Dynamic Connectedness between Fintech Applications, Carbon Emission and Carbon Pricing

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Abstract

Climate change poses significant challenges for environmental sustainability and societal well-being. The integration of technology into finance has led to the development of innovative fintech applications that can effectively address environmental challenges. This study aims to examine the dynamic connections among fintech applications, carbon emissions, and carbon pricing. Using the Time-Varying Parameter VAR-based dynamic connectedness model, the study investigates the time-varying associations among robo-advisors, crowdfunding, green cryptocurrencies, carbon emissions, and carbon pricing. The study uses the daily frequency data from 2018 to 2022. The results show that the fintech applications, particularly robo-advisory and crowdfunding, are significantly interconnected in a network with carbon emissions and carbon pricing.

Keywords: Fintech, Robo-Advisory, Crowdfunding, Green Cryptocurrencies, Carbon Emission, Carbon Pricing.

Introduction

As the danger of climate change become apparent, the financial system has begun to integrate sustainability preferences into its core financial and investment decisions (Michie, 2022). In particular, advancements in financial technologies are increasingly play an important role in addressing environmental challanges (Teng & Shen, 2023). Though Fintech itself is not a climate change solution, it supports environmental well-being by mobilising private capital towards sustainable investments and by advancing real-time emissions measurement and carbon pricing mechanisms. Moreover, through operationally efficient and decentralised processes, Fintech reduces carbon footprints and supports environmental sustainability. Digitalisation, particularly digital payments, digital operations, and automated platforms, has reduced the need for cash-based transactions, physical interaction, and the establishment of office branches. This reduces the energy consumption and carbon emissions from printing, transportation, and workspace occupancy (Kuosuwan et al., 2024). Moreover, several digital platforms allow investors and firms to track and review the carbon footprint information of financial transactions (Alabi, 2025). Real-time emission accounting and automated ESG reporting improve the regularity and pricing of carbon emissions (Li et al., 2025).

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Modern fintech platforms, from Robo-advisory to sustainable crowdfunding and from blockchain to green cryptocurrencies, all consider environmental concerns while offering investment and financial services. In particular, Robo-advisors, sustainable crowdfunding, and green cryptocurrencies have effectively incorporated the climate concerns into their financial and investment services (Lamba & Transformation, 2022; Maehle et al., 2021; Shan et al., 2022). Considering the growing role of Fintech in reducing carbon footprints and improving carbon pricing mechanisms, this study aims to investigate the time-varying linkages of Fintech applications, particularly robo-advisors, crowdfunding, and green cryptocurrencies, with carbon emission and carbon pricing. A robo-advisor is an AI-driven digital financial advisor that provides automated advice on investing and portfolio management. It functions as an expert system specifically designed for financial services, using algorithms and data analysis to deliver personalised recommendations (Zhang et al., 2021). Moreover, with the rise of social and environmental consciousness among investors and an increase in the volume of sustainable investments, robo-advisors are increasingly offering socially responsible investment (SRI) portfolios (SustainFi, 2021). Robo-advisors are taking SRI a step ahead by offering tailored portfolios for socially responsible investors. Crowdfunding is a way to raise money from a large number of people to finance businesses and projects through an online platform. It is generally executed through crowdfunding platforms that connect fundraisers and funders online to raise funds for a particular project or campaign (Belleflamme et al., 2015). Crowdfunding is an appropriate source of financing for green and renewable investments (Lam et al., 2016). It enables sustainable projects to acquire private funds from a broader investor base without relying on traditional intermediaries. Especially, green crowdfunding enables investors to access sustainable investment options with easy access to information and quick subscription processes. Cryptocurrency is a type of currency accessible only in electronic form (Härdle et al., 2020). Like traditional currencies, digital currencies are used as a medium of exchange for goods and services (Baur, Hong, Lee, & Money, 2018). Green cryptocurrencies use environmentally friendly technologies to reduce energy requirements and carbon footprint. Most energy-efficient cryptocurrencies prioritise sustainability to address investors' climate concerns (Brooke, 2023).

The results exhibit that Robo-advisory, crowdfunding, and green cryptocurrencies are significantly connected in a network with greenhouse gas emissions and Carbon pricing. Robo-advisory and crowdfunding, in particular, are leading contributors to the network, highlighting the importance of integrating financial technology with environmental concerns. The carbon Emissions and carbon emission futures prices are more responsive to Robo-advisory and Crowdfunding in the network.

Literature Review

Robo-advisors

Robo-advisors integrate advanced technologies, including machine learning and data mining, to offer financial planning and investment services. Robo-advisors gather client information regarding clients' investment preferences, financial position, investment timeline, risk tolerance, and so forth through internet-based digital surveys, and process client data in light of market information using deep learning algorithms to tailor advice on investment and portfolio management. The growing sustainability preferences among young investors (Sachs, 2012) have increased demand for impact investment options and prompted Robo-advisors to begin offering sustainable portfolios comprising shares of companies with a positive environmental and social impact (Faradynawati & Söderberg, 2022).

Crowdfunding

Crowdfunding is a method of raising capital by collecting small contributions from a large number of individuals via online platforms to support business projects. Crowdfunding platforms are web applications that enable fundraisers to interact with and raise money from the crowd worldwide. It is a collective effort of a large number of people who collaborate to pool their resources to achieve a certain goal (Donelli et al., 2022). Startup companies and small and medium enterprises SMEs often engage in crowdfunding as an alternate source of funds. These platforms enable small projects to access private funding from a large investor base without relying on traditional intermediaries (Bonzanini et al., 2016).

Cryptocurrencies

Cryptocurrency is a type of currency that exists only in electronic form and has no physical existence (Härdle et al., 2020). Like traditional currencies, digital currencies can be used as a medium of exchange for goods and services (Baur et al., 2018). They require Computers and electronic wallets connected to the designated networks to make transactions (Tarasova et al., 2020). They enable instant transactions that can be executed impeccably across the globe. Nowadays, many energy-efficient cryptocurrencies prioritise environmental sustainability to attract a larger audience of potential investors (Brooke, 2023). These cryptocurrencies are known as green cryptocurrencies and are specially designed to support pro-environmental projects and sustainable initiatives (Lobão, 2022).

Greenhouse Gas Emissions

Greenhouse gas emissions are the release of carbon dioxide and other harmful gases into the atmosphere, primarily from the combustion of fossil fuels such as coal, crude oil, and natural gas. Carbon dioxide (CO2) emissions are a major contributor to air pollution and have been linked to climate change, as excess CO2 in the atmosphere traps heat, leading to rising temperatures and other climate changes. According to the Intergovernmental Panel on Climate Change (IPCC), CO2 emissions from human activities, primarily the burning of fossil fuels in the industrial and transportation sectors, have increased the atmospheric CO2 concentration by 40% since the pre-industrial era (IPCC, 2013).

Carbon Pricing

Carbon pricing is a policy that charges a fee for polluting the atmosphere, from individual, public, and corporate operations, to limit greenhouse gas emissions. It sets a price on carbon emissions to shift the cost of polluting the environment from society to the individuals and firms directly involved in emitting carbon gases (Boyce, 2018). This restricts emitters to either limit emissions or pay a price for the adverse environmental effects they cause. There are several forms of carbon pricing. The most common forms are the carbon tax and the cap-and-trade system. A carbon tax sets a price on each ton of greenhouse gas emissions, while a cap-and-trade system grants a certain number of emissions allowances and allows their buying and selling (Goulder & Schein, 2013).

Methodology

Data and Sample

The study employs the daily frequency data of five years from 2018 to 2022. The high-frequency data for the study variables are obtained from multiple online repositories, including DataStream, CoinMarketCap, and the U.S. Securities and Exchange Commission.

Study Variables, Their Measurement, and Source

Table 1: Variables, Index Selection, and Data Source

Variable	Index Selection	Description	Data Source
Robo-advisory	The AI-Powered US Equity Index	AIPEX is the first and only rules-based equity strategy that leverages IBM Watson to transform data into actionable investment insights.	HSBC
Crowdfunding	Peer-to-Peer Lending and Equity Crowdfunding Index	This reflects the peer-to-peer lending and equity crowdfunding sector by monitoring the price and total return performance of companies.	Solactive
Green Cryptos	Value-Weighted Index of 10 Green Cryptocurrencies	Value-Weighted Index of cryptocurrencies	CoinMarketCap
Carbon Emission	Daily CO2 Emission	U.S. Aggregate National CO2 Emission	U.S. Environmental Protection Agency
Carbon Pricing	Carbon Emission Futures Prices	Carbon Emission Futures Prices	Datastream

Time-Varying Parameter VARs-based Dynamic Connectedness

The study employs the Time-Varying Parameter VARs-based dynamic connectedness approach of Antonakakis, Chatziantoniou, Gabauer, and Management (2020) to investigate the interconnectedness between fintech and carbon markets. The precise description of Antonakakis et al. (2020)'s method is as follows.

First, the Time-varying VAR(p) model with m variables is defined as;

$$z_t = A_t z_{t-1} + u_t \qquad u_t \sim N(0, S_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \tag{2}$$

where, z_t, $z_{t-1}$and u_t is a dimensional vector of $k \times 1$, whereas A_t and $S_t$are dimensional matrices of $k \times k$. $vec(A_t)$ and v_t are dimensions vector $k^2 \times 1$, and $R_t$is a dimensional matrix of $k^2 \times k^2$. Next, the TVP-VAR is transformed to TVP-VMA based on the world presentation theorem to estimate the generalized forecast error variance decomposition (GFEVD). The process is illustrated below,

$$\emptyset^g_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}(t_i' A_t S_t t_j)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}(t_i A_t S_t A_t' t_i)} \qquad \tilde{\emptyset}^g_{ij,t}(H) = \frac{\emptyset^g_{ij,t}(H)}{\sum_{j=1}^{k}\emptyset^g_{ij,t}(H)} \tag{3}$$

Where, $\sum_{j=1}^{k}\tilde{\emptyset}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k}\tilde{\emptyset}^g_{ij,t}(H) = k$, t_i equal to a vector with unity on the ith position or 0 otherwise. Based on GFEVD, we derived the following connectedness measures:

$$TO_{jt} = \sum_{i=1,1\neq j}^{k}\tilde{\emptyset}^g_{ij,t}(H) \tag{4}$$

Where, $\tilde{\emptyset}^g_{ij,t}(H)$ represent the impact of change in variable j on variable i. Thus, Equation 4 illustrates the impact of changes in asset j on other assets and practices, which is called directional connectedness to others.

$$FROM_{jt} = \sum_{i=1,1\neq j}^{k}\tilde{\emptyset}^g_{ji,t}(H) \tag{5}$$

Equation 5 illustrates the effect of all other assets on asset j, which is called directional connectedness from others.

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{6}$$

Equation 6 illustrates the net directional connectedness by subtracting the influence of asset j on others from the effect on others from asset j. This explains whether an asset is a net receiver or transmitter of shocks.

$$\mathrm{TCI_t} = \mathrm{k}^{-1} \sum_{j=1}^{k} \mathrm{TO_{jt}} \equiv \mathrm{k}^{-1} \sum_{j=1}^{k} \mathrm{FROM_{jt}} \tag{7}$$

Equation 7 illustrates the average influence of one asset on all the other assets, which is called the total connectedness index.

$$\mathrm{NPDC}_{ij,t} = \emptyset^{g}_{ij,t}(\mathrm{H}) - \emptyset^{g}_{ji,t}(\mathrm{H}) \tag{8}$$

Equation 8 presents the net pairwise directional connectedness that shows the bilateral connectedness between asset j and i and provides information on whether asset j drives i or asset i drives j.

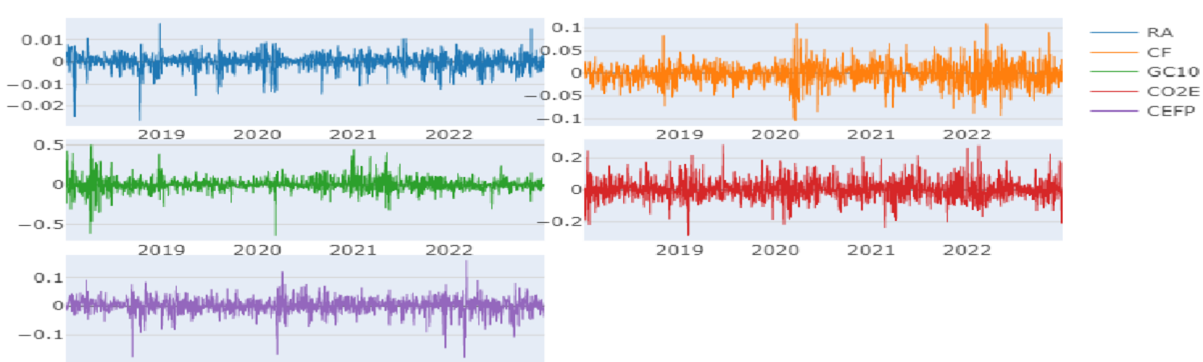
Results and Discussion

Time Series Plots of Fintech Applications, Carbon Emissions, and Carbon Pricing

Figure 1 shows the time series plots of study variables, including Robo-Advisory (RA), Crowdfunding (CF), Green Cryptocurrencies (GC10), Carbon Emissions (CO2E), and Carbon Emissions Future Pricing (CEFP), for the period from 2018 to 2022. These plots highlight the dynamic evolution and variability of each variable during the study period. The blue line (RA) shows moderate fluctuations throughout the study period, with small and consistent peaks and troughs. The orange line (CF) shows more noticeable variations, with a broader range of values and significant peaks, largely around 2020. The green line (GC10) shows a noticeable variability, with significant fluctuation around early 2018 and 2021. The red line (CO2E) shows sharp and frequent spikes throughout the study period. The purple line (CEFP) shows noticeable fluctuations with noticeable peaks and troughs throughout the study period.

This figure illustrates the different levels of fluctuations in the study variables RA, CF, GC10, CO2E, and CEFP across the study period from 2018 to 2022. The CF, GC10, CO2E, and CEFP exhibit high volatility, while RA remains relatively stable over the study period.

Figure 1: Time series plots of Fintech Applications and Carbon Market variables



This figure illustrates the time-series plots of robo-advisors (blue line), crowdfunding (orange line), green cryptocurrencies (green line), carbon emission (red line), and carbon emission futures pricing (purple line).

Summary Statistics

Table 2 presents the summary statistics for robo-advisors, crowdfunding, green cryptocurrencies, carbon emissions, and carbon emission futures prices.

Table 2 Summary Statistics of Fintech Applications, Carbon Emissions, and Carbon Pricing

	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(10)	Q2(10)
RA	0.000	0.000	-0.950***	4.464***	1227.755***	-5.442***	4.99	125.450***
CF	-0.001	0.001	-0.082	1.728***	157.201***	-16.523***	12.981**	329.605***
GC10	0.000	0.008	-0.197***	7.522***	2959.351***	-7.214***	41.516***	155.053***
CO2E	-0.001	0.004	0.274***	1.921***	208.196***	-12.200***	64.942***	33.582***
CEFP	0.002	0.001	-0.607***	4.497***	1132.007***	-16.690***	21.544***	104.584***

The table illustrates the summary statistics of RA, CF, GC10, CE, and CEFP. ***, **, and * represent the level of significance at 1 %, 5% and 10% level.

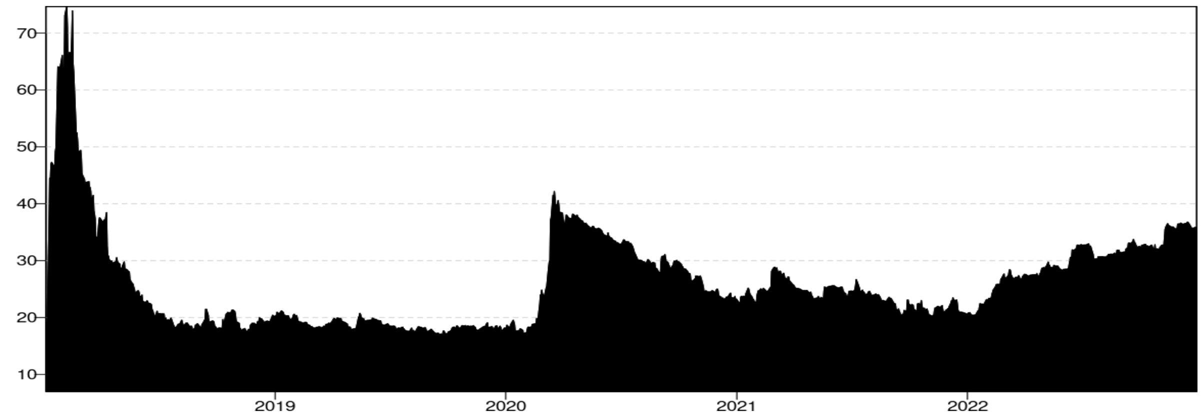
The arithmetic mean of all the study variables, RA, CF, GC, CO2E, and CEFP, is close to zero. The variance of GC10 (0.008) is the highest among all validating cryptos as the most volatile digital asset. The CF shows moderate variance (0.001), while the remaining variables, RA, GC10, CO2E, and CEFP, show very low variance. The skewness test exhibits that only carbon emissions exhibit right skewness, while all other variables show left skewness. The excess kurtosis test indicates that all variables have significant positive kurtosis. This indicates that all the distributions of all these variables have fat tails. The significant ERS statistics for all variables indicated that all the variable series are stationary, and their statistical properties, like mean and variance, remain consistent over the study period. The Q(10) statistic shows that, except for RA, all variables exhibit significant autocorrelation. This indicates that for each variable, past values explain the future ones. Moreover, the $Q^2(10)$ statistic shows a significant heteroskedasticity in all study variables.

Dynamic Total Connectedness

Figure 2 exhibits the dynamic total connectedness of fintech applications and carbon markets from 2018 to 2022. The x-axis shows the time period from 2018 to 2022. The y-axis shows the level of total connectedness. The figure shows that the total interconnectedness among the study variables starts at around 70% in early 2018 but slowly decreases to its lowest point of 20% towards the late 2018. The total connectedness remains low throughout 2019 and suddenly rises to around 40% in early 2020. Then gradually decline throughout 2020 and 21 and remain low until early 2022. The total connectedness gradually increases again from early 2022 and reaches 35% by the end. The gradual increase toward late 2022 indicates reemerging interconnectedness, possibly due to increased adoption of technologies and economic recovery after the COVID-19 pandemic.

Moreover, the sharp spike in the total connectedness index around early 2020 shows the impact of the COVID-19 Pandemic on the global market, that cause financial assets to move more together. On the other hand, gradual declines in the connectedness index reflect periods where the effects of these shocks decrease, causing decreased spillovers among the study variables. The sharp rise followed by a gradual decline in total connectedness indicates that interdependence among Fintech and Environmental Initiatives increases in response to market shocks and then gradually declines as markets stabilize. However, the steady increase in total connectedness during 2022 might suggest a period of steady interdependence, potentially reflecting increased reliance on information technology and greater global integration as a result of the post-COVID recovery.

Figure 2: Dynamic Total Connectedness of Fintech and Environmental Initiatives



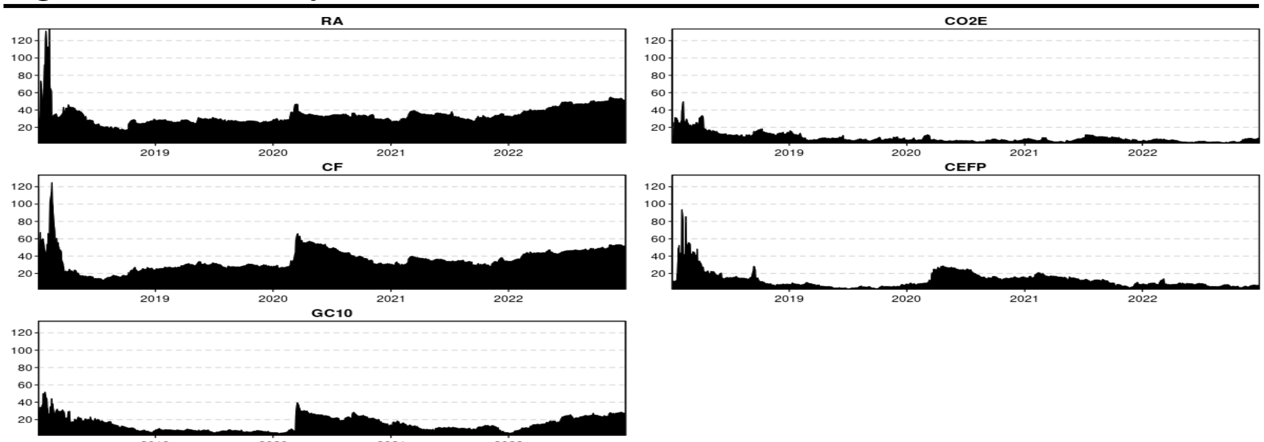
This figure shows the Dynamic Total Connectedness of Fintech Applications and Environmental Initiatives.

To others Dynamic Connectedness

Figure 3 illustrates the "To Others" dynamic connectedness measures for each study variable, including RA, CF, GC, CO2E, and CEFP. "To Others" here refers to the extent to which each variable contributes to affecting the other variables in the network over the period from 2018 to 2022.

The top-left plot shows that Robo-advisory exhibits a high level of influence on other variables in early 2018, with a connectedness level close to 120. This influence decreased abruptly and remained stable around 20 to 40 till 2020 and onwards. From early 2022, the influence slightly increased towards the end of 2022. The slight and steady increase in influence is likely due to post-pandemic recovery and extensive adoption of financial technologies.

Figure 3: To Others Dynamic Connectedness of Fintech and Environmental Initiatives



This figure exhibits the "To Other" dynamic connectedness for the study variables.

The middle-left plot illustrates that Crowdfunding shows a high level of influence in early 2018 with a connectedness level of around 100, which then declines abruptly and stabilizes between 20 and 40 till 2020. In early 2020, a significant increase in influence is visible with a connectedness level close to 60, and again gradually reduced and remained stable till late 2021. The influence again gradually increases towards 2022, suggesting that CF is becoming more interconnected with other variables, likely due to the growing importance of alternative financing during post COVID-19 market recovery.

The bottom-left plot exhibits that the GC10's influence on other variables starts at around 40% in early 2018 and declines gradually to around 10% and remains low until a sharp spike around early 2020. The spike gradually declined towards late 2021 and then a gradual increase towards 2022. The influence of GC10 remains relatively low but shows a slow upward trend towards the end of the study period.

The top-right plot shows that carbon emissions exert a low influence on other variables throughout the study period, with an initial spike that declines and remains stabilized at a low level below 20%. This indicates that the influence of CE on other variables is consistently low throughout the study period from 2018 to 2022. The middle-right plot illustrates that Carbon Emission Future Prices show a moderate influence on other variables at the start, which rapidly decrease and remain low at around 10%.

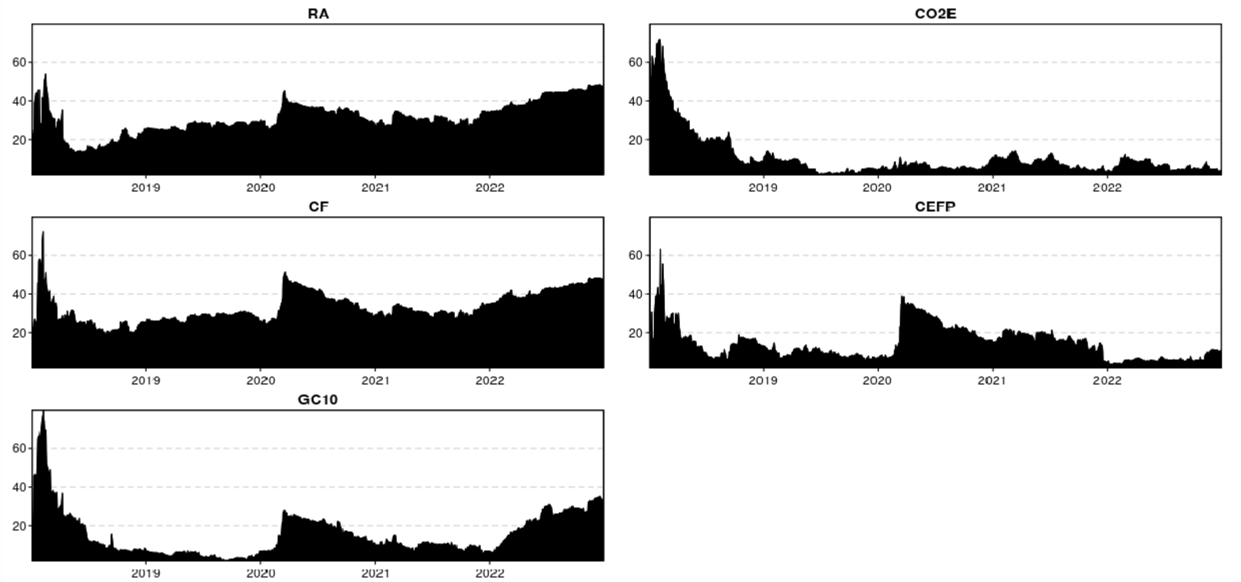
"To Other" dynamic connectedness plots illustrate that RA and CF have a stronger influence on other variables, particularly during market stress, while CO2E and CEFP show relatively low influence on other variables. Moreover, the significant spikes around early 2020 indicate how global crises, like the COVID-19 pandemic, intervene in the level of influence of one variable exerted on others in the system.

From others Dynamic Connectedness

Figure 4 presents the "From Others" dynamic connectedness plots for each study variable, including RA, CF, GC, CO2E, and CEFP. "From Others" here refers to how much each variable is influenced by other study variables in the network over the period from 2018 to 2022. Each plot in Figure 4.4 indicates the extent to which each variable receives influence from other variables in the network.

The top-left plot shows that Robo-advisory is significantly influenced by other variables at the start of 2018, with a connectedness level above 40. This influence declines and stabilizes around 20-30 till 2020. In early 2020, the influence rose abruptly to above 40 and then declined gradually towards the end of 2021. From 2021, it steadily increases towards the end of 2022. This indicates that, except for the initial spikes and bump around 2020, RA is increasingly becoming responsive to all other variables in the network. The middle-left plot exhibits that Crowdfunding receives strong influence from other variables initially in early 20i8, but later declines and stabilizes around 30% towards late 2019. Afterward, it resurged abruptly around early 2020, then declined gradually around 2021, with a significant recovery towards the end of 2022. The bottom-left plot demonstrates that Green Cryptocurrencies have become highly reactive to other variables in the network initially, but decline sharply and remain low till the end of 2019. The influence increased abruptly in early 2020, then declined gradually around 2021, with a significant recovery towards the end of 2022. The fluctuating responsiveness of GC10 to other variables during market stress highlights that it is a highly sensitive digital asset.

Figure 4: From Others' Dynamic Connectedness of Fintech and Environmental Initiatives



This figure exhibits “from other” dynamic connectedness for the above 5 variables.

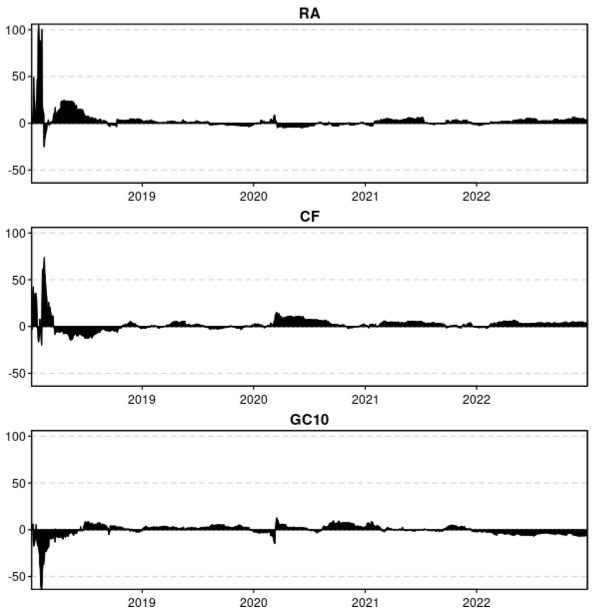
The top-right plot (CO2E) initially exhibits a strong influence from other variables, which decreases sharply around late 2018 and remains low towards the end of 2022. This shows that carbon emissions become less responsive during the COVID-19 pandemic. The middle-right plot (CEFP) takes a strong influence from other variables initially, but declined sharply and remained low until 2019. The influence reemerges sharply from early 2020 to around 30% and again declines gradually and stabilizes by 2022. The sharp increase around 2020 suggests that during periods of the COVID-19 pandemic, the carbon futures received strong influence from the fintech applications.

“From other” plots jointly illustrate that each variable receives a fluctuating degree of influence from the other variables in the network over the study period. RA and CF receive a relatively high level of influence from other variables, while GC10, CO2E, and CEFP receive a relatively moderate or low level of influence from other variables in the network.

Net Total Directional Connectedness

Figure 5 presents the net total directional connectedness plots for each variable, including RA, CF, GC, CO2E, and CEFP. These plots illustrate how each variable influences or is influenced by other variables over the study period.

Figure 5: Net Total Directional Connectedness of Fintech and Environmental Initiatives



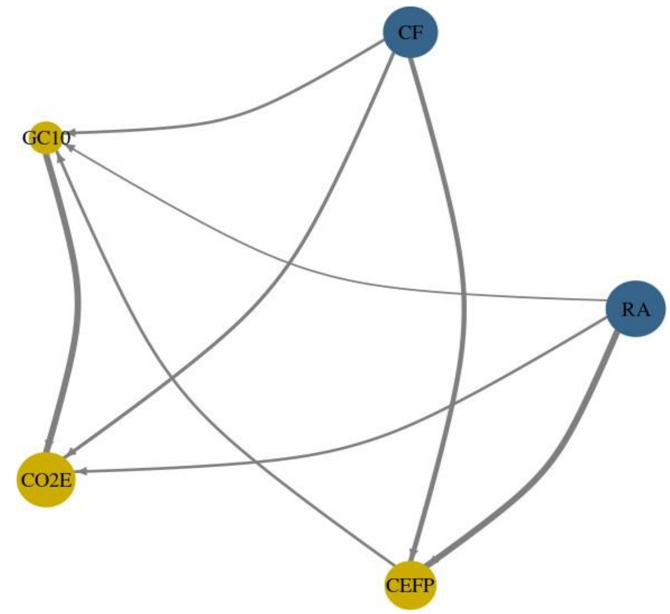
This figure illustrates the net total directional connectedness for RA, CF, GC10, CO2E, and CEFP. The X-axis shows the timeline from 2018 to 2022. The Y-axis represents the values of net directional connectedness.

The top-left plot (RA) shows a sharp fluctuation during 2018 and stabilizes after 2019, around close to zero. Initially, RA plays a volatile role within a network, but as the market matures, the RA becomes stable, transmitting influence more often than it receives from other variables in the network. The middle-left plot (CF) shows sharp fluctuation around zero, with positive trends initially and then shifting to negative around mid-2018. It turns positive again in 2019, and remains positive till 2022. The CF initially shifts between the contributor and receiver of influence, but after 2020, it became a transmitter of influence within the network. The bottom-left plot (GC10) starts with significant negative spikes and switches to positive around mid-2018 and remains stabilized close to zero towards 2021. After 2022, it shifts and remains negative towards the end. The top-right plot (CO2E) shows a negative spike initially, then turns positive around late 2018. From 2019, CO2E stabilizes and remains around zero throughout the study period. This suggests that CO2 emissions neither consistently contribute to the network nor are significantly driven by the system in the long run. The middle-right plot (CEFP) shows some noticeable fluctuations initially around the first half of 2018, but later stabilizes and remains close to zero with more negative deviation throughout the study period. In this later phase, the CEFP acts as a net receiver of influence from other variables in the network. This highlights the times when carbon pricing is more reactive to fintech applications.

Network Plot

Figure 6 illustrates the interconnections between the study variables, including RA, CF, GC10, CO2E, and CEFP. The blue and yellow nodes represent variables and their respective roles in the network. The direction of the arrows represents the direction of the connection, and the thickness of the arrows represents the strength of the connection. The blue nodes denote the dominant variables in the network. The blue nodes RA and CF are highly influential and are more interconnected with other nodes like CEFP, CO2E, and GC10 in the network. The yellow nodes GC10, CO2E, and CEFP also show noticeable interconnections within a network. The direction of the arrows signifies that RA and CF transmit the influence to GC10, CO2E, and CEFP. The figure shows that RA and CF are the major transmitters of the influence in the network, and GC10, CO2E, and CEFP are the receivers of the influence. Overall, this network plot shows a highly interconnected system where robo-advisory and crowdfunding are strongly connected to carbon emissions and carbon emission future pricing.

Figure 6: Network Plot of Fintech and Environmental Initiatives



This figure illustrates the network plot of RA, CF, GC10, CO2E, and CEFP.

Average Dynamic Connectedness

Table 3 shows a summary of the average dynamic connectedness among the study variables. The row headers denote the 'From Other' dynamic connectedness. It shows the percentage variance that each variable receives from the other variables in the network. For instance, the first-row header RA shows that the 31.29% variance in Robo-advisory is explained by other variables in the network, including 22.83% from CF, 4.25% from GC10, 1.9% from CO2E, and 2.30% from CEFP. The column headers denote the 'To Other' dynamic connectedness. It shows the percentage influence passed on by one variable to others in the network. For instance, the first column header RA accounted for a total of 34.05% variation in the other variables in the network, including 23.09% in CF, 4.69% in GC10, 2.55% in CO2E, and 3.72% in CEFP. The diagonal values show the proportion of variance in each variable that is explained by that variable. For instance, a value of 68.71 for robo-advisory indicates that 68.71% of the variance in RA is attributed to its own shocks. Similarly, 67.0 for Crowdfunding shows that 67.0% of the variance in CF is due to its own shocks. For GC10, the value is 84.71; for CO2E, 89.70; and for CEFP, 85.80. The final column header, FROM, denotes the proportion of each variable's variance explained by all other variables in the network. For example, the FROM value for RA is 31.29, indicating that 31.29% of the variance in RA is jointly explained by all the other variables in the network. Similarly, for CF, 33% of the variance in crowdfunding is explained by all the other variables in the network combined. For GC10, 15.29% of the variance in Green Cryptocurrencies is explained by RA, CF, CO2E, and CEFP. The FROM value for CO2E is 10.30, indicating that 10.3% of carbon emissions are explained by RA, CF, GC10, and CEFP. For CEFP, 14.20% of CEFP is explained by other variables in the network.

Table 3: Average Dynamic Connectedness among RA, CF, GC10, CO2E, and CEPF

	RA	CF	GC10	CO2E	CEFP	FROM
RA	68.71	22.83	4.25	1.90	2.30	31.29
CF	23.09	67.00	4.56	1.50	3.84	33.00
GC10	4.69	5.23	84.71	1.70	3.66	15.29
CO2E	2.55	2.29	3.08	89.70	2.38	10.30
CEFP	3.72	4.92	3.00	2.56	85.80	14.20
TO	34.05	35.27	14.90	7.66	12.19	104.07
Inc.Own	102.76	102.27	99.61	97.36	98.00	cTCI/TCI
NET	2.76	2.27	-0.39	-2.64	-2.00	26.02/20.81
NPT	4.00	3.00	1.00	1.00	1.00	

This table presents a summary of the average dynamic connectedness among RA, CF, GC10, Co2E, and CEFP.

On the other hand, the row header TO indicates the extent to which each variable transmits influence to all other variables within the network collectively. For instance, RA (34.05) contributes 34.05% to the variation of other variables in the network. Similarly, the TO values for CF (35.27), GC10 (14.90), CO2E (7.66), and CEFP (12.19) indicate the percentage contribution each variable makes to the change in all other variables within the network. The row header Including Own (Inc.Own) shows the total contribution each variable makes within a network, including the influence it exerts on itself. For example, RA (102.76) indicates the sum of the contribution it makes to change other variables, as well as itself. Similarly, Including Own values for CF (102.27), GC10 (99.61), CO2E (97.36), and CEFP (98.0) shows the total influence each variable contributes to other variables and to itself. The row header NET represents the net total directional connectedness, calculated as the difference between TO and FROM values for each variable. Positive NET values indicate that a variable acts as a net transmitter of influence, like RA (2.76) and CF (2.27). In contrast, negative NET values indicate that a variable acts as a net receiver of influence, such as CO2E (-2.64) and CEFP (-2.0). The row header NPT stands for net pairwise transmission, which ranks variables based on their net pairwise directional connectedness, ranging from 1 to 4. The rank 4 represents the most contributing variable in the network. The lower ranks reflect relatively low contributing variables in the network. The NPT values of RA are 4, and CF is 3, which shows that both RA and CF are the most contributing variables in the network. The NPT value of GC10, CO2E, and CEFP is 1, which shows that these are the least contributing variables in the network.

The cTCI/TCI ratio shows the proportion of the conditional total connectedness index (cTCI) to the total connectedness index (TCI). The conditional total connectedness index (cTCI) represents the spillovers within a specific subset of variables under certain conditions within the network. On the other hand, the total connectedness index TCI represents the overall spillovers among all variables in the network. The cTCI/TCI ratio (26.02/20.81) shows that the conditional total connectedness (cTCI) surpasses the total connectedness (TCI) by around 25%. This suggests that in the specific subsets of variables or under specific conditions, the network exhibits stronger connectivity among study variables than the overall connectivity observed across the entire system. The higher value of cTCI during the study period is substantially attributed to the significant structural disruptions of the COVID-19 pandemic, which accelerated the adoption of fintech applications. As a result, these applications reshape how organizations and communities approach environmental challenges.

The TVP-VAR dynamic connectedness results show that robo-advisors, crowdfunding, and green cryptocurrencies are structurally connected in a network with carbon emissions and Carbon Emission Futures Prices. Robo-advisors and crowdfunding evolve as net transmitters of influence, while carbon emission and carbon emission future prices act as net receivers of influence within the network. In line with Cheng et al. (2023), these results highlight the crucial role of Fintech applications like Robo-advisors and crowdfunding in addressing increasing carbon footprints and environmental issues. The enormous capability of Robo-advisors in prioritizing sustainability and integrating climate concerns into regular financial and investment decisions has made digital advisory an important factor in achieving environmental sustainability. Similarly, the evolving role of crowdfunding in mobilizing private capital towards sustainable projects highlighted the effective role of alternative finance in decarbonization and achieving environmental goals. These results support the findings of Appiah et al. (2025) and Shan et al. (2022).

Conclusion

Climate change poses significant challenges with complex consequences for environmental sustainability and societal well-being. Government and private institutions are working collectively to address the potential adversaries of climate change. As a part of global efforts, the financial system plays a crucial role in mitigating environmental hazards and promoting sustainability. The integration of technology into finance has led to the development of innovative fintech applications that effectively address environmental challenges. Although Fintech is not a direct solution to environmental challenges, it plays an important role in addressing these challenges by mobilizing private capital to sustainable investments, by improving emission measurements, and carbon pricing mechanisms (Wan et al., 2025). The study empirically investigates the dynamic connectedness of Fintech applications, with carbon emissions, and carbon emission futures prices. The results show that the fintech applicants are structurally connected in a network with carbon emissions and Carbon Emission Futures Prices. In particular, Robo-advisors and crowdfunding evolve as net transmitters of influence, while carbon emission and carbon emission future prices act as net receivers of influence within the network. These results suggest that, if the potential of fintech applications such as Robo-advisors and crowdfunding platforms is optimally utilized, they can significantly support decarbonization efforts and enhance the effectiveness of carbon pricing mechanisms. Moreover, the transition of interrelationships from unstable to more stable and balance relationship towards the later phase suggests that with the passage of time, fintech is becoming increasingly integrated with carbon markets, where fintech applications like Robo-advisory and crowdfunding play a crucial role in real-time emission accounting and regularization of carbon pricing (Li et al., 2025).

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