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NONLINEAR EFFECTS OF CRUDE OIL DEPENDENCY ON FOOD PRICES IN CHINA: EVIDENCE FROM QUANTILE-ON-QUANTILE APPROACH

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Abstract. The repercussions of disruptions in the global crude oil market have a substantial influence on economies worldwide. Oil shocks are considered important estimators of many economic variables. The current research examines the effects of oil price shocks on food prices in China using monthly data from 2000M1 to 2021M12. The estimation is done using the Quantile on Quantile (QQ) estimation technique. The BDS test is used to test nonlinear dependence in variables. The results of this test confirm the presence of nonlinear dependence in variables. The estimated results of the QQ technique suggest a strong association between oil prices and food prices nexus in China with significant disparities across the quantiles. The lower and medium quantiles show a poor negative effect of crude oil prices on food prices. Nevertheless, it has been shown that there exists a strong positive correlation in the higher quantiles of the distribution, which suggests that an increase in global oil prices directly impacts the costs of food. The outcome of the study offers significant policy recommendations aimed at mitigating the detrimental impact of oil prices on food prices in China.

Keywords: oil price shocks, food prices, BDS test, quantile-on-quantile regression, China.

JEL Classification: C22, Q11, Q43.

Introduction

During the last two decades, both oil prices and food prices have experienced major fluctuations. The food price increase is a pressing issue in terms of poverty, income inequality, and

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crime. Thus, instability, distortions, and loss of buying power in many countries require a concerted global attempt to lift people out of their plight (Von Braun, 2007). There is fear that the high and unpredictable prices of crude oil will begin to drive up food prices. During the past few years, there has been a marked increase in the price of food throughout the world, particularly with the start of the global financial crisis and COVID-19 due to a shortage of food supply (Naeem et al., 2022). The shock in food prices, caused by a shift in supply and demand levels and market manipulation, have changed the food prices (Jones & Hiller, 2017; Kapusuzoglu et al., 2018; Kapusuzoglu & Karacaer Ulusoy, 2015). However, if the shock is significant enough, it will begin to affect food prices globally.

These food price shocks are undoubtedly directly and indirectly affected by crude oil prices. Around two-third of the world energy demand is satisfied by crude oil, which has been recognized as one of the major energy sources (Karasu et al., 2020). In the agriculture sector, crude oil plays an important role in the production process. It is utilized in the agriculture sector as transportation and to power farming machinery (Adam, 2016). Therefore, any rise in crude oil immediately affects the cost of agricultural output, which raises food prices (T. Wei et al., 2017). In January 2005, the crude oil price was $40.37 per barrel but within the next three years (July 2008) it started increasing and reached the record high price of $146.08 per barrel. For the next half a year in January 2009, it came to a low level of $35.4 per barrel.

According to the China Petroleum and Chemical Industry Federation, in 2021, China was the world's largest oil importer with net imports of 513 million tones. The ratio of oil import dependence was about 72%. China's heavy dependence on oil suggests that rising oil prices will undoubtedly affect food prices in China. Just like other countries, a major political goal in China is to ensure food security. China has the world's largest population, and any food crises could exacerbate man-made disasters. Such anxiety can have a wide range of negative economic, social, and psychological consequences.

In both rural and urban areas of China, food expenditure ranges from 35 to 41 percent of total consumer expenditures. Given this high share of food expenditures, a significant increase in production cost of food would undoubtedly affect domestic price stability and the level of headline inflation (Huang & Rozelle, 2006). If the price of the most important raw material i.e. oil in the world market starts to rise, it will have a big impact on China's food economy. This is because various foodstuffs can be freely exchanged across China's borders. As a result of this strong co-integration, domestic food prices are rapidly affected by changes in global food prices. The available empirical evidence also indicates that rising oil prices are the main cause of rising food prices (Bala & Chin, 2018; Salisu et al., 2017).

Empirical literature has developed two categories to gauge the connections between oil prices and food prices. The first category examines the associations between both variables by using conventional methods like cointegration, regression analysis, correlation analysis, etc. (Zmami & Ben-Salha, 2019). On the other hand, some studies use advanced econometric techniques to analyze connectivity between both variables (Adeosun et al., 2023; Ben Hassen & El Bilali, 2022; Mokni, 2023; Mokni & Ben-Salha, 2020; Taghizadeh-Hesary et al., 2019). Previous studies have shown different types of empirical findings between oil prices and food prices. According to the first aspect, there is no correlation between food and oil prices (Fowowe, 2016; Gilbert, 2010; Reboredo, 2012; Z. Zhang et al., 2010). Another literature group have argued that the relationship between the two markets is important (Meyer et al., 2018; T. Wei et al., 2017; Yu & Zhang, 2019). However, in a symmetrical situation, research has found that prices of agricultural commodities change dramatically in response to changes in oil prices (de Nicola et al., 2016; Jones & Hiller, 2017). In turn, in asymmetric regime, it is found that food prices respond differently to rising and falling oil prices (Adeosun et al., 2023; Rafiq & Bloch, 2016).

Previous studies have shown that standard econometric techniques like regression, and cointegration that have failed to capture the true dependence between oil-food prices at lower to medium and medium to high quantiles. These time series econometric techniques do not provide appropriate solutions to the policymakers and market investors to formulate the policies, especially policies related to oil and food sectors. In this situation, it is important to check which type of oil-food relationship exists in China, while analyzing the dependence trend between lower to medium and medium to high quantiles. Therefore, it is necessary to reinvestigate this important dimension of the oil-food prices nexus using an advanced and refined method that is never used before. This is the key innovation of the study in addition to successfully directing the policymakers in China.

To fill this gap, this study uses monthly data from 2000 to 2021 and applies quantile-on-quantile (QQ) regression technique of (Sim & Zhou, 2015) to examine the relationship between food prices and oil prices in China. Compared to traditional quantile regression, this method gives more precise information about the structure and relationships between variables. The study is motivated and complements the current rich literature on oil and food prices in many important aspects. Using the Brock, Dechert, and Scheinkman (BDS) test of independence and the QnQ approach, the authors of this research believe they have conducted the first investigation of the link between oil and food. This approach is interesting in this case because the impact of oil prices on food prices may depend on the success of the business cycle and the signs and magnitude of oil and food price shocks. The projected findings may help to implement long-term defensible and sustainable food and oil preservation strategies.

The remainder of the paper is structured as follows. An overview of the available oil and food literature is presented in Section 1. In Section 2, data and methods are explained. Section 3 provides explanation of the estimated results. Conclusion along with policy recommendations are presented in the study's last part.

1. Literature review

Over the last three decades, a number of empirical studies have been conducted to examine the relationship between oil and food price shocks in various nations. Table 1 summarizes a few empirical research that make an effort to determine how oil prices and food prices relate to one another. The table demonstrates that prior research on the relationship between oil and food prices has produced conflicting and ambiguous findings (Taghizadeh-Hesary et al., 2019). These disparities can be recognized for a variety of reasons, including the country selection, the model, data span, data forms, data frequency, estimated techniques, etc.

Furthermore, these studies have used various proxies to calculate global oil and food prices. It is evident from the literature that limited research is available for China and none of the studies has checked the dependency factor at lower, medium, and upper quantiles. Hence, there is enough space to conduct research for China using quantiles analysis.

Table 1. Review of existing studies

Author	Time Period	Methodology	Findings
Sun et al. (2023)	1993M1–2020M9	QQ	Energy and food prices are positively associated across the quantiles.
Guan et al. (2023)	2021M1-2022M9	EEMRIO	Oil prices and household prices are positive relationship.
Dadzie et al. (2023)	2011–2021	VECM, VAR	Oil prices tend to have a long-term effect on food costs.
	1995M1–2021M12	ARDL	Food prices and oil prices have positive and significant relationship in both long run and short run.
Mokni (2023)	1974–2018	SVAR	Food prices and oil prices have positive and significant relationship.
Mastroeni et al. (2022)	2000–2018	Wavelet analysis	Food and oil prices have a strong positive connection.
Naeem et al. (2022)	2006M1-2020M10	Connectedness Approach	Short and long run spillovers between oil volatility and commodity prices are less, whereas intra-correlations are stronger.
Allahyari et al.	2001–2020	ARDL, VAR	Food and crude oil prices are positively associated over the long run.
Shokoohi and Saghaian (2022)	1974–2018	Panel-VAR	Food costs and oil prices are positively associated.
Hung (2021)	2018M2–2020M5	Wavelet	Food costs and oil prices are positively associated.
Zakaria et al. (2021)	1980M1–2018M12	VECM, NARDL	Oil prices and inflation have a positive link. There is a one-way causal relationship from oil prices to inflation.
Mokni and Youssef (2020)	2003M1-2017M4	ARMA-FI-GARCH; Copula Models	Crude oil and agriculture prices have a negative impact each other.
Chen et al. (2020)	1999M1–2016M12	SVAR	Oil prices and CPI has positive relationship.
Taghizadeh-Hesary et al. (2019)	2000–2016	Panel-VAR	Energy prices and food prices are positively and significantly association.
Bala and Chin (2018)	1995–2014	ARDL	In long rum, oil prices have a favorable impact on inflation.
Long and Liang (2018)	1998–2014	ARDL, NARDL	There is asymmetric impact between Oil and CPI in the long run.
Salisu et al. (2017)	2000–2014	OLS, GMM, ARDL	There is a robust positive link between oil prices and inflation.
Sek (2017)	1980–2015	ARDL, NARDL	The effects of fluctuating oil prices on the country's food supply might be either symmetrical or asymmetrical.

End of Table 1

Author	Time Period	Methodology	Findings
Wong and Shamsudin (2017)	Q1 2000–Q2 2016	NARDL	In long-run oil prices and food prices have significant relationship but in short-run both have insignificant relationship.
López Cabrera and Schulz (2016)	2003W1–2012W4	VECM, GRACH	Agriculture commodities and oil prices have positive long run association.
Dillon and Barrett (2016)	2000–2012	ECM	Global oil prices positively affect food prices.
Nwoko et al. (2016)	2000–2013	VECM, GARCH	The findings demonstrate a positive effect of oil prices on food prices, indicating a unidirectional causal relationship from oil to food prices.
Olayungbo and Hassan (2016)	2001–2013	ARDL	Food commodities prices and oil prices have positive long run association.
C.-C. Wei and Chen (2016)	2006–2012	VAR	The rising price of oil on the global market has a substantial beneficial effect on agricultural goods.
Ibrahim (2015)	1971–2012	NARDL	The correlation between the cost of oil and the cost of food is considerable and asymmetric.
C. Zhang and Qu (2015)	2004M9–2014M4	ARMA, GRACH	The relationship between the cost of oil and the cost of agricultural goods is unbalanced. More so than a positive oil price shock, a negative one has an effect on agricultural goods.
Gao et al. (2014)	1974Q1–2014 Q4	VAR	There is a positive oil price shock on energy-intensive CPIs.
Wang et al. (2014)	1998M1–2013M12	ARDL	Crude oil has positively affected agricultural products in the short and long run.
Udoh and Egwaikhide (2012)	1970–2008	VAR	Oil prices have a beneficial effect on food prices, and this effect is unidirectional from oil to food prices.
Nazlioglu and Soytas (2011)	1994M1–2010M12	VAR	There is no association between the cost of crude oil and the cost of food.
Tang et al. (2010)	1998–2008	ECM	The cost of oil has a salutary effect on inflation.
Z. Zhang et al. (2009)	1989–2008	VECM	Oil prices are not related to agricultural commodities in the long run.
Q. Zhang and Reed (2008)	2000M1–2007M12	VARMA	There is no association between the cost of crude oil and the cost of food.

The empirical studies investigates the correlation between oil prices and food prices by using different estimation techniques. These methodologies encompass copula function, vector autoregressive models, structural vector autoregressive models, the Granger causality test, detrended cross-correlation analysis, and asymmetric detrended cross-correlation analysis. Additionally, both linear and nonlinear frameworks are employed to analyze the connection between food and oil prices. These methodologies suffer from the limitation of disregarding the possibility of a change in the relationship between food and oil prices as a result of variations in distribution patterns (Mokni & Ben-Salha, 2020). Furthermore, since oil prices fluctuate according to various market conditions, these techniques neglect the possibility of changes in food prices due to oil prices may differ.

2. Global oil prices and food inflation in China

Figure 1 elucidates the temporal trends of oil prices and food prices in China from 2000 onwards. The chart exhibits a distinct correlation between oil prices and food prices, since both variables demonstrate a consistent pattern of oscillations. The prices of both oil and food exhibited an upward trend between 2000 and 2008, followed by a decline in 2009. Subsequently, there was a resurgence in prices starting in 2010, which was then followed by a fall after 2014. Subsequent to the year 2016, there was an additional increase in the pricing of oil. The worldwide trade restrictions implemented in 2020 due to the COVID-19 epidemic resulted in a decrease in energy prices and a concomitant increase in food expenses. The findings provided evidence for the presence of a positive relationship between oil prices and food prices in China.

Figure 1. Food and oil prices pattern in China (2000M1–2021M12)

3. Theoretical framework

Literature has shown that high oil prices increase food prices through different channels. *First*, oil is used as energy input both in primary and secondary production levels (Taghizadeh-Hesary et al., 2019). At primary production level it is used in agricultural machinery like tractors, harvesters, etc. While at secondary level it is used for transport and storage of agriculture products. Thus, when oil price increases, agriculture production cost increases and food prices will increase. *Secondly*, due to high oil prices globally, oil importing countries have increased the production of biofuel energy to meet their energy needs. It has reduced the food supply, which, in turn, has increased the food prices (Subramaniam et al., 2019). *Thirdly*, high oil prices create trade deficit for oil importing countries, so less foreign exchange reserves are available for these countries to import food, which creates shortage of food in these countries (Chang et al., 2023). It increases food prices in oil importing countries. *Fourthly*, high oil prices discourage investment in agriculture sector. It will decrease agricultural production and hence food prices will increase (Hung, 2021). Figure 2 provides the schematic representation of these channel variables.

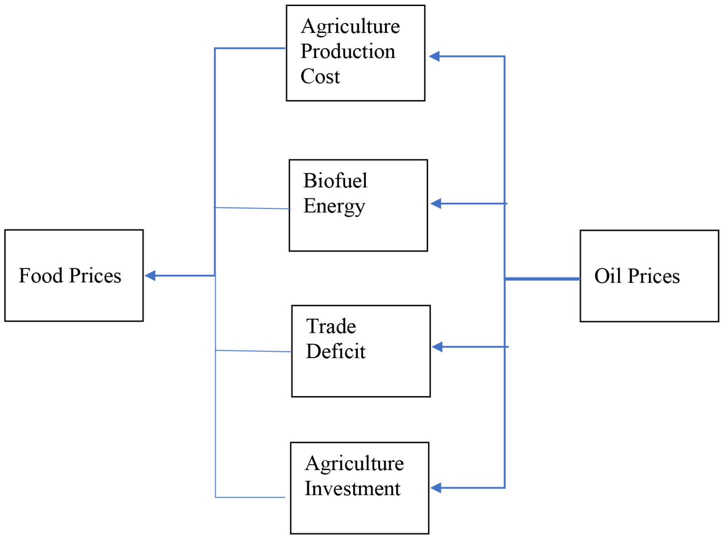

Figure 2. Schematic representation of oil prices on food prices

4. Econometric methodology

4.1. BDS test for non-linearity

The primary method used for assessing non-linear dependency in time series data is the BDS test of non-linearity, as introduced by Broock et al. in 1996. The present examination is grounded on the null hypothesis that the data within the time series exhibit independence and identical distribution (iid). If the null hypothesis is rejected, it may be concluded that the model exhibits nonlinear dependence. One notable characteristic of this test is its ability to identify nonlinearities in data regardless of any linear relationships. Moreover, this particular examination demonstrates its use in the context of limited data samples (Brock et al., 1991).

4.2. Quantile-on-quantile regression (QQR)

To gauge the impact of oil prices on food prices QnQ approach is used. This technique has several advantages over traditional regression techniques like least squares. This method is proven to be more successful and delivers predictable outcomes when the relationship between variables is complicated. Quantile regression (QR) and nonparametric estimation methods are combined in the QQR method, which regresses quantiles of one variable on quantiles of other variables. Furthermore, it considers the non-linear relationship between variables. Therefore, QQR analysis is a very effective tool to find the impact of quantiles of oil prices on quantiles of food prices in China. It gives an accurate and detailed picture of the overall dependence of food prices on oil prices. This innovative method has been used in some recent studies to approximate asymptotic relationships between variables (Sim & Zhou, 2015). In this work, we explain the QnQ approach proposed by (Sim & Zhou, 2015). The basic non-parametric QQR is written as follows:

$$FPI_t = \alpha^{\delta}\left(OP_t\right) + \varepsilon_t^{\delta}, \quad (1)$$

where FPI_t denotes the food price index and OP_t denotes the crude oil price and t is time period. α^{δ} denotes a parameter that is unknown because we do not have previous information related to this relationship. Whereas δ is the δ-quantile of the conditional distribution of the food prices and ε_t^{δ} is the quantile error term.

To study the relationship between δ -quantile of food prices and γ -quantile of oil prices (OP^{γ}), equation (1) is examined in the neighborhood of OP^{γ}. Since $\alpha^{\delta}(.)$ is not known, this function is linearized by taking first order Taylor Expansion of $\alpha^{\delta}(.)$ around OP^{γ}, it gives

$$\alpha^{\delta}\left(OP_t\right) \approx \alpha^{\delta}\left(OP^{\gamma}\right) + \alpha^{\delta'}\left(OP^{\gamma}\right)\left(OP_t - OP^{\gamma}\right). \quad (2)$$

One notable feature in above equation is that its $\alpha^{\delta}\left(OP^{\gamma}\right)$ and $\alpha^{\delta'}\left(OP^{\gamma}\right)$ parameters are dual indexed in δ and γ. Moreover, it is noticed that OP^{γ}, the γ-quantile of oil price, is function of γ only. Hence, the $\alpha^{\delta}\left(OP^{\gamma}\right)$ and $\alpha^{\delta'}\left(OP^{\gamma}\right)$ are both functions of δ and γ. Additionally, let us redefine the function $\alpha^{\delta}\left(OP^{\gamma}\right)$ and $\alpha^{\delta'}\left(OP^{\gamma}\right)$ as $\alpha_0(\delta,\gamma)$ and $\alpha_1(\delta,\gamma)$, respectively. Now the above equation can be written as

$$\alpha^{\delta}\left(OP_t\right) \approx \alpha_0(\delta, \gamma) + \alpha_1(\delta, \gamma)\left(OP_t - OP^{\gamma}\right). \quad (3)$$

By substituting Equation (3) into Equation (1), we get

$$FPI_t = \underbrace{\alpha_0(\delta, \gamma) + \alpha_1(\delta, \gamma)\left(OP_t - OP^{\gamma}\right)}_{*} + \varepsilon_t^{\delta}. \quad (4)$$

The (*) is δ conditional quantile of food prices. Equation (4) represents an exact relationship among δ δ -quantile of food prices and γ -quantile of oil prices given that the parameters α_0 and α_1 are doly indexed in δ and γ. The δ-quantiles of food prices and the γ-quantiles of oil prices can influence these parameters. Thus, the approach only maintains a linear relationship between the variables' quantiles. The overall dependency structure amid food and oil prices is also defined in the equation due to linking of their respective distributions.

Finally, to estimate Equation (4) OP_t and OP^{γ} are replaced with their estimated counterparts $\widehat{OP_t}$ and $\widehat{OP^{\gamma}}$, respectively. Now the following equation would be solved

$$\min_{a_0, a_1} \sum_{i=0}^{n} \psi_{\delta}\left[FPI_t - a_0 - a_1\left(\widehat{OP_t} - \widehat{OP^{\gamma}}\right)\right] K\left(\frac{\mathcal{F}_n\left(\widehat{OP_t}\right) - \gamma}{\omega}\right) \quad (5)$$

to get the estimates $\alpha_0(\delta, \gamma)$ and $\alpha_1(\delta, \gamma)$. Where the approximate parameters a_0 and a_1 of local linear regression are the estimates of α and α_1, respectively. ψ_δ is quantile function which gives the δ-conditional quantile of FPI_t as a solution. To find the effect of γ-quatile of oil price shocks,

Gaussian kernel $(.)$ is applied to weight the observations of $\widehat{OP^\gamma}$ based on bandwidth ω.

These weights are contrariwise related to the difference of $\widehat{OP_t}$. and $\widehat{OP^\gamma}$ . . Now the distance of the empirical distribution function from γ can be expressed as:

$$\mathcal{F}_n\left(\widehat{OP_t}\right) = \frac{1}{n}\sum_{k=1}^{n} I\left(\widehat{OP_k} < \widehat{OP_t}\right), \tag{6}$$

where γ is distribution functional value which links with OP^γ. The key advantage of using a nonparametric estimation method is that it makes bandwidth selection even more important. For the smooth estimation results, the bandwidth parameter $\omega = 0.05$ is used, which specifies the scale of the neighborhood around the target point. If small bandwidth is selected, then bias estimates would be small, but their variances would increase and vice versa. Thus, the selection of bandwidth is crucial, as it also maintains a balance between bias and variance.

5. Estimated results

5.1. Data overview

This research investigates the impact of oil prices on food prices in China by using monthly data spanning from January 2000 to December 2021. The measurement of food price is conducted via the use of the Food Price Index, which is developed and maintained by the Food and Agriculture Organization (FAO). The price of oil is represented by the West Texas Intermediate (WTI) crude oil, denoted in dollars per barrel ($/b). Table 2 presents the descriptive information pertaining to the prices of food and oil. The mean value for food is 91.937, with a range between 50.468 and 137.62, and the mean value for oil is 61.02 ($/b), which fluctuates between 16.550 and 133.93. The standard deviation of oil prices is slightly larger than food prices, which indicates that oil prices are relatively more volatile than food prices. The observed correlation coefficient between food and oil prices is 0.8334, indicating a positive relationship that is deemed statistically significant. This shows that as global oil prices rise, so do food prices.

Table 2. Summary statistics (source: author's calculations)

	Food Price	Oil Price
Mean	91.937	61.020
Standard Deviation	25.270	25.559
Minimum	50.468	16.550
Maximum	137.622	133.93
Correlation	0.833	–

Figure displays a scatterplot illustrating the connection between food prices (Y) and oil prices (X). The data demonstrates a favourable correlation between oil prices and food costs. This graphic further supports the results of the correlation study, indicating a positive association between oil prices and food prices in China.

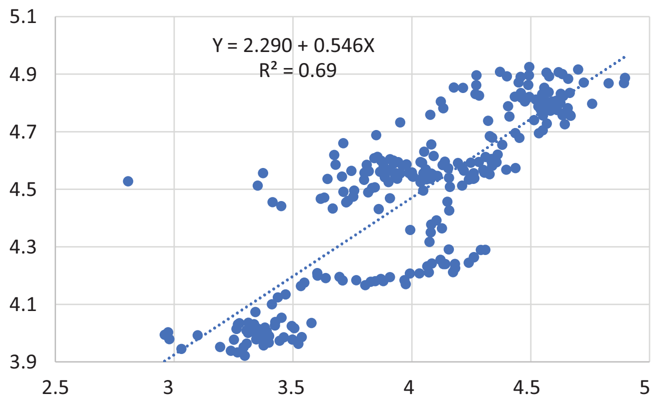

Figure 3. Scatter diagram

5.2. BDS results

First, we have examined the nonlinear dependence in the variables by applying BDS test (Broock et al., 1996). This examination assesses the null hypothesis of whiteness, which refers to the assumption that the series being analyzed are identically and independently distributed (iid). It is contrasted with the alternative hypothesis of non-whiteness, which implies that the series are distributed in a nonlinear manner. The results of BDS test are reported in Table 3. These results show that the all BDS test statistics values are significant, which suggests that the underlying series are nonlinear dependent.

Table 3. BDS test results (source: author's calculations)

Food Price Index				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
m^2	0.201241	0.003514	57.26808	0.0000
m^3	0.341373	0.005577	61.21129	0.0000
m^4	0.438609	0.006629	66.16335	0.0000
Oil Price				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
m^2	0.171585	0.003105	55.26868	0.0000
m^3	0.286407	0.00492	58.20902	0.0000
m^4	0.360587	0.00584	61.74508	0.0000

Since nonlinearities are present in data, we cannot estimate the model using traditional econometric techniques like least square. Rather, we have to apply the estimation technique which takes into account nonlinear dependence like QnQ regression technique.

5.3. Quantile-on-quantile regression (QQR) results

This section presents the results of QQR approach between oil prices and food prices. Figure 4 shows slope coefficient estimates $\alpha_1(\delta, \gamma)$ that capture the effect of the γ-quantile of oil prices on the δ-quantile of food prices for different values of δ and γ for the variables under consideration.

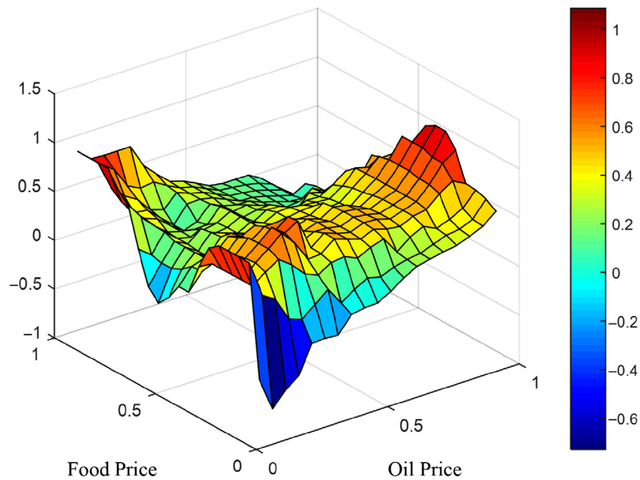

Figure 4. QnQ regression estimates

The figure provides some important results. The field that mixes the low to medium quantiles of oil price (0.2–0.70) and the low quantiles of food price (0.2–0.5) is shown as the negative effect of oil prices on food prices in China. At the highest oil price quantiles (0.80–0.95) and the highest food price quantiles (0.60–0.95), there is a positive impact of crude oil on food prices. The figure also indicates that as quantiles of both oil and food prices close to 1, the positive impact of oil prices on food prices further increases and becomes strong. These findings suggest that oil and food prices are strongly correlated, but only at the highest quantiles, with higher price of oil leading to higher price of food and vice versa. Thus, it may be deduced that rising oil prices have pushed up food prices in China. This recommends that reducing crude oil prices in China have a favorable effect on food prices. The estimation results are consistent with (Al-Maadid et al., 2017; Esmaeili & Shokoohi, 2011; Meyer et al., 2018) who also discovered that rising price of crude oil has a huge positive influence on food prices. It is also worth noting that failing to account for quantile variability will lead to incorrect conclusions as, the connection between the variables is not consistent across quantiles.

5.4. Checking the QQR technique validity

The QQR method basically decomposes the quantile regression (QR) model estimates and allows new estimates for different quantiles of oil prices. The QQR model regresses the impact of γ-quantile of oil prices onto the δ-quantile of food prices, while the QR parameters are determined only by δ-quatiles. Since QQR approach recognizes the theoretically heterogeneous relationships between different quantiles of variables, it provides more rough knowledge of the oil prices and food prices correlation than the quantile regression. Given the inherent decomposition properties of the QQR method, the QQR calculation can be used to find QR estimates. Averaging the QQR parameters along γ can be used to generate quantile regression parameters. For example, the slope coefficient of the quantile regression model, denoted by $\varphi_1(\delta)$, can be calculated using the effect of oil prices on food prices as

$$\varphi_1(\delta)=\overline{\alpha}_1(\delta)=\frac{1}{s}\sum_{\gamma}\widehat{\alpha_1}(\delta,\gamma). \tag{7}$$

In this case, a comparison of the approximate quantile regression parameter and the γ mean QQR parameter is adequate to check the validity of the QQR method. Figure 5 shows the mean QQR estimates of slope coefficients that calculate the impact of oil prices on food prices.

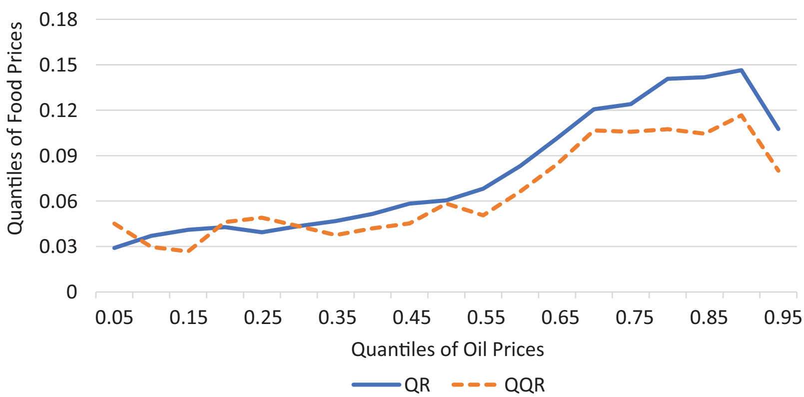

Figure 5. QR and QQR estimate comparison

Note: QR line is estimated using quantile regression, while QQR line is the average of QQR parameters.

The figure shows that the QQR line has the same trend as the QR line with slightly changed values. The graph demonstrates the key characters of the QR model that can be derived by summarizing the detailed information found in the QQR estimates, thus providing a straightforward confirmation of the QQR methodology. Thus, this figure confirms the earlier reported QQR analysis results that the influence of rising oil prices on food prices is positive across the quantiles. This positive impact even becomes strong at upper quantiles (0.65–0.90). These findings support the QQR approach once more and the graphical analysis endorses the previous findings that oil prices have a positive impact on food prices across the quantiles.

Conclusions

Using monthly data from 2000M1 to 2021M12, the research empirically evaluates the impact of oil prices on food prices in China. First nonlinear dependence of the variables is examined using BDS test. The results of the BDS test reveal nonlinear dependency between the variables. The model is estimated using the QnQ Regression (QQR) approach once the variables' non-linearity has been confirmed. This method offers a thorough description of the overall structure of dependency between oil and food price levels and allows for the estimation of the influence of oil price quantiles on food price quantiles. The projected findings demonstrate a significant relationship between oil and food prices in China. The oil price has a negative effect on food prices at its lower quantiles. But this impact becomes positive at high quantiles of both oil prices and food prices.

For Chinese policymakers, these results have a number of significant policy ramifications. For instance, to lessen the negative effects of oil price shocks on food prices, policymakers in China may develop monetary and exchange rate policies. The Chinese government may turn to renewable energy sources to counter the negative effects of rising oil prices on food costs. In order to minimize the dependency on oil, it is also crucial to encourage the use of effective energy production techniques, such as wind, solar, and coal energy, in the food production process. The findings also demonstrate that the supply and demand of oil prices have a beneficial influence on the indices of food prices, emphasizing the need for international organizations like OPEC, the WTO, and the FAO to step in and control these impacts on a global scale. The measures taken by these institutions will encourage oil-producing countries to provide agriculturally-producing countries oil at a reduced price while also benefiting from the decreased prices of agricultural goods.

There are several limitations that future researchers should take into account. The main limitation of the study is that it has considered the full set of food price indices and did not consider the prices of individual agricultural commodities. Therefore, it is important to examine the influence of oil prices on individual agriculture commodities as it may provide more accurate findings. Further, to determine if the effect of the oil price pass-through is time-varying, data may be separated into several time periods. The research can also account for interest rates and exchange rate into analysis. Because it will make it easier to assess how changes in monetary and exchange rate policy have contributed to a stabilization of the effect of the oil price on food prices.

References

Adam, P. (2016). The response of bank of Indonesia's interest rates to the prices of world crude oil and foreign interest rates. *International Journal of Energy Economics and Policy*, *6*(2), 266–272.

Adeosun, O. A., Tabash, M. I., & Anagreh, S. (2023). Revisiting the oil prices – domestic food inflation nexus in Nigeria: The role of global geopolitical risk. *African Journal of Economic and Management Studies*. https://doi.org/10.1108/AJEMS-09-2022-0399

Allahyari, M. S., Marzban, S., El Bilali, H., & Ben Hassen, T. (2022). Effects of COVID-19 pandemic on household food waste behaviour in Iran. *Heliyon*, *8*(11), Article e11337. https://doi.org/10.1016/j.heliyon.2022.e11337

Al-Maadid, A., Caporale, G. M., Spagnolo, F., & Spagnolo, N. (2017). Spillovers between food and energy prices and structural breaks. *International Economics*, *150*, 1–18. https://doi.org/10.1016/j.inteco.2016.06.005

Bala, U., & Chin, L. (2018). Asymmetric impacts of oil price on inflation: An empirical study of African OPEC member countries. *Energies*, *11*(11), Article 3017. https://doi.org/10.3390/en11113017

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271–296. https://doi.org/10.1093/jjfinec/nby001

Ben Hassen, T., & El Bilali, H. (2022). Impacts of the Russia–Ukraine war on global food security: Towards more sustainable and resilient food systems? *Foods*, *11*(15), Article 2301. https://doi.org/10.3390/foods11152301

Brock, W. A., Hsieh, D. A., & LeBaron, B. (1991). *Nonlinear dynamics, chaos, and instability: Statistical theory and economic evidence*. MIT Press.

Broock, W. A., Scheinkman, J. A., Dechert, W. D., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, *15*(3), 197–235. https://doi.org/10.1080/07474939608800353

Chang, L., Mohsin, M., Gao, Z., & Taghizadeh-Hesary, F. (2023). Asymmetric impact of oil price on current account balance: Evidence from oil importing countries. *Energy Economics*, *123*, Article 106749. https://doi.org/10.1016/j.eneco.2023.106749

Chen, J., Zhu, X., & Li, H. (2020). The pass-through effects of oil price shocks on China's inflation: A time-varying analysis. *Energy Economics*, *86*, Article 104695. https://doi.org/10.1016/j.eneco.2020.104695

Dadzie, P., Nambie, Nicholas Bamegne, & Obobi, Belinda Ameh. (2023). Impact of Petroleum Energy Price Volatility on Commodity Prices in Ghana. *International Journal of Economics and Financial Issues, 13*(1), 73–82. https://doi.org/10.32479/ijefi.13928

de Nicola, F., De Pace, P., & Hernandez, M. A. (2016). Co-movement of major energy, agricultural, and food commodity price returns: A time-series assessment. *Energy Economics*, *57*, 28–41. https://doi.org/10.1016/j.eneco.2016.04.012

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Dillon, B. M., & Barrett, C. B. (2016). Global oil prices and local food prices: Evidence from East Africa. *American Journal of Agricultural Economics*, *98*(1), 154–171. https://doi.org/10.1093/ajae/aav040

Esmaeili, A., & Shokoohi, Z. (2011). Assessing the effect of oil price on world food prices: Application of principal component analysis. *Energy Policy*, *39*(2), 1022–1025. https://doi.org/10.1016/j.enpol.2010.11.004

Fowowe, B. (2016). Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy*, *104*, 149–157. https://doi.org/10.1016/j.energy.2016.03.101

Gao, L., Kim, H., & Saba, R. (2014). How do oil price shocks affect consumer prices? *Energy Economics*, *45*, 313–323. https://doi.org/10.1016/j.eneco.2014.08.001

Gilbert, C. L. (2010). How to understand high food prices. *Journal of Agricultural Economics*, *61*(2), 398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x

Guan, Y., Yan, J., Shan, Y., Zhou, Y., Hang, Y., Li, R., Liu, B., Nie, Q., Bruckner, B., Feng, K., & Hubacek, K. (2023). Burden of the global energy price crisis on households. *Nature Energy*, *8*, 304–316. https://doi.org/10.1038/s41560-023-01209-8

Huang, J., & Rozelle, S. (2006). The emergence of agricultural commodity markets in China. *China Economic Review*, *17*(3), 266–280. https://doi.org/10.1016/j.chieco.2006.04.008

Hung, N. T. (2021). Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Resources Policy*, *73*, Article 102236. https://doi.org/10.1016/j.resourpol.2021.102236

Ibrahim, M. H. (2015). Oil and food prices in Malaysia: A nonlinear ARDL analysis. *Agricultural and Food Economics*, *3*(1), 1–14. https://doi.org/10.1186/s40100-014-0020-3

Jones, A., & Hiller, B. (2017). Exploring the dynamics of responses to food production shocks. *Sustainability*, *9*(6), Article 960. https://doi.org/10.3390/su9060960

Kapusuzoglu, A., Liang, X., & Ceylan, N. (2018). Macroeconomic impacts of global food price shocks on the economy of Turkey. *Agricultural Economics – Zemedelska ekonomika*, *64*(11). https://doi.org/10.17221/261/2017-AGRICECON

Kapusuzoglu, A., & Karacaer Ulusoy, M. (2015). The interactions between agricultural commodity and oil prices: an empirical analysis. *Agricultural Economics*, *61*(9), 410–421. https://doi.org/10.17221/231/2014-AGRICECON

Karasu, S., Altan, A., Bekiros, S., & Ahmad, W. (2020). A new forecasting model with wrapper-based feature selection approach using multi-objective optimization technique for chaotic crude oil time series. *Energy*, *212*, Article 118750. https://doi.org/10.1016/j.energy.2020.118750

Long, S., & Liang, J. (2018). Asymmetric and nonlinear pass-through of global crude oil price to China's PPI and CPI inflation. *Economic Research-Ekonomska Istraživanja*, *31*(1), 240–251. https://doi.org/10.1080/1331677X.2018.1429292

López Cabrera, B., & Schulz, F. (2016). Volatility linkages between energy and agricultural commodity prices. *Energy Economics*, *54*, 190–203. https://doi.org/10.1016/j.eneco.2015.11.018

Mastroeni, L., Mazzoccoli, A., Quaresima, G., & Vellucci, P. (2022). Wavelet analysis and energy-based measures for oil-food price relationship as a footprint of financialisation effect. *Resources Policy*, *77*, Article 102692. https://doi.org/10.1016/j.resourpol.2022.102692

Meyer, D. F., Sanusi, K. A., & Hassan, A. (2018). Analysis of the asymmetric impacts of oil prices on food prices in oil-exporting, developing countries. *Journal of International Studies*, *11*(3). https://doi.org/10.14254/2071-8330.2018/11-3/7

Mokni, K. (2023). Detrended cross-correlations analysis between oil shocks and world food prices. *International Journal of Energy Sector Management*. https://doi.org/10.1108/IJESM-10-2021-0019

Mokni, K., & Ben-Salha, O. (2020). Asymmetric causality in quantiles analysis of the oil-food nexus since the 1960s. *Resources Policy*, *69*, Article 101874. https://doi.org/10.1016/j.resourpol.2020.101874

Mokni, K., & Youssef, M. (2020). Empirical analysis of the cross-interdependence between crude oil and agricultural commodity markets. *Review of Financial Economics*, *38*(4), 635–654. https://doi.org/10.1002/rfe.1096

Naeem, M. A., Karim, S., Hasan, M., Lucey, B. M., & Kang, S. H. (2022). Nexus between oil shocks and agriculture commodities: Evidence from time and frequency domain. *Energy Economics*, *112*, Article 106148. https://doi.org/10.1016/j.eneco.2022.106148

Nazlioglu, S., & Soytas, U. (2011). World oil prices and agricultural commodity prices: Evidence from an emerging market. *Energy Economics*, *33*(3), 488–496. https://doi.org/10.1016/j.eneco.2010.11.012

Nwoko, I. C., Aye, G. C., & Asogwa, B. C. (2016). Effect of oil price on Nigeria's food price volatility. *Cogent Food & Agriculture*, *2*(1), Article 1146057. https://doi.org/10.1080/23311932.2016.1146057

Olayungbo, D., & Hassan, W. (2016). Effects of oil price on food prices in developing oil exporting countries: a panel autoregressive distributed lag analysis. *OPEC Energy Review*, *40*(4), 397–411. https://doi.org/10.1111/opec.12090

Rafiq, S., & Bloch, H. (2016). Explaining commodity prices through asymmetric oil shocks: Evidence from nonlinear models. *Resources Policy*, *50*, 34–48. https://doi.org/10.1016/j.resourpol.2016.08.005

Reboredo, J. C. (2012). Do food and oil prices co-move? *Energy Policy*, *49*, 456–467. https://doi.org/10.1016/j.enpol.2012.06.035

Salisu, A. A., Isah, K. O., Oyewole, O. J., & Akanni, L. O. (2017). Modelling oil price-inflation nexus: The role of asymmetries. *Energy*, *125*, 97–106. https://doi.org/10.1016/j.energy.2017.02.128

Sek, S. K. (2017). Impact of oil price changes on domestic price inflation at disaggregated levels: Evidence from linear and nonlinear ARDL modeling. *Energy*, *130*, 204–217. https://doi.org/10.1016/j.energy.2017.03.152

Shokoohi, Z., & Saghaian, S. (2022). Nexus of energy and food nutrition prices in oil importing and exporting countries: A panel VAR model. *Energy*, *255*, Article 124416. https://doi.org/10.1016/j.energy.2022.124416

Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, *55*, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Subramaniam, Y., Masron, T. A., & Azman, N. H. N. (2019). The impact of biofuels on food security. *International Economics*, *160*, 72–83. https://doi.org/10.1016/j.inteco.2019.10.003

Sun, Y., Gao, P., Raza, S. A., Shah, N., & Sharif, A. (2023). The asymmetric effects of oil price shocks on the world food prices: Fresh evidence from quantile-on-quantile regression approach. *Energy*, *270*, Article 126812. https://doi.org/10.1016/j.energy.2023.126812

Taghizadeh-Hesary, F., Rasoulinezhad, E., & Yoshino, N. (2019). Energy and food security: Linkages through price volatility. *Energy Policy*, *128*, 796–806. https://doi.org/10.1016/j.enpol.2018.12.043

Tang, W., Wu, L., & Zhang, Z. (2010). Oil price shocks and their short-and long-term effects on the Chinese economy. *Energy Economics*, *32*, S3–S14. https://doi.org/10.1016/j.eneco.2010.01.002

Udoh, E., & Egwaikhide, F. O. (2012). Does international oil price volatility complement domestic food price instability in Nigeria? An empirical enquiry. *International Journal of Economics and Finance*, *4*(1), 235–246. https://doi.org/10.5539/ijef.v4n1p235

Von Braun, J. (2007). *The world food situtation: new driving forces and required actions.* International Food Policy Research Institute.

Wang, Y., Wu, C., & Yang, L. (2014). Oil price shocks and agricultural commodity prices. *Energy Economics*, *44*, 22–35. https://doi.org/10.1016/j.eneco.2014.03.016

Wei, C.-C., & Chen, S.-M. (2016). Examining the relationship of crude oil future price return and agricultural future price return in US. *International Journal of Energy Economics and Policy*, *6*(1), 58–64.

Wei, T., Glomsrød, S., & Zhang, T. (2017). Extreme weather, food security and the capacity to adapt – the case of crops in China. *Food Security*, *9*(3), 523–535. https://doi.org/10.1007/s12571-015-0420-6

Wong, K. K. S., & Shamsudin, M. N. (2017). Impact of crude oil price, exchange rates and real GDP on Malaysia's food price fluctuations: Symmetric or asymmetric? *International Journal of Economics & Management*, *11*(1).

Yu, Y., & Zhang, W. (2019). The role of China's demand in global oil price dynamics. *Emerging Markets Finance and Trade*, *55*(6), 1199–1215. https://doi.org/10.1080/1540496X.2018.1445621

Zakaria, M., Khiam, S., & Mahmood, H. (2021). Influence of oil prices on inflation in South Asia: Some new evidence. *Resources Policy*, *71*, Article 102014. https://doi.org/10.1016/j.resourpol.2021.102014

Zhang, C., & Qu, X. (2015). The effect of global oil price shocks on China's agricultural commodities. *Energy Economics*, *51*, 354–364. https://doi.org/10.1016/j.eneco.2015.07.012

Zhang, Q., & Reed, M. R. (2008). *Examining the impact of the world crude oil price on China's agricultural commodity prices: The case of corn, soybean, and pork.*

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2009). Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. *Energies*, *2*(2), 320–339. https://doi.org/10.3390/en20200320

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2010). Food versus fuel: What do prices tell us? *Energy Policy*, *38*(1), 445–451. https://doi.org/10.1016/j.enpol.2009.09.034

Zmami, M., & Ben-Salha, O. (2019). Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. *Economies*, *7*(1), Article 12. https://doi.org/10.3390/economies7010012