

Time-frequency dependence between fintech and development of carbon neutrality under climate policy uncertainty in China: implications for the ocean carbon sink market

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Zhenhua Qin

Department of Finance, Ocean University of China, Qingdao, China, and

Xiao-Lin Li

School of Economics, Ocean University of China, Qingdao, China

Abstract

Purpose – This paper explores whether fintech paves the way for the transition to carbon neutrality in the context of China’s climate policy uncertainty (CCPU) and the influence of the ocean carbon sink market.

Design/methodology/approach – We apply a novel wavelet analysis technique to investigate the time-frequency dependence between the CCPU index, the CSI (China Securities Index) Fintech Theme Index (CFTI) and the Carbon Neutral Concept Index (CNCI).

Findings – The empirical results show that CCPU and CFTI have a detrimental effect on CNCI in high-frequency bands. Furthermore, in low-frequency domains, the development of CFTI can effectively promote the realization of carbon neutrality.

Practical implications – Our findings show that information from the CCPU and CFTI can be utilized to forecast the movement of CNCI. Therefore, the government should strike a balance between fintech development and environmental regulation and, hence, promote the use of renewable energy to reduce carbon emissions, facilitating the orderly and regular development of the ocean carbon sink market.

Originality/value – The development of high-quality fintech and positive climate policy reforms are crucial for achieving carbon neutrality targets and promoting the growth of the marine carbon sink market.

Keywords Fintech, Climate policy uncertainty, Carbon neutrality, Ocean carbon sink market, Wavelet analysis

Paper type Research paper

1. Introduction

Achieving the “Dual Carbon” goal requires a broad systemic approach and is vital to building a community with a shared future. Scholars generally agree that two main ways to achieve this goal are reducing carbon emissions and increasing carbon sinks. According to a report by the United Nations Environment Programme (UNEP) titled “Blue Carbon: The Role of Healthy Oceans in Binding Carbon—A Rapid Response Assessment,” about 93% of the world’s carbon is stored and recycled in marine ecosystems, which play a significant role in



filtering water sources, reducing seawater pollution and mitigating extreme climate impacts. However, due to the devastating destruction of human production and life in recent years, the rate of disappearance of “Blue Carbon” has increased sharply, and the development of the marine carbon sink market has been dramatically restricted. Numerous studies have shown that the role and status of marine carbon sinks in ecosystems are underestimated, and the ocean’s unique carbon sink mechanism and efficient carbon sink capacity are often better than terrestrial carbon sinks. Therefore, it is of great significance to vigorously develop the marine carbon sink market to achieve the goal of carbon neutrality.

Carbon neutrality refers to achieving net-zero carbon emissions, which can be accomplished through new energy sources, energy conservation and emission reduction (Auffhammer, 2018; Hu *et al.*, 2021). Cryptocurrency has emerged as a significant product of financial technology (Fintech), reducing the dependence of financial transactions on intermediaries and promoting digital economy growth. However, the environmental impact of cryptocurrency mining’s high electricity consumption cannot be ignored (Jiang *et al.*, 2021). The increased carbon emissions from mining processes contribute to global warming, creating an unprecedented obstacle to long-term economic progress in several countries (Difffenbaugh and Burke, 2019; Pástor *et al.*, 2021). In response to climate change and sustainable growth challenges, Chinese authorities have proposed achieving carbon neutrality by 2060.

International debates on climate change have been ongoing for over 2 decades, and governments worldwide have taken critical legislative steps to address the issue (Lee and Chen, 2020; Sun *et al.*, 2021). The Paris Agreement, which came into effect in November 2016, is a significant milestone that has strengthened the global response to climate change and provided a new framework for climate policy. This initiative aims to cut carbon dioxide (CO₂) emissions and prevent climate change to keep the global temperature under 2°C within this century. The Paris Agreement supports using clean energy, carbon emission allowances and green bonds to achieve this goal.

Despite significant progress in climate policy implementation, uncertainties still exist. For instance, the US withdrawal from the Paris Agreement in 2017 has created significant uncertainty regarding the execution of climate policies, which might have far-reaching consequences for the macroeconomy and the carbon neutrality target (Wang *et al.*, 2019; Lee *et al.*, 2021; Su *et al.*, 2021a, b; Wen *et al.*, 2022). Furthermore, emerging economies that are rapidly industrializing confront trade-offs between climate governance and economic development. Most countries develop their economy at the expense of the environment under the old rough development paradigm (Khan *et al.*, 2022). It should not be surprising that greenhouse gas (GHG) emissions increased during this period. According to the Global Energy Review 2021 released by the International Energy Agency (IEA), the total GHG emissions 2021 will reach a new high of 33.0 billion tons of carbon dioxide equivalent (GtCO₂E). This report also notes that more than two-thirds of global CO₂ emissions come from developing countries and emerging economies.

Over the past 2 decades, China has experienced the highest rate of economic expansion and energy consumption as a prominent country among the emerging economies. Since the energy structure in the past was dominated by coal (Su *et al.*, 2021a, b), the annual GHG emissions in China accounted for 27% points of the total global GHG emissions in 2019. For the first time, this proportion exceeded the total emissions of the Organization for Economic Cooperation and Development (OECD) [1]. Based on the above background, China has already committed to peaking its CO₂ emissions by 2030 and achieving the carbon neutrality target by 2060 (Wang *et al.*, 2019). At the same time, policymakers enact various climate measures and climate policy implementation is uncertain.

The economic and environmental impacts of climate policy uncertainty have been noted in recent research (Monasterolo *et al.*, 2019; Barnett *et al.*, 2020, 2021; Chen *et al.*, 2021;

Chenet *et al.*, 2021; Fried *et al.*, 2021; Hansen, 2022). Previous studies have considered policy uncertainty, especially economic policy uncertainty (EPU), as a critical factor that influences carbon neutrality (Jiang *et al.*, 2021; Abbasi *et al.*, 2021; Zhang *et al.*, 2021; Liu and Zhang, 2022; Nakhli *et al.*, 2022; Shabir *et al.*, 2022). In addition, Gavriilidis (2021) also starts to study the impact of uncertainty caused by climate policy. Notably, based on the novel concept of carbon neutrality, a Carbon Neutral Concept Index (CNCI) is constructed by the Wind Economic Database of China that includes information on companies regarding new energy sources, energy conservation and environmental protection. It has been proven that ocean carbon sinks can greatly promote energy conservation and emission reduction, thereby facilitating the achievement of carbon neutrality goals (Chen *et al.*, 2024), which means the ocean carbon sink market also has a certain impact on the CNCI. Based on these facts, in the current paper, we apply a novel wavelet analysis method to empirically explore whether Fintech paves the way for the transition to carbon neutrality, as well as the influence of China's climate policy uncertainty, in data from July 2017 to December 2021, thus filling the gap in the existing studies. The empirical results are as follows: first, CCPU has a significantly negative effect on CNCI at a high frequency from 4Q-2018 to 1Q-2019 and 2Q-2021 to 3Q-2021, and the impact of improving environmental degradation has become more positive at low frequencies from 1Q-2019 to 2Q-2020. Second, the influence of CFTI on CNCI is also affirmed to be positive at a low frequency from 1Q-2019 to 3Q-2020. Third, CFTI also has shown a significant negative impact on CNCI in high-frequency and middle-frequency bands.

The main marginal contributions of our study to the literature are as follows. First, there is a consensus that innovation is conducive to achieving carbon neutrality (Umar *et al.*, 2020). However, studies concerning the role of financial innovation on the CNCI are still scant in China, and we expand on relevant research and provides evidence from China for this purpose. Further, we have incorporated the ocean carbon sink market into our research, providing certain theoretical insights for the development of the ocean carbon sink market. Second, CCPU-related research is still in its infancy, and the current paper pays attention to the impact of CCPU on carbon-neutral stock prices, which helps the future development of the carbon-neutral market and further promotes research in this field. Finally, we employ a novel partial wavelet analysis method to reveal the time and frequency effects of the concerned variables on the CNCI. The time and frequency analysis we use can enrich our understanding of the determinants of carbon neutrality, and these research results will provide some insights on how to adjust policy arrangements to achieve China's 2060 carbon neutrality target.

The remaining sections of this paper are organized as follows. The related literature is included in Section 2. Section 3 provides the empirical methods as well as the data sources. Section 4 reports the empirical findings. Section 5 concludes with the conclusions and implications.

2. Literature review

Previous research has argued whether Fintech innovations or financial development paved the way for the transition to carbon neutrality. Moreover, in recent years, due to Baker *et al.* (2016) releasing the new metric policy uncertainty index, researchers have also concentrated on the influence of policy uncertainty on CO₂ emissions. Therefore, to gain insight into how each factor affects the achievement of carbon neutrality, a literature review on each topic is undertaken as follows.

2.1 Financial development and carbon emissions

In the literature, financial development plays a vital role in the determinants of CO₂ emissions. A growing body of studies has captured the relationship between financial development and

carbon emissions at the regional and country levels. Scholars have extensively used different methodologies and periods to uncover the underlying nexus. However, the empirical results in the existing studies are mixed.

The first part of the literature shows that financial development positively impacts carbon emissions. For instance, [Shahbaz et al. \(2020\)](#) investigated the effect of financial development on carbon emissions using historical data spanning from 1870 to 2017 for the UK by employing a novel ARDL approach and found that financial development has a positive impact on CO₂ emissions in the long term. [Wang et al. \(2020\)](#) used the augmented mean group analysis method to detect the dynamic effect of financial development on CO₂ emissions from 1990 to 2017 in N-11 countries. Their empirical outcomes reveal a positive relationship between financial development and carbon emissions. [Yin et al. \(2019\)](#) also found that financial development leads to more emissions by using city-level data over the period 2007–2014 in China and applying the seemingly unrelated regression (SUR) model. The positive effect of financial development on CO₂ emissions can also be found in [Cetin and Ibrahim \(2020\)](#), [Kayani et al. \(2020\)](#) and [Shoaib et al. \(2020\)](#).

Different from the above point of view, other scholars have concluded that financial development harms carbon emissions. For example, [Shahbaz et al. \(2018\)](#) investigated the influence of financial development on carbon emissions in France using data from 1955 to 2016. Their findings suggested that financial development can reduce French carbon emissions. Moreover, [Umar et al. \(2020\)](#) applied the wavelet analysis method to estimate the causal relationship between financial development and carbon emissions in China. Using annual data from 1971 to 2018, their empirical findings revealed that there are negative correlations between financial development and CO₂ emissions in the long term. Likewise, [Zhao and Yang \(2020\)](#) used the static panel analysis method to investigate the impact of financial development on CO₂ emissions in China. Their findings showed a significant and negative impact of financial development on CO₂ emissions in most Chinese provinces. The negative effect of financial development on CO₂ emissions can also be found in [Shahbaz et al. \(2021\)](#).

Despite the confirmation from previous studies that financial development can have significant positive or negative impacts on CO₂ emissions, there is evidence contradicting this claim. For instance, [Bekhet et al. \(2017\)](#) applied an autoregressive distributed lag (ARDL) approach to investigate the impact of financial development on CO₂ emissions in Gulf Cooperation Council (GCC) countries and found no significant relationship between carbon emissions and financial development. [Acheampong et al. \(2020\)](#) also examined the effect of financial market development on CO₂ emissions intensity in 83 countries using annual data from 1980 to 2015 and found no direct impact on CO₂ emission intensity. Similarly, [Koshta et al. \(2020\)](#) used the case of 12 emerging economies to explore the causal relationship between CO₂ emissions, GDP, financial development, agriculture value-added, foreign trade and renewable and nonrenewable energy consumption for the period 1990 to 2014, and they found that financial development did not have a statistically significant impact on CO₂ emissions. The same research team also investigated the causal relationship between financial development and carbon emissions in those 12 emerging economies and found that financial development had no statistically significant impact on carbon emissions between 1990 and 2014. These findings are consistent with the research conducted by [Nasreen and Anwar \(2015\)](#), [Ehigiamusoe and Lean \(2019\)](#) and [Acheampong et al. \(2020\)](#).

2.2 Policy uncertainty and carbon emissions

The economic impact of policy uncertainty has been extensively studied since [Baker et al. \(2016\)](#) proposed the EPU index. In recent years, as climate issues have intensified, several studies have explored the environmental consequences of policy uncertainty shocks

(Adams *et al.*, 2020; Abbasi *et al.*, 2021; Gavriilidis, 2021; Zhang *et al.*, 2021; Liu and Zhang, 2022; Nakhli *et al.*, 2022; Shabir *et al.*, 2022; Xue *et al.*, 2022). However, the conclusions drawn from the literature are inconsistent.

Some researchers have claimed that increasing policy uncertainty may lead to serious environmental aggravation. In this regard, by applying a novel parametric Granger causality test, Jiang *et al.* (2021) pointed out that CO₂ emissions are Granger-caused by US EPU. In addition, as noted by Adams *et al.* (2020), a high level of EPU is positively correlated with environmental pollution. Similarly, using the panel Granger causality approach, Pirgaip and Dinçergök (2020) demonstrated considerable support for the influence of EPU on carbon emissions in three G7 nations (Canada, Germany and the USA). Moreover, Atsu and Adams (2021) documented similar evidence when assessing the effect of EPU on the determinants of carbon emissions with the help of a cross-sectional augmented ARDL approach. Their findings suggested that EPU significantly positively impacts carbon emissions in BRICS economies. In addition, Anser *et al.* (2021) used the extended ARDL method in terms of the top ten carbon emitters to assess the effect of the world uncertainty index (WUI) on CO₂ emissions. Their findings also noted that the positive change in WUI increases emissions in both the short and long term. Considering the regional heterogeneity of policymaking, Yu *et al.* (2021) made a new EPU index in China and used a two-way fixed-effects model to investigate how EPU affects the carbon intensity of manufacturing firms. Their findings show that EPU is a key driver in increasing the carbon intensity level of manufacturing firms. Similar findings are also confirmed by Amin and Dogan (2021), Khan *et al.* (2022) and Xue *et al.* (2022).

However, different from the above point of view, several scholars have confirmed that increased policy uncertainty could slow carbon emissions. In this regard, Adedoyin and Zakari (2020) applied bound estimation to find that EPU reduces the growth of CO₂ emissions. Ahmed *et al.* (2021) uncovered comparable evidence when investigating the effect of EPU on environmental degradation by utilizing the asymmetric ARDL approach in the USA. Their findings revealed that a positive change in EPU adversely affects emissions in the long term. Moreover, by using the panel quantile regression model, Syed *et al.* (2022) documented that EPU mitigates carbon emissions at the middle and lower quantiles. After constructing a novel US CPU index, Gavriilidis (2021) utilized a VAR model to show that the US CPU index significantly and negatively influences carbon emissions at the aggregate and sector levels. Likewise, by employing panel data model estimation to detect the influences of EPU on carbon emissions in China, Liu and Zhang (2022) showed that EPU adversely affects CO₂ emissions in the eastern region.

Although the above studies confirmed that EPU shocks significantly influence carbon emissions positively and negatively, evidence exists to the contrary. Abbasi and Adedoyin (2021), for example, concluded that EPU did not influence carbon emissions in China after employing the ARDL technique. Similarly, using panel data from 2003 to 2017 to detect the effect of EPU on CO₂ emissions in China, Liu and Zhang (2022) also found that EPU has a nonsignificant impact on carbon emissions in China's western and central regions. Moreover, Nakhli *et al.* (2022) used bootstrap rolling window estimation to uncover the time-varying effect of EPU on carbon emissions. The disparities in the findings of several recent studies might be attributed to the differing circumstances of the sampling periods and the following methodological frameworks that were addressed.

Several shortcomings and weaknesses should be addressed and improved upon based on the preceding literature research. First, China is the largest Fintech investment market in the world (Zheng *et al.*, 2021). As China seeks to attain carbon neutrality by 2060, it is worth studying the role of the Fintech industry development in achieving carbon neutrality. However, studies concerning the role of Fintech are still scant. Moreover, there are indeed uncertainties about China's climate policy, for example, China's current carbon market is a

pilot policy, but there are only seven pilot policies, while for other regions, the specific carbon market design and operation mechanism have not yet been fully determined. As a result, companies in these regions may face climate policy uncertainties related to carbon market policies in the future. But existing research mainly focuses on the impact of policy uncertainty on carbon emissions but ignores the impact of policy uncertainty on carbon-neutral concept index volatility. In addition, little available research uncovers the effect of CCPU on the carbon-neutral concept index. Especially in recent years, climate issues have become increasingly prominent, and the corresponding climate governance policy uncertainties have increased. The lack of research on the impact of CCPU is not conducive enough for the Chinese government to achieve carbon neutrality by 2060. Therefore, this paper bridges these gaps and aims to detect the connectedness among Fintech, CCPU and CNCI in China, which may be vital for authorities and policymakers. To investigate the impact of climate policy uncertainty on CNCI, this study utilizes the Chinese climate policy uncertainty index developed by [Tian and Li \(2023\)](#) to measure uncertainty regarding climate policy in China (CPU). By mining the text of ten well-known newspapers in mainland China, [Tian and Li \(2023\)](#) construct a monthly index to capture the volatility in China's climate policy. The data of CNFI and CNCI from the Wind financial database, the CPU data comes from this website ([Google.com](#)).

2.3 Ocean carbon sink market

Developing a market for marine carbon sinks is essential to protect biodiversity, improve the ecological environment and capitalize on marine carbon sink resources ([Sabine et al., 2004](#); [Mikaloff Fletcher et al., 2006](#); [Dai et al., 2012](#); [Follett et al., 2014](#)). The existing literature on marine carbon sink market development can be divided into three strands. The first strand covers the theoretical basis, which includes the principle of shared responsibility, the theory of payment for ecosystem services and the theory of land-sea integration ([Wunder, 2006](#)). The principle of shared responsibility and the theory of land-sea integration are prerequisites for the development of the marine carbon sink market, and the theory of payment for ecosystem services is the market principle that must be followed in the transaction process. The second strand covers the development mechanism, which includes the process of capitalization of clear property rights, the process of productization using ecological technology, the process of transforming products or services into capital through value accounting and trading, and the operation process of marine carbon sink capital feeding and carbon sink resources caused by ecological investment. The third strand covers the legal approach, emphasizing the importance of complete legal guarantees for developing the marine carbon sink market ([Justine and Lovelock, 2019](#)).

2.4 Wavelet analysis

The wavelet analysis is a new data analysis method applied to the financial field in recent years, which can take into account the time domain, frequency domain and causal relationship and can obtain more reliable results as a time-varying nonlinear method. [Ko and Lee \(2015\)](#) selected 11 European countries as the research objects and used wavelet analysis to explore the impact between economic policy uncertainty and stock market in these countries based on frequency and time and studied the fluctuation spillover effect of China's energy market, stock market and economic policy uncertainty. [Aguiar-Conraria et al. \(2020\)](#) use the wavelet analysis approach to estimate the Okun coefficient and the leading/lagging relationship between output exceeding unemployment at each moment and cycle frequency. In addition, [Liu et al. \(2023\)](#) employ wavelet methods to examine how EPU interacts with total credit, housing prices, stock prices and GDP in China, respectively.

3. Methods and materials

3.1 Wavelet analysis

To investigate the impact of CFTI and CCPU on CNCI from an empirical perspective, we employ a unique multivariate wavelet analysis approach that can reveal the dynamic connectedness between variables from the time and frequency dimensions (Aguilar-Conraria *et al.*, 2018).

When a time series $x(t)$ is examined, its continuous wavelet transformation (CWT) with a regarded wavelet ψ is a function of two variables, $W_x(\tau, s)$ scaling by s and translation by τ :

$$W_x(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \overline{\psi\left(\frac{t-\tau}{s}\right)} dt \quad (1)$$

where $\tau, s \in \mathbb{R}, s \neq 0$. When $|s| < 1$, the windows of function $W_x(\tau, s)$ become narrower, suggesting that it is at a greater frequency. Similarly, for $|s| > 1$, the windows become larger, indicating a function with lower frequency.

The wavelet power spectrum (WPS) is an important concept in a wavelet domain that may be stated as:

$$(WPS)_x = W_x \overline{W_x} = \left| \overline{W_x} \right|^2 \quad (2)$$

The WPS can provide us with a measure of the variance of the time series at each time-frequency. Because the wavelet ψ is complex-valued, the W_x is likewise a complex value, and a polar form may express this transform $W_x = |W_x| e^{i\phi_x}$, $\phi_x \in (-\pi, \pi]$. The angle ϕ_x is known as the (wavelet) phase.

Considering two time series, $x(t)$ and $y(t)$, the cross-wavelet transform W_{yx} can be described by:

$$W_{yx} = W_y \overline{W_x} \quad (3)$$

where W_x and W_y are the wavelet transformations of x and y , respectively. The absolute value $|W_{yx}|$ is the cross-wavelet power, representing the covariance between x and y over time and frequency.

The complex wavelet coherency of two time series, $x(t)$ and $y(t)$, is given by:

$$\mathfrak{d}_{yx} = \frac{S(W_{yx})}{\left[S(|W_x|^2) S(|W_y|^2) \right]^{1/2}} \quad (4)$$

where S indicates a smoothing operator in scale and time. For simplicity, we denote $S_{yx} = S(W_{yx})$ and use σ_x and σ_y to represent $\sqrt{S(|W_x|^2)}$ and $\sqrt{S(|W_y|^2)}$. Therefore, the complex wavelet coherency of two variables can be expressed as follows:

$$\mathfrak{d}_{yx} = \frac{S_{yx}}{\sigma_x \sigma_y} \quad (5)$$

The wavelet coherency is the absolute value of the complex wavelet coherency (R_{yx}), which is denoted as follows:

$$R_{yx} = |\mathfrak{d}_{yx}| = \frac{|S_{yx}|}{\sigma_x \sigma_y} \quad (6)$$

Next, we can compute the wavelet phases of two time series, $x(t)$ and $y(t)$, using a complex-valued wavelet. Furthermore, we can further capture the probable leading-lag connection between $x(t)$ and $y(t)$ by computing their phase difference (ϕ_{yx}) at each time and frequency. Specifically, the series is in phase, with y leading x if $\phi_{yx} \in [0, \pi/2]$ and x leading y if $\phi_{yx} \in [-\pi/2, 0]$. Likewise, the series are in anti-phase, with x leading y if $\phi_{yx} \in [\pi/2, \pi]$ and y leading x if $\phi_{yx} \in [-\pi, -\pi/2]$. Finally, the complex wavelet gain of y over x is defined by \mathcal{G}_{yx} , which is equivalent to

$$\mathcal{G}_{yx} = \frac{S_{yx}}{S_{xx}} = \vartheta_{yx} \frac{\sigma_y}{\sigma_x} \tag{7}$$

Following [Mandler and Scharnagl \(2014\)](#), we refer to the wavelet gain of y over x and define the modulus of \mathcal{G}_{yx} as G_{yx} , which can be expressed as:

$$G_{yx} = \frac{|S_{yx}|}{S_{xx}} = R_{yx} \frac{\sigma_y}{\sigma_x} \tag{8}$$

Moreover, considering three variables, y , x and z , the squared multiple wavelet coherency among them is denoted by $R_{y(xz)}^2$, as follows:

$$R_{y(xz)}^2 = \frac{R_{yx}^2 + R_{yz}^2 - 2\Re(\vartheta_{yx}\vartheta_{xz}\overline{\vartheta_{yz}})}{1 - R_{xz}^2} \tag{9}$$

We define that the multiple wavelet coherency among these three variables $R_{y(xz)}$ is the positive square root of $R_{y(xz)}^2$.

In terms of partial wavelet coherency, we derive the complex partial wavelet coherency between y and x after controlling for z as follows:

$$\vartheta_{yx.z} = \frac{\vartheta_{yx} - \vartheta_{yz}\overline{\vartheta_{xz}}}{\left[(1 - R_{yz}^2)(1 - R_{xz}^2)\right]^{1/2}} \tag{10}$$

Furthermore, after adjusting for z , we can derive the partial wavelet coherency ($R_{yx.z}$) and partial phase-difference ($\phi_{yx.z}$) between y and x , which are the absolute value and the angle of $\vartheta_{yx.z}$, respectively.

Finally, after controlling for z , we can calculate the complex partial wavelet gain between series y and x , which can be written as:

$$\mathcal{G}_{yx.z} = \frac{\vartheta_{yx} - \vartheta_{yz}\overline{\vartheta_{xz}}}{(1 - R_{xz}^2)} \frac{\sigma_y}{\sigma_x} \tag{11}$$

In addition, we define the partial wavelet gain $G_{yx.z}$ as the absolute value of $\mathcal{G}_{yx.z}$, that is,

$$G_{yx.z} = \frac{|\vartheta_{yx} - \vartheta_{yz}\overline{\vartheta_{xz}}|}{(1 - R_{xz}^2)} \frac{\sigma_y}{\sigma_x} \tag{12}$$

It is worth noting that conventional wavelets can only identify positive and negative relationships between variables without quantifying the extent of their influence or estimating coefficients. However, the partial wavelet gain employed in this study can serve as an estimate of multivariate regression in the time-frequency domain. This approach allows for the direct estimation of both time-varying and frequency-varying coefficients. As [Equation \(12\)](#) indicates, the partial wavelet gain is an absolute value of a complex number,

which lacks a typical regression coefficient's positive or negative sign convention. Consequently, other standard wavelet tools like wavelet partial coherency and phase difference should also be utilized to interpret the partial wavelet gain accurately.

3.2 Data

The primary purpose of this paper is to examine the influence of the CFTI and CCPU on the CNCI in China. The novel CCPU index from Li *et al.* has been used. The CFTI and CNCI datasets were extracted from China's Wind Economic Database. In addition, the existing studies have uncovered the influence of economic policy uncertainty (EPU) on CNCI. Therefore, to exclude the influence of EPU on CNCI, we adopted the ideas proposed by Zeng *et al.* (2022), controlling the impact of EPU on CNCI. Specifically, we selected China's EPU (CEPU) from Weebly's data website (<https://economicpolicyuncertaintyinchina.weebly.com>) as proxy variables. Considering the availability of the data, the datasets in the current study span from July 2017 to December 2021. Moreover, we have taken a logarithmic process for the data, and the return series have been calculated by $R_t = \ln(P_t) - \ln(P_{t-1})$. Table 1 reports the statistical characteristics of the CNCI, CCPU, CFTI and CEPU in China.

The descriptive statistics demonstrate that there is apparent heterogeneity among these series. The standard deviation of CCPU is much larger than those of the other variables, implying that there have been more changes in climate policies during the sample period. In addition, the normal distribution trend of CFTI has been statistically verified by the Jarque–Bera test, as the series cannot reject the null hypothesis.

Additionally, following the methodology of Aguiar-Conraria *et al.* (2018), we conduct an initial statistical examination in both time and frequency domains by utilizing the single wavelet power spectrum. This approach differs from the conventional descriptive statistics used for variables and can potentially uncover additional features of time series that are typically overlooked. In our study, we used Matlab2015 software and a wavelet analysis package to empirically test the time-frequency relationship between the variables, all charts are exported from the Matlab2015 software platform. The corresponding findings are depicted in Figure 1.

Figure 1 shows the monthly logarithmic returns of the CNCI, CCPU, CFTI and CEPU on the left-hand side (a.1-a.4), while the corresponding wavelet power spectra are presented on the right-hand side (b.1-b.4). The wavelet power spectrum provides information on the intensity of time-series variance for each time and frequency, which is not captured by traditional descriptive statistics. Specifically, for the CNCI, the volatility is more significant at high frequencies (less than 4 months) from the second half of 2018–2019. Similarly, for the CCPU, there is one dominant volatility region at high frequencies, which occurred from the

Variable	CNCI	CCPU	CFTI	CEPU
Minimum	-0.093	-1.052	-0.17	-0.337
P25	-0.015	-0.251	-0.036	-0.152
P50	0.006	-0.011	-0.003	0.013
P75	0.029	0.249	0.029	0.147
Maximum	0.142	1.208	0.235	0.377
Mean	0.007	0.012	0.006	0.006
Std. Dev	0.045	0.414	0.076	0.184
Skewness	0.441	0.323	0.689	-0.01
Kurtosis	4.027	3.563	4.321	2.002
Jarque–Brea	4.045	1.625	8.052**	2.199

Note(s): Asterisks ** represent significance levels of 5%

Source(s): Table created by authors

Table 1.
Descriptive statistics

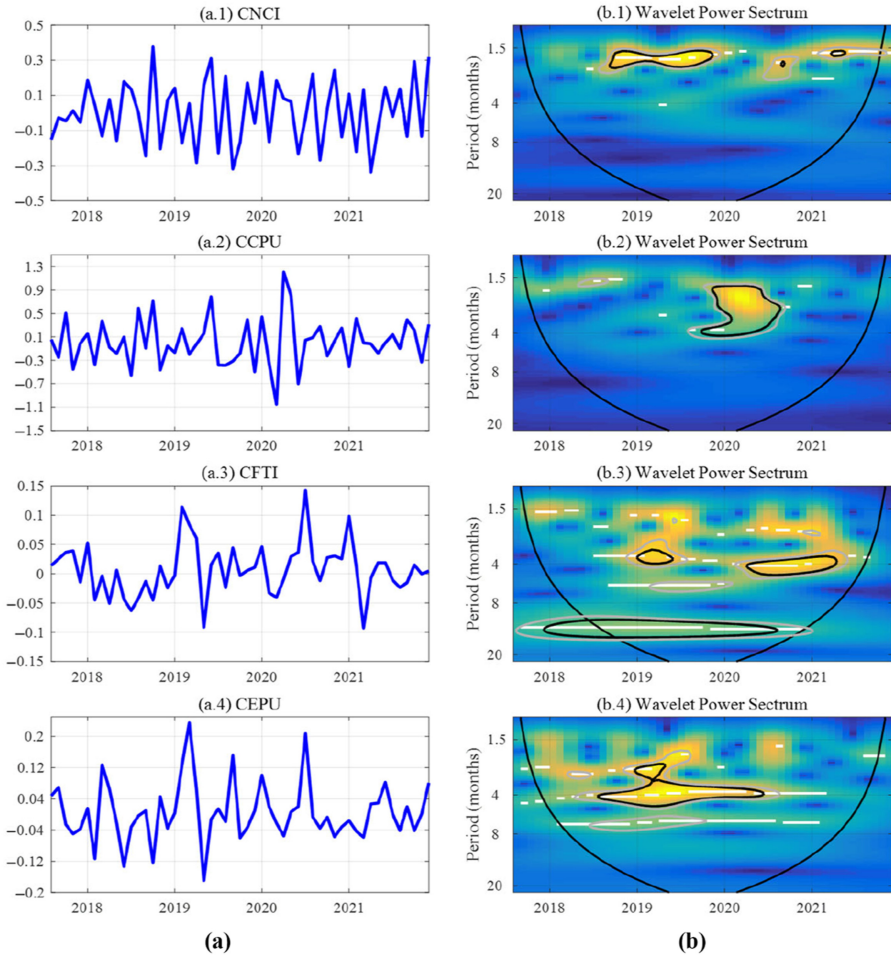


Figure 1. (a) displays the monthly logarithmic return for each variable. (b) represents each wavelet power spectrum

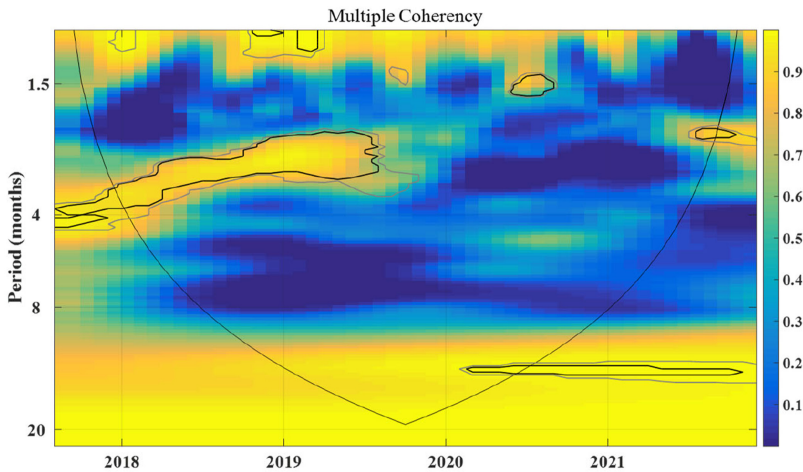
Note(s): The thick black (gray) curve represents the significance threshold of 5% (10%). The black contour at the edge represents the cone of influence (COI), which denotes the edge effects. The yellow spectrum denotes high volatility, whereas the blue spectrum represents low volatility

Source(s): Figure created by authors

second half of 2019 to the first half of 2020. For the CFTI, three volatility regions are observed, spanning high and low frequencies during 2019 and 2021. Finally, for the CEPU, the volatility regions are mainly concentrated in the middle and low frequencies between the second half of 2018 and early 2020.

4. Empirical result

Figure 2 presents the wavelet analysis outcomes for the three indices, which facilitate identifying their strongest interactions across the time and frequency domains. The



Note(s): The thick black (gray) curve represents the significance threshold of 5% (10%). The black contour at the edge represents the cone of influence (COI), which denotes the edge effects. The color code identifies distinct levels of coherency, ranging from blue (low coherency) to yellow (high coherency)

Source(s): Figure created by authors

Figure 2.
Wavelet multiple coherency between the variables

significance level of 10% (5%) is represented by the thick gray (black) curve. Near the edge, the black contours are cone of influence (COI) that indicate unreliable indications of comovement and causality beyond the COI due to edge effects. Moreover, the degree of coherency is distinguished by the different color spectrums, ranging from cold (low coherency, close to blue) to warm (high coherency, close to yellow). To facilitate the interpretation of the interactions at each frequency band, we define a high-frequency range between 1–4 months, a middle-frequency region between 4–8 months and a low-frequency area between 8–20 months.

Figure 2 presents the multivariate wavelet coherencies among the variables, with five locations showing high coherency at the 5% significance level, indicating that the evaluated factors have a jointly significant influence on each other. Notably, the most important high coherency region is observed in the 1–4 months frequency band, spanning from the first half of 2018 to the middle of 2019, with another high coherency region observed in the same frequency band from the second quarter of 2020 to the third quarter of 2020. Additionally, a considerable coherency area is observed in the 8–20 months frequency band, spanning from the first quarter of 2020 to the second quarter of 2020.

Although many coherencies can identify the strong linkages among CCPU, CFTI and CNCI, they cannot distinguish the individual effects of each index. Therefore, we utilize the partial coherence, in conjunction with the partial phase difference and the partial gains, to disentangle the influence of CCPU and CFTI after accounting for the impact of CEPU. The findings, which exhibit comparable results, are presented in Figures 3 and 4.

Figure 3 displays the partial wavelet coherency, partial phase differences and partial wavelet gains between CCPU and CNCI. The left panel of Figure 3 shows three regions with high interactions. Two regions exhibit considerably high coherency in the 1–4 months frequency band. The first region spans from the fourth quarter of 2018 to the first quarter of 2019. We observe that the phase differences are between $\pi/2$ and π , indicating a negative

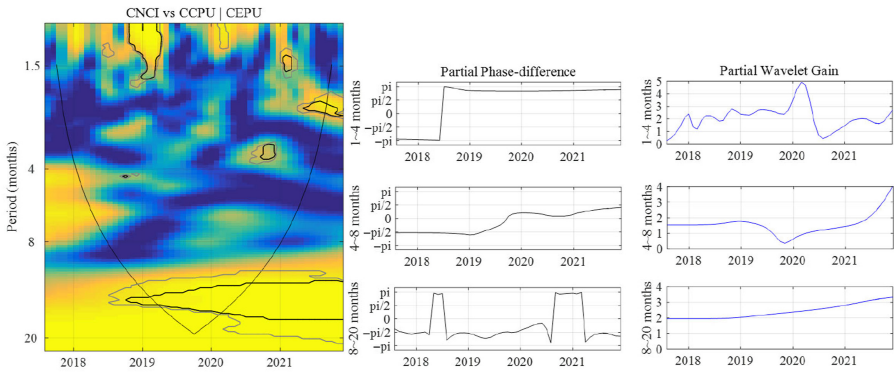


Figure 3. The partial wavelet coherency between the variables is depicted on the left

Note(s): The thick black (gray) curve represents the significance threshold of 5% (10%). The black contour at the edge represents the cone of influence (COI), which denotes the edge effects. The color code identifies distinct levels of coherency, ranging from blue (low coherency) to yellow (high coherency). The partial phase difference is shown in the middle. The partial wavelet gain is shown on the right

Source(s): Figure created by authors

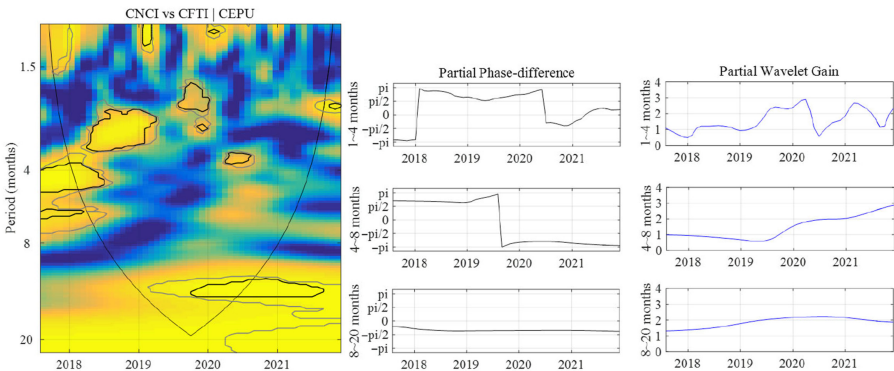


Figure 4. The partial wavelet coherency between the variables is depicted on the left

Note(s): The thick black (gray) curve represents the significance threshold of 5% (10%). The black contour at the edge represents the cone of influence (COI), which denotes the edge effects. The color code identifies distinct levels of coherency, ranging from blue (low coherency) to yellow (high coherency). The partial phase difference is shown in the middle. The partial wavelet gain is shown on the right

Source(s): Figure created by authors

nexus with CCPU leading. As a result, the rise of CCPU in the short term has a negative impact on CNCI, implying that it is not conducive to realizing the carbon neutrality goal. This finding is consistent with the research of [Zeng et al. \(2022\)](#). The partial wavelet gains suggest that the effect of CCPU on CNCI is approximately 2.5. The second-high coherency region runs from the second to the third quarter of 2021. The phase difference between $\pi/2$ and π suggests a negative relationship with CCPU leading. The magnitude of the impact of CCPU on CNCI is approximately 2. The possible reason behind this is that when CCPU increases in the short

term, firms might tend to cut down on green innovation investment to avoid policy risk, leading to an increase in carbon emissions, which has a detrimental effect on CNCI. This finding is supported by [Wen et al. \(2022\)](#), indicating that policy uncertainty shocks increase carbon emissions.

We observe a region of significantly high coherency at a lower frequency band (8–20 months), which spans from the first quarter of 2019 to the second quarter of 2020. The partial phase differences in this region range between $-\pi/2$ and 0, indicating a positive nexus between the two variables with CCPU leading. This means that the rise of CCPU will contribute to achieving the carbon neutrality goal. The partial wavelet gains also suggest a stable relationship with a value close to 2.3. The economic implications of these findings are that continued climate policy reforms in the long term raise the cost of highly polluting energy consumption. As a result, enterprises will reduce their consumption of fossil energy in the long term, considering the cost, leading to a subsequent reduction of carbon emissions and helping to achieve carbon neutrality.

[Figure 4](#) shows similar partial wavelet coherency, partial phase differences and partial wavelet gains between CFTI and CNCI. The figure reveals three central high-coherency regions spanning low-frequency and high-frequency bands. The first high coherency region spans from the second quarter of 2018 to the first quarter of 2019, in the 1–4 months frequency band. The partial phase differences in this region range from $\pi/2$ to π , indicating a negative relationship between CFTI and CNCI, with CFTI leading. This implies that the more advanced the Fintech, the more difficult it is to achieve carbon neutrality. The corresponding partial wavelet gain suggests a magnitude of impact of approximately 1.2. The second-high coherency region spans from the first quarter of 2018 to the second quarter of 2018, in the 4–8 months frequency band. The partial phase differences in this region are also between $\pi/2$ and π , indicating a negative relationship with CFTI leading. This means that the rise in Fintech level will reduce the possibility of achieving carbon neutrality. The corresponding partial wavelet gain for this region is approximately 1. The economic implication of these findings is that the current development of Fintech might contribute to environmental degradation, which is not sustainable for economic growth and carbon neutrality. In particular, mining cryptocurrency, which requires exorbitant electricity usage, results in significant carbon emissions ([Jiang et al., 2021](#)). Therefore, the development of the Fintech industry, which is reflected in the value of Fintech industry stocks, has a negative effect on CNCI.

Furthermore, within the 8–20 months frequency band, we have identified a region of significant coherence between CFTI and CNCI from Q1 2019 to Q3 2020. The partial phase differences suggest a positive relationship between the two variables, as [Dong et al.'s \(2022\)](#) findings supported. Additionally, the partial wavelet gain for this region is the highest at 2.2, indicating a strong and stable relationship. From an economic perspective, this suggests that the government can proactively promote Fintech development and encourage energy companies to adopt this technology to reduce emissions and achieve long-term emission reduction goals. Thus, a positive outlook for Fintech development can benefit carbon neutrality, with CFTI having a positive impact on CNCI in the long term.

Moreover, we have summarized the above findings in [Table 2](#), which provides a clearer view of the relationship between variables and enables us to identify their different impacts more precisely. It is evident that after controlling for the influence of CEPU, CCPU has a negative relationship with CNCI at high frequencies (1–4 months). These connections will be shorter in 2021 but will last longer between 2018 and 2019. On the other hand, the relationship between CCPU and CNCI becomes positive at low frequencies (8–20 months). Similar results were found for the relationship between CFTI and CNCI. After controlling for the effect of CEPU, CFTI has a negative impact on CNCI in the high-frequency region (1–4 months) and the medium-frequency region (4–8 months). However, the relationship becomes positive in

Table 2.
Summary of the empirical results in the current study

Frequency band	Time span	Partial co-movement	Wavelet gains coefficient	Partial causality
<i>Panel A: Results between CNCI and CCPU CEPU</i>				
1–4 months	4Q-2018 to 1Q-2019	Negative	Approximately 2.5	CCPU→CNCI
1–4 months	2Q-2021 to 3Q-2021	Negative	Approximately 2	CCPU→CNCI
8–20 months	1Q-2019 to 2Q-2020	Positive	Approximately 2.3	CCPU→CNCI
<i>Panel B: Results between CNCI and CFTI CEPU</i>				
1–4 months	2Q-2018 to 1Q-2019	Negative	Approximately 1.2	CFTI→CNCI
4–8 months	1Q-2018 to 2Q-2018	Negative	Approximately 1	CFTI→CNCI
8–20 months	1Q-2019 to 3Q-2020	Positive	Approximately 2.2	CFTI→CNCI

Source(s): Table created by authors

the low-frequency region (8–20 months). We can conclude that the partial wavelet gain of CCPU in the high frequency is greater than in the low frequency, indicating that the link between CCPU and CNCI is stronger in the short term. Conversely, the partial wavelet gain of CFTI in the low frequency is greater than in the high frequency, indicating that the link between CFTI and CNCI is stronger in the long term. Based on these varying characteristics of time and frequency among the variables, we can conclude that the uncertainty of climate policy implementation and Fintech industry development harms carbon neutrality in the short term. However, positive climate policy reforms and high-quality Fintech development will benefit carbon neutrality in the long run.

To confirm the robustness of the empirical results, we re-estimated the model using a dynamic Autoregressive Distributed Lag (DARDL) approach [2]. The novel DARDL model is commonly used to analyze the long-term relationship between two or more variables. The main advantage of the DARDL model is that it can capture the dynamic relationship between variables over time and explore the short-term and long-term effects of explanatory variable changes on the dependent variable. In addition, the ability of the DARDL model to handle non-stationary data is also one of the reasons why it is often chosen in the empirical process. The DARDL approach’s estimated findings are comparable to those from the wavelet analysis. As a result, we can demonstrate that alternative model estimating approaches do not influence the effects of the explanatory variables studied in this work on CCPU. That is, the effect of CFTI and CNCI on CCPU is significant.

The marine carbon sink market is a crucial component of the global effort to achieve carbon neutrality. Climate policy is the foundation for formulating trading rules in this market, while Fintech is a booster promoting high-quality development. However, the uncertainty of climate policy implementation and the rapid development of the Fintech industry may undermine the realization of short-term carbon neutrality goals. This is likely to be caused by the uncertainty of climate policy affecting corporate green investment and the increase in energy use due to the rapid development of science and technology. In this context, the marine carbon sink market may lack funds. To alleviate its financing difficulties and overcome the impact of short-term climate policy uncertainty, governments should provide more financial support, especially by developing the fintech industry to promote the high-quality development of the ocean carbon sink market. At the same time, the urgency of achieving the goal of carbon neutrality will provide an excellent macro environment for the rapid development of the marine carbon sink market. The marine carbon sink market should seize this stage of rapid development. In the long run, active climate policy reform and high-quality scientific and technological development will be conducive to carbon neutrality. At this stage, the marine carbon sink market should use mature financial technology to achieve

short-term rapid development and empowerment and shift from rapid development to high-quality development. On the other hand, it is also necessary to take advantage of the environment where the pressure to achieve the goal of carbon neutrality is weakened to adjust its structure quickly. The marine carbon sink market should remove the disadvantages brought about by rapid development to improve the quality of its development.

5. Conclusions

The study investigated whether the development of Fintech under the uncertainty of China's climate policy affects the realization of China's carbon neutrality goal and implications for developing the marine carbon sink market. We applied the newly developed multivariate wavelet analysis to detect the potential correlations with Chinese data from July 2017 to December 2021. Considering the time-frequency interaction between variables, this paper investigates the effects of CCPU and CFTI on CNCI from a time-frequency perspective.

The empirical outcomes suggest that CCPU has a significantly negative effect on CNCI at a high frequency from 2018:4Q to 2019:1Q and 2021:2Q to 2021:3Q after controlling for the impact of CEPU. In comparison, this influence becomes positive at low frequencies from 2019:1Q to 2020:2Q, which improves environmental deterioration. This finding suggests that the information originating from the CCPU can provide helpful information to predict the returns of CNCI. Additionally, the influence of CFTI on CNCI is also affirmed to be positive at a low frequency from 2019:1Q to 2020:3Q. In this case, governments should consider Fintech's use to achieve the carbon neutrality goal. However, CFTI has also shown a significant negative impact on CNCI in the high- and middle-frequency bands. Therefore, while promoting Fintech development, the negative impact of Fintech use on carbon emissions cannot be ignored. The conclusions of this paper can also provide some theoretical enlightenment for developing the marine carbon sequestration market. In the short term, the marine carbon sink market should seize the opportunity of carbon neutrality to expand rapidly and increase the market size. In the long run, the marine carbon sink market should take advantage of the convenience of financial transactions brought about by scientific and technological progress to promote the high-quality development of the market.

The study provides the following policy recommendations. First, policymakers should pay attention to the changes in climate policies to avoid excessive volatility in CNCI, given that the CCPU effectively affects the movement of CNCI in different frequency bands. Policymakers should also make full use of the carbon neutrality comprehensive assessment system to assess according to the period and needs, thus providing a reference for policymakers to identify the impact of climate policies and make policies in the next stage. Second, since CFTI has a negative effect on CNCI at a high frequency, the government should focus on the negative short-term environmental impact of Fintech uses. Governments should curb the disorderly expansion of Fintech and prohibit the overmining of cryptocurrencies from limiting the resulting carbon dioxide emissions. Possible measures such as increasing penalties for violations, establishing a publicity system and regulating market access, among others, should be considered. Third, the outcomes of this study also show the positive impact of CFTI on CNCI at a low frequency. Therefore, governments should support the development of Fintech by supporting the construction of the regulatory system and the implementation of incentive policies, the low-carbon transformation of financial institutions and improving operational efficiency and the construction of the green finance market. Fourth, governments should encourage Fintech development to solve the financial difficulties while developing the marine carbon sink market. In addition, governments should provide appropriate subsidy policies and balance the development of Fintech with environmental governance, which is critical to achieving carbon neutrality goals.

However, this study still has some limitations. Our study's research sample period is only from July 2017 to December 2021, which is relatively short. In addition, our study did not conduct a detailed discussion on the correlations of CCPU, CFTI and CNCI. Therefore, future research can start by further expanding the sample interval or delving into its internal influencing mechanism, thereby enriching research in related fields.

Notes

1. <https://rhg.com/research/preliminary-China-emissions-2019/>
2. The results are available upon request to authors.

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Corresponding author

Zhenhua Qin can be contacted at: qzh013166@126.com