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# Quantile and Time–Frequency Risk Spillover Between Climate Policy Uncertainty and Grains Commodity Markets

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## ABSTRACT

This paper aims to study the dynamic risk connection between the Climate Policy Uncertainty Index (CPU) of the United States and the grain commodity market. Our findings denote that (a) quantile spillover is stronger at extreme than median levels, underscoring the value of systematic risk spillovers in extreme market conditions. (b) Wavelet coherence analysis proposes that the structure of the CPU connection with the grain commodity market is heterogeneous at time–frequency scales. (c) Under conditions of market stability, CPU's capability to predict risks in the most segmented grain commodity markets was not as pronounced as in extreme market scenarios. (d) The spillovers between CPU and major grain commodities under diverse quantile states were significantly influenced by climate change. Results from this paper have practical implications for investors managing climate-related risk exposures and will also assist policymakers in developing countries to develop a sensible policy package.

**JEL Classification:** G13, E44, G15, E60, G18

## 1 | Introduction

Climate transition significantly impacts agricultural industries, particularly grain production, with notable social and economic implications (Swan 1981; Pfister and Brázdil 2006; Kelly and Ó Gráda 2013). A critical aspect requiring specific attention is climate policy uncertainty (CPU), the unpredictability in governmental responses to climate challenges through regulations, incentives, or tariffs related to agricultural practices and trade. Such policy fluctuations create an environment of risk and instability in grain commodity markets, potentially affecting global food security (Wheeler and von Braun 2013; Harkness et al. 2020). Beyond traditional market factors like crude oil returns, supply–demand dynamics, and exchange rates, CPU poses unique challenges due to its impact on agricultural commodity supply against relatively stable demand (Rahman et al. 2022). This uncertainty, combined with climate risks, leads to significant disruptions in agricultural outputs and market stability (Matošková 2011; Tripathi et al. 2016).

More specifically, our article's focus on the connection between CPU and grain commodities is essential in understanding the broader implications of climate transition on food security. The potential for climate transition to escalate food insecurity is particularly pronounced in key agricultural regions. It is worth noting that unpredictable policies can amplify the adverse effects on crop growth and market stability (Hasegawa et al. 2018; Trisos et al. 2020; Zeng et al. 2024). Therefore, effective management of climate policy is crucial in mitigating these risks and ensuring global food security (Myers et al. 2017).

Previous limited literature has explored related topics. Mei and Xie (2022) confirmed the influence of Trade Policy Uncertainty (TPU) on the risk of major grain commodity futures by checking the link between the three main grain futures in the United States and TPU. Liu et al. (2023) conducted a Frequency Granger Causality Test to check the influence of climate uncertainty indices on the three major grain commodity futures in the United States, finding that the influence of climate on various grain futures was heterogeneous. Despite the growing recognition of CPU's importance in agricultural markets, there remains a critical gap in our understanding of how CPU specifically impacts grain commodity markets across different market conditions and time horizons. Previous research has largely focused on isolated aspects of climate or policy impacts, without comprehensively examining the complex interactions between CPU and grain market dynamics, especially the risk links between them. In comparison to these studies, our paper offers additional marginal contributions: (1) We emphasize the influence of changes in US climate policies on the risks of five major grain commodities under various market states. (2) For the first time, this study examines the volatility connection among CPU and major grain commodity risks from a time–frequency domain perspective. (3) Last but certainly not least, we consider the influence of climate data on the volatility connectedness between CPU and grain commodities, a perspective not previously integrated in prior research. This lends our study to incremental economic and theoretical contributions.

The channels through which CPU influences risks in the grain commodity market are noteworthy. We posit the existence of two mechanisms. First, the production and supply chain of grains are highly susceptible to the influences of climate transition. This susceptibility is further intensified by the financialization of grains, subsequently affecting the grain commodity market (Pinto-Ávalos et al. 2024). Specifically, climate conditions will influence climate policies, transportation and trade policies, and agricultural subsidy policies (Dafermos et al. 2018). Second, the frequent happening of extreme climate exposes investors not only to the traditional uncertainties of the grain commodity market but also to heightened uncertainties implied by climate change policies (Hasegawa et al. 2021).

It is crucial to emphasize that climate transition is regarded as one of the primary systemic risks faced by financial markets (Chen et al. 2023). Furthermore, prior research underscores that climate risks have been proven to affect investment decisions (Engle et al. 2020). In summary, from the insight of behavioral finance, in the context of the grain commodity market sensitive to extreme climate and climate policy changes, alterations in climate policies can exacerbate market volatility by influencing investor attention and psychological expectations.

This paper examines how uncertainty in climate change policies influences the behavior of grain commodity markets. Our data set spans three and half decades and covers various crisis periods. Our analysis compares the sensitivity of different grain commodity market prices to the CPU Index. We also carefully examine how CPU affects grain commodity risks and what such an outcome means for investors and policymakers.

Our study addresses the research gaps of previous studies by providing a comprehensive analysis of CPU's impact on grain commodity markets through three innovative approaches. In the empirical analysis section, we apply the method of the mean-based time-varying parameter (TVP)–vector autoregressive (VAR) approach to the quantile-based scenario (Dai et al. 2023). It is imperative to note that the approach employed in this study represents an enhanced iteration of Ando et al.'s (2022) methodology. Specifically, Ando et al.'s (2022) quantile VAR (QVAR) connectedness method exhibited the following drawbacks: (1) The necessity of configuring a rolling window in Ando et al.'s (2022) method, with the size of the rolling window significantly influencing the outcomes. (2) The establishment of a rolling window resulted in the loss of a portion of observational data, leading to data wastage. This is particularly crucial given the limited nature of our sample set, emphasizing the need to mitigate data loss. (3) Ando et al.'s (2022) technique demonstrated heightened sensitivity to outliers. Then we test for the connectedness of extreme lower-tail and upper-tail risk spillovers. The critical implication of doing so is that the size of the connectedness may change among different market environments and time-varying due to global crises (Khalfaoui et al. 2022). We then employed the wavelet coherence approach referenced by Goodell and Goutte (2021) to investigate the correlation between the CPU and grain commodities in entire time–frequency domains. In contrast to conventional frequency techniques, wavelet coherence enables the simultaneous analysis of time series in multiple frequencies. This facilitates the examination of pairwise volatility correlations, a task challenging to accomplish with other statistical methods. While traditional approaches assess parameters on one or two scales, wavelets enable the concurrent examination of time–frequency domain connections. This capability enables us to comprehend diverse perceptions of linked time points and frequencies (Tiwari et al. 2020). Furthermore, this paper supplements our analysis with the quantile-on-quantile regression (QQR) method. This approach offers more precise insights into the cross-quantile risk relationships between CPU and subsegmented grain commodity markets compared with existing methodologies. By accounting for nonlinear and asymmetric effects, our approach enables a more profound understanding of the risk impact patterns of CPU across various quantile levels under different market conditions in grain commodity markets.

Our contributions are multiple. First, we increase the scholarly paper on environmental economics and agricultural economics and, for the first time, examine how an index of CPU affects grain commodity markets. It should be noted that agricultural commodities are priced in US dollars and the United States is a major international grain exporter that CPU may lead to a weaker dollar or poor grain production (see Rezitis 2015). These factors will then affect the food supply and, more critically, make it difficult for governments to maintain well-planned food market development policies. Our dynamic analysis will contribute to the scarce and fragmented initiatives to foster global food security and supply stability that require understanding parameters that result in temporary or permanent price volatilities in these critical commodities. Second, we applied TVP–QVAR estimation techniques to evaluate the direction and magnitude of volatility connectedness in response to extreme spillovers. Third, as previously mentioned, the wavelet coherence method captures the temporal and frequency features of the CPU, and the grain commodities in heterogeneous time domains. This helps us examine the risk aversion properties of the grain commodity market. Fourth, our additional contribution is that, relying on the CPU definition, we summary that climate or policy change coverage in the central US press significantly impacts on wheat and soybean market risks when the market is stable. At the same time, for most periods in the sample interval, the major US press cannot forecast the influence of impending climate or policy changes on most grain commodity market risks in advance. Moreover, this study represents the inaugural attempt to explore the impact and relationship of CPU on segmented grain commodity markets using the QQR approach. This method yields more robust results concerning the dynamic, nonlinear, and asymmetric risk association patterns between the CPU and segmented grain commodity markets (Mallick et al. 2019; Umar et al. 2022). Finally, to enrich the theoretical significance of this paper, we further employed the Niño 3.4 index as a macro climate exogenous variable to examine its impact on the overall connectedness between CPU and the major grain commodity markets in the United States under heterogeneous market conditions. This revealed the significant influence of climate transition on the adjustments in the agricultural industry and climate policies in the United States.

Several key findings are derived from this study. (1) The connection between markets is, therefore, stronger under extraordinarily bullish and bearish market states. It is reported that CPU significantly influenced the volatility of grains only during market stability. Using a nonrolling window TVP method indicates that the connectedness patterns in the extreme quantiles exhibit time-varying and asymmetric characteristics. (2) The outcomes of the wavelet analysis reveal that, at different time–frequency scales, the volatility dependence structure between CPU and grain commodities displays heterogeneity, especially in the short-to-medium-term frequency domain. Notably, oats exhibit the strongest risk correlation with the CPU Index, and in the medium-to-long-run frequency domain, there is no significant risk correlation observed between soybeans and corn with the CPU. (3) Through the QQR method, we found that the unique influence of the CPU on these markets exhibited heterogeneity and nonlinearity, contingent upon quantile conditions. Finally, we employed standard ordinary least squares (OLS) and quantile regression (QR) methods to demonstrate the impact of the Niño 3.4 index under heterogeneous market conditions on the total connectedness indices (TCIs) between CPU and major grain commodities in the United States.

The other parts of this study are structured as follows. Section 2 is a literature review. Section 3 offers the methodological procedures and data employed in this study. Section 4 follows a comprehensive discussion of our empirical findings. Section 5 summarizes our work and offers pertinent recommendations for investors and policymakers.

## 2 | Literature Review

To provide a comprehensive theoretical foundation for our research, this section systematically reviews relevant literature in three main areas: the impact of CPU on financial markets, the relationship between agricultural production and climate risk, and the methodological approaches in market analysis. This review helps identify research gaps and positions our study within the existing academic system.

### 2.1 | Climate Risk, CPU, and Financial Markets

Recent empirical evidence has further enriched our understanding of the complex relationship between climate risk and financial markets. Dutta et al. (2023) evaluated the impact of climate risk on green energy stock returns and volatility using a CPU Index, finding that increased climate risk leads to higher returns. Banerjee (2024) investigates the second-order moment risk connectedness across climate and geopolitical risk and global commodity markets, revealing that both climate and geopolitical risks act as net transmitters of shocks in the network, with notable implications for precious metals' hedging capabilities against geopolitical risks. Wang et al. (2024) provide compelling evidence from China, demonstrating that climate risks significantly influence the realized higher-order moments of financial markets, with time-varying Granger causality flows particularly prominent in realized volatility measures.

Previous literature summarizes the multifaceted influences of CPU on financial markets, with many policies and scenarios still in the formative stages and significant policy uncertainties in many regions. Golub et al. (2018) argue that uncertainty of climate policy discourages firms from investing in emissions reductions, forcing firms to face the systemic risk of promptly rising future expenditures to control carbon emissions. Liang et al. (2022) find a great adverse influence of CPU on the long-run volatility of the world sustainable energy with excellent out-of-sample predictive effects. Bouri et al. (2022) provided the first empirical evidence on the impact of CPU on energy stock performance, demonstrating that such uncertainty significantly enhances the performance of green energy stocks relative to traditional energy stocks, particularly during periods of crisis, which carries important implications for investment decision-making. Moreover, Zeng et al. (2022) demonstrate that CPU outperforms the uncertainty of the economic policy of China in forecasting the Carbon Neutral Concept Index when the market is at risk. CPU significantly negatively impacts European Union Allowances Futures. Regarding the connection between CPU and the green finance index, Tian et al. (2022) conclude that CPU will likely be a key factor affecting green bond returns in the future. Furthermore, Nagar and Schoenfeld (2022) also consider climate risk as a risk element in the cross-section of market performances. On the other hand, the influence of CPU on the investment strategies of China's energy firms is reported to be significantly nonlinear (Ren et al. 2022). Hoang (2022) finds that CPU has a great negative influence on research and development investments by US heavy emitters. Meanwhile, Ginglinger and Moreau (2023) argue that climate risk can reduce a company's leverage by increasing the risk of financial distress and lowering the company's credit rating.

## 2.2 | Agricultural Production and Climate Risk

Much literature reflects the dependence on agricultural production, agricultural markets and climate risk. Isakson (2015) argues that introducing an initial derivative agricultural insurance can help mitigate weather-based risks. Hansen et al. (2019) denoted that climate transition is a significant risk to agricultural production and income, especially in dryland areas. Gaupp et al. (2020) indicate that the spatial dependence of climate extremes leads to an increased risk of global agricultural production decline, particularly for wheat, corn, and soybean crops due to extreme weather conditions. Janssens et al. (2020) assess trade and climate-induced adaptation mechanisms and argue that the capacity to link food surpluses to shortage areas needs to be strengthened. Gurgel et al. (2021) use the Global Grid Crop Model to outline that global welfare influences are sometimes greater when climate affects all crops and livestock. Fujimori et al. (2022) further examine the potential negative influences of land-related emission reduction strategies on food security, arguing that better coordination between emission reduction and agricultural management policies is necessary.

## 2.3 | Methodologies in Spillover Relationships Between Markets

In examining spillover relationships between markets, previous research has involved a variety of approaches. Some previous studies have investigated causality and spillovers through structural VAR methods (Luu Duc Huynh 2019), Johansen cointegration tests (Ahsan et al. 2020), and Granger causality analysis (Dastgir et al. 2019). Some scholars have used DY methods (Diebold and Yılmaz 2012, 2014) to check the connectedness (Kang and Yoon 2016; Al-Yahyaee et al. 2020; Naeem et al. 2024). Meanwhile, generalized autoregressive conditional heteroskedasticity (GARCH) family models and multivariate GARCH models are widely used to estimate market volatility linkages (Saiti et al. 2020; Zeng and Ahmed 2023; Marchese et al. 2020). However, the above approaches can only be applied to conduct spillovers tests between average returns and risks among the study variables but ignore return and risk spillovers under extreme market conditions, especially since extreme upper tails (bull markets) or extreme lower tails (bear markets) are not necessarily equal to volatility shocks (regular market condition). Even the correlation between extreme tail quantiles can differ from that of the mean quantile. Furthermore, investors' risk preferences differ even in the cases of bull and bear market conditions (Urom et al. 2020).

Through this comprehensive literature review, we can observe that while extensive research exists on CPU's impact on various financial markets and the relationship between climate risk and agricultural production, there remains a significant gap in understanding how CPU specifically affects grain commodity markets. Additionally, the methodological approaches used in previous studies have certain limitations in capturing market dynamics under extreme conditions. These identified gaps in the literature provide a solid foundation for our research, which aims to address these limitations through innovative methodological approaches and comprehensive analysis of CPU's impact on grain commodity markets.

# 3 | Methodology and Data

Market connectedness can be measured as the return or volatility shock formed by information from one market (or index) to another. It can also be done by analyzing cross-market integration, that is, the connection between two or more unrelated markets (or indices). The degree of market integration can be assessed through various measures, including average correlation and tail-based correlation approaches, which provide insights into market dependencies under both normal and extreme quantile conditions.

The applicability of the TVP–QVAR model in this study is motivated by economic volatility or cycles and financial symmetry theory. CPU and grain commodity markets have irregular cycles (boom and burst periods; regular periods) due to, among other things, changing climatic conditions and uncertainty about the future path of government policies, and consequently, shocks to volatilities in grain commodity markets. Our investigation enables an examination of the influence of diverse spillovers on systemic risk by adjusting the quantile level. Generally, a higher quantile might be linked to an ascending trend in the condition, signifying bullish conditions, and vice versa.

The feature of our TVP–QVAR methodology is that QVAR models can best capture the impact of the dimensional distribution of spillovers on continuity. This is because the quantile model is used to quantify covariates' impact beyond the distribution center, including upper and lower tails. While both average and tail-based correlation methods can provide valuable insights into market integration, our chosen TVP–QVAR approach offers additional advantages in capturing asymmetric distributions of the dependent element and market dynamics under varying quantile conditions (Chen et al. 2022).

## 3.1 | QVAR Function

According to the research of Koenker and Bassett (1978). QR presents two primary advantages through the least-squares approach. The initial advantage lies in its robustness to non-Gaussian or heavy-tailed time series. The subsequent highlight pertains to the ease with which QR models furnish interpretable regression evaluates derived over quantiles $\in(0, 1)$. We will estimate the dependence of $y_t$ on $x_t$ for quantile $\tau(\tau \in (0, 1))$. It will show below:

$$Q_\tau(y_t \mid \chi_t) = \chi_t \beta(\tau), \tag{1}$$

where $Q_\tau$ denotes the $\tau$th conditional quantile framework of $y_t$;$\chi_t$ is the series of spillover shown at time $t-1$;$\beta(\tau)$ is an element vector which shows the connection among $\chi_t$ and $Q_t$, and $\beta(\tau)$ will evaluated for every quantile by minimizing the following equations as $\beta(\tau)$:

$$\hat{\beta}(\tau) = \underset{\beta(\tau)}{\operatorname{argmin}} \sum_{t=1}^{T} \left(\tau - 1_{\{y_t < \chi_t \beta(\tau)\}}\right) |y_t - \chi_t \beta(\tau)|. \tag{2}$$

So, the $p$-order QVAR function is as follows:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), \quad t = 1, \dots, T. \tag{3}$$

In the above formula, $c(\tau)$ represents the intercept in quantile $\tau$, $e_t(\tau)$ stands for the residual at quantile $\tau$, and $B_i(\tau)$ denotes the matrix of lag coefficient at quantile $\tau$. Following the framework established by Koenker and Xiao (2006), this study uses the validity of the optimal lag order for the conditional average framework at every quantile. It is postulated that $e_t(\tau)$ meets the quantile restrictions and is employed to evaluate $\hat{B}_i(\tau)$ and $\hat{c}(\tau)$, where $Q_\tau(e_t(\tau) | y_{t-1}, \dots, y_{t-p}) = 0$, $i = 1, \dots, p$. Consequently, the equation defining the $\tau$th conditional quantile $y$ is as follows:

$$Q_\tau(y_t \mid y_{t-1}, \dots, y_{t-p}) = \hat{c}(\tau) + \sum_{i=1}^{p} \hat{B}_i(\tau) y_{t-i}. \tag{4}$$

Every equation in the series of formulas be given framework is rely on quantile method, and the $\tau \in (0, 1)$.

In detail, the $i$th formula is in Equation (5):

$$y_{it} = \beta_i'(\tau) z_t + e_{it}(\tau), \quad i = 1, \dots, m, \tag{5}$$

where $z_t$ is a vector of parameters, including the intercept $c(\tau)$. $\beta_i(\tau)$ includes the regression regressors calculated at the $\tau$th quantile. The specify quantile framework is given as

$$E(\psi_\tau(e_{it}(\tau)) \mid z_t) = 0, \tag{6}$$

where $\psi_\tau(z) = \tau - 1_{[z \le 0]}$. Equation (6) denotes $\int_{-\infty}^{\beta_i(\tau) z_t} f_{y_{it}|z_t}(t \mid z_t)\, dt = \tau$, where $f_{y_{it}|z_t}(t \mid z_t)$ is the density framework of $y_{it}$ on $z_t$. For any amount of $\tau$ in $(0, 1)$, the calculation of the QR is obtained as follows:

$$\hat{\beta}_i(\tau) = \min_{\beta_i(\tau)} \sum_{t=1}^{T} \xi_\tau\left(y_{it} - \beta_i'(\tau) z_t\right). \tag{7}$$

According to Koenker and Hallock (2001), $\xi_\tau(z) = z(\tau - 1_{[z \le 0]})$.

### 3.2 | Quantile Forecast Error Variance Decomposition (FEVD)

Several articles have obtained calculations for FEVD in VAR functions assessed at the conditional average. This study, however, centers on the QVAR, according to Ando et al. (2022).

Rewriting the QVAR model is as follows:

$$y_t = \sum_{i=1}^{p} B_i(\tau) y_{t-i} + c^*(\tau) + e_t(\tau), \quad \text{where } c^*(\tau) = c(\tau). \tag{8}$$

The Wold representation is on Equation (9),

$$Q_\tau(y_t \mid y_{t-1}, \dots, y_{t-p}) = \sum_{i=0}^{\infty} \Phi_i(\tau) e_{t-i}(\tau), \tag{9}$$

where $\Phi_i(\tau) = B_1(\tau)\Phi_{i-1}(\tau) + B_2(\tau)\Phi_{i-2}(\tau) + \cdots$, $i = 1, 2, \dots$ and $\Phi_0(\tau) = I$ and $\Phi_i(\tau) = 0$, where $i < 0$.

We posited that the quantile remained constant throughout the whole horizon of the forecast. Consequently,

$$u_{t+h}(\tau) = \sum_{l=0}^{h} \Phi_l(\tau) e_{t+h-l}(\tau). \tag{10}$$

With the total FEV matrix in Equation (11),

$$\mathrm{Cov}(u_{t+h}(\tau)) = \sum_{l=0}^{h} \Phi_l(\tau) S \Phi_l'(\tau). \tag{11}$$

### 3.3 | TVP–QVAR Connectedness

To explore extreme connectedness and elucidate the systemic shock transmission process among variables, numerous scholars integrate the quantile method with the connectedness introduced by Diebold and Yılmaz (2012, 2014). They advocate the time-varying connectedness approach grounded in VAR and utilize the FEVD. However, the method employs a rolling window, presenting several drawbacks, such as the rolling window's size significantly impacting model estimation results, the inevitable loss of samples at the outset leading to data wastage, and the susceptibility of calculation outcomes to outliers. In light of these limitations, this study adopts the TVP–VAR function developed by Antonakakis et al. (2018). This model is coupled with quantile methods to scrutinize extreme connectedness. Guided by the BIC, this article employs the TVP–VAR(1) function, incorporating the quantile method:

$$y_t = B_t(\tau) y_{t-1} + e_t(\tau), \tag{12}$$

$$B_t(\tau) = B_{t-1}(\tau) + v_t(\tau), \tag{13}$$

$$y_t = \Phi_t(\tau) e_{t-1}(\tau) + e_t(\tau). \tag{14}$$

The parameter $y_t$ represents the $N \times 1$-dimensional logarithmic data on indices, where $p_t$ indicates the exponential data at time $t \cdot e_t(\tau)$ and is subject to random disturbance element at quantile $\tau$ in $N \times 1$ aspects with index variance adhering to condition $e_t(\tau) \sim N(0, S_t(\tau))$. The matrix of time-varying conditional covariance $S_t(\tau)$ at quantile $\tau \cdot v_t(\tau)$ is a $N \times 1$-dimensional Gaussian white noisy with identically distributed and independent at quantile $\tau$, satisfying condition $v_t(\tau) \sim N(0, R_t(\tau))$, $R_t(\tau)$ as a non-time-varying diagonal matrix of quantile $\tau$. The $N \times N$-dimensional dynamic parameter matrix at quantile $\tau$ follows a random wandering process of $B_t(\tau)$. Equation (14) represents the Wold articulation for the TVP–VAR function relying on quantile $\tau$.

Diebold and Yilmaz (2012) introduced an approach for examining connectedness, relying on vector moving average elements. This model utilizes the impulse response of generalized framework, as opposed to Cholesky decomposition, to compute the generalized forecast error variance decomposition (GFEVD) matrix. These methodologies carefully consider the variable ordering, effectively addressing issues associated with variable order. Each component of the quantile framework over-estimated $H$-step GFEVD matrix is defined in accordance with Pesaran and Shin (1998).

$$\omega^{g}_{ij,t}(H,\tau) = \frac{\sigma^{-1}_{jj,t}(\tau)\sum_{t=0}^{H-1}\left(e'_i(\tau)\Phi_t(\tau)S_t(\tau)e_j(\tau)\right)^2}{\sum_{t=0}^{H-1}\left(e'_i(\tau)\Phi_t(\tau)S_t(\tau)\Phi'_t(\tau)e_i(\tau)\right)}. \tag{15}$$

In the above context, $\omega^{g}_{ij,t}(H,\tau)$ represents the contribution of index $j$ to the FEV of index $i$ at time $t$ within the forecast range $H$, and the quantile is denoted by $\tau$. The selection vectors, represented by $e_i(\tau)$ and $e_j(\tau)$, correspond to the $i$th and $j$th column vectors of unit matrix of the quantile framework, respectively. $\sigma_{jj,t}(\tau)$ signifies the $j$th diagonal parameter of $S_t$, representing the standard deviation of the $j$th formula error element relies on quantiles. The contributions to the major diagonal and off-diagonal estimators with cross-variance consist of and independent, respectively, in the GFEVD matrix.

In the context of the GFEVD, as the proportions of cross-sectional variance and independent components do not add up to 1, the spillover value is normalized based on its row summation. This normalization is implemented to guarantee that the row summation in the matrix of variance decomposition equals 1:

$$\tilde{\omega}^{g}_{ij,t}(H,\tau) = \frac{\omega^{g}_{ij,t}(H,\tau)}{\sum_{j=1}^{N}\omega^{g}_{ij,t}(H,\tau)}. \tag{16}$$

In this study, diverse connectedness indices at a specified quantile are derived through the application of the quantile GFEVD within the function established by Antonakakis et al. (2018). Initially, the TCI at the specified quantile is formulated as follows:

$$\mathrm{TCI}^{g}_{t}(\tau) = \frac{\sum_{i,j=1, i\neq j}^{N}\tilde{\omega}^{g}_{ij,t}(\tau)}{\sum_{i,j=1}^{N}\tilde{\omega}^{g}_{ij,t}(\tau)} \times 100, \tag{17}$$

where $\tilde{\omega}^{g}_{ij,t}(\tau)$ is the connectedness indicator at quantile $\tau$. This indicator quantifies the overall connectedness transmission across indices. The off-diagonal parameters of the matrix obtained through the GFEVD depict the cross-connectedness value of the index at quantile $\tau$, whereas the diagonal parameters signify the connectedness value of the index itself at quantile $\tau$. Subsequently, the directional connectedness value from $i$ to another index at quantile $\tau$ is delineated as follows:

$$\mathrm{DI}^{g}_{i\to j,t}(\tau) = \sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\omega}^{g}_{ji,t}(\tau) \times 100. \tag{18}$$

The directional spillover index from another index to index $i$ at quantile $\tau$ is

$$\mathrm{DI}^{g}_{i\leftarrow j,t}(\tau) = \sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\omega}^{g}_{ij,t}(\tau) \times 100. \tag{19}$$

The net spillover index at quantile $\tau$ is evaluated as

$$\mathrm{NI}^{g}_{i,t}(\tau) = \mathrm{DI}^{g}_{i\to j,t}(\tau) - \mathrm{DI}^{g}_{i\leftarrow j,t}(\tau). \tag{20}$$

The determination of whether element $i$ functions as a receiver or sender of system spillovers is discernible from the net connectedness index. Specifically, a positive net connectedness index designates variable $i$ as a sender, while a negative value indicates its role as a recipient. Finally, the computation of the net pairwise direction connectedness (NPDC) value at quantile $\tau$ is expressed as follows:

$$\mathrm{NPDC}_{ij}(\tau) = \left(\tilde{\omega}^{g}_{ji,t}(\tau) - \tilde{\omega}^{g}_{ji,t}(\tau)\right) \times 100. \tag{21}$$

In instances where the net connectedness index is not negative, the influence of spillovers originating from $i$ on $j$ is more substantial; conversely, the influence of spillovers emanating from $j$ on $i$ is more pronounced.

On the basis of previous works (e.g., Cui and Maghyereh 2023; Uddin et al. 2023), we apply three quantile levels of 0.05, 0.5, and 0.95 to show periods of extreme downside, normal market conditions, and extreme upside, respectively.

### 3.4 | Wavelet Transformation Coherence

The wavelet coherence approach serves as an essential complement to our quantile-based connectedness analysis for several compelling reasons. While the TVP–QVAR connectedness methodology effectively captures the dynamic relationships between markets under different quantile scenarios, the wavelet coherence technique provides unique insights into the time–frequency domain that are not accessible through traditional quantile analysis. This complementarity is particularly crucial when examining the complex, multidimensional relationships between CPU and grain commodity markets.

The wavelet coherence technique effectively identified linkages between CPU and segments of grain commodity markets over diverse temporal scales, essential for investors possessing varied investment horizons. This suggests that, given their distinct risk appetites and regulatory limitations, investors demonstrate varied temporal preferences in asset retention. Such diversities potentially hold critical insights across various investment periods. Furthermore, while quantile-based analysis excels at capturing market dependencies under different market conditions, wavelet coherence uniquely reveals how these relationships evolve across different frequency bands simultaneously, providing a more comprehensive understanding of market dynamics (Zeng et al. 2025).

Additionally, the wavelet coherence approach enhances our analysis by offering robust results even in the presence of statistical challenges that might affect quantile-based methods.

The application of wavelet coherence methods adeptly navigates challenges related to nonlinearities, nonstationarities, and seasonal or cyclical trends present within the variables. This methodological synergy between quantile-based connectedness and wavelet coherence analysis provides a more robust and nuanced understanding of the complex relationships between CPU and grain commodity markets, offering insights that might not be apparent through either approach alone.

The wavelet coherence coefficient between two smooth series on each time scale varies between $R_n^2(s) \in [0, 1]$. The cross-wavelet, denoted as $W_n^{XY}(s)$, is the covariance among the two variables at time and frequency. The cross-wavelet of two time series $x(t)$ and $y(t)$ will be described as

$$W_n^{XY}(s) = W_n^X(s) W_n^{*Y}(s), \tag{22}$$

where $W_n^X(s)$ and $W_n^{*Y}(s)$ are used for two series of continuous wavelet transforms. $S$ denotes the complex conjugate. The phase of the wavelet coherence is described by the following equation:

$$\varnothing_n^{XY} S = \tan^{-1}\left(\frac{\mathrm{In}\left\{S\left(S^{-1}W_n^{XY}(s)\right)\right\}}{\mathrm{Re}\left\{S\left(S^{-1}W_n^{XY}(s)\right)\right\}}\right), \tag{23}$$

where In and Re are the imaginary and actual sections of the smoothed power spectrum, respectively.

### 3.5 | Quantile-on-Quantile Regression

As Sim and Zhou (2015), this study denotes QQ approach as follows:

$$\mathrm{Grain}_t = \beta^\theta(\mathrm{CPU}_t) + \mu_t{}^\theta. \tag{24}$$

The $\mathrm{CPU}_t$ and $\mathrm{Grain}_t$ denote CPU and the risk of Grain commodity markets in moment $t$.$\beta$, $\theta$, and $\mu_t$ express element, $\theta$th quantile and error element, separately. This article applies to a first-order Taylor expansion for $\mathrm{CPU}^\tau$ to linearize $\beta^\theta(\cdot)$ as follows:

$$\beta^\theta(\mathrm{CPU}_t) \approx \beta^\theta(\mathrm{CPU}^\tau) + \beta^{\theta'}(\mathrm{CPU}^\tau)(\mathrm{CPU}_t - \mathrm{CPU}^\tau), \tag{25}$$

where $\mathrm{CPU}^\tau$ is the $\tau$th quantile of CPU, $\beta^{\theta'}$ points out the partial derivative of $\beta^\theta(\mathrm{CPU}_t)$ respective to CPU. As Equation (25), $\beta^\theta(\mathrm{CPU}^\tau)$ and $\beta^{\theta'}(\mathrm{CPU}^\tau)$ are clearly frameworks of $\theta$, and $\mathrm{CPU}^\tau$ is a framework of $\tau$, so both elements are twice constructed in $\theta$ and $\tau$. This article also utilizes $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ to exchange $\beta^\theta(\mathrm{CPU}^\tau)$ and $\beta^{\theta'}(\mathrm{CPU}^\tau)$ as follows:

$$\beta^\theta(\mathrm{CPU}_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(\mathrm{CPU}_t - \mathrm{CPU}^\tau). \tag{26}$$

Considering the Equations (26) and (24) together, we formulate a new equation:

$$\mathrm{Grain}_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(\mathrm{CPU}_t - \mathrm{CPU}^\tau) + \mu_t^\theta. \tag{27}$$

Due to $\beta_0$ and $\beta_1$ are frameworks of $\theta$ and $\tau$, the connection between CPU and the risk of grain commodity markets can be obtained in every quantile. With the aim to calculate Equation (27), we apply $\hat{\mathrm{CPU}}_t$ and $\hat{\mathrm{CPU}}^\tau$ to change $\mathrm{CPU}_t$ and $\mathrm{CPU}^\tau$. The local linear regression estimates of the elements $b_0$ and $b_1$ are the measures of $\beta_0$ and $\beta_1$ over which the below equation:

$$\begin{aligned} \min_{b_0, b_1} \sum_{i=1}^{N} \rho\theta\left[\mathrm{Grain}_t - b_0 - b_1(\hat{\mathrm{CPU}}_t - \hat{\mathrm{CPU}}^\tau)\right] \\ \times K\left(\frac{F_n(\hat{\mathrm{CPU}}_t) - \tau}{h}\right). \end{aligned} \tag{28}$$

In Equation (28), $\rho\theta(\mu)$ indicates the quantile loss framework. $K(\cdot)$ is the kernel framework. $h$ denotes the kernel bandwidth element and is set to 0.05. The kernel framework is applied to weight the observations in the neighborhood of $\mathrm{CPU}_t$. The symmetric framework centers around zero and selects minimal weights to distant observations. The inverse relationship exists between these weights and the distance involving the distribution framework of $\hat{\mathrm{CPU}}_t$, as represented by

$$F_n(\hat{\mathrm{CPU}}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\hat{\mathrm{CPU}}_k < \hat{\mathrm{CPU}}_t). \tag{29}$$

### 3.6 | Data and Sample Characteristics

Our analysis employs two main categories of data: the CPU Index and grain commodity market data. The sample period spans from May 1987 to August 2023, representing the most extensive time range available at the time of data collection, with a total of 435 monthly observations.

For the CPU Index, we utilize monthly data from the US CPU Index (available at https://www.policyuncertainty.com/). This index, constructed by Gavriilidis (2021), measures uncertainty in climate policy by analyzing climate policy-related terms from eight major US newspapers. It should be noted that the CPU data are specifically designed to measure the degree of uncertainty surrounding climate policy decisions and implementation. This index captures the unpredictability and ambiguity in climate policy frameworks, rather than their volatility per se. The index reflects the level of policy uncertainty over time, including factors, such as regulatory changes, implementation timelines, and policy direction shifts (Gavriilidis 2021). For grain commodity markets, we collect monthly closing prices for five major grain commodities (oats, corn, wheat, soybeans, and rough rice) from the US Chicago Mercantile Exchange via Datastream.

The choice of monthly frequency data, rather than daily observations, is motivated by several important considerations for market participants. First, climate policy changes and their associated uncertainties typically evolve over longer time horizons, making monthly data more suitable for capturing meaningful policy shifts and their market impacts. Second, monthly data helps filter out short-term market noise and speculation effects that might obscure the fundamental relationships between CPU and grain market dynamics. Third, institutional investors and policymakers, who are primary stakeholders in grain commodity markets, often operate with longer-term investment horizons aligned with monthly rather than daily trading frequencies.

Regarding data transformation, we apply logarithmic transformations to all variables to address nonstationarity issues in the original time series and to maintain consistency across our analysis. Specifically, for the CPU Index, we apply the natural logarithm to the raw index values to address potential nonstationarity and reduce the impact of extreme values. For grain commodity data, we implement logarithmic transformations in two stages: First, for volatility calculations, we apply the natural logarithm to the high–low price ratio, expressed as $V_t = \ln(H_t/L_t)$, where $H_t$ and $L_t$ represent the highest and lowest prices during month $t$, respectively. Second, we use log-difference computed as $R_t = \ln(P_t/P_{t-1})$, where $P_t$ represents the volatility data at month $t$. These transformations not only help stabilize the variance of our time series but also make our data more suitable for subsequent econometric analyses by making the distributions more symmetric and closer to normal.

The choice of the high–low price range method for volatility calculation, rather than GARCH models, is motivated by two factors: first, the relatively limited sample size of monthly observations ($n = 435$) could challenge the reliability of GARCH parameter estimation (Angelidis et al. 2004); second, the high–low range method effectively captures volatility changes within specific trading periods while reducing the impact of market noise (Hasbrouck and Saar 2013).

## 4 | Result Analysis

Table 1 presents summary statistics for our transformed data series: the logarithmic values of the CPU Index, and the logarithmic volatility measures for grain commodities calculated using the high–low price range method. As the findings show, all variables have positive mean, and the Jarque–Bera (JB) statistical test is significant at the 1% significance level, indicating that no Gaussian distribution is found. Also, all the series are asymmetrical and spiky, rejecting normality.

Checking on the transformed data characteristics in detail, we observe that among the grain commodity volatility measures, rough rice exhibits the highest mean (0.568), followed by wheat (0.447), while corn shows the lowest (0.205). The transformed CPU Index shows a mean value of 0.289. The positive skewness values for all grain commodities indicate more frequent large positive deviations, while the negative skewness for the CPU Index (−0.175) suggests more frequent small negative deviations from the mean.

The most crucial aspect is that the unit root checks for ERS in Table 1 denote that the volatility data used for the analysis of all variables are stationary. Subsequently, the findings of the Granger Causality check are summarized in Table 2. We observed that the null hypothesis of no Granger causality by the CPU in any grain commodity market is rejected at least at a 10% significance level. This suggests that relying on the Granger Causality examination, we can infer that the risk of CPU transmits to all grain commodity markets.

Figure 1 shows the plots of the series for all variables. We observe a typical fluctuation in volatilities for all variables around 1995 and a significant fluctuation for most variables following the COVID-19 outbreak.

In Table 3, Panel B provides the findings of volatility connectedness of median quantile (0.5). The TCI for the median is 18.57%. This shows a low correlation between the CPU and grain commodity markets at middle quantile levels. This relatively weak interconnection during normal market conditions suggests that investors and policymakers may have more flexibility in implementing targeted interventions without significant concern for systemic ripple effects across markets. The spillover contributed by each index to the system is quantified in the third penultimate row (TO). The results show that Corn (42.33%) and Soybeans (21.84%) have the highest volatility spillover effect on the system, while CPU (2.65%) has the lowest volatility spillover effect on the system. The dominant role of corn and soybeans in transmitting volatility highlights their strategic importance in agricultural commodity markets, suggesting that policymakers should prioritize stabilizing these markets to maintain overall market stability. The low spillover effect from CPU indicates that CPU has a limited immediate impact during normal market conditions, providing a window

**TABLE 1** | Key summary statistics.

| | CPU | Corn | Oats | Wheat | Soybean | RoughRice |
|---|---|---|---|---|---|---|
| Mean | 0.289 | 0.205 | 0.398 | 0.447 | 0.299 | 0.568 |
| Variance | 1309.908 | 2530.212 | 2702.637 | 2215.940 | 2450.924 | 2951.420 |
| Skewness | −0.175 | 0.150 | 0.223* | 0.309 | 0.023 | 0.059 |
| Kurtosis | 0.818 | 0.595 | 0.482 | 1.033 | −0.349 | 0.344 |
| JB | 14.397*** | 8.064** | 7.827** | 26.309*** | 3.249** | 3.398** |
| ERS | −12.041*** | −5.868*** | −2.866*** | −2.256*** | −5.621*** | −2.880*** |

*Note:* JB reports the Jarque–Bera statistic, and ERS shows the unit-root test with constant.
Abbreviations: CPU, climate policy uncertainty; ERS, Elliott–Rothenberg–Stock; JB, Jarque–Bera.
* $< 0.1$.
** $< 0.05$.
*** $< 0.01$.

**TABLE 2** | Granger causality test between climate policy uncertainty (CPU) and Grain commodity markets.

| | Null hypothesis | Stat | *p* value | Outcome |
|---|---|---|---|---|
| CPU versus Corn | CPU not Granger causes Corn | 1.759 | 0.066 | $H_0$ is rejected |
| CPU versus Oats | CPU not Granger causes Oats | 6.615 | 0.002 | $H_0$ is rejected |
| CPU versus Wheat | CPU not Granger causes Wheat | 9.720 | 0.001 | $H_0$ is rejected |
| CPU versus Soybeans | CPU not Granger causes Soybeans | 3.372 | 0.080 | $H_0$ is rejected |
| CPU versus RoughRices | CPU not Granger causes RoughRices | 9.719 | 0.001 | $H_0$ is rejected |

*Note:* Table 2 presents the Granger causality test between the CPU and segmented grain commodity markets. We report the respective statistics and corresponding *p* values for each set of Granger tests.

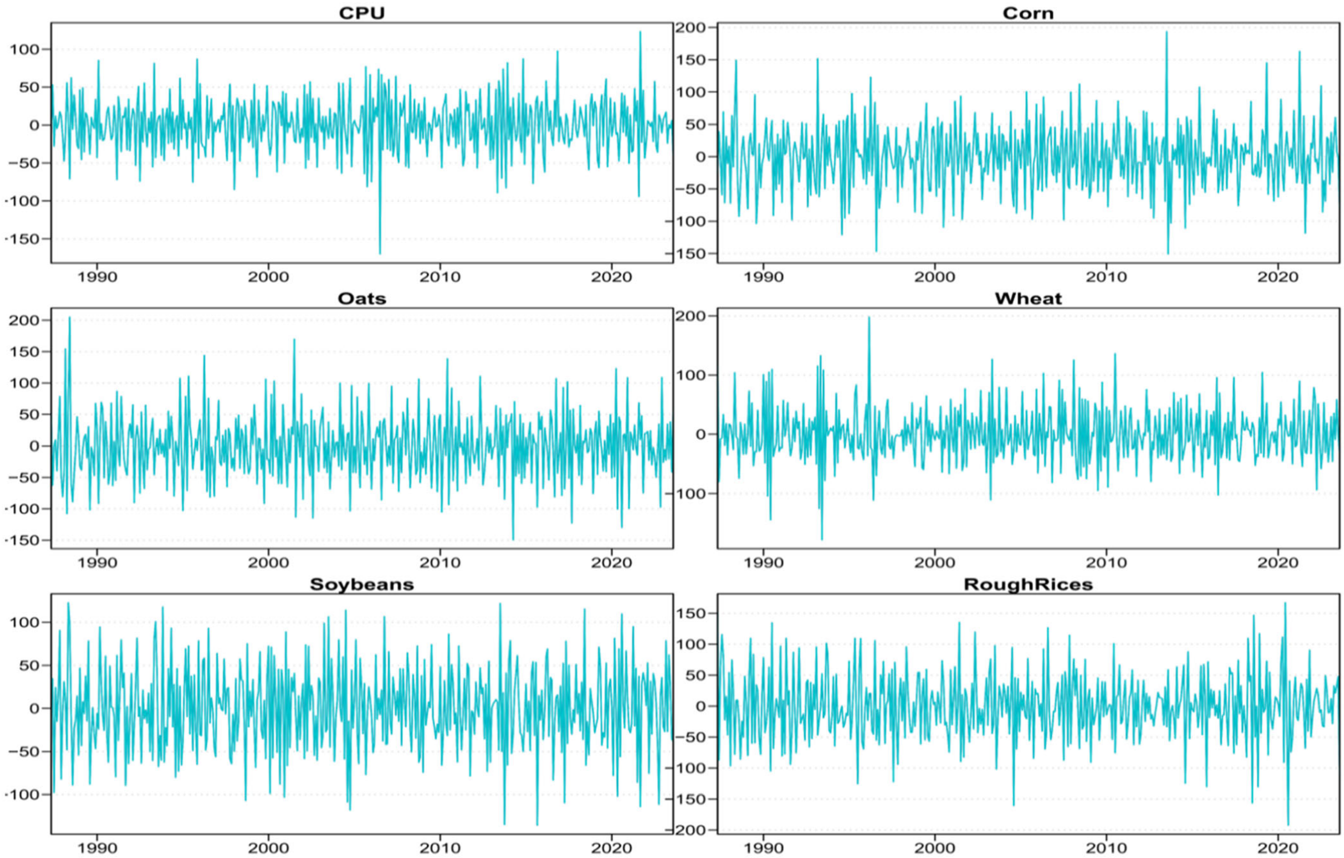



**FIGURE 1** | Dynamics of sample volatilities. *Note:* Findings provide the dynamic of risk of CPU and specify grain commodity markets. CPU, climate policy uncertainty. [Color figure can be viewed at wileyonlinelibrary.com]

of opportunity for implementing climate policies with minimal market disruption.

Conversely, the first column on the right (FROM) indicates the volatility shock from one market to each variable. The highest spillover is from other markets to Corn (33.21%) and Soybeans (25.53%). In contrast, the spillover effect from the system to the CPU (2.6%) is the lowest. The high vulnerability of corn and soybean markets to external shocks emphasizes the need for robust risk management strategies in these sectors. Market participants, particularly commodity traders and agricultural businesses, should maintain adequate hedging positions and diversification strategies to mitigate these spillover risks. The last row (NET) represents the net spillover effect, with Oats, Soybeans and Wheat being the net recipients of the volatility spillover effect. Conversely, Corn, CPU, and RoughRice are net senders of spillovers.

Panels A and C of Table 3 deliver connectedness at the extreme lower quantile (0.05) and upper quantile (0.95). We observe that in terms of connectedness, total connectedness is more significant at the extreme high quantile (73.94%) and extreme low quantile (74.76%) compared with total median connectedness (18.57%) at the middle quantile (0.5). This substantial increase in market interconnectedness during extreme conditions has crucial implications for systemic risk management. The heightened connectedness during market stress suggests that traditional diversification strategies may become less effective precisely when they are most needed, requiring market participants to develop more sophisticated risk management

**TABLE 3** | Volatility connectedness based on quantile VAR.

| | CPU | Corn | Oats | Wheat | Soybeans | RoughRice | FROM |
|---|---|---|---|---|---|---|---|
| *Panel A: Lower quantile ($\tau = 0.05$)* | | | | | | | |
| CPU | 28.28 | 14.07 | 14.84 | 14.69 | 14.52 | 13.59 | 71.72 |
| Corn | 11.69 | 24.36 | 15.75 | 16.44 | 17.49 | 14.27 | 75.64 |
| Oats | 12 | 17.38 | 24.92 | 15.95 | 15.28 | 14.47 | 75.08 |
| Wheat | 12.53 | 17.01 | 15.61 | 24.91 | 15.53 | 14.41 | 75.09 |
| Soybeans | 12.45 | 17.59 | 15.78 | 15.32 | 24.84 | 14.02 | 75.16 |
| RoughRice | 12.88 | 15.89 | 14.92 | 15.76 | 16.44 | 24.11 | 75.89 |
| TO | 61.54 | 81.94 | 76.9 | 78.17 | 79.26 | 70.76 | 448.58 |
| Inc.Own | 89.83 | 106.3 | 101.82 | 103.08 | 104.1 | 94.87 | TCI |
| NET | −10.17 | 6.3 | 1.82 | 3.08 | 4.1 | −5.13 | 74.76% |
| *Panel B: Median quantile ($\tau = 0.5$)* | | | | | | | |
| CPU | 97.4 | 0.89 | 0.07 | 0.05 | 0.11 | 1.48 | 2.6 |
| Corn | 0.39 | 66.79 | 8.47 | 8.61 | 13.36 | 2.39 | 33.21 |
| Oats | 0.03 | 10.5 | 78.33 | 5.94 | 4.89 | 0.3 | 21.67 |
| Wheat | 0.14 | 13.95 | 4.34 | 76.93 | 3.03 | 1.6 | 23.07 |
| Soybeans | 1.17 | 14.7 | 6.32 | 2.71 | 74.47 | 0.63 | 25.53 |
| RoughRice | 0.92 | 2.29 | 0.34 | 1.38 | 0.45 | 94.63 | 5.37 |
| TO | 2.65 | 42.33 | 19.54 | 18.69 | 21.84 | 6.39 | 111.45 |
| Inc.Own | 100.04 | 109.12 | 97.86 | 95.63 | 96.32 | 101.02 | TCI |
| NET | 0.04 | 9.12 | −2.14 | −4.37 | −3.68 | 1.02 | 18.57% |
| *Panel C: Upper quantile ($\tau = 0.95$)* | | | | | | | |
| CPU | 28.13 | 15.17 | 14.39 | 14.29 | 14.6 | 13.43 | 71.87 |
| Corn | 13.31 | 23.88 | 15.37 | 15.92 | 17.83 | 13.69 | 76.12 |
| Oats | 13.27 | 16.9 | 26.1 | 15.86 | 15.18 | 12.69 | 73.9 |
| Wheat | 13.64 | 16.8 | 14.26 | 25.21 | 14.79 | 15.3 | 74.79 |
| Soybeans | 13.96 | 17.92 | 15.52 | 13.8 | 24.97 | 13.82 | 75.03 |
| RoughRice | 13.56 | 15.71 | 13.87 | 13.86 | 14.94 | 28.06 | 71.94 |
| TO | 67.75 | 82.49 | 73.4 | 73.74 | 77.33 | 68.93 | 443.64 |
| Inc.Own | 95.87 | 106.37 | 99.51 | 98.95 | 102.3 | 96.99 | TCI |
| NET | −4.13 | 6.37 | −0.49 | −1.05 | 2.3 | −3.01 | 73.94% |

*Note:* The connectedness index is measured relying on a 10-step forecast horizon.
Abbreviations: CPU, climate policy uncertainty; TCI, total connectedness index; VAR, vector autoregressive.

approaches for extreme quantile conditions. The importance of tail dependence is highlighted by the extreme high quantile and extreme low quantile risk connectedness, which provides investors with crucial information for portfolio management in extreme quantile conditions.

Next, we observe the information on each index's contribution to the system's spillover effects in panels A and C of Table 3, which provides evidence that spillover effects are asymmetric across quantile conditions. This asymmetry has important implications for both market participants and policymakers. During extreme quantile conditions, the increased interconnectedness suggests that policy interventions may have amplified effects, requiring more careful calibration of regulatory responses. Referring to row (TO), we can observe that in Panel A, Corn (81.94%) and Soybeans (79.26%) have the highest spillover effect on the system at the extreme lower quantile (0.05) of connectedness results. In comparison, CPU (61.54%) and RoughRices (70.76%) have the lowest contribution to the system's spillover. As a comparison, we look at row (TO) in Panel C. In the highly high quantile (0.95) of connectedness results, Corn (82.49%) and Soybeans (77.33%) have the highest contribution to the spillover effect of the system. In comparison, CPU (67.75%) and RoughRices (68.93%) make the lowest contribution to the spillover of the market. Next, we focus on the (FROM) row to obtain results on the system's risk shocks to a variable. We make a summary that in the extreme low quantile (0.05), Corn (75.64%) and RoughRices (75.89%) receive the most risk shocks from the system, while in the extreme high quantile (0.95), Soybean (75.03%) and Corn (76.12%) receive the most risk shocks from the system. This illustrates that Corn markets receive more risk shocks under extreme market conditions. This result is in line with Ji et al. (2018), who confirm that Corn markets face the most significant exposure during periods of market stress.

We then look at the findings in panels A and C of Table 3. This presents the contribution of a given market to the net spillover of the system in an extremely low quantile (0.05) and extremely upper quantile (0.95). An important conclusion, based on the data in a row (NET), is that the CPU is a net receiver of shock (−10.17%) in the extremely low quantile (0.05) connectedness result. At the same time, it is a net recipient of connectedness (−4.13%) in the highest high quantile (0.95) connectedness results. These results illustrate that the connectedness results are heterogeneous across quantile conditions. In contrast, at the market's median level (0.5), the CPU acted as a net sender of connectedness in the system (0.04%). We note that the TCI (74.76%) is more significant at the low quantile (0.05) than at the extremely upper quantile (0.95) (73.94%).

In summary, the TCI of the extreme low tails (0.05) and extreme high tails (0.95) is more significant than the medium magnitude. This suggests that for extreme shocks, the strength of connectedness rises with the correlation of the spillover. Specifically, the TCI was 18.57% at the medium scale, while the total connectedness was 74.76% and 73.94% at the extreme lower tail (extreme low quantile, 0.05) and extreme high tail (0.95), respectively. For the Corn market, the upper, middle, and lower quantiles are all net senders of spillover. In addition, the CPU is the leading net sender of spillovers in the medium quantile, and investors should closely monitor the movement of the CPU to assist in developing risk-averse strategies for grain commodity markets. Of interest is that RoughRice is the biggest net recipient of spillovers at the extreme lower quantile (−5.13%).

Next, we will further discuss the differences in contributions of various grain commodity markets to other markets and the potential economic reasons behind these impacts. On the basis of the static connectedness outcomes in Table 3, we observed variations in the FROM and TO contributions of each variable under different quantile conditions. It is noteworthy that corn played the role of a net sender of paired spillover contributions to other grain commodity markets under all quantile conditions. In contrast, the roles of other grain commodity markets in contributing spillover volatility to other markets changed frequently. It should be emphasized that the significance of the US corn market and its influence on other grain commodity markets is underscored by Roberts and Schlenker (2013) due to the reliance on corn as a raw material for US fuel ethanol production. Last but not least, the CPU received net paired spillover contributions from all grain commodity markets under extreme market conditions. Our analysis also revealed that, at the median level (0.5), the CPU sent net paired spillover contributions to the wheat and soybean markets. This implies that even in relatively stable markets, the sensitivity of wheat and soybeans to climate policy reflects the complexity of grain commodity markets and market participants' concerns about future uncertainty (Wang et al. 2023).

Figure 2 offers the time-varying TCI at different quantile levels, and we follow Dai et al. (2023). The TCI levels fluctuated over time across different quantile levels. Notably, the time-varying dynamics of extremely lower quantile (0.05) connectedness exhibited more pronounced fluctuations than other quantiles, particularly at the onset of the sample. It is worth mentioning that the trends of TCI at different quantile levels gradually converged in the later part of the sample, offering insight into symmetrical time-varying risk connectedness. Consequently, market participants should devise a stable risk mitigation strategy tailored to heterogeneous quantile conditions. Furthermore, it is noteworthy that we observed heightened volatility and crisis periods during the recent 20-year sample interval: 2003–2005 (severe weather and pests in 2003–2004), 2006–2008 (drought and rising oil prices in food-producing countries), 2014–2015 (commodity prices entering a downward cycle led by oil) and 2020 (COVID-19 pandemic and supply chain disruptions), we notice sharp fluctuations in TCI.

Figure 3 reveals the relative tail dependence (RTP) among the CPU and grain commodity markets. RTP is measured as the difference between the TCI of the extreme upper and the lower quantiles (0.95 and 0.05). The results from Figure 3 indicate that RTP experienced extremely negative values at the early stage of the sample time range, gradually rising and approaching 0. This suggests that the connectedness level at the very low quantile (0.05) was relatively higher compared with the very high quantile (0.95). In other words, this supports the earlier conclusion that the correlation between the CPU and grain commodity markets is higher when the market is in extreme lower quant.

Figure 4 shows the findings for net time-varying volatility spillover. The outcomes reveal that the position of the different variables as net receivers or senders of volatility connectedness varies with time and market conditions (at different quantile levels). The main addition here is the time-varying dynamics of the records in Table 2 regarding the cyclicality of the outcomes on the net connectedness contribution of different markets to the system (NET). In line with the records in Table 2, we observed in Figure 4 that corn was the primary contributor to spillovers across all quantiles. Additionally, at the median and extremely low quantiles, most grain commodity markets exhibited seemingly larger fluctuations in the magnitude of spillovers during the sample range compared with the very high quantile. Interestingly, at all quantile levels, RoughRice was predominantly a net receiver of spillovers for the majority of the sample range. However, after 2020, there was a sharp increase in net risk spillovers sent by RoughRice, transforming it into a net spillover sender within the system. The pattern and range of net spillovers are heterogeneous at the median (0.5), extremely low and high (0.05 and 0.95), suggesting that policymakers or investors may modify their policies and portfolios in response to changing market states.

Figure 5 illustrates the paired risk contagion between the CPU and grain commodity markets. Upon careful examination, we observed that, for the majority of the time periods, the CPU acted as a net recipient of paired risk spillovers among the grain commodity markets. Furthermore, the network connectedness patterns at different quantile levels were nearly symmetric, suggesting that policymakers should maintain policy measures to address the changing climate risks and market conditions.

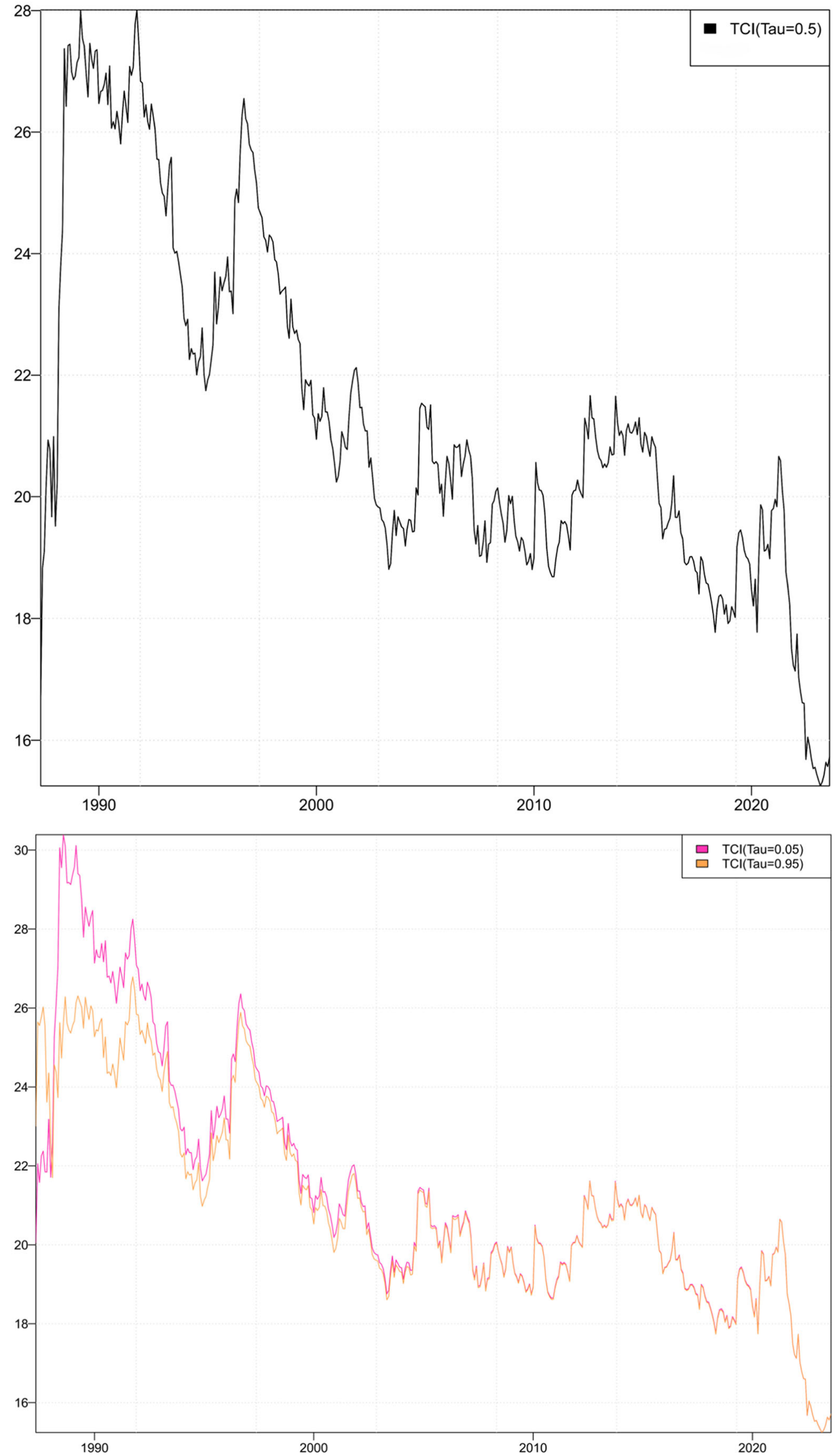



**FIGURE 2** | Different quantile-based TCIs. *Note:* Findings of dynamic TCIs rely on a lag length of order 1 with a 10-step-ahead GFEVD. GFEVD, generalized forecast error variance decomposition; TCI, total connectedness index. [Color figure can be viewed at wileyonlinelibrary.com]

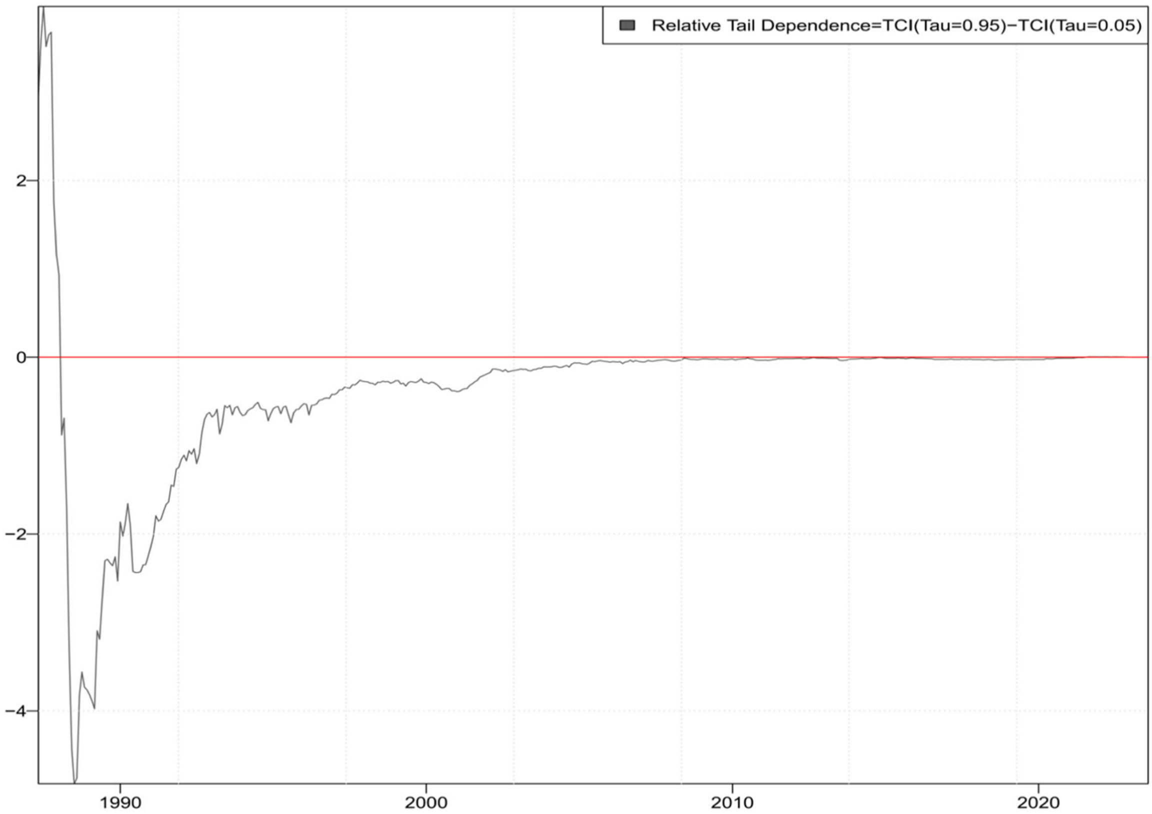


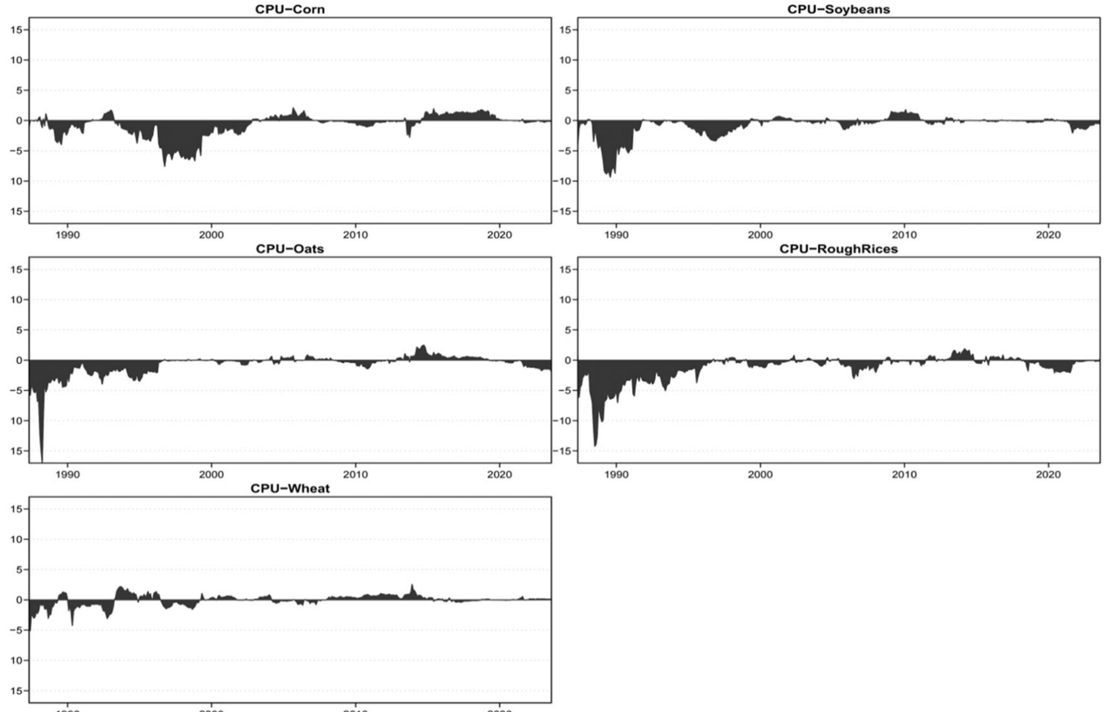

**FIGURE 3** | Relative tail dependence (RTP). *Note:* Findings of dynamic RTP rely on a lag length of order 1 with a 10-step-ahead GFEVD. GFEVD, generalized forecast error variance decomposition; TCI, total connectedness index. [Color figure can be viewed at wileyonlinelibrary.com]

Upon further scrutiny of Figure 5, we identified that during periods of extreme quantile (very low quantile, 0.05), in the face of negative news, the CPU exhibited a stronger susceptibility to the risk impact from grain commodity markets, evident in a higher level of received paired risk spillover. This was particularly notable from the sample start to the mid-1990s. A possible explanation could be traced back to the period between 1988 and 1997 when the United States briefly reduced agricultural subsidy intensity, initiating market-oriented adjustments to agricultural policies. This included lowering target prices for agricultural products, reducing minimum support prices, and adopting fixed subsidies decoupled from production and prices. The strengthening financial attributes of grain markets during this time intensified the risk contagion effect in very low quantile states in the US grain commodity markets (Cepni et al. 2023), thereby exacerbating the risk spillover to the CPU. In contrast, during periods of extreme bull markets (very high quantile, 0.95), in response to positive news, the risk spillover effect of net paired connectedness between the CPU and all grain commodity markets was not significantly pronounced compared with extreme low quantile. However, under normal quantile market conditions (0.5), we observe relatively flat returns on net pairwise CPU connectedness with all grain commodity markets for most of the sample, with only a few periods of sharp fluctuations corresponding to the extreme weather of 2005–2006, the shock of the shale oil revolution in 2014–2015. This also suggests that the net pairwise connectedness of CPUs with all grain commodity markets is influenced by supply and demand factors in addition to climate, politics, or shocks from major public events (Hobbs 2020).

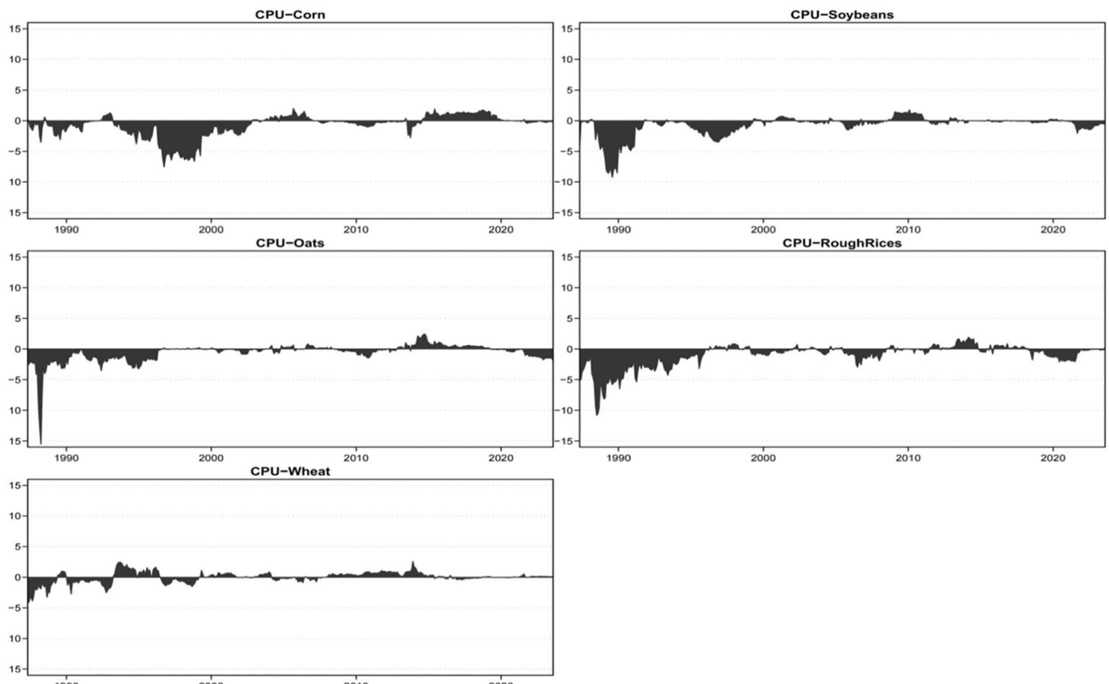
The TVP–QVAR results do not permit the observation of lead–lag relationships between the CPU and specific grain commodity markets across different time and frequency domains. This is highly significant as, on the one hand, time–frequency analysis provides substantial insights for heterogeneous investors with diverse preferences, aiding them in making informed investment decisions. For instance, speculators may focus more on short-term investments, while institutional investors tend to lean towards long-term holdings (Baruník and Křehlík 2018). On the other hand, it facilitates policymakers and international organizations in monitoring the long-term or short-term influences of climate policy risks on grain commodity markets. Our findings can offer them crucial initial information for formulating preventive policy evaluations. To gain a more comprehensive and in-depth understanding of the dynamic connections between the CPU and specific grain commodity markets, we will extend our empirical analysis using wavelet coherence techniques.

By examining the results in Figure 6, we identified heterogeneous time–frequency dependency patterns between the CPU Index and grain commodity returns. We will summarize and discuss the key findings. First, we observed that the correlation between the CPU Index and the volatility of the oat market was primarily concentrated in the high-frequency domain (32–64 months), corresponding to the sample interval of 1997–2005. Particularly, during the sample period of 1999–2002, there was a pronounced dependence between the two, as indicated by the left-upper arrow. This arrow suggests that due to weather-related issues causing a slowdown in oat cultivation


**FIGURE 4** | Net connectedness in quantile VAR. *Note:* Findings of dynamic NET Connectedness rely on a lag length of order 1 with a 10-step-ahead GFEVD. CPU, climate policy uncertainty; GFEVD, generalized forecast error variance decomposition; VAR, vector autoregressive. [Color figure can be viewed at wileyonlinelibrary.com]

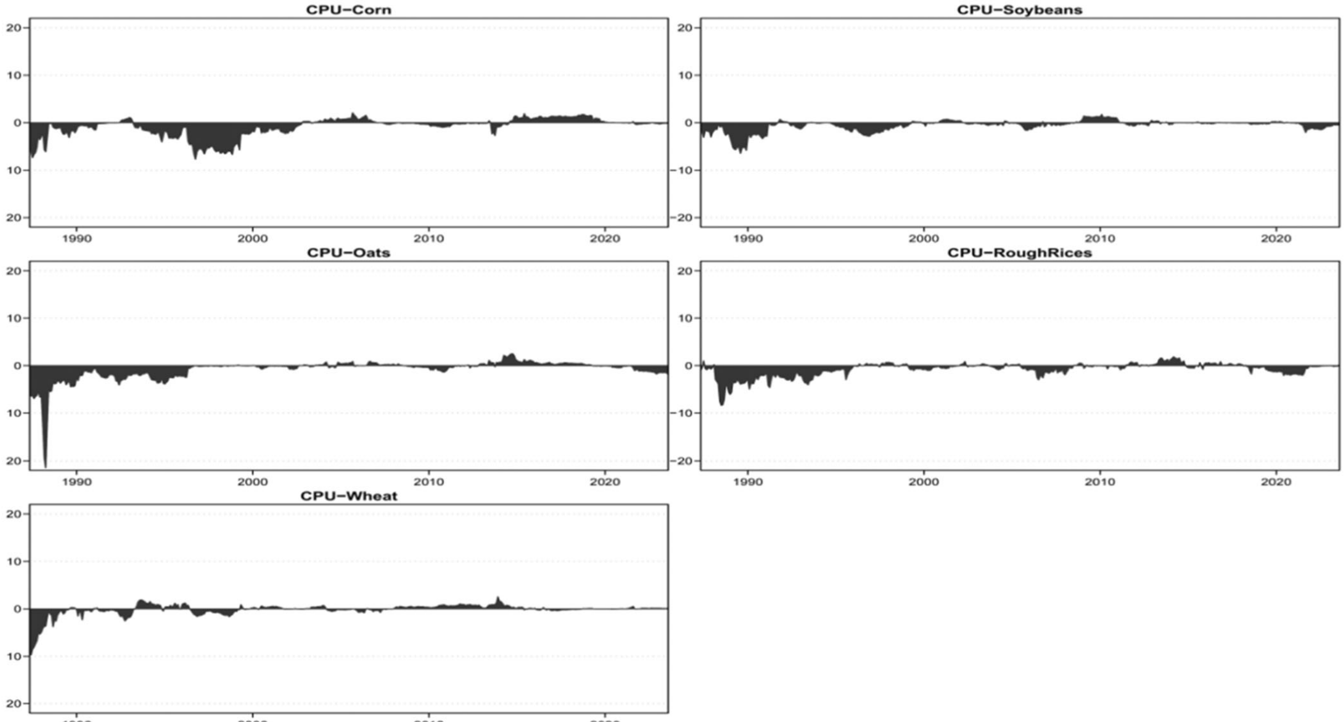



(a) Net pairwise connectedness between CPU and specify Grain Commodities. (Lower quantile, $q$=0.05)




(b) Net pairwise connectedness between CPU and specify Grain Commodity markets. (Medium quantile, $q$=0.5)

**FIGURE 5** | Net pairwise risk connectedness between CPU and Grain Commodities. *Note:* Findings rely on a lag length of order 1 with a 10-step-ahead GFEVD. (a)–(c) describe the net pairwise connectedness from CPU to segmented grain commodity markets at different quantile levels, respectively. (a) Net pairwise connectedness between CPU and specify Grain Commodities (lower quantile, $q = 0.05$). (b) Net pairwise connectedness between CPU and specify Grain Commodity markets (medium quantile, $q = 0.5$). (c) Net pairwise connectedness between CPU and specify Grain Commodity markets (upper quantile, $q = 0.95$). CPU, climate policy uncertainty; GFEVD, generalized forecast error variance decomposition.




(c) Net pairwise connectedness between CPU and specify Grain Commodity markets. (Upper quantile, $q$=0.95)

**FIGURE 5** | (Continued)

in the United States, the oat market prices preceded those of the CPU Index. On the basis of the earlier definition of the CPU Index, our first significant finding suggests that major US media outlets were unable to predict the impact of upcoming climate policy changes on oat market volatility during the years 1999–2002. Furthermore, in the low-frequency domain (4–8 months), both markets exhibited strong correlations again within the sample intervals of 1999–2000 and 2002–2003. We observed that the CPU Index led the oat market (right-upper arrow), implying that climate-related reports by major US media outlets might have anticipated the upcoming influence of climate or related policy changes on oat market prices.

Additionally, we noticed intermittent correlations between the CPU Index and the corn market in the short-term frequency domain (0–4 months). Correspondingly, during the sample period of 2013–2014, the two markets demonstrated a significant dependency, with corn market volatility being opposite to that of the CPU (left-pointing arrow). Lastly, but not less importantly, we no longer observed any significant time–frequency correlations between the CPU Index and the corn market (red islands with arrows). This also suggests that the influence of climate or policy reports by major US media outlets on corn market volatility can be considered negligible.

Subsequently, we investigated the cross-market time–frequency correlation between the CPU and the wheat market. It is noteworthy that, initially, we observed a close correlation between the CPU and the wheat market in the short-term frequency domain (around 4 months), corresponding to the sample period of 1999–2000. During this period, the CPU Index demonstrated a tight comovement pattern with the volatility of the wheat market (right-pointing arrows). However, in the midterm domain (8–16 months), corresponding to the sample period of 1995–1997, the volatility of the wheat market significantly led to that of the CPU Index (upper-left arrow). This leads us to speculate that climate policy-related reports by major US media outlets were generally unable to anticipate the impact on wheat market volatility for the majority of the periods.

Regarding the interplay between the CPU and the soybean market, we identified occasional brief periods of interdependence between the two markets. Specifically, in the short-term frequency domain (0–4 months) and the corresponding sample period of 2001–2002, soybean market volatility led to that of the CPU (arrow pointing to the lower right). Similarly, within the same frequency domain, during the years 2020 and 2021, a left-bottom arrow indicated that the CPU Index preceded the soybean market. While our analysis shows that the correlation between the CPU Index and soybean market persists for a maximum duration of approximately 12 months, this finding is consistent with the soybean market's fundamental characteristics. The relatively short-term nature of this

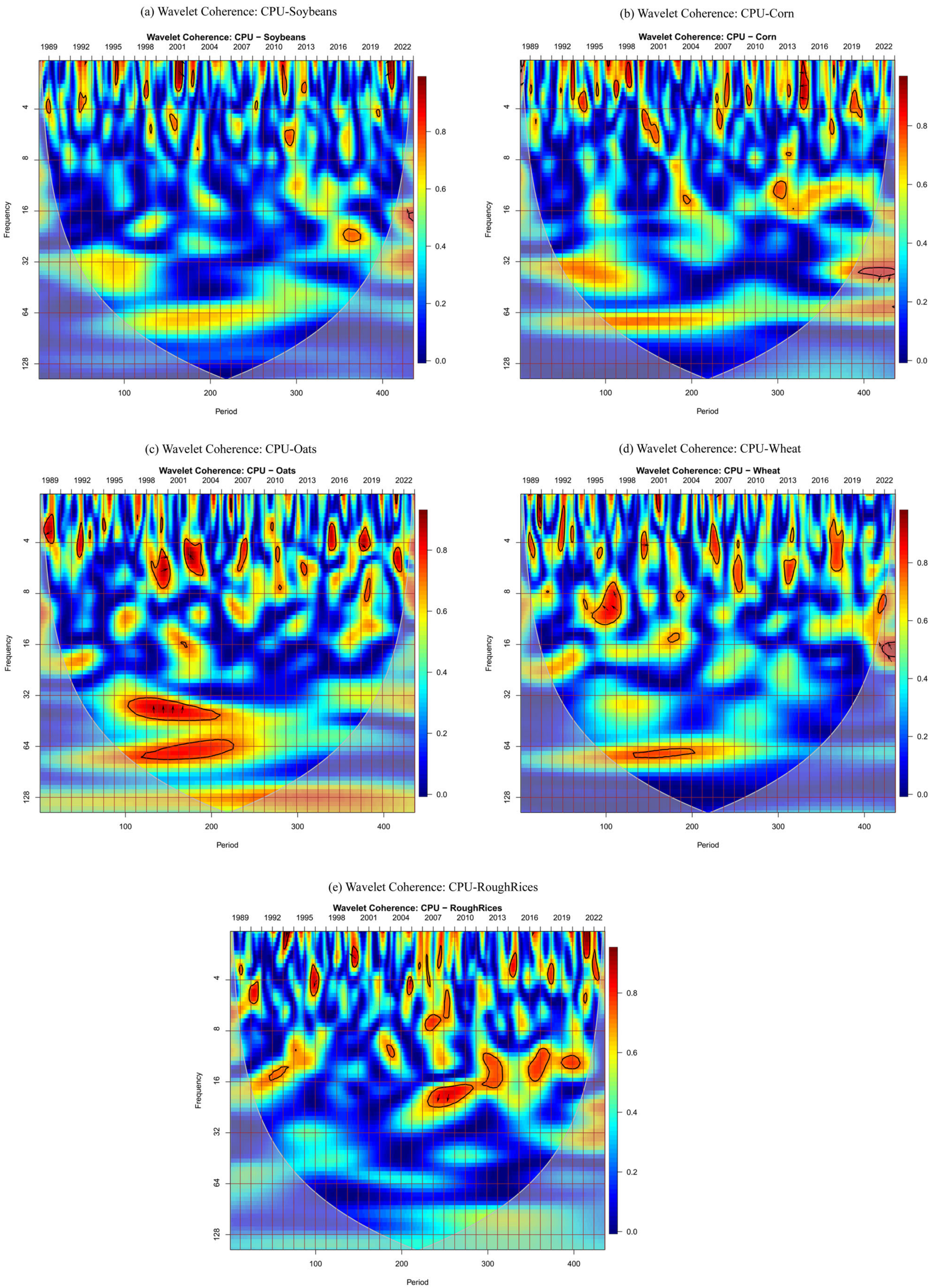



**FIGURE 6** | Legend on next page.

relationship can be attributed to the market's global supply chains, diverse growing regions, and sophisticated risk management infrastructure, which collectively enable soybean market participants to adapt to climate policy uncertainties. This suggests that while climate policy events reported in major US media can create temporary market disruptions, the soybean market has developed effective mechanisms to absorb and adapt to these shocks over longer time horizons.

Finally, we observed the time–frequency dependency patterns between the CPU Index and RoughRice. In the medium-to-long–term frequency domain (8–32 months), evident connections were identified during the sample period of 2007–2009, illustrated by islands with arrows in red. Subsequently, the risk indicated by the CPU Index was observed to precede that of the RoughRice market (arrow pointing to the lower left). Some small red islands also displayed faint time–frequency connections, such as in the short-term domain (0–4 months) during the sample interval of 1999–2000, where RoughRice volatility significantly led that of the CPU Index. However, these correlations quickly diminished, lasting for less than a year. Considering the definition of the CPU, it can be concluded that, for the most part, reports on climate-related issues by major US media outlets were generally unable to anticipate the impact of upcoming climate or policy changes on RoughRice market prices.

In summarizing our wavelet coherence results, we find that the heterogeneity of the CPU-grain commodity linkage structure is more pronounced at different time–frequency scales in the mid-to-short-term frequency domain compared with the long-term frequency domain. In other words, our observations from wavelet coherence indicate that the correlation between the CPU and grain commodity markets mostly occurred within 32 months. Furthermore, over the past 35 years, we observed the closest connection between oat commodity market volatility and the CPU, while the connection between the soybean commodity market and the CPU was relatively weak. Specifically, in the medium-to-long-term frequency domain, there was almost no observed association between soybean commodity market volatility and the CPU Index. Importantly, based on the definition of the CPU, we understand that, for the majority of the periods, the external risk shocks formed by climate policy changes reported by major US media outlets had intermittent and heterogeneous impacts on the volatility of most grain commodity markets, excluding soybeans.

Due to the inability of the TVP–QVAR connectedness model and wavelet methods to elucidate the heterogeneous and asymmetric impact mechanisms of CPUs at different quantiles on the segmented grain commodity market at various quantile levels, Figure 7 employed the QQR technique as a supplementary approach, to gain a deeper understanding of these asymmetric effects. Our QQR findings reveal that, apart from Wheat, the influence of CPU on all grain commodity markets predominantly manifests alternatingly in negative and positive correlations. The strength of these conditional relationships varies with the percentiles of CPU and grain commodity markets.

Specifically, CPU exhibits positive risk impacts on Soybeans within specific percentile intervals (0.2–0.3, 0.4–0.5, and 0.6–0.7). Concurrently, the positive correlation between CPU and Soybeans is observed to be robust at higher (lower) percentiles of CPU. Similar observational outcomes apply to RoughRice, where CPU is observed to exhibit cross-market positive correlations only within specific percentile intervals of RoughRice (0.2–0.3 and 0.4–0.5), often coinciding with extreme percentiles of CPU.

For Oats and Corn, generally, the positive influence of CPU on Oats and Corn appears less pronounced compared with that on Soybeans and RoughRice. However, they are more susceptible to significant positive conditional effects of extreme CPU variations under normal quantile conditions (0.4–0.6). This suggests that Oats and Corn serve as hedges against CPU during periods of recession and prosperity. Our research findings complement existing studies on the responses of other markets to CPU shocks (e.g., Liu et al. 2023). It is noteworthy that the charts in Figure 7 distinctly illustrate the predominantly positive effects of CPU on Wheat across most percentiles. Particularly, this correlation is observed positively and strongly across nearly all percentile levels of Wheat, especially at extreme downward percentiles of CPU.

In general, we find evidence supporting the alternative hypothesis that extreme variations in CPU induce changes in the risk across most grain commodities, denoting that the impact of climate policies may be minimal under median market conditions. We reiterate the conclusions of the TVP–QVAR connectedness method, suggesting that under stable market conditions, CPU's predictive ability for risk in grain commodity markets is inferior to the conditions of extreme quantiles. Other insights from our QQR methodology indicate that the magnitude and direction of CPU's impact on the risk within grain commodity markets depend on specific markets and market conditions.

**FIGURE 6** | Wavelet transformation coherence (WTC) between CPU and Grains commodity markets. *Note:* The horizontal axis represents both time and the number of samples, while the vertical axis illustrates the frequency of conversion into time units, ranging from 4 to 64 months. Contours with dense shading signify areas of 5% horizontal significance. Arrows denote the right (left) direction when two variables are in-phase (anti-phase) dependent. Furthermore, cooler colors (blue) indicate a significantly lower level of dependence between the two variables, whereas warmer colors (red) highlight regions of high correlation. Then the phase differences are denoted by black arrows on the wavelet coherence plot. A right-pointing arrow signifies that the two variables exhibit the same trend of movement at a given scale, while a left-pointing arrow indicates an opposite phase, implying opposite movement at a given scale. When the arrows show right up or left down, the CPU leads the risks of a specific grain commodity market. Conversely, when the arrows show right down and left up, the risks of a given grain commodity market lead the CPU. (a) Wavelet coherence: CPU-Soybeans. (b) Wavelet coherence: CPU-Corn. (c) Wavelet coherence: CPU-Oats. (d) Wavelet coherence: CPU-Wheat. (e) Wavelet coherence: CPU-RoughRices. CPU, climate policy uncertainty. [Color figure can be viewed at wileyonlinelibrary.com]

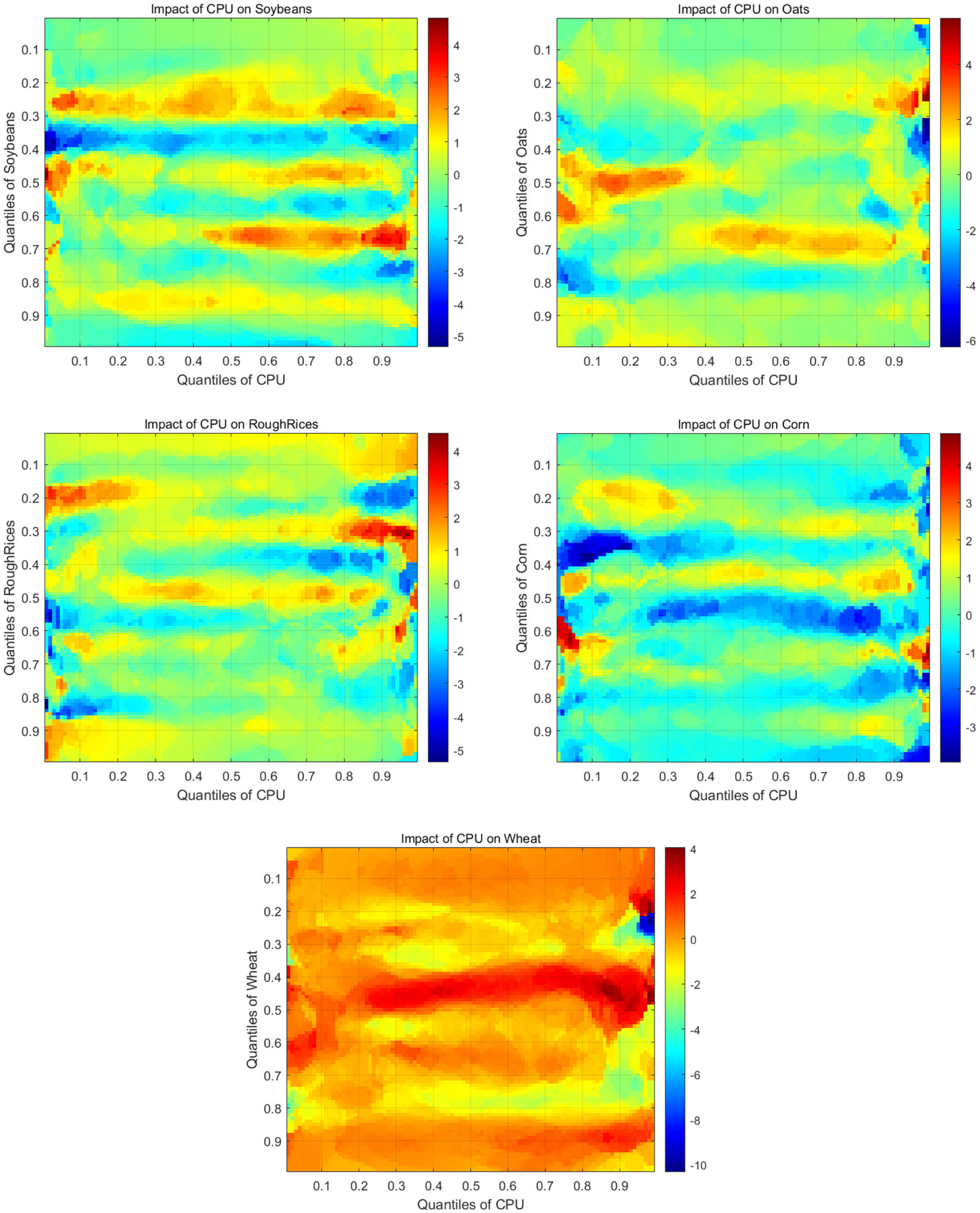



**FIGURE 7** | The impact of CPU on specifies grain commodity market. *Note:* The figure presents QQR in a two-dimensional graphical format. For the dependent variable (segmented grain commodity markets) and the explanatory variable (CPU), these graphs represent the quantile slope coefficients as a function of quantile parameters (Umar et al. 2022). CPU, climate policy uncertainty; QQR, quantile-on-quantile regression. [Color figure can be viewed at wileyonlinelibrary.com]

**TABLE 4** | Summary statistics of different TCIs.

| | Mean | Variance | Skewness | Kurtosis | JB |
|---|---|---|---|---|---|
| TCI ($\tau = 0.05$) | 21.441 | 3.124 | 0.828 | 3.285 | 51.230*** |
| TCI ($\tau = 0.5$) | 21.317 | 2.879 | 0.567 | 2.722 | 24.784*** |
| TCI ($\tau = 0.95$) | 21.075 | 2.555 | 0.348 | 2.590 | 11.870*** |

*Note:* The Jarque–Bera (JB) check is for the null hypothesis of normality of the TCIs.
Abbreviation: TCI, total connectedness index.
***, **, and * point levels of significance at the 1%, 5%, and 10%.

**TABLE 5** | The Niño 3.4 index on the TCI at three different interquantile levels.

| | OLS | Quantile (0.05) | Quantile (0.95) |
|---|---|---|---|
| Niño3.4-TCI ($\tau = 0.05$) | 0.792*** | 0.646*** | 1.026*** |
| Niño3.4-TCI ($\tau = 0.5$) | 0.788*** | 0.642*** | 0.997*** |
| Niño3.4-TCI ($\tau = 0.95$) | 0.779*** | 0.647*** | 0.764*** |

*Note:* Table 3 provides the results of regressing the Niño 3.4 index on the TCI at three different interquantile levels, using OLS and quantile regression (Quantile = 0.05 and 0.95, as TVP–QVAR connectedness model quantile setting), respectively.
Abbreviations: OLS, ordinary least squares; QVAR, quantile vector autoregressive; TCI, total connectedness index; TVP, time-varying parameter.
***, **, and * point out statistical significance at the 1%, 5%, and 10% levels, respectively.


**FIGURE 8** | TCI in the extreme lower and upper quantiles (forecast horizon = 15). *Note:* Findings of TCI rely on a lag length of order 1 with an alternative 15-step-ahead GFEVD. GFEVD, generalized forecast error variance decomposition; TCI, total connectedness index. [Color figure can be viewed at wileyonlinelibrary.com]

## 4.1 | The Impact of Climate Change Data on Total Connectedness Under Different Quantile Conditions

After investigating the risk spillover effects between CPU and the major grain commodity markets, to examine the driving factors behind these spillover effects, in this part, we discussed the potential determinants of TCI under different quantile conditions through a set of explanatory variables related to global climate and anomalies in Sea Surface Temperature (SST) dimensions, that is, the Niño 3.4 index. Following the pattern proposed by Zhang et al. (2023), we initially conducted a JB test to assess the normality of TCI's sequence.

Table 4 presents the descriptive statistics of TCIs at various percentiles. The JB statistical test indicated that the sequences of all TCIs were not normally distributed, suggesting that using OLS regression may not be optimal. Therefore, considering the distribution of data sequences and in line with methods applied in previous literature (Saeed et al. 2021; Zhang et al. 2023), we incorporated QR alongside OLS regression.

Grains possess a natural attribute of high dependence on weather conditions. Extreme weather not only has an immediate impact on grain growth but also exerts a delayed influence on subsequent growth by affecting soil moisture and fertility. Furthermore, concerns over supply caused by extreme weather exacerbate volatility in the grain commodity market. On the basis of existing paper (Wei et al. 2022; Dhifaoui et al. 2023), we opted for the Niño 3.4 index as the explanatory variable for climate data. The anomaly of the Niño 3.4 index is considered to represent the average SST from the date line to the coast of South America, making it the preferred data for defining global extreme climate phenomena, such as El Niño and La Niña events (Wei et al. 2023). The El Niño-Southern Oscillation events can lead to alterations in global weather patterns, potentially resulting in extreme weather events in the Great Plains region of the United States, where agricultural production is highly concentrated, spanning from the Midwest to the Great Lakes. It is worth mentioning that the North Atlantic Oscillation (NAO) index has a much greater impact on Western Europe than on the United States. NAO often affects climatic conditions on the Eastern Coast and Atlantic regions of North America. Considering the distribution of agricultural regions in the United States, we selected the Niño 3.4 index as a proxy for climate change data, rather than the NAO index.

The findings of the estimation are displayed in Table 5. The OLS regression shows a notable influence of climate change on TCI across all quantiles. The QR results align with those of the OLS regression. These results emphasize the substantial influence of climate change on the spillovers of volatility between the CPU and the primary grain commodity markets, varying across different quantiles. The theoretical significance lies in emphasizing the strong correlation between climate change, the grain industry, and climate policies in the United States.

## 4.2 | Robustness Tests

To mitigate the sensitivity of the data to different forecast horizons, following the method of Dai et al. (2023), we adjusted the forecast horizons to 15 and 20 steps, and replicated the empirical analysis. Figures 8 and 9 present the results compared with Figure 2. The trends and values of the dynamic TCI based on the tail quantiles for a forecast horizon of 10 steps are essentially similar to those of the dynamic TCI based on the tail


**FIGURE 9** | TCI in the extreme lower and upper quantiles (forecast horizon = 20). *Note:* Findings of TCI rely on a lag length of order 1 with an alternative 20-step-ahead GFEVD. GFEVD, generalized forecast error variance decomposition; TCI, total connectedness index. [Color figure can be viewed at wileyonlinelibrary.com]

quantiles for forecast horizons of 15 and 20 steps. Therefore, we assert that the TCI exhibits broadly similar behavior, with minimal variations. Overall, the empirical findings of our study remain robust across various forecast horizons.

## 5 | Conclusions and Policy Suggestions

Climate change and related policy uncertainties significantly impact agricultural markets, particularly grain commodities that are essential for global food security. While existing research has examined various aspects of CPU and commodity markets independently, the complex dynamics between CPU and grain market volatility, especially under different quantiles, remained understudied. This study addressed this gap by analyzing the time–frequency relationships and volatility connectedness between CPU and major grain commodity markets using monthly data from May 1987 to August 2023.

Our methodological approach combined three sophisticated techniques: the TVP–QVAR connectedness method, wavelet coherence analysis, and QQR. This comprehensive framework enabled us to examine market relationships across different market conditions, time frequencies, and risk levels, providing insights beyond traditional analytical approaches. Notably, our study is the first to apply this integrated methodology to examine CPU's impact on grain commodity markets.

Our empirical analysis revealed several robust and economically significant patterns in the relationship between CPU and grain markets. The TCI shows substantial variation across market conditions, reaching 82.09% during extreme high quantile level and 76.69% during downturns, compared with 70.70% in normal conditions. This pattern demonstrates that market integration intensifies precisely when diversification benefits are most needed. The finding that CPU transitions from a net contributor during stable periods to a net receiver during extreme conditions provides crucial insights for policy timing and effectiveness. Furthermore, our identification of corn as a consistent volatility transmitter, along with the documented 32-month persistence of CPU-market relationships, offers concrete guidance for risk assessment timeframes.

These empirical results translate into specific, actionable implications for market participants. Investment managers can enhance their portfolio performance by implementing state-dependent strategies: during stable periods, they should overweight climate policy monitoring for wheat and soybean positions, while during extreme conditions, they should prioritize fundamental market factors. For example, a portfolio manager might maintain higher wheat and soybean allocations during stable periods when these markets demonstrate greater sensitivity to policy changes but shift toward corn-based instruments during volatile periods, given corn's consistent role in volatility transmission.

For policymakers in grain-importing nations, our findings suggest concrete policy measures aligned with empirical patterns. The documented 32-month maximum duration of significant CPU effects provides a specific timeframe for strategic reserve planning. For instance, a developing country might structure its grain storage program with a 3-year horizon, maintaining larger strategic reserves of commodities showing higher CPU sensitivity. Additionally, the asymmetric market responses we identified suggest timing import decisions to coincide with periods of market stability, when price dynamics are more predictable, and policy impacts are more transparent.

Agricultural businesses can apply our findings to enhance their risk management frameworks. The strong relationship we found between the Niño 3.4 index and market connectedness suggests implementing integrated monitoring systems that combine climate indicators with policy tracking. For example, agribusiness firms might develop early warning systems that trigger risk mitigation measures when both climate indicators and policy uncertainty metrics exceed certain thresholds. The consistent role of corn as a volatility transmitter indicates its potential use as a leading indicator for broader market movements.

Directions for future research could consider higher-frequency data (e.g., weekly or daily) and include a broader range of agricultural commodities in the analysis. Research could explore the development of real-time monitoring systems that integrate our findings about market connectedness patterns, climate indicators, and policy uncertainty measures. Such systems could help stakeholders better anticipate and respond to market disruptions, ultimately contributing to enhanced food security globally.

### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

Data supporting this study is available from the corresponding author upon reasonable request.

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