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RESEARCH ARTICLE

How Do Energy Resources Affect Agricultural Market? Insights from Quantile-on-Quantile Approach

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Abstract: Based on the important role that energy and agricultural commodities play in sustainable development, this article investigates their price movements to understand their impact on each other. By utilizing an innovative quantile-on-quantile (QQ) approach with causality tests in conditional quantiles, the results show that (i) energy prices heterogeneously affect agricultural commodities prices, which can be attributed to the dynamic nature of the agricultural commodity market, different energy price shocks, and distinct market conditions; (ii) energy has a mixed positive and negative impact on agricultural commodities; and (iii) at higher or lower quantiles, that is, under extreme bear or bull market conditions, energy markets are more likely to have a significant impact on agricultural markets. The asymmetry of these impacts on the prices of agricultural commodities necessitates the implementation of distinct policy measures for effective governance. The findings can inform such measures by accounting for changes in food quantiles and different price shocks from the three primary energy sources.

Keywords: quantile-on-quantile, energy, agriculture, causality-in-quantiles, sustainability

1. Introduction

This study investigates the marginal effect of energy on agricultural commodities. Both energy and agricultural commodities play crucial roles in sustainable development by ensuring environmental, social, and economic sustainability. They are indispensable for meeting the basic needs of society and driving economic development [1]. In order to meet the targets of carbon peak and carbon neutrality, as well as to advance sustainable development, fossil energy and food security are becoming increasingly important to nations worldwide [2].

As a global challenge, climate change poses a significant threat to agricultural production. The increased frequency and intensity of extreme weather events, droughts, and floods have had a negative impact on crop yields and quality. In response to these challenges, governments and international organizations worldwide are promoting a range of climate change mitigation strategies aimed at reducing greenhouse gas emissions and fostering sustainable development. However, the implementation of these strategies may have an impact on energy markets, which in turn affects the cost structure and market dynamics of the agricultural sector [3, 4].

The state of world food and energy security is not optimistic, particularly given the context of the COVID-19 epidemic. Against this backdrop, energy demand has been affected, thereby directly impacting the operation of the agricultural market [5, 6]. The spatial spillover effects of improper land resource allocation and its nonlinear relationship with environmental pollution cannot be overlooked. Poor land resource management can lead to environmental degradation, which in turn affects the productivity of agricultural land and the sustainability of energy resources. The misallocation can also result in the inefficient use of water, land, and energy resources in agricultural trade, leading to tensions in these resource relationships [7]. As urban areas expand, the demand for agricultural products increases, which may lead to changes in agricultural practices and an increased reliance on energy-intensive production methods. This urbanization can also lead to the loss of arable land, further stressing the agricultural market and energy resources [8, 9]. Other factors, such as fluctuating grain prices, soaring energy, and fertilizer costs, have impacted the global food industry chain and supply chain, exacerbating the increasingly severe global food shortage. Meanwhile, the Russia–Ukraine conflict has further led to international trade tensions. Elevated energy prices have contributed to an increase in agricultural production expenditures, encompassing transportation, fertilizers, pesticides, and irrigation [10]. As a result, food costs have escalated, exacerbating food security concerns and presenting challenges to global food security.

The financialization of commodity markets leads to an increasingly interconnected relationship between markets [11, 12], which has further deepened the interdependency between energy and food. On the one hand, with the inflow of financial capital, speculative activities in the commodity futures market increase, which may lead to bubbles in the prices of energy and agricultural commodities. Speculators may operate simultaneously in both the energy and agricultural markets, thereby making the price fluctuations of the two markets more correlated [13]. On the other hand, financialization has increased the systemic risk between the energy and agricultural markets [14]. As the price fluctuations of the two markets tend

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to synchronize, instability in one market can quickly spread to the other, increasing the vulnerability of the entire system. Both the energy and agricultural markets are affected by macroeconomic factors such as global economic growth, inflation, and monetary policy. Financialization makes the impact of these macroeconomic factors on both markets more significant, thereby strengthening the connection between them. Thus, by exploring the common movement of energy prices and agricultural commodities prices, we can monitor the price dynamics of energy and food and anticipate future price movements. This provides valuable insights for policymakers and investors in decision-making processes.

Therefore, this study aims to examine how energy resources affect the agricultural market and to identify any potential causal relationships between the two in various market circumstances, including bull, bear, or normal markets. The specific impacts of energy resources (coal, crude oil, natural gas) on agricultural commodities (corn, soybeans, wheat) can be studied by considering their futures market. In regard to methodology, this article employs the quantile-on-quantile (QQ) method proposed by Sim and Zhou [15] in conjunction with the causality-in-quantiles test developed by Troster [16]. The empirical results create a complete three-dimensional picture of the influence pattern of energy resources, providing a more sophisticated comprehension of their interactions. They help to provide insight into the dynamics of these linkages in order to inform risk management and decision-making procedures in the markets for agriculture and energy commodities.

Why do energy prices have impacts on agricultural commodities? This study is conducted based on the following theoretical foundations. First, the promotion effect. The proliferation of fossil fuels has led to an increased reliance on mechanized power in agricultural production, enhancing productivity and advancing the green productivity of agriculture. Mechanization shifts labor toward machinery-dependent tasks, such as irrigation, significantly boosting the efficiency of staple crop production, suggesting that advancements in technology, spurred by the availability of energy resources, can augment agricultural output [17].

Second, cost theory. Production costs in agriculture will rise in response to rising energy prices. The fuel used in agricultural machinery, transportation costs, fertilizers, etc., are all directly or indirectly affected by energy prices, especially crude oil. This results in a change in the price of the final agricultural product [10, 18, 19]. What's more, bioenergy relieves demand pressure on traditional energy sources and prevents inflation caused by high oil prices. It can be seen as an alternative to energy that serves the goal of sustainable development [20, 21].

Third, substitution effect. High oil prices and environmental concerns will stimulate the need for bioenergy. As a result, there will be an increase in demand for biomass, like corn, which drives up the cost of biomass [18]. Additionally, large-scale cultivation of biomass will occupy agricultural land, which will eventually cause the cost of other foods to fluctuate [22–24].

Fourth, in the context of fossil fuels and their impact on the grain market, the theory of externality is particularly relevant due to the environmental impacts associated with the extraction, processing, and burning of fossil fuels. The combustion of fossil fuels contributes to climate change, which can lead to increased frequency and intensity of extreme weather events, such as droughts, floods, and heat waves. These events can significantly disrupt agricultural production, affecting grain yields and supply stability.

This study enriches the body of literature on the topic in several ways. First, it employs the QQ technique to examine the marginal effects of the price return of energy futures on agricultural commodities futures at various points of both energy and agricultural commodities price distributions. The extant literature uses a variety of economic approaches, such as frequency TVP-VAR, NARDL, and Granger causality tests using the copula model [10, 18, 25–27]. However, these methods are not effective in identifying how agricultural commodity prices react to fluctuations in energy commodity prices under different circumstances in both the energy and agriculture markets. Therefore, the results of the QQ method used in this paper can supplement the existing literature. QQ is able to measure the asymmetry of these impacts of various quantiles of independent variables on various quantiles of the dependent variables. It can capture the full price dynamics as well as draw a complete relationship diagram of the full price distribution [15].

Second, to study the causal relationship between quantiles of energy prices and agricultural commodities, this article uses a causality-in-quantiles method as a complement to the QQ regression. This method makes it possible to obtain causal relationships between the two on different quantile distributions. The asymmetric and nonlinear causality between the energy and grain markets is clearly illustrated through the causality-in-quantiles method.

Finally, as for the policy implications, this article can provide policymakers and market participants with more effective information according to the results. This is because the implementation of differentiated policies is more effective than uniform policies under different market conditions. However, most of the existing literature lacks specific recommendations for market participants in different market situations [20, 28]. They only consider the average market situation and ignore the targeted recommendations when the market conditions are bull, bear, or normal, respectively. Recommendations in this paper are more comprehensive and targeted.

Briefly, this article brings a new look to the existing literature in the following areas: (I) the application of the QQ method to examine the asymmetric impact of energy prices on agricultural commodity prices across different quantiles of the price distribution; (II) the use of quantile Granger causality tests to identify the direction and strength of causality between energy and agricultural markets at various quantile levels; (III) the integration of these methods to provide a more comprehensive understanding of the dynamic relationship between energy and agricultural prices, accounting for market conditions; and (IV) the provision of tailored policy recommendations for different market scenarios.

It is organized as follows throughout the remainder of the article. Section 2 provides some related key literature. Section 3 introduces the methodology and data. Section 4 presents the research findings and related theoretical explanations. Section 5 makes some of the discussions. Section 6 makes conclusions and policy proposals in combination with the current economic and social background.

2. Literature Review

Due to the significant role of energy and agriculture, several studies focus on the interrelationship between them. Chowdhury et al. [29] demonstrated that agriculture and energy have an asymmetrical and nonlinear connection. Specifically, in the short term, only positive energy shocks impact the prices of food; however, from the long perspective, the prices of food are affected by both positive and negative energy shocks. Guo and Tanaka [20] obtained heterogeneous results. Gasoline price returns are always positively correlated with corn price returns, both in the short and long run. Short-term corn price returns and ethanol have a positive correlation, but long-term corn price returns and ethanol have a negative correlation. Ji et al. [30] found that the energy market has a significant spillover effect on agricultural products. Using a multiple linear regression model, Liu and Wang [31] discovered that the price of corn is significantly affected by oil. Li [32] demonstrated that in China, grain prices have been profoundly and positively influenced by crude oil, with maize and soybean prices responding more strongly than rice and wheat prices. In developing countries, which primarily export oil, long-term analysis reveals a heavily positive relationship between oil and grains [25]. Similarly, in the case of Iran, Radmehr and Rastegari Henneberry [33] drew the same conclusion. Rising energy prices lead to higher food prices. Additionally, Taghizadeh-Hesary et al. [34] revealed a positive correlation between food and oil prices in Asia. Unlike studying the relationship and common movement between energy and agriculture prices, El Montasser et al. [35] studied the leading versus co-explosivity effects between them. Strong evidence of explosivity in agricultural commodities and oil prices is found.

Diverse perspectives exist about the correlation between energy and agricultural commodities. For example, Zhang et al. [36] asserted that the prices of energy and agricultural commodities are not directly correlated over the long run. Even if a short-term relationship exists, it is limited. Yoon [37] pointed out that WTI, ethanol, and corn do not have a long-term equilibrium. Pindyck and Rotemberg [38] investigated the interactions of energy, grain, and metal prices, concluding that their supply and demand have nearly zero cross-price elasticities. They explain the co-movement of prices by macroeconomic shocks. For example, all commodities are in a bear market or bull market in the financial markets.

In summary, although energy prices have a direct impact on the cost of food production, this impact can vary greatly under different times and market conditions. Some studies have found that there is a lack of long-term dependency between crude oil prices and agricultural product prices. This means that while there may be some fluctuations in the short term, there may be no stable connection between the two in the long term. Different studies may use different economic models and statistical methods to analyze the relationship between energy prices and food prices. For example, some studies may use linear regression models, while others may adopt nonlinear models or time-series analysis. These different methods may lead to different interpretations of the causal relationships. The datasets and time spans covered by the studies also affect the results. In addition, market conditions and policy changes in different regions can also lead to different outcomes.

With the development of emerging energy sources, there are a lot of literatures focusing on the interplay between traditional energy, bioenergy, and agricultural commodities. According to Abbott et al. [39], the energy and food markets were not linked until 2006, when ethanol was sufficient to influence energy prices. Thanks to the development of biofuel, energy and food are more closely linked [40, 41]. Specifically, concerning high oil prices, future energy security, and environmental threats, bioenergy is widely used [21]. Jeong et al. [42] concluded that WTI futures can be used as a safe-haven tool for palm oil futures, so long as information is shared between markets. Kocak et al. [22] argued that the production of ethanol can stimulate the price of corn. Employing quantile tests, Yoon [37] studied the correlations between agricultural products, fossil fuels, and biofuels and discovered that a strong Granger causal relationship runs from WTI or ethanol to corn. Kirikkaleli and Darbaz [19] illustrated that high oil prices stimulate demand for biofuels and energy crops, which has led to higher prices for energy crops and other grains. This can cause many problems, including rising agricultural prices and a food crisis [34]. Additionally, a positive link exists between the prices of food and bioenergy, whereas the link between oil and bioenergy is negative [43].

Various approaches have been used to investigate how energy prices affect agricultural markets, including traditional and advanced technologies. Gong et al. [44] used the CEEMDAN method and TVP-VAR model to find out the connections between the futures markets for agricultural and crude oil. Ma et al. [45] constructed a price endogenous partial equilibrium model to evaluate the effects of energy on production in agriculture. Kirikkaleli and Darbaz [19] used three recent techniques, including Toda-Yamamoto causality, Fourier Toda-Yamamoto causality, and spectral breitung–candelon (BC) causality tests, to examine bidirectional causality between energy and food price indices at various frequencies. Albulescu et al. [46] employed a local Kendall's tau methodology based on copula to explore the dependence between energy, agricultural, and metals markets. The findings show that co-movements within and between bullish and bearish markets were asymmetrical and more pronounced under extreme conditions. Pal and Mitra [47] used detrended cross-correlation analysis and found positive interdependence on longer time scales. Additionally, applying a time-varying copula with switching dependence, Ji et al. [30] explored the conditional reliance of energy and agriculture markets.

However, most studies neglect the heterogeneous impacts of the marginal energy price. Traditional methodologies, predominantly linear in nature, such as vector autoregression (VAR), linear Granger causality, and autoregressive distributed lag (ARDL), are not capable of depicting the asymmetric effect of a specific independent variable's quantiles on each quantile of the dependent variables. It is therefore not possible to track how energy and agricultural commodities relate to one another in the context of different market circumstances (at different quantiles). Meanwhile, when considering the relationship between energy and agricultural commodities, most studies have overlooked the impact of climate risks and economic factors at the quantile level. Therefore, the conclusions they draw are very limited. To compensate for these shortcomings, this paper uses the QQ method and quantile Granger causality to comprehensively study the influence pattern of energy futures prices on the futures prices of agricultural commodities. For instance, while some studies have shown no significant causal relationship between energy and food prices, QQ regression can reveal that this relationship may be stronger in certain quantiles, particularly during periods of high volatility in energy prices.

3. Research Methodology

This section delves into two distinct yet complementary statistical methodologies employed in the analysis of time-series data: the QQ method and the Granger causality test. These methods are pivotal in understanding the heterogeneous effects and causal relationships between energy and agricultural markets, respectively.

3.1. Quantile-on-quantile

To study the effects of crude oil, natural gas, and coal futures markets on corn, soybean, and wheat futures markets, an innovative QQ method developed by Sim and Zhou [15] was used. The QQ method is a combination of conventional quantile regression and nonparametric estimation and has been applied in economic studies to examine how independent variable quantiles affect dependent variable quantiles at various quantile distributions. The following are the benefits of the QQ method: First, it can use traditional quantile regression to analyze the impact of independent variables on different quantiles of dependent variables while avoiding the limitations of the method, such as failure to capture the influence pattern. Second, the QQ technology is more robust to outliers and non-normal values, and it can handle possible structural breaks in the data, making it more precise in capturing the relationship between economic performance in different environments. Third, the QQ method can adapt to the nonlinear relationship between variables, and fourth, it can alleviate the endogeneity problem caused by simultaneity by accounting for how the explanatory variable's temporal-lag term affects the dependent variable. Additionally, the QQ method was improved by using cross-validation to determine a suitable bandwidth, and thus, this article employs the QQ to model the marginal impacts of the quantiles of energy futures prices in this study.

To illustrate the QQ method in more detail, the model can begin by considering the nonparametric quantile regression model presented below. In this model, the quantile of agricultural commodities futures prices (AP_t) is determined by the shock of energy futures prices (E_{t-1}):

$$AP_t = \beta^{\theta}(E_{t-1}) + \alpha^{\theta} EPU_t + \varepsilon_t^{\theta} \tag{1}$$

where E_{t-1} stands for the futures prices of crude oil, natural gas, or coal at time t-1; the θ-quantile of the residual term ε_t^{θ} is zero; θ represents the θ-quantile of the agricultural commodities futures prices; and α^{θ} describes the effects of the θ-quantile of the economic policy uncertainty (EPU) on its contemporaneous term (AP_t). $\beta^{\theta}(\cdot)$ depicts how the price of energy futures affects the agricultural commodities. Without knowing the specific relationship between energy and agricultural commodities, $\beta^{\theta}(\cdot)$ is regarded as being unknown.

The unknown function's first-order Taylor expansion $\beta^{\theta}(\cdot)$ around E^{τ} is built for the purpose of investigating how the τ-quantile of the energy futures prices (E^{τ}) impacts the θ-quantile of the agricultural commodities futures prices. Here, τ denotes the τ-quantile of the prices of energy futures.

$$\begin{aligned} \beta^{\theta}(E_{t-1}) &\approx \beta^{\theta}(E^{\tau}) + \beta^{\theta\prime}(E^{\tau})(E_{t-1} - E^{\tau}) \\ &\equiv b_0(\theta,\tau) + b_1{}'(\theta,\tau) \times (E_{t-1} - E^{\tau}) \end{aligned} \tag{2}$$

By instituting Equation (2) into Equation (1), the equation becomes the following form:

$$G_t = \beta^{\theta}(E^{\tau}) + \beta^{\theta}(E^{\tau})(E_{t-1} - E^{\tau}) + \alpha^{\theta} EPU_t + \varepsilon_t^{\theta} \tag{3}$$

Afterward, Equation (3) can be calculated by taking into account

$$\begin{pmatrix} \hat{b}_0(\theta,\tau) \\ \hat{b}_1(\theta,\tau) \\ \hat{\alpha}^{\theta}(\tau) \end{pmatrix} = \arg\min_{b_0, b_1, \alpha^{\theta}} \sum_{t=1}^{n} \rho_{\theta}\left[AP_t - b_0 - b_1(E_{t-1} - E^{\tau}) - \alpha^{\theta} EPU_t\right] K\left(\frac{F(E_{t-1}) - \tau}{h}\right) \tag{4}$$

where $\rho_{\theta}(y) = y(\theta - I_{\{y<0\}})$. Set A's designator function is I_A. K represents the Gaussian kernel function on $\mathbb{R}$, with the bandwidth defined as h > 0. The definition of the empirical distribution function is $F(E_{t-1}) = \frac{1}{T}\sum_{k=1}^{T} I(E_k < E_{t-1})$. The best α^{θ} can be determined by the average method as follows:

$$\tilde{\alpha}^{\theta} = \frac{1}{n}\sum_{i=1}^{n} \hat{\alpha}^{\theta}(\tau_i) \tag{5}$$

In practical analysis, selecting a proper bandwidth is crucial since it can balance the variance and bias. In accordance with Stone [48] and Li and Racine [49], this article employs a method known as cross-validation (CV), which can be applied to asymmetric relationships. The CV approach considers asymmetric data by minimizing synthetic estimation errors.

3.2. Granger causality in quantiles

To enhance the comprehension of the causal connection between grain and energy prices, this article employs the causality-in-quantiles technique created by Troster [16] as a supplement to the QQ approach.

Quantile Granger causality testing is a statistical method that extends the traditional Granger causality test to examine the causal relationships between time series at different points of their conditional distributions. Compared to the traditional quantile causality test, it has more advantages. First, traditional Granger causality tests are based on linear models, which may not fully capture the complex, nonlinear relationships that can exist between energy prices and food prices. The Granger causality-in-quantiles approach allows for the examination of causality across different quantiles of the distribution, revealing nonlinear causal relationships that linear models might miss. Second, the Granger causality-in-quantiles approach provides a more detailed analysis of the entire conditional distribution, not just the mean. This is crucial because the impact of energy prices on food prices may vary across different segments of the distribution, with potentially different dynamics at the upper and lower tails compared to the central part of the distribution. Third, traditional tests can be sensitive to outliers, which can skew the results. The Granger causality-in-quantiles approach, by focusing on specific quantiles, can be more robust to extreme values, providing a clearer picture of the causal relationships within the data [50].

In accordance with Granger [51], if the past Z_t cannot be used to forecast the future Y_t based on the past Y_t, then a series Z_t cannot be said to Granger-cause another series Y_t. Consider an explanation vector $I_t \equiv (I_t^Y, I_t^Z)' \in \mathbb{R}^d$, $d = s + q$, in which I_t^Z represents the historical data set of Z_t, $I_t^Z := (Z_{t-1}, ..., Z_{t-p})' \in \mathbb{R}^q$. The Granger non-causal null hypothesis from Z_t to Y_t can be described as follows:

$$H_0^{Z \nrightarrow Y} : F_Y(y|I_t^Y, I_t^Z) = F_Y(y|I_t^Y), \text{ for all } y \in \mathbb{R}, \tag{6}$$

where $F_Y(\cdot|I_t^Y, I_t^Z)$ represents the conditional distribution function of Y_t in the case of a specified (I_t^Y, I_t^Z). The null hypothesis of Equation (6) illustrates that there is no Granger causality in the distribution pattern.

Then, test the Granger non-causality in conditional quantiles for its determination of the causal pattern, and provide an adequate precondition to test the null hypothesis in Equation (6), since the quantiles completely describe a distribution. Let $Q_{\tau}^{Y,Z}(\cdot|I_t^Y, I_t^Z)$ be the τ-quantile of $F_Y(\cdot|I_t^Y, I_t^Z)$. Equation (6) can be expressed as follows:

$$H_0^{QC:Z \nrightarrow Y} : Q_{\tau}^{Y,Z}(Y_t|I_t^Y, I_t^Z) = Q_{\tau}^{Y}(Y_t|I_t^Y), a.s. \text{ for all } \tau \in T \tag{7}$$

where T is a compact set such that $T \subset [0,1]$, and the conditional τ-quantiles of Y_t meet the following constraints:

$$\begin{aligned} \Pr\left\{Y_t \le Q_{\tau}^{Y}(Y_t|I_t^Y)|I_t^Y\right\} &:= \tau, a.s. \text{ for all } \tau \in T, \\ \Pr\left\{Y_t \le Q_{\tau}^{Y,Z}(Y_t|I_t^Y, I_t^Z)|I_t^Y, I_t^Z\right\} &:= \tau, a.s. \text{ for all } \tau \in T. \end{aligned} \tag{8}$$

Considering an explanatory vector I_t, then $\Pr\{Y_t \le Q_{\tau}(Y_t|I_t)|I_t\} = E\{1\left[Y_t \le Q_{\tau}(Y_t|I_t)\right]|I_t\}$, where $1\left[Y_t \le y\right]$ is a function that indicates whether or not Y_t is smaller than or equal to y. The τ-quantile of $F_Y(\cdot|I_t)$ is estimated using a parametric model, with the assumption that $Q_\tau(\cdot|I_t)$ is accurately characterized via a parametric model $m(\cdot,\theta(\tau))$ that belongs to a group of functions. $\mathrm{M} = \{m(\cdot,\theta(\tau))|\theta(\cdot) : \tau \mapsto \theta(\tau) \in \Theta \subset \mathbb{R}^p, for\, \tau \in T \subset [0,1]\}$. Let $\mathrm{B} \subset \mathrm{M}$ be a set of functions with uniform boundaries $\tau \mapsto \theta(\tau)$ such that $\theta(\tau) \in \Theta \subset \mathbb{R}^p$. A parametric model $m(I_t^Y, \theta_0(\tau))$ therefore appropriately specifies the τ-conditional quantile $Q_\tau^Y(\cdot|I_t^Y)$, and then the null hypothesis of non-Granger causation in conditional quantiles can be modified:

$$H_0^{Z\nrightarrow Y} : E\{1\left[Y_t \leq m\left(I_t^Y, \theta_0(\tau)\right)\right]|I_t^Y, I_t^Z\} = \tau, \text{ a.s. for all } \tau \in T \tag{9}$$

Versus

$$H_A^{Z\nrightarrow Y} : E\{1\left[Y_t \leq m\left(I_t^Y, \theta_0(\tau)\right)\right]|I_t^Y, I_t^Z\} \neq \tau, \text{ a.s. for some } \tau \in T \tag{10}$$

where $m(I_t^Y, \theta_0(\tau))$ accurately describes the genuine conditional quantile $Q_\tau^Y(\cdot|I_t^Y)$, for each $\tau \in T$. Hence, the null hypothesis given by Equation (9) can be defined using a series of unconditional moment restrictions:

$$E\{\left[1\left(Y_t - m\left(I_t^Y, \theta_0(\tau)\right) \leq 0\right) - \tau\right] \exp(i\omega' I_t)\} = 0, \text{ for all } \tau \in T \tag{11}$$

where $\exp(i\omega' I_t) := \exp\left[i(\omega_1(Y_{t-1}, Z_{t-1})' + ... + \omega_r(Y_{t-r}, Z_{t-r})')\right]$ is a weighting function, for all $\omega \in \mathbb{R}^r$ with $r \leq d$, and $i = \sqrt{-1}$ is the imaginary root. The test statistic is a sample analog of $E\{\left[1\left(Y_t - m\left(I_t^Y, \theta_0(\tau)\right) \leq 0\right) - \tau\right] \exp(i\omega' I_t)\}$:

$$v_T(\omega, \tau) := \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \left[1\left(Y_t - m(I_t^Y, \theta_T(\tau)) \leq 0\right) - \tau\right] \exp(i\omega' I_t) \tag{12}$$

where θ_τ is a $\sqrt{T}$-consistent estimator of $\theta_0(\tau)$, for all $\tau \in T$. Following that, the test statistic that Troster [16] developed is used:

$$S_\tau := \int_T \int_w |v_T(\omega, \tau)|^2 \, dF_\omega(\omega) dF_\tau(\tau) \tag{13}$$

where $F_\omega(\cdot)$ represents the conditional distribution function of a random vector with d-variate standard normal distribution, the distribution of $F_\tau(\cdot)$ is uniformly discrete on a T-grid with n evenly spaced points, $\mathrm{T}_n = \{\tau_j\}_{j=1}^n$, and the vector of weights $\omega \in \mathbb{R}^d$ can be derived from a standard normal distribution. The sample analog can be used to estimate the test statistic in Equation (13). Make Ψ a $T \times n$ matrix which has elements $\psi_{i,j} = \Psi_{\tau_j}(Y_i - m(I_i^Y, \theta_T(\tau_j)))$, where $\Psi_{\tau_j}(\cdot)$ is the function $\Psi_{\tau_j}(\varepsilon) := 1(\varepsilon \leq 0) - \tau_j$.

Afterward, it employs the subsequent test statistic:

$$S_T = \frac{1}{Tn} \sum_{j=1}^{n} |\psi'_{\cdot j} \boldsymbol{W} \psi_{\cdot j}| \tag{14}$$

where W denotes the $T \times T$ matrix, which has elements $\boldsymbol{w}_{t,s} = \exp\left[-0.5(I_t - I_s)^2\right]$, and $\psi_{\cdot j}$' represents the jth column of Ψ. The null hypothesis in Equation (9) is rejected anytime meeting large values of S_T in Equation (14).

To obtain critical values for S_T in Equation (14), the subsampling method developed by Troster [16] is employed. Considering the series $\{X_t = (Y_t, Z_t)\}$ of sample size T, the model constructs $B = T - b + 1$ subsamples of size b (derived directly from the original data) of the form $\{X_i, ..., X_{i+b-1}\}$. The test statistic S_T in Equation (14) is then computed for every subsample; p-values can be calculated by taking the mean of the B subsamples test statistics. Then the formula picks a subsample of size $b = \left[kT^{2/5}\right]$ in line with Sakov and Bickel [52], where $[\cdot]$ represents a number's integer component and k denotes a constant parameter.

Given the null hypothesis of Granger non-causality in Equation (14), three quantile auto-regression (QAR) models $m(\cdot)$ are shown below, for all $\tau \in T \subset [0,1]$, for the sake of applying the S_T test in Equation (14) as follows:

$$\begin{aligned}
QAR(1) &: m^1\left(I_t^Y, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \sigma_t \Phi_u^{-1}(\tau) \\
QAR(2) &: m^2\left(I_t^Y, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} \\
&\qquad + \sigma_t \Phi_u^{-1}(\tau) \\
QAR(3) &: m^3\left(I_t^Y, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} \\
&\qquad + \mu_4(\tau)Y_{t-3} + \sigma_t \Phi_u^{-1}(\tau)
\end{aligned} \tag{15}$$

where the estimation of the parameters $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \mu_4(\tau), \sigma_t)'$ is performed using the maximum likelihood in a grid with evenly distributed quantiles and $\Phi_u^{-1}(\cdot)$ denotes the inverse of a standard normal distribution function. In order to confirm the direction of the causality between the series, this article adds the lagged variables of the other series in the quantile autoregressive models in Equation (15). For ease of presentation, this article just uses a QAR(3) model as is shown below:

$$\begin{aligned}
Q_\tau^Y(Y_t|I_t^Y, I_t^Z) = {} & \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} \\
& + \mu_4(\tau)Y_{t-3} + \beta(\tau)Z_{t-1} + \sigma_t \Phi_u^{-1}(\tau)
\end{aligned} \tag{16}$$

3.3. Data

This study used daily WTI crude oil futures prices, Rotterdam coal futures prices, NYMEX natural gas futures prices, and corn, soybean, and wheat futures prices from the Chicago Board of Trade between December 19, 2013, and December 18, 2023. The price trends during the sample period are displayed in Figure 1. Table 1 summarizes the descriptive statistics of the seven variables. The time-series price data in Table 1 exhibit fat tails, as shown by the positive kurtosis. The kernel density plots of the variables displayed in Figure 2 indicate that all the price series are non-normal. Testing the time-series data's stationarity is crucial. This study used a traditional Augmented Dickey-Fuller test (ADF) test and found that the price series are stable since the null hypothesis of unit roots is rejected at the 1% significance level.

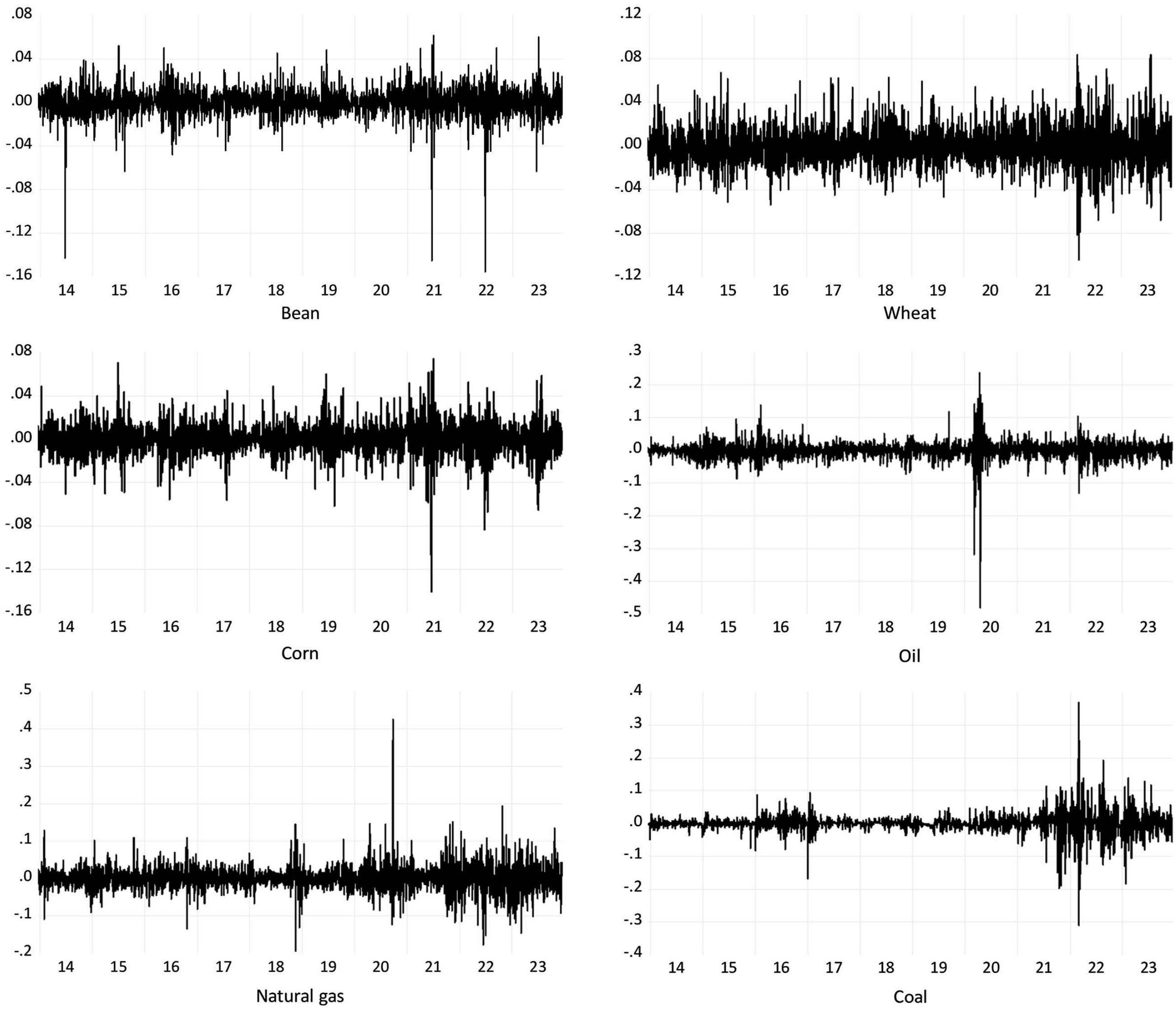
4. Results

Based on the data being stationary and non-normal with fat tail characteristics, this article needs to use the QQ method for further analysis. This method is appropriate because it enables us to investigate the asymmetric influence of independent variables on dependent variables at different quantile distributions (i.e., different market conditions). Additionally, it is crucial to examine the causality between variables. Therefore, the results report two findings in this part: estimations from the QQ method, which illustrate the effect of energy on agriculture markets under different energy and agricultural commodities market conditions, and the results of quantile causality testing. The aims are to identify the heterogeneous connection between the variables and the causality between them.

4.1. Quantile-on-quantile (QQ) estimates

In this section, this study shows and analyzes the findings of the QQ estimation of the impact of the price returns of three major energy futures on the three agricultural commodities futures.

Figure 1
Sequence diagram of the daily prices return



Note: Figure 1 displays the time series of daily returns for six types of futures prices, beans, wheat, wheat, oil, natural gas, andcoal, from 2013-12-19 to 2023-12-18.

Figure 3 summarizes the coefficient $b_1(\theta, \tau)$ (which represents the effect of the τth quantile of the energy futures price on the θth quantile of the agricultural commodities prices). To make the image more explicit, we further present the 2-D image of Figure 3 respectively, which are shown in Figure 4.

At distinct quantiles of the dependent and explanatory variables, the effect of energy on agricultural commodities is characterized differently. Specifically, the results of the QQ estimation are reported as follows. Regarding the impacts of coal on agricultural commodities presented in Figure 3(a–c), the findings show that coal has both positive and negative effects on soybean, corn, and wheat at different quantiles, indicating that changes in coal prices asymmetrically impact agricultural commodities prices across the agricultural commodities futures price distribution. The positive impact of coal is dominant. However, there are also negative effects in certain regions. When in the area combining the higher quantile of coal (0.65–0.75) and the quantile of agricultural commodities from low to high (0.05–0.95), it can be observed that the strongest positive effects are from coal. However, owing to the dynamic nature of the agricultural commodities markets, the impact of coal on these three agricultural commodities is heterogeneous. When both coal (around 0.3) and soybean (0.1–0.3) are in the lower quantiles, coal has a noticeable negative influence on soybean. This means that when both the coal market and the soybean market are in a bear market, the price trend of coal futures and soybean futures is opposite. Considering the effect of coal on wheat, the findings illustrate that the largest negative effect of coal on wheat occurs in the region combining the 0.7 quantile of coal and the middle and upper quantiles of wheat (0.5–0.95).

Then, this study explores the influence of WTI crude oil on agricultural commodities. These three types of agricultural commodity futures show different response patterns to the shock of oil prices. Crude oil's effects on agricultural commodities present mixed results, both positive and negative. In Figure 3(d), it can be observed that crude oil has the greatest negative effect on soybeans in the region, where the 0.85 quantile of crude oil is combined with the lower to higher quantile of soybean (0.1–0.9). When crude oil is in normal market conditions (at middle quantiles), the

Table 1
Descriptive statistics

	EPU	Soybean	Wheat	Corn	WTI	Coal	Natural gas
Min	–1.9103	–0.1555	–0.1045	–0.1408	–0.4808	–0.3102	–0.1945
Max	3.2156	0.0614	0.0840	0.0740	0.2375	0.3695	0.4253
Mean	–0.0002	0.0000	0.0000	0.0000	–0.0001	0.0001	–0.0002
25th quartile	–0.3242	–0.0068	–0.0112	–0.0077	–0.0119	–0.0073	–0.0177
75th quartile	0.3091	0.0067	0.0102	0.0080	0.0125	0.0078	0.0166
Stdev	0.5273	0.0131	0.0184	0.0147	0.0278	0.0293	0.0339
Skewness	0.2257	–1.6656	0.2814	–0.4292	–2.1956	0.4536	0.7466
Kurtosis	4.3151	23.1074	4.8903	8.9052	49.0467	30.5329	15.1998
JB test	209.6719***	45140.9900***	422.1485***	3883.7090***	232382.5000***	82395.4100***	16413.5200***
ADF test	–28.8427***	–51.8918***	–50.8399***	–50.0893***	–28.5414***	–32.5411***	–51.2991***

Notes: The descriptive statistics cover price returns of crude oil futures, natural gas futures, coal futures, soybean futures, wheat futures and corn futures from Dec 19, 2013 to Dec 18, 2023; The null hypothesis of the JB test is that the sequence is normal, and the null hypothesis of the ADF test is the non-stationarity of the serious, where *, **, and *** denote 10%, 5%, and 1% significance level.

positive impact of crude oil will become greater as the soybean market improves. According to Figure 3(e), in the middle to higher quantile of crude oil (0.5–0.95), the influence of crude oil on corn is mainly positive. However, negative values are observed in the area combining lower quantiles of oil (0.33–0.47) and lower to higher quantile of corn (0.05–0.7). In Figure 3(f), crude oil's impact on wheat is presented. It is remarkable that crude oil positively affects wheat in the middle quantile of crude oil and the middle to higher quantile of wheat.

Lastly, this study looks into how natural gas affects agricultural commodities, which are shown in Figure 3(g)–(i). The positive effects of natural gas on agricultural commodities are relatively weak. This positive effect is concentrated when the natural gas market is in a bull market or the agricultural commodity market is in a bull market. Natural gas has obvious negative impact on agricultural commodities when the natural gas market is in a recession and agricultural commodities are in bearish or normal market conditions. Figure 3(g) further reveals that in the region where the higher quantile of the natural gas futures market (0.6–0.75) is combined with the middle to high quantile of the soybean futures market (0.5–0.9), natural gas negatively affects soybean. This negative impact increases as the soybean market situation improves. In this region, the effects of natural gas on corn have taken on a similar pattern, as shown in Figure 3(h).

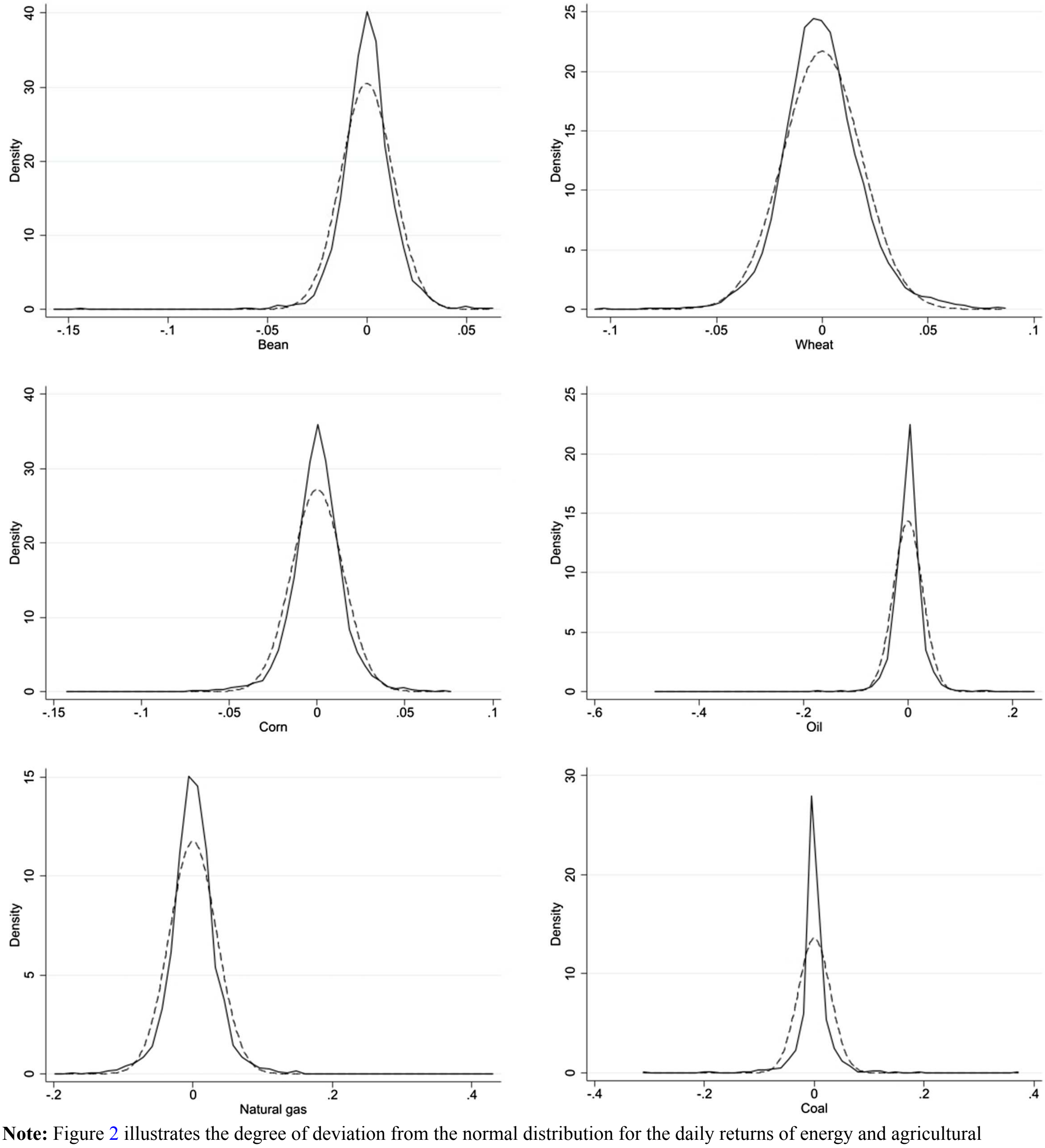
Overall, the empirical results show that the effects of coal, natural gas, and crude oil on agricultural commodities (i.e., soybean, corn, wheat) prices vary asymmetrically across different energy and agricultural commodities quantiles. Each energy source exhibits unique impact patterns on each type of agricultural commodities, owing to the dynamic nature of the agricultural commodity markets as well as energy price shocks. Energy futures can have both positive and negative effects on agricultural commodity futures at different quantiles. Specifically, coal positively impacts agricultural commodity futures at most quantiles. At higher or lower quantiles, that is, under extreme bear or bull market conditions, energy markets are more likely to have a significant positive or negative impact on agricultural commodity markets. The degree of the effect of energy futures on wheat futures is greater, thus showing that wheat is more vulnerable to the effect of energy than two other agricultural commodities.

Specifically, considering the cost effect, the rise in fossil energy prices usually increases the production cost of grain, thereby driving up agricultural commodities prices. During the energy crisis, such as the situation in Europe in 2023, the rise in coal prices had a significant positive impact on agricultural commodity prices. In the United States, due to the increase in natural gas production and the leveling off of consumption, natural gas prices fell by 62% in 2023 compared to the previous year. This price drop may alleviate the cost of agricultural inputs, thereby potentially reducing the market prices of agricultural commodities. In 2021, the supply and demand gap in international natural gas production led to a price surge, which in turn stimulated the rise in international fertilizer and agricultural product prices. The prices of urea, potassium chloride, and glyphosate almost doubled, and global grain prices rose by 40% over the past 15 months.

Considering the substitution effect, the rise in fossil energy prices increases the demand for bioenergy, and many grain crops are the main raw materials for bioenergy, thereby driving up grain prices. In 2020, the fluctuation in crude oil prices affected the demand for biofuels and downstream chemical products, which was transmitted to agricultural product prices. For example, the United States uses more than 40% of its corn for fuel ethanol, and oil prices can affect the demand for fuel ethanol, thereby affecting international corn demand and prices.

However, in certain market conditions, energy can have a negative impact on grain prices, which is usually related to market supply and demand, policy regulation, market expectations, and other factors. In 2023, global grain prices fell by 9%, mainly due to the abundant supply of several important crops, especially wheat and corn. Amid the Russia–Ukraine conflict that triggered a rise in international energy prices, the surge in agricultural commodities prices prompted farmers to increase the production of wheat and corn, leading to a bumper harvest for these two major crops in recent months, thus keeping world grain prices at a lower level. In addition, the cost of agricultural production is an important factor in determining the price of agricultural products, and energy costs are an important part of the cost of agricultural production. In some cases, the rise in energy prices may lead to an increase in agricultural production efficiency or the use of alternative energy sources, thereby reducing the driving effect on grain prices to a certain extent.

Figure 2
Kernel density plots of returns



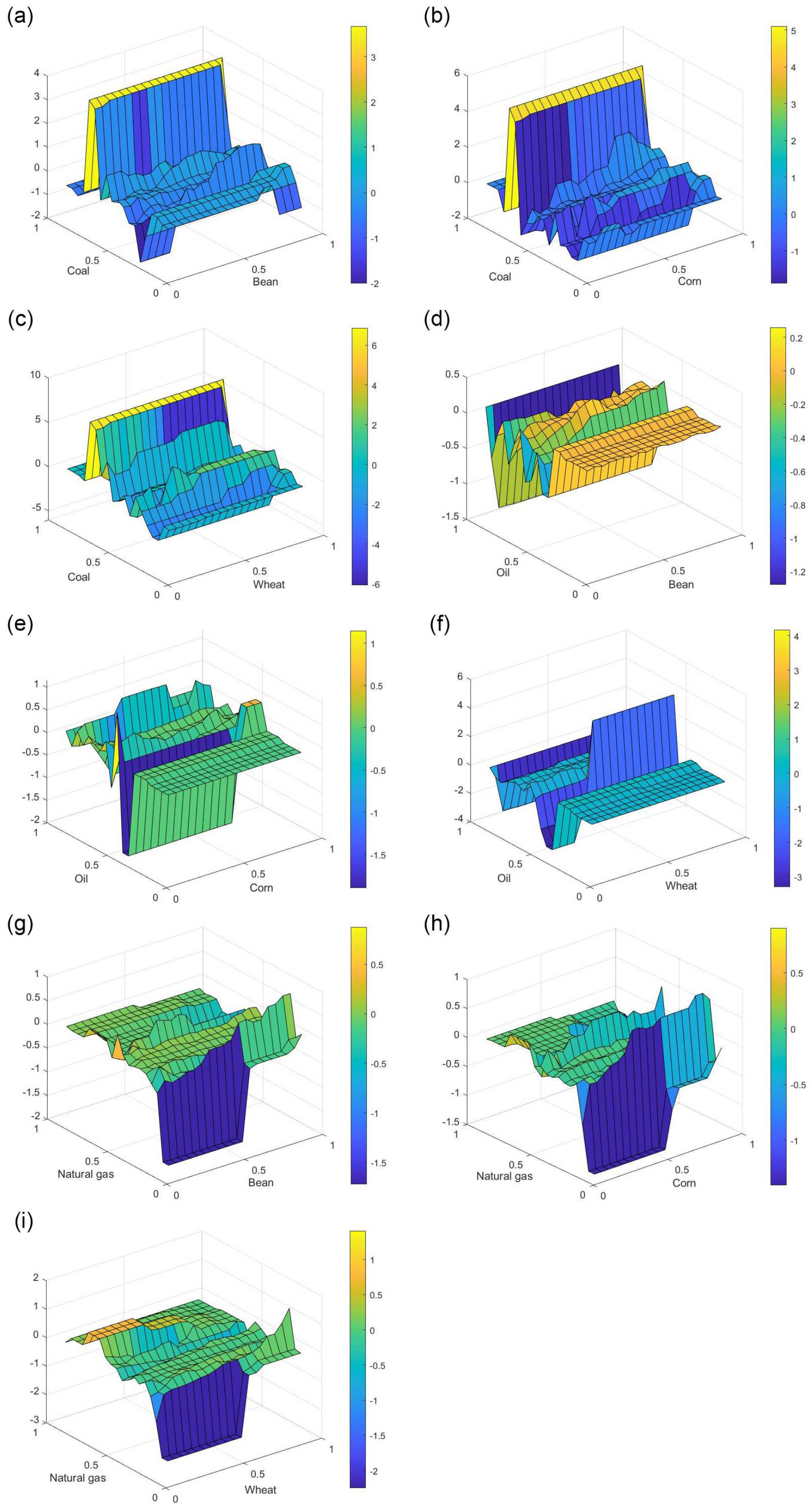
Note: Figure 2 illustrates the degree of deviation from the normal distribution for the daily returns of energy and agricultural commodities futures prices.

By examining the diverse effects of energy on agricultural commodities at different quantiles, people can better comprehend their relationships under distinct market conditions. Thus, targeted references for policymakers, practitioners, and speculators in different market situations can be provided in this article. What's more, by identifying the vulnerabilities of the agricultural sector to energy price shocks, this study can inform adaptation strategies to climate change, including adjusting agricultural practices to become more resilient to the indirect effects of climate change on energy markets.

4.2. Causality-in-quantiles test

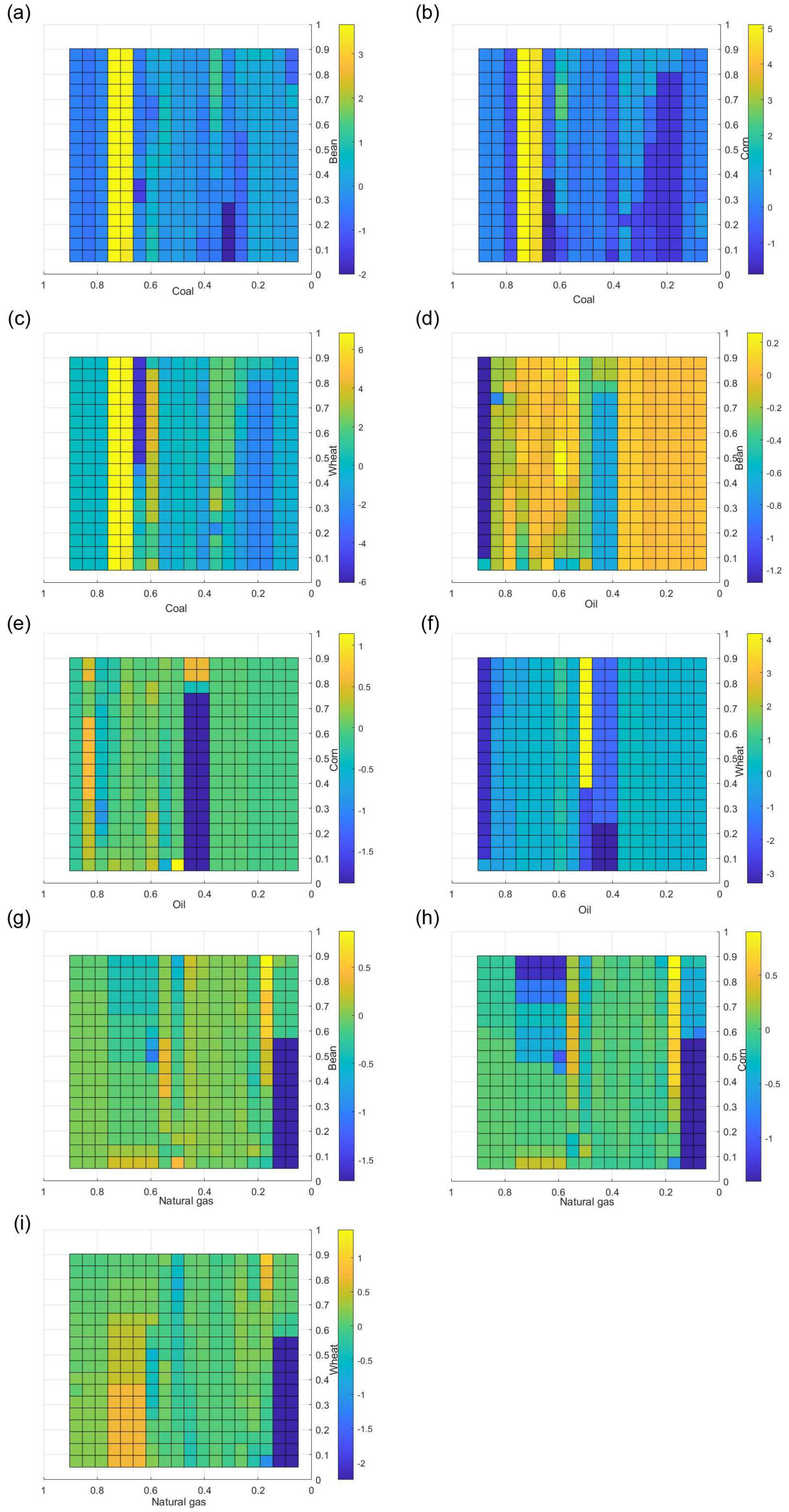
Tables 2, 3, and 4 show the p-values of S_T test for Granger causality in each conditional quantile from three main energy resources to soybean, corn, and wheat, respectively. Variations in the price returns of the three main energy sources can Granger-cause variations in price returns of agricultural commodities at 1% level, taking into account all quantiles. This means that, in general, there is a very high probability of causality between the prices of energy and agricultural commodities. Yet, the causal relations running

Figure 3
The impact of the futures price returns of energy on the agricultural commodities



Note: In Figure 3, the z-axis displays the coefficient b_1, which represents the magnitude of the impact of energy futures price returns on grain futures price returns.

Figure 4
The heat map of the coefficient *b1*



Note: Figure 4 is the 2-D version of Figure 3, representing the same results, with the degree of color representing the magnitude of the impact.

Table 2
Granger-causality from energy to soybean: *p*-values

	$\Delta Cold_t$ to $\Delta Bean_t$			ΔGas_t to $\Delta Bean_t$			ΔGas_t to $\Delta Bean_t$		
θ	1	2	3	1	2	3	1	2	3
[0.05: 0.95]	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.05	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.10	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.15	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.20	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.25	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.30	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.35	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.40	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.45	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.50	0.3788	0.2191	0.2063	0.3788	0.2191	0.2063	0.3788	0.2191	0.2063
0.55	0.2652	0.2616	0.1625	0.2644	0.2600	0.1625	0.2652	0.2616	0.1625
0.60	0.0004	0.0068	0.0016	0.0004	0.0068	0.0016	0.0004	0.0068	0.0016
0.65	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.70	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.75	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.80	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.85	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.90	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.95	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004

Table 3
Granger-causality from energy to corn: *p*-values

	$\Delta Coal_t$ to $\Delta Corn_t$			ΔOil_t to $\Delta Corn_t$			ΔGas_t to $\Delta Corn_t$		
θ	1	2	3	1	2	3	1	2	3
[0.05: 0.95]	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.05	0.0004	0.0012	0.0004	0.0004	0.0012	0.0004	0.0004	0.0012	0.0004
0.10	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.15	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.20	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.25	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.30	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.35	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.40	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.45	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.50	0.8977	0.4543	0.6645	0.8977	0.4587	0.6645	0.8977	0.4543	0.6645
0.55	0.1216	0.0851	0.1340	0.1216	0.0851	0.1340	0.1216	0.0851	0.1340
0.60	0.0012	0.0024	0.0004	0.0012	0.0024	0.0004	0.0012	0.0024	0.0004
0.65	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.70	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.75	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.80	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.85	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.90	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.95	0.0161	0.0004	0.0004	0.0161	0.0004	0.0004	0.0161	0.0004	0.0004

from energy to agricultural commodities are not always significant for each quantile distribution. For example, as shown in Tables 2 and 3, around the conditional median (θ = 0.50, 0.55), none of the three energies have a robust Granger causal relationship between soybean and corn at 10% statistical level. Concerning the Granger causality from energy to wheat illustrated in Table 4, the causality is insignificant when $\theta = \{0.35, 0.40, 0.95\}$. Moreover, the findings show that the pattern of the causality from different energy sources to the same food is consistent. Overall, energy prices can Granger-cause variations in agricultural commodities (i.e., soybean, wheat, corn) prices at a 1% significance level, except for some middle and extremely high quantiles.

Table 4
Granger-causality from energy to wheat: *p*-values

	$\Delta Coal_t$ to $\Delta Wheat_t$			ΔOil_t to $\Delta Wheat_t$			ΔGas_t to $\Delta Wheat_t$		
θ	1	2	3	1	2	3	1	2	3
[0.05: 0.95]	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.05	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.10	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.15	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.20	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.25	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.30	0.0008	0.0008	0.0012	0.0008	0.0008	0.0012	0.0008	0.0008	0.0012
0.35	0.4077	0.3660	0.2528	0.4033	0.3660	0.2528	0.4077	0.3660	0.2528
0.40	0.1653	0.1601	0.1469	0.1653	0.1601	0.1469	0.1653	0.1601	0.1469
0.45	0.0016	0.0016	0.0020	0.0016	0.0016	0.0020	0.0016	0.0016	0.0020
0.50	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.55	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.60	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.65	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.70	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.75	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.80	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.85	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.90	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
0.95	0.2604	0.2677	0.2612	0.2604	0.2677	0.2604	0.2604	0.2677	0.2604

Note: Tables 2, 3, and 4 report the subsampling *p*-values of the S_T test in Equation (13). $\Delta Coal_t$, ΔOil_t, ΔGas_t, $\Delta Bean_t$, $\Delta Wheat_t$, $\Delta Corn_t$ represent the lag-difference of coal, oil, gas, soybean, wheat, corn respectively. 1, 2, 3 are the lag lengths of the dependent variable. θ is the quantile of dependent variable

The introduction of this methodology provides a new perspective and analytical tool for existing literature, offering a quantile-based perspective on the causal relationship between energy and agricultural commodity futures, revealing the nonlinear characteristics of this relationship and its variations under different market conditions. The identification of this nonlinear relationship enhances the understanding of market dynamics. The relationship between energy and grain futures is not uniform under all market conditions but varies with changes in market situations. Policymakers can use this information to formulate more effective market intervention measures to stabilize grain prices and ensure food security.

5. Discussion

Energy's influence on agricultural commodities is a complex and multifaceted issue. This paper, aligning with the existing literature [25, 29], discovers that the effects of coal, natural gas, and crude oil on agricultural commodities prices vary asymmetrically across different energy and agricultural commodities quantiles, owing to the volatile nature of the agricultural commodity market and distinct energy price shocks.

Under specific market conditions of energy and grain futures, energy positively impacts agricultural commodities futures prices, which is well-documented in the existing literature. The findings resonate with those of Guo and Tanaka [20], who found that gasoline price returns are always positively correlated with corn price returns, both in the short and long run. This is primarily attributed to the increased cost of agricultural production due to higher energy costs, including the operation of agricultural machinery and the production of fertilizers [10, 18, 19]. As Baffes [53] noted, the transmission of oil price fluctuations is particularly pronounced in the index of fertilizer costs, with agriculture being the subsequent most affected sector, which supports the observation of a direct correlation between energy prices and grain prices. Moreover, the substitution effect comes into play when energy prices rise; people may turn to biofuels as an alternative energy source when energy prices increase, leading to the demand for biomass such as corn rising, as well as related agricultural commodities [1, 12, 24].

The results demonstrate that at higher or lower quantiles, that is, under extreme bear or bull market conditions, energy markets are more likely to have a significant impact on agricultural commodity markets, which is similar to existing research [1, 54]. As Tiwari et al. [1] noted, the connectivity at the left and right tails of the conditional distribution is stronger than at the mean and median, emphasizing the importance of systemic risk spillover during periods of extreme market movements. Furthermore, under certain specific combinations of market conditions, energy has a negative impact on agriculture. As noted by Esmaeili and Shokoohi [43], rising energy prices are often seen as a harbinger of a recession. This perception can lead to a decline in societal expectations for the economy, leading to a decline in the prices of agricultural commodity futures. Zhang and Qu [55] share the same view. Second, the negative impacts of energy markets may be attributed to capital flows globally, as suggested by Farid et al. [11]. When economic liquidity tightens and capital shifts to bulk commodities such as coal and natural gas, the capital flowing to grain decreases, resulting in an opposite movement trend between the two. Third, when energy prices rise and prices fluctuate dramatically, governments may impose restrictions on changes in agricultural commodity prices.

The research improves the body of literature by employing a novel QQ approach and presenting a comprehensive asymmetric pattern of energy's marginal effects, which provide targeted references for policymakers, practitioners, and speculators in different market situations.

6. Conclusion

The scientific aim of the work is to enhance the understanding of the dynamic interactions between energy and agricultural commodity prices in the context of sustainable development. The subject of the research was to obtain a detailed analysis of how energy futures price returns influence the price distribution of agricultural commodities and to identify the causal relationships between these markets at various quantile levels. This study extends the existing research in several innovative ways: the novel method at the quantile level and the targeted suggestions proposed for different market scenarios. Specifically, this paper examines how the price of agricultural commodities futures is affected by energy futures prices, specifically studying the asymmetric influence pattern of energy prices on agricultural commodities prices at full energy-agricultural commodity quantiles utilizing the QQ method and the Granger causality-in-quantiles test. The findings suggest that 1) the influence of energy on agricultural commodities is heterogeneous across the energy-agricultural commodity price distribution, indicating that different types of price shocks or market conditions can contribute to this asymmetry; 2) energy has a mixed positive and negative impact on agricultural commodities; 3) at higher or lower quantiles, that is, under extreme bear or bull market conditions, energy markets are more likely to significantly affect agricultural commodity markets; and (4) the causality-in-quantiles method reveals that there is significant causal relationships from energy prices to agricultural commodities prices at the 1% significant level except at some medium and extreme quantiles.

The conclusions have important implications for policymakers. Thanks to the QQ approach, the results can fully reveal the impact of energy prices at different quantiles, that is, under different market conditions. A precise description of how energy affects agricultural commodities contributes to the formulation of effective policies toward healthy and sustained market development, which plays a role in alleviating inflation and the food crisis worldwide. The implementation of policies for different situations is more effective than a single policy. Since energy can have both positive and negative impacts on agricultural commodities under different market conditions, policymakers need to focus on market dynamics and formulate targeted policies. This research supports the development of sustainable economic models that consider environmental costs. The balance is vital for achieving long-term sustainability in both energy and agriculture systems.

The study may be limited by the choice of models, as different models may lead to different conclusions, and the selection of an appropriate model may be influenced by subjective factors. In terms of the selection of research subjects, we only focused on energy and agricultural commodity futures. The commodities market, however, could be impacted by other markets, such as the stock markets. These issues require further research in the future.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The datasets generated or analyzed during this study are available from the corresponding author upon reasonable request.

Author Contribution Statement

Wei Jiang: Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Shuqi Yuan:** Software, Data curation, Writing – original draft, Visualization. **Sonia Chien-I Chen:** Supervision.

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