Dynamic Interactions Among the Carbon Market, Commodity Market, and Climate Policy Uncertainty: A Wavelet-based Analysis

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Abstract. This study examines how China's carbon market, commodity market, and climate policy uncertainty interact with each other, particularly in the context of the country's dual-carbon objectives. Using continuous wavelet transform (CWT) and wavelet coherence (WC) methods on data from January 2016 through August 2024, the analysis picks out volatility patterns and cross-market linkages that operate at different time scales. The results indicate that carbon price movements tend to cluster in shorter time frames and are heavily influenced by policy changes, while commodity market volatility follows longer cycles driven by broader macroeconomic trends and geopolitical events. A robust long-run positive comovement emerges between the carbon and commodity markets—with commodity prices consistently leading—while a sustained negative association characterizes the carbon market's long-term relationship with climate policy uncertainty. Around 2023, however, this linkage turns positive over short horizons. These findings highlight why regulatory clarity and coordination across markets matter for keeping extreme price swings in check. The paper suggests improving policy transparency and setting up real-time information sharing to help carbon prices better reflect underlying fundamentals and reduce lags in responding to policy signals. By mapping out these shifting cross-market dependencies over time, the research offers practical guidance for designing more effective carbon markets amid ongoing economic transformation.

Keywords: Carbon market, Commodity market, CPU, Wavelet coherence

1 Introduction

In line with its ambitious commitment to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, China has positioned the carbon market as a central pillar within its broader climate governance framework. This market-based tool is anticipated to do two things at once: speed up the shift toward cleaner energy systems and push forward the green transformation of industrial structures. Carbon trading pilots first got off the ground back in 2011 in Beijing, Shanghai, Guangdong, and seven other provincial-level regions, and since then, China's carbon pricing experiment has been through more than ten years of trial and error—complete with both setbacks and institutional

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improvements along the way. All of this gradual learning eventually opened the door for the national Emissions Trading Scheme (ETS) to launch in July 2021, which marks a major step toward more standardized and centralized carbon pricing. At present, the national market runs on a hybrid design that puts allowance-based compliance and free allocation first, with the Certified Emission Reduction (CCER) offset mechanism added into the mix. This setup now extends to carbon-heavy industries like power generation, iron and steel, and cement manufacturing. On top of its regulatory role, the carbon market also plays a crucial part in reshaping corporate incentives to cut emissions, directing private capital toward low-carbon technologies, and pushing forward long-term decarbonization goals.

As global efforts to combat climate change continue to intensify—a situation that is further complicated by ongoing geopolitical realignments and broader macroeconomic instability—climate policy uncertainty has emerged as a critical external force that can disrupt both overall economic activity and financial market stability, creating ripple effects across different sectors. As the world's largest emitter of greenhouse gases and its biggest developing economy, China runs a climate policy framework that stands out for its long-term strategic goals, institutional adaptability, and phased implementation approach, which sets it apart from other nations. Within this larger context, commodity markets act as a fundamental bridge connecting the real economy to the financial system, covering energy carriers, base metals, agricultural products, and various industrial raw materials that are essential for economic activity. Price movements in these markets not only reflect shifting supply-demand fundamentals but are also closely linked to macroeconomic fluctuations and broader industrial policy shifts, making them highly sensitive to policy changes. Importantly, these movements indicate strong persistence and are most noticeable over medium to long-term horizons, suggesting that their effects are not short-lived.

Earlier research has already established that commodity markets and carbon markets influence each other in both directions[18] (Wang & Yang, 2021). There is evidence indicating that carbon allowance prices react quite sensitively to price movements coming from commodity markets. Meanwhile, a growing collection of studies also points out multiple channels—both direct and indirect pathways—through which uncertainty stemming from climate policy ends up influencing carbon pricing outcomes. Even though these developments have been made, existing studies still haven't managed to give a systematic picture of how volatility actually spreads across the three domains at the same time, nor have they sufficiently described the way their interdependence keeps evolving. Continuous wavelet analysis, mainly because it can pick up on co-movements that are both localized and change over time without having to impose strict parametric assumptions, has turned into an increasingly popular method for studying financial linkages across different markets[11][16] (Vacha & Barunik, 2012; Reboredo & Rivera-Castro, 2014). Building on this methodological tradition, the current study makes use of wavelet-based techniques to try to uncover the multi-scale associations that link together the carbon market, commodity prices, and climate policy uncertainty.

In order to map the temporal structure and interconnected dynamics of these three spheres, the investigation focuses on the interval from January 2016 to August 2024—a period that spans critical junctures in China’s climate policy evolution and external economic shocks. In selecting indicators, the study carefully balances empirical validity with data accessibility. The Guangdong carbon emissions trading price serves as a proxy for carbon market conditions; the aggregate commodity price index captures broad trends in commodity valuation; and the China Climate Policy Uncertainty Index developed by Ma et al. (2023)[7] is used to measure policy-driven volatility. Using continuous wavelet transform, the study identifies the main volatility cycles and structurally significant episodes for each time series. Wavelet coherence analysis is then employed to assess how strongly pairs of variables correlate across the time–frequency plane, while phase difference diagnostics clarify lead–lag configurations and directional influence.

This study pushes forward the existing literature in two main ways. On the methodological side, it goes beyond the usual time-domain or purely linear approaches by bringing together continuous wavelet transform, wavelet coherence, and phase difference analysis into a single analytical framework. This makes it possible to look at both short-term disturbances and long-term trends at the same time, which helps capture the full range of cross-market interactions that simpler single-scale models tend to miss. In terms of substance, earlier studies have generally treated carbon–commodity linkages as if they were fixed or one-directional, often overlooking how policy uncertainty can modulate these connections and neglecting the inherently time-varying nature of cross-market relationships. By decomposing each variable's trajectory into its constituent frequency components, this research provides a detailed account of when, at which horizons, and in which direction these interdependencies actually manifest. In doing so, it addresses a noticeable gap in the literature concerning time–frequency transmission mechanisms and offers practical guidance that is grounded in empirical evidence for refining how carbon pricing policies are designed and for improving coordination across different regulatory agencies.

2 Literature Review

Carbon allowances and physical commodities each indicate features of both storable goods and financial assets. This dual nature creates pathways for bidirectional spillovers, which are transmitted through real economic activity as well as through financial risk channels[18] (Wang & Yang, 2021). At the level of market microstructure, however, a foundational distinction persists: the carbon market is organized around an artificially constructed scarcity—emission permits whose supply is administratively determined—whereas commodity markets derive their price signals from the production, storage, and consumption of tangible goods. Because of this built-in asymmetry, the process of carbon price formation remains structurally dependent on how prices evolve in commodity markets. Empirical research has long recognized the deep linkage between energy commodities and carbon allowances. The co-movement of crude oil, natural gas, coal, and carbon permit prices is well documented: when energy prices rise, they typically push up marginal abatement costs and, by extension, carbon prices, while falling energy costs put downward pressure on emission allowance values[2][6] (Kanen, 2006; Convery

& Redmond, 2007). Subsequent investigations have reaffirmed the predominant influence of energy prices on carbon market outcomes[1][9] (Alberola et al., 2008; Mansanet-Bataller et al., 2011).Further evidence suggests that volatility transmission between the two markets is markedly asymmetric, with shocks that originate in commodity markets propagating more forcefully to carbon prices than the reverse. In addition, commodity price disturbances may also transmit indirectly through macroeconomic aggregates, thereby exerting delayed or amplified effects on how carbon allowances are valued[15][14] (Tan et al., 2020; Tian et al., 2022).

Running alongside this line of research, another stream of work has focused specifically on how to define and measure climate policy uncertainty. In this area, Gavriilidis (2021)[3] was among the first to develop a newspaper-based index that tracks discussions about climate policy across major U.S. publications. Taking a different methodological path suited to China's particular context, Ma et al. (2023)[7] built the China Climate Policy Uncertainty Index. They did this by applying the MacBERT deep learning model to a collection of six major domestic newspapers. The resulting index makes it possible to conduct systematic empirical investigations into how policy ambiguity actually interacts with carbon pricing dynamics in practice. From a theoretical standpoint, the carbon market stands out for its strong sensitivity to policy changes. Its price mechanism is relatively fragile and especially vulnerable to sudden regulatory shifts when compared to other types of assets[14] (Tan et al., 2020). Empirical research also shows that green financial assets as a whole react noticeably to climate policy signals[12] (Ren et al., 2023), and as a key part of this asset class, the carbon market is naturally exposed to these influences. When climate policy changes, it often involves adjustments to emissions caps or sectoral coverage, which directly alters the supply-demand balance for allowances and consequently affects their equilibrium price[13] (Ren et al., 2022). In addition to these direct regulatory pathways, uncertainty also works through market participants' expectations. When participants anticipate stricter climate measures, they perceive higher compliance costs and financing difficulties for emission-intensive firms, which reduces their trading activity and shapes carbon price trajectories[4] (Hsu et al., 2023).

Methodologically speaking, continuous wavelet analysis has become quite widely used in energy and financial economics, mainly because it has two particularly valuable strengths that set it apart from more traditional approaches. Permitting researchers to spot localized, time-varying co-movements that conventional frequency-domain methods would typically miss in practice. Second, it can handle the typical features of financial return series—fat tails, volatility clustering, and non-Gaussian distributions—without needing to impose a rigid parametric structure[5][8][10][11][16][17] (Vacha & Barunik, 2012; Jammazi, 2012; Reboredo & Rivera-Castro, 2013, 2014; Vacha et al., 2013; Madaleno & Pinho, 2014). Drawing on these methodological advantages, the present study employs wavelet analysis to map out the multi-horizon relationships connecting carbon allowance prices, commodity price indices, and climate policy uncertainty. This approach allows for a systematic description of how these relationships actually change across both time and frequency—a dimension that has been largely missing from earlier studies.

3 Research Model and Sample Data

3.1 Research Model

Continuous Wavelet.

A wavelet family usually originates from a single mother wavelet$\psi(t)$, which is a real-valued square-integrable function that satisfies certain specific admissibility criteria. In practice, each member of this family is generated through translation and dilation operations:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

Within this mathematical expression,$\frac{1}{\sqrt{s}}$serves to ensure unit energy preservation;$\tau$and also$s$respectively govern the wavelet's temporal location and its scale—or equivalently speaking, its frequency localization. For effective practical application, it is required that the mother wavelet should exhibit compact or near-compact support in both the time domain and the frequency domain.

Consistent with established practice in economic and financial research, this study adopts the Morlet wavelet, defined as:

$$\psi(t) = \pi^{-\frac{1}{4}}e^{i\omega_0 t}e^{-\frac{t^2}{2}}$$

The term, in this context,$\pi^{-\frac{1}{4}}$serves to normalize the function,$e^{-t^2/2}$provides a Gaussian envelope with unit standard deviation, and also$e^{i\omega_0 t}$introduces a complex sinusoidal oscillation. Meanwhile, to balance temporal and spectral resolution, the parameter$\omega_0$is assigned a value of 6 in this configuration.

Continuous Wavelet Transform.

For a given time series $x(t)$, its continuous wavelet transform $W_x(s,\tau)$ is obtained by projecting $x(t)$ onto the wavelet basis:

$$W_x(s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t}{s}\right)$$

The asterisk denotes complex conjugation. The scale parameter s determines whether the transform captures high-frequency (short-scale) or low-frequency (long-scale) dynamics.

Wavelet Coherence.

When we need to quantify the degree of synchronization between two series in the time-frequency plane, three auxiliary quantities are actually required: the wavelet power spectrum, cross-wavelet power, and also the cross-wavelet transform. The wavelet power spectrum, in particular, measures how much each scale contributes to the overall variance of the series at every time point; meanwhile, its cross analogue is what captures the localized covariance structure between the two series. For two series$x(t)$and also$y(t)$with their respective transforms$W_x(s,\tau)$and also$W_y(s,\tau)$, then the cross-wavelet transform is then defined as:

$$W_{x,y}(s,\tau) = W_x(s,\tau)W_y^*(s,\tau)$$

Here, * denotes the complex conjugate.

Building on this foundation, the squared wavelet coherence coefficient—analogous to a localized correlation measure—is expressed as:

$$R^2(s,\tau) = \frac{\left|S\left(s^{-1}W_{xy}(s,\tau)\right)^2\right|}{S(s^{-1}|W_x(s,\tau)^2|)S\left(s^{-1}\left|W_y(s,\tau)^2\right|\right)}$$

In the discussion that follows,$S$the symbol is used to denote a smoothing operator that works across both time and scale.$R^2(s,\tau)$this parameter takes on values between 0 and 1, and values that approach unity indicate strong local correlation. For statistical inference, Monte Carlo simulations are conducted with phase-specifically randomized surrogates (Torrence & Compo, 1998; Torrence & Webster, 1999).

Phase.

Directional information—whether two series move pro-cyclically or counter-cyclically, and which variable leads—is encoded in the phase difference:

$$\phi_{x,y}(s,\tau) = tan^{-1}\left(\frac{\Im S\left(s^{-1}W_{x,y}(s,\tau)\right)}{\Re S\left(s^{-1W_{x,y}(s,\tau)}\right)}\right)$$

The symbols being discussed $\Im$ and $\Re$ refer specifically to the imaginary and real components of the smoothed cross-wavelet spectrum, respectively. Within graphical depictions, right-pointing arrows are used to signify in-phase behavior (positive co-movement), while left-pointing arrows represent anti-phase behavior (negative co-movement). Upward arrows indicate that the first series leads the second, while downward arrows indicate the reverse.

3.2 Data and Summary Statistics

The empirical analysis in this study focuses on three core variables observed over the period from January 21, 2016, to August 30, 2024. Specifically, the Guangdong carbon emissions trading price (denoted Carbon) is used as the indicator for China's carbon market, while the aggregate commodity price index (CI) captures movements in the broader commodity market. In practical terms, both series are converted into continuously compounded returns through logarithmic first differences, which is a standard transformation applied to such price data.

$$Y_t = ln(X_t) - ln(X_{t-1}) = ln\left(\frac{X_t}{X_{t-1}}\right)$$

All of the price data used in this study come directly from the Wind database. To measure climate policy uncertainty, we rely on the China Climate Policy Uncertainty Index (CCPU) that was developed by Ma et al. (2023)[7]. This particular index is built by applying the MacBERT deep learning model for the purpose of identifying and quantifying news articles that deal with climate policy ambiguity, drawing from six major Chinese newspapers with national circulation. The resulting measurements are then normalized to make comparisons across different time periods more straightforward.

Table 1 shows the descriptive statistics of each variable. From the table, it can be seen that the variance of climate policy uncertainty is the largest, indicating that the fluctuation of climate policy uncertainty is significantly influenced by policy impacts, while the variance of carbon market prices is the smallest, indicating that China's carbon market is still in its early development stage, with low market volatility. All variables passed the ADF test and JB test, demonstrating the robustness of the above data, consistent with the assumptions of the wavelet model.

Table 1. Descriptive Statistics

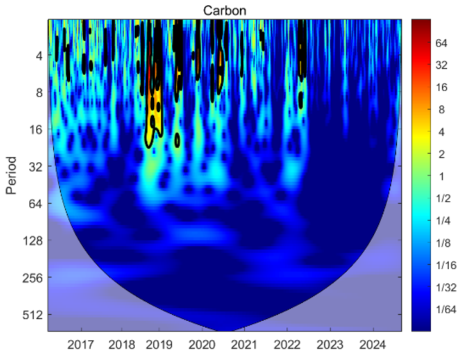
Variable	Mean	Variance	Minimum	Maximum	Skewness	Kurtosis	ADF Test	JB Test
carbon	0.0003	0.0110	-0.0526	0.0555	-0.4562	44.9582	0.000***	0.000***
CI	0.0005	0.1743	-2.3972	2.0075	-0.0790	5.4108	0.000***	0.000***
CPU	0.0006	0.2562	-1.1237	1.3511	0.0459	4.0584	0.000***	0.000***

***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively.

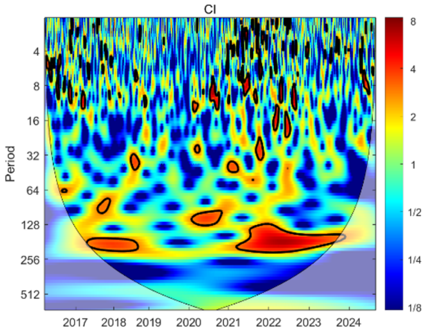
4 Empirical Result Analysis

4.1 Volatility Characteristics: Continuous Wavelet Spectra

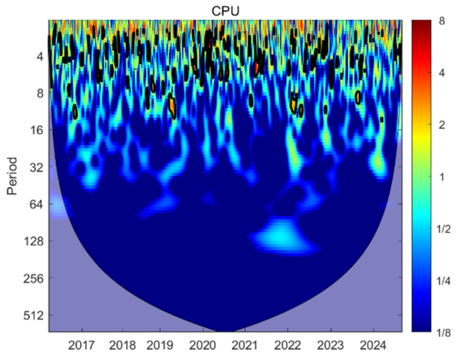
Figure 1 presents the continuous wavelet power spectra calculated for each variable. In these diagrams, the horizontal axis (abscissa) tracks chronological time, while the vertical axis (ordinate) represents frequency, expressed in units of days.The intensity of the colour shading reflects the magnitude of localized variance, where warmer hues specifically indicate regions of elevated volatility. The thick black contours that appear on the plots delineate regions achieving statistical significance at the 5% level, with these thresholds having been established through Monte Carlo simulations employing phase-randomized surrogates. Additionally, the cone of influence—marked by a solid black line on each plot—encloses those areas that are potentially subject to boundary distortions or edge effects.



(a) Carbon Market



(b) Commodity Market



(c) Climate Policy Uncertainty

Fig. 1. Continuous Wavelet Analysis

Panel (a) shows the wavelet power spectrum for carbon returns. The elevated volatility we see is mainly concentrated at frequencies that correspond to short and intermediate time horizons. This overall pattern lines up with what we would expect in an immature market environment, where regulatory announcements, compliance deadlines, and periodic policy recalibrations all exert an outsized influence on short-run price expectations. Frequent modifications to allocation rules and coverage thresholds, in particular, tend to introduce episodic uncertainty, which in turn manifests as transient bursts of volatility.

Panel (b) reports the corresponding spectrum for the commodity price index. In contrast to the carbon market, we can observe that a significant mass of volatility extends toward lower frequencies, indicating pronounced medium- to long-term variability (64–256 day cycles). Two distinct episodes of heightened volatility are clearly evident: the first spanning 2017–2019, and the second covering 2021–2023. The earlier episode coincides with the implementation of far-reaching supply-side structural reforms, which materially altered production costs and capacity utilization across China's industrial sector, thereby transmitting directly to commodity valuations. At the same time, concurrent trade policy tensions between China and the United States exacerbated uncertainty surrounding agricultural and metal commodities. The latter episode reflects the confluence of post-pandemic demand recovery, disruptions to global energy supply chains precipitated by geopolitical conflict in Eastern Europe, and monetary tightening in advanced economies. As a major importer of fossil fuels and industrial raw materials, China encountered significant external price shocks that propagated through domestic commodity markets over prolonged intervals.

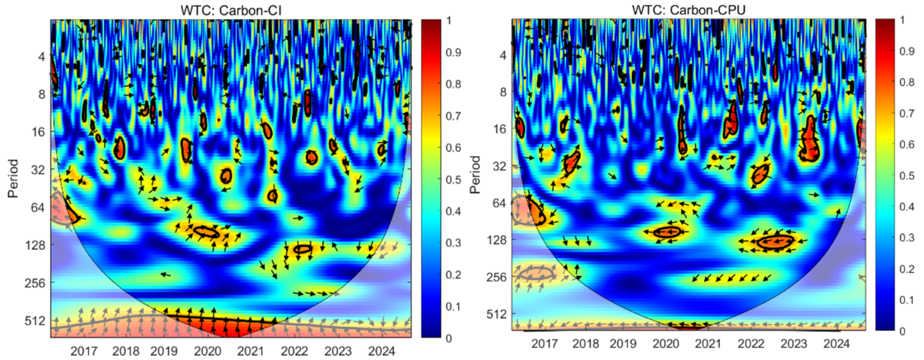
Panel (c) provides a visual representation of the wavelet spectrum derived from the China Climate Policy Uncertainty Index. The observed volatility is overwhelmingly concentrated at high frequencies, which correspond to shorter time horizons, while only a limited amount of spectral mass can be detected at longer temporal scales. In our analysis, we find that two complementary explanations can account for this observed pattern. First, the dual-carbon framework fundamentally embeds a long-term policy commitment, thereby anchoring expectations and attenuating low-frequency variation. Second, short-run uncertainty spikes tend to be closely associated with discrete political events—such as major conferences, leadership statements, or sudden regulatory proposals—that are rapidly assimilated and priced by market participants. Moreover, authorities have demonstrated a clear tendency to adjust their policy stances in response to exogenous shocks or extreme meteorological events, which further contributes to high-frequency volatility.

When we synthesize these findings, what stands out is a fairly clear contrast: the volatility observed in carbon markets and climate policy uncertainty appears to be anchored in cycles that operate over short to intermediate time horizons, whereas commodity market volatility, in contrast, demonstrates a marked persistence that stretches across longer temporal scales. This heterogeneity across different market types really drives home the point that we need multi-horizon analytical tools that can actually accommodate these divergent frequency dynamics as they manifest in practice.

4.2 Cross-Market Linkages: Wavelet Coherence Evidence

In Figure 2, we present wavelet coherence maps for the two bivariate pairings that are of primary interest in this analysis. The axes and significance contours in these maps follow the same conventions that were already established in Figure 1. The colour scheme gradations are designed to index the strength of local correlation, where deep red indicates coherence near unity and cool blue denotes near-zero association. Arrows, for their part, encode phase information according to the convention that was described in Section 3.1.4.

Panel (a) illustrates the time-frequency relationship between carbon returns and commodity index returns. The coherence pattern is mainly concentrated at low frequencies (128–256 day scales) and becomes most evident during the 2019–2021 period. The arrow orientation consistently points to the right and upward, which implies strong positive comovement coupled with a clear lead of the commodity market over the carbon market. This overall configuration suggests that while idiosyncratic shocks tend to dominate short-horizon dynamics, common underlying drivers—most notably the macroeconomic cycle and broad-based shifts in industrial policy—serve to synchronize the two markets over longer time intervals. During the 2019–2021 period, the economy witnessed a protracted recovery in domestic economic activity, which in turn stimulated demand for both industrial commodities and the energy inputs whose combustion generates compliance obligations. Rising commodity prices then signaled higher marginal abatement costs, thereby transmitting positive upward pressure to carbon allowance valuations. Importantly, the directional asymmetry captured by the phase arrows corroborates the structural dependency of carbon pricing on antecedent movements in physical commodity markets: price signals propagate from commodities to emission permits, rather than the reverse.



(a) Carbon Market-Commodity Market (b) Carbon Market-Climate Policy Uncertainty

Fig. 2. Wavelet Coherence Chart

Panel (b) illustrates the coherence between carbon returns and the climate policy uncertainty index. In this visualization, the pattern exhibits marked time-frequency variation. During the 2022–2023 period, significant coherence appears at low frequencies (128–256 days) and is specifically characterized by leftward-pointing arrows—indicative of a robust negative association. A qualitatively different configuration emerges around 2023 at intermediate frequencies (16–32 days). In this case, arrows point to the right and upward, signifying positive comovement with policy uncertainty leading carbon prices. These contrasting regimes reflect distinct behavioral mechanisms. Over extended horizons, persistently high policy ambiguity depresses investment in emission allowances. When faced with an uncertain regulatory trajectory, risk-averse firms and financial intermediaries tend to prefer liquid, low-risk assets, which reduces demand for carbon permits and exerts sustained downward pressure on prices. At shorter horizons, however, speculative dynamics may dominate. Perceiving heightened policy uncertainty as a precursor to future supply restrictions or more stringent caps, speculators accumulate allowance positions in anticipation of price appreciation, thereby generating a transitory positive correlation.

Looking at the overall picture, the coherence analysis brings out two main insights. First, the carbon market generally plays a reactive role: both commodity prices and climate policy uncertainty tend to drive carbon price movements across most of the significant coherence islands we examined. Second, the sign of the carbon-policy linkage is, in actual fact, horizon-dependent—it turns out negative over longer periods, but positive in the short term—whereas the carbon-commodity association stays uniformly positive when we look at longer horizons. What this contrast really highlights in practice is that two fundamentally different transmission channels are operating side by side: on one hand, real economic demand links carbon markets to commodity markets, and on the other hand, expectation formation and speculative positioning shape how carbon relates to policy uncertainty.

5 Research Conclusions and Policy Implications

5.1 Research Conclusions

This study draws on continuous wavelet transform and wavelet coherence techniques to investigate the time-varying patterns and cross-market linkages that connect China's carbon market with broader commodity price movements and climate policy uncertainty, with the analysis spanning the years 2016 through 2024. Looking at the results, three main findings stand out. First, the volatility patterns differ quite noticeably across the three areas. Carbon price volatility tends to concentrate at short-to-medium frequencies, which appears to reflect both the occasional regulatory interventions and the fact that the national ETS infrastructure is still developing. Commodity market volatility, by contrast, shows strong low-frequency components, consistent with the drawn-out nature of macroeconomic cycles and the lasting impact of structural reforms and geopolitical shocks. Climate policy uncertainty volatility, meanwhile, is overwhelmingly a short-run phenomenon, linked to specific political communications and reactive policy adjustments. Second, over longer time horizons, the carbon and commodity markets indicate tight coupling, with commodity prices consistently taking the lead over carbon prices. This setup suggests that carbon pricing remains structurally dependent on earlier developments in real economic activity and physical input markets. Third, the link between carbon prices and climate policy uncertainty is fundamentally regime-dependent. Over extended time scales, a strong negative relationship holds, while a positive but short-lived connection emerges around 2023—a pattern that seems to stem from the opposing effects of long-run investment behavior and short-run speculative positioning.

5.2 Policy Implications

These findings suggest several practical implications for how China's carbon pricing system could be designed and governed. First, the clear sensitivity of carbon prices to short-term policy shifts shows that regulatory predictability really matters. When policymakers keep making sporadic changes to allocation methods, coverage thresholds, or compliance schedules, it becomes much harder for market participants to form stable price expectations, which may in turn limit the market's ability to guide efficient abatement decisions. Because of this, policymakers should prioritize continuity in rulemaking and, when adjustments are needed, communicate them through pre-announced, transparent calendars. Putting in place formal medium-term guidance on allowance supply trajectories and sectoral phase-in schedules would help anchor expectations and reduce excess short-run volatility.

Second, the strong long-run linkage with commodity markets—coupled with the consistent leadership of commodity prices—indicates that carbon pricing cannot be managed in isolation. Close coordination between carbon market regulators and authorities overseeing commodity derivatives, trade policy, and industrial planning is essential. Establishing joint information-sharing protocols and developing capacity for synchronized market monitoring would facilitate early detection of cross-market stress and enable proportionate, coherent policy responses. High-energy-consuming industries, which are simultaneously exposed to both carbon costs and commodity price fluctuations, should be encouraged—through a combination of price transparency initiatives and targeted incentives—to integrate both sets of signals into their investment and operational planning.

Third, the way carbon prices tend to adjust with a noticeable lag to movements in both commodity markets and climate policy uncertainty really points to some underlying frictions in price discovery and in how expectations get transmitted across the market. Addressing these delays will require meaningful improvements in the informational efficiency of the carbon market itself. In practice, this means enhancing the timeliness and granularity of emissions data, actively facilitating broader participation by more diversified trading entities, and developing deeper, more liquid forward and derivatives markets. All of these steps would work together to strengthen the price formation process. At the same time, concurrent efforts to improve cross-market data disclosure—particularly when it comes to policy developments and macroeconomic indicators that affect carbon demand—would further align carbon prices with the underlying fundamentals.

The evolution of China's carbon market, which began as a policy experiment and is gradually becoming a more mature instrument of climate governance, will ultimately depend not just on its internal institutional design but also on whether it can successfully integrate into the broader ecosystem that spans both commodity and financial markets. This study, by illuminating the multi-horizon dependence structure that links these domains, and by mapping out these connections it provides an empirical foundation for such integration.

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