://doi.org/10.1186/s40854-021-00319-0.
Ozili, P.K., 2018. Impact of digital finance on financial inclusion and stability. Borsa Istanb. Rev. *18* (4), 329–340. https://doi.org/10.1016/j.bir.2017.12.003.
Qin, L., Aziz, G., Wasim, M., Qadeer, A., Sarwar, S., 2024. Empirical evidence of fintech and green environment: Using the green finance as a mediating variable. Int. Rev. Econ. Financ. *89* (PA), 33–49. https://doi.org/10.1016/j.iref.2023.07.056.
Rafiuddin, A., Gaytan, J.C.T., Mohnot, R., Sisodia, G.S., Ahmed, G., 2023. Growth evaluation of fintech connectedness with innovative thematic indices – an evidence through wavelet analysis. J. Open Innov.: Technol., Mark., Complex. *9* (2), 100023 https://doi.org/10.1016/j.joitmc.2023.100023.
Rubbaniy, G., Khalid, A.A., Rizwan, M.F., Ali, S., 2022. Are ESG stocks safe-haven during COVID-19? Stud. Econ. Financ. *39* (2), 239–255. https://doi.org/10.1108/SEF-08-2021-0320.
Sachs, J., Kroll, C., Lafortune, G., Fuller, G., Woelm, F.Sustainable Development Report 2022. https://doi.org/10.1017/9781009210058.
Salampasis, D., Mention, A.L., 2018. FinTech: Harnessing Innovation for Financial Inclusion (1 ed., Vol. 2). Elsevier Inc. https://doi.org/10.1016/B978-0-12-812282-2.00018-8.
Salvia, A.L., Leal Filho, W., Brandli, L.L., Griebeler, J.S., 2019. Assessing research trends related to Sustainable Development Goals: local and global issues. J. Clean. Prod. *208*, 841–849. https://doi.org/10.1016/j.jclepro.2018.09.242.
Sanchís, C.E., Gubareva, M., 2024. ESG rating changes and portfolio returns: a wavelet analysis across market caps. Financ. Res. Lett. *63*, 105306 https://doi.org/10.1016/j.frl.2024.105306.
Schwinn, R., Teo, E.G.S., 2018. Inclusion or Exclusion? Trends in Robo-advisory for Financial Investment Services (1 ed., Vol. 2). Elsevier Inc. https://doi.org/10.1016/B978-0-12-812282-2.00021-8.
Senyo, P.K., Osabutey, E.L.C., 2020. Technovation Unearthing antecedents to financial inclusion through FinTech innovations. Technovation, 102155. https://doi.org/10.1016/j.technovation.2020.102155.
Setiawan, B., Afin, R., Wikurendra, E.A., Nathan, R.J., Fekete-Farkas, M., 2022. Covid-19 pandemic, asset prices, risks, and their convergence: a survey of Islamic and G7 stock market, and alternative assets. Borsa Istanb. Rev. *22*, S47–S59. https://doi.org/10.1016/j.bir.2022.11.011.
Shaban, M., Girardone, C.G., Sarkisyan, A., 2019. Financial Inclusion: Trends and Determinants. Palgrave Macmillan, Cham, pp. 119–136. https://doi.org/10.1007/978-3-030-16295-5.
Shaik, M., Rehman, M.Z., 2023. The dynamic volatility connectedness of major environmental, social, and governance (ESG) stock indices: evidence based on DCC-GARCH model. Asia-Pac. Financ. Mark. *30* (1), 231–246. https://doi.org/10.1007/s10690-022-09393-5.
Shrestha, K., Naysary, B., Philip, S.S.S., 2023. Fintech market efficiency: A multifractal detrended fluctuation analysis. Fin. Res. Lett. 54, 103775.
Soni, G., Kumar, S., Mahto, R.V., Mangla, S.K., Mittal, M.L., Lim, W.M., 2022. A decision-making framework for Industry 4.0 technology implementation: the case of FinTech and sustainable supply chain finance for SMEs. Technol. Forecast. Soc. Change *180* (2021), 121686. https://doi.org/10.1016/j.techfore.2022.121686.
Taera, E.G., Setiawan, B., Saleem, A., Wahyuni, A.S., Chang, D.K.S., Nathan, R.J., Lakner, Z., 2023. The impact of Covid-19 and Russia–Ukraine war on the financial asset volatility: evidence from equity, cryptocurrency and alternative assets. J. Open Innov.: Technol. Mark. Complex. *9* (3) https://doi.org/10.1016/j.joitmc.2023.100116.
Tay, L.Y., Tai, H.T., Tan, G.S., 2022. Digital financial inclusion: a gateway to sustainable development. Heliyon *8* (6), e09766. https://doi.org/10.1016/j.heliyon.2022.e09766.
Teng, M., Shen, M., 2023. Fintech and energy efficiency: evidence from OECD countries. Resour. Policy *82* (January), 103550. https://doi.org/10.1016/j.resourpol.2023.103550.
Torrence, C., Compo, G.P., 1998. A practical guide to wavelet analysis. Bull. Am. Meteorol. Soc. *79* (1), 61–78. https://doi.org/10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2.
Udeagha, M.C., Muchapondwa, E., 2023a. Green finance, fintech, and environmental sustainability: fresh policy insights from the BRICS nations. Int. J. Sustain. Dev. World Ecol. *00* (00), 1–17. https://doi.org/10.1080/13504509.2023.2183526.
Udeagha, M.C., Muchapondwa, E., 2023b. Striving for the United Nations (UN) sustainable development goals (SDGs) in BRICS economies: the role of green finance, fintech, and natural resource rent. *Sustain. Dev.*(Dec. 2022) 1–16. https://doi.org/10.1002/sd.2618.
Ullah, A., Ullah, S., Pinglu, C., Khan, S., 2023. Impact of FinTech, governance and environmental taxes on energy transition: pre-post COVID-19 analysis of belt and road initiative countries. Resour. Policy *85* (PA)), 103734. https://doi.org/10.1016/j.resourpol.2023.103734.
Umar, Z., Gubareva, M., 2021. The relationship between the Covid-19 media coverage and the Environmental, Social and Governance leaders equity volatility: a time-frequency wavelet analysis. Appl. Econ. *53* (27), 3193–3206. https://doi.org/10.1080/00036846.2021.1877252.
Vacha, L., Barunik, J., 2012. Co-movement of energy commodities revisited: evidence from wavelet coherence analysis. Energy Econ. *34* (1), 241–247. https://doi.org/10.1016/j.eneco.2011.10.007.
Wan, J., Yin, L., Wu, Y., 2024. Return and volatility connectedness across global ESG stock indexes: evidence from the time-frequency domain analysis. Int. Rev. Econ. Financ. *89* (PB), 397–428. https://doi.org/10.1016/j.iref.2023.10.038.
Wang, D., Peng, K., Tang, K., Wu, Y., 2022. Does FinTech development enhance corporate ESG performance? Evidence from an Emerging Market. Sustain. (Switz.) *14* (24), 1–21. https://doi.org/10.3390/su142416597.
Zhang, W., He, X., Hamori, S., 2022. Volatility spillover and investment strategies among sustainability-related financial indexes: evidence from the DCC-GARCH-based dynamic connectedness and DCC-GARCH t-copula approach. Int. Rev. Financ. Anal. *83* (January), 102223 https://doi.org/10.1016/j.irfa.2022.102223.
Zhang, Y., Chen, J., Han, Y., Qian, M., Guo, X., Chen, R., Xu, D., Chen, Y., 2021. The contribution of Fintech to sustainable development in the digital age: ant forest and land restoration in China. Land Use Policy *103* (January)), 1–9. https://doi.org/10.1016/j.landusepol.2021.105306.
Zhou, G., Zhu, J., Luo, S., 2022. The impact of fintech innovation on green growth in China: mediating effect of green finance. Ecol. Econ. *193*, 107308 https://doi.org/10.1016/j.ecolecon.2021.107308.