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Modeling the Relationship between Crude Oil and Agricultural Commodity Prices

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Abstract: The food-energy nexus has attracted great attention from policymakers, practitioners, and academia since the food price crisis during the 2007–2008 Global Financial Crisis (GFC), and new policies that aim to increase ethanol production. This paper incorporates aggregate demand and alternative oil shocks to investigate the causal relationship between agricultural products and oil markets. For the period January 2000–July 2018, monthly spot prices of 15 commodities are examined, including Brent crude oil, biofuel-related agricultural commodities, and other agricultural commodities. The sample is divided into three sub-periods, namely: (i) January 2000–July 2006, (ii) August 2006–April 2013, and (iii) May 2013–July 2018. The structural vector autoregressive (SVAR) model, impulse response functions, and variance decomposition technique are used to examine how the shocks to agricultural markets contribute to the variance of crude oil prices. The empirical findings from the paper indicate that not every oil shock contributes the same to agricultural price fluctuations, and similarly for the effects of aggregate demand shocks on the agricultural market. These results show that the crude oil market plays a major role in explaining fluctuations in the prices and associated volatility of agricultural commodities.

Keywords: agricultural commodity prices; volatility; crude oil prices; structural vector autoregressive model; impulse response functions; decomposition

1. Introduction

The co-occurrence of several world-changing events, such as the 2007–2008 Global Financial Crisis (GFC), the 2007–2008 World Food Price Crisis, and the emergence of biofuel production, has raised the complexity of the food-energy nexus that world leaders and elites need to fully understand in order to make appropriate public and private policies. The depletion of fossil fuels and environmental concerns has increased demand to develop renewable energy sources that can replace oil [1,2]. The possibility of food price increases under the introduction of biofuels may hurt the welfare of the poor, and decrease the urgency and speed in eradicating world poverty [3,4]. Chakravorty et al. [5] show that biofuels can even increase the CO_2 emission due to reducing oil price and cutting down forest land for farming. The trade-off between food and energy security has encouraged an investigation of the causal links between the agricultural and energy markets. Any empirical findings would be expected to provide evidence to advise public policymakers to find countermeasures against the adverse effect of biofuels.

The causal links between energy prices and agricultural markets are mostly found to run from the former to the latter [6]. Research has considered oil prices as predetermined, and have examined the contribution of oil prices to agricultural commodity price and volatility variations. For example, Taghizadeh-Hesary et al. [7] show that food prices respond positively to oil price increases in the period 2010–2016 for eight Asian countries using a panel vector autoregression (Panel-VAR) model. For purposes of forecasting error variance decomposition, the oil price contributed 4.81% of the food price volatility in the second period and increased to 62.49% in the 20th period [7].

The causal links from agricultural commodity prices to oil prices have been considered less important in the empirical literature. In a theoretical model, Ciaian and Kancs [8] demonstrate possible channels through which agricultural markets could affect oil prices. First, a positive agricultural productivity shock can reduce the demand for fuel, implying that decreases in food prices can lower oil prices. This mechanism is called the input channel. Second, the so-called biofuel channel has two opposite effects. Drops in agricultural prices will make biofuels more attractive because some agricultural commodities are inputs for biofuel. Increases in demand for biofuels will increase biomass production and oil prices, as oil is used as an input for agricultural commodities. However, increases in biofuel production will increase the total energy supply, and therefore lead to reductions in oil prices.

Despite being somewhat limited, there is some empirical evidence of causality from agricultural commodity prices to oil prices. Deren Unalmis's comment on Baumeister and Kilian [9] shows that the US Department of Agriculture has released a report which leads to a drop in corn prices. The decrease in corn prices is then followed by a decrease in oil prices within half an hour. As the report is specific to agricultural markets, the oil price reaction indicates that shocks to agricultural commodity prices can have an impact on energy prices. Similarly, Dimitriadis and Katrakilidis [10] observe both long-run and short-run causal relationships from corn prices to crude oil prices for the US economy from January 2005 to December 2014, using both the autoregressive distributed lag (ARDL) methodology and error correction models.

Other studies have also reached similar results [11–14]. However, these studies often do not recognize the empirical findings as evidence to support the impact of agricultural price shocks on oil prices. The main reason is that the co-movements between oil prices and agricultural commodity prices may reflect the global business cycle instead of causality. Therefore, studies that have used only the time series of the two prices cannot isolate the impacts of each variable from the effects of global economic activity.

Differing from previous studies that only use time series price data, this paper adds aggregate demand and alternative oil shocks to investigate the causal relationship from agriculture to oil markets, which is a novel contribution of the paper. In recent years, there have been many studies that have used the Kilian index to disentangle the relationship between oil prices, agricultural commodity prices and macroeconomic variables [15–18]. Following these studies, another novel contribution of the paper is to address the relative importance and contribution of agricultural commodity prices to global economic activity and hence to the total variability of oil prices.

The idea that oil prices are endogenous is not new in the literature. Kilian [19] presents an overview of the main causes of oil price fluctuations, which are argued to be better explained through the demand side than political events in oil-exporting countries that can trigger changes in the global oil supply. From the demand side, there are shocks for energy consumption (for example, transportation, heating, and cooking), while other shocks are for inventory and speculative purposes. This paper considers and evaluates agricultural markets as an alternative source of shocks that can cause fluctuation in oil prices.

In addition, the literature has often used a limited number of agricultural commodities in the model specifications. It is recognized that the impacts on oil prices are not the same for different types of agricultural commodities. By using a wide range of different commodities, we find that commodities which are more likely to be used as inputs for biofuels have a stronger relationship with crude oil prices than others. The heterogeneity in the empirical discovery supports the hypothesis that increasing the size of the biofuel market is important in connecting the food-energy nexus.

This empirical finding suggests that oil price forecasting can be improved by observing the appropriate agricultural commodities that are more likely to impact on oil prices. In terms of public policymaking, the findings suggest that policymakers can sustain energy security by increasing the supply of agricultural commodities that are inputs for biofuel production.

The paper is structured as follows. Section 2 presents an overview of the related studies in the literature, while Section 3 discusses the methodology. Sections 4 and 5 provide a discussion of the data and the results of the empirical analysis. Section 6 provides some concluding remarks.

2. Literature Review

In recent years, there have been many published studies on the relationship between oil prices and agricultural commodity prices, most of which have focused on the unidirectional causal relationship from oil prices to agricultural commodity prices. López Cabrera and Schulz [20] find a cointegrating relationship between crude oil, rapeseed, and biodiesel using the vector error correction model (VECM), where rapeseed and biodiesel react to the long run equilibrium while crude oil remains exogenous. However, there did not seem to be any long-run or short-run relationships from rapeseed to crude oil. Kapusuzoglu and Karacaer Ulusoy [21] show that crude oil prices can Granger-cause corn, soybeans, and wheat. Fernandez-Perez, Frijns, and Tourani-Rad [22] find that oil prices can Granger-cause soybeans, corn and wheat, and has a contemporaneous effect on soybeans and wheat. Wang et al. [23] find that most of the agricultural commodity prices investigated respond to oil price shocks during 2006m5–2012m12 using impulse response functions derived from the structural vector autoregression (SVAR).

However, some studies have found limited evidence for a causal relationship from oil prices to agricultural commodity prices. Fowowe [24] conducts a cointegration test with a structural break and nonlinear Granger causality tests and finds that there is no long-run or short-run relationship between oil prices and agricultural commodity prices in South Africa. Nazlioglu and Soytas [25] use the Toda-Yamamoto procedure to test for long-run Granger causality between oil prices, agricultural commodity prices and the exchange rate in Turkey, but cannot find any Granger causal relationship from oil prices to agricultural commodity prices. There is also no transmission from oil price shocks to agricultural commodity prices, either directly or through the exchange rate. Chiu et al. [14] find Granger causality from corn prices to oil prices, but not the reverse, in the USA, using the VAR and VECM models. According to Zhang et al. [26], there is no cointegration between agricultural commodity prices and energy prices. Sugar prices can Granger-cause oil prices, but oil prices cannot Granger-cause any agricultural commodity prices. Of the studies that confirm the neutrality of agricultural markets to oil price shocks, the outcomes are frequently attributed to governmental efforts to insulate the domestic agricultural sectors from international competition [24,25].

Several studies have found evidence of the bi-directional causal relationship between agricultural markets and crude oil prices. Nazlioglu and Soytas [11] examine 24 agricultural commodity variables in a panel vector error correction (Panel-VEC) model and find that agricultural prices and oil prices can Granger-cause each other in the short run, while long-run causality is from oil prices to agricultural prices. According to Nazlioglu [12], linear Granger causality tests show that there is no relationship between agricultural prices and oil prices in either direction. However, after accounting for nonlinearity, it is possible to find bi-directional causal relationships between oil prices and soybeans prices, oil prices and wheat prices, and a unidirectional relationship from oil prices to corn prices. Rosa and Vasciaveo [27] find that wheat prices have a bi-directional relationship with oil prices after considering the Diks and Panchenko test [28] for nonlinear Granger causality.

The authors show that Granger causality goes from oil prices to corn and soybeans prices. Avalos [13] uses the VECM model and finds that oil prices Granger-cause soybean prices, while both soybean and corn prices Granger-cause oil prices. Moreover, corn prices can Granger-cause oil prices in the long run, with all the relationships being discovered after the implementation of the Energy

Policy Act 2005. Bi-directional relationships between the oil and agricultural markets are observed not only in prices but also in the associated volatility (for related analysis, see Chang and McAleer [29,30]).

Nazlioglu et al. [31] use the Lagrange multiplier test for causality in variance proposed by Hafner and Herwartz [32] (see also Chang and McAleer [33] for a simple test of causality in volatility), and find that there is no causal relationship between corn, soybeans, wheat, sugar and oil volatilities in the pre-crisis period. However, the tests detect causal relationships from oil volatility to corn and wheat volatilities, and a bi-directional causal relationship between oil volatility and soybean volatility in the post-crisis period.

There are many explanations for the co-movements between the energy and agricultural markets. The extant literature recognizes four channels through which this can occur, including the cost-push effect, aggregate demand, exchange rate, and biofuels. Some authors have argued that oil prices Granger-cause agricultural commodity prices as oil is an important input for the agriculture sector that is rapidly becoming more energy intensive [9,34]. Baumeister and Kilian [9] argue that such co-movements are the outcome of increasing aggregate demand for both agricultural products and crude oil. They find that fertilizer prices respond to oil price shocks, even though the main input for nitrogen fertilizer production is natural gas, which confirms the joint demand for oil and agricultural commodities. For a detailed analysis of modeling the effects of oil prices on global fertilizer prices and volatility, see Chen et al. [35].

The exchange rate is seen as an intermediate channel that connects agricultural commodities and crude oil [11,23]. Many studies have compared the pre- and post-crisis periods to identify the relevance of biofuels in explaining the relationship between the crude oil and agricultural markets. These studies have shown that the links between the two markets became stronger after the food price crisis [8,36], and attribute biofuels to such co-movements. Recognizing that the relationships between the agricultural and oil markets may be subject to events that can occur contemporaneously, research attempts have been made to separate these mechanisms. Paris [37] uses the cointegrating smooth transition regression model proposed by Choi [38] to detach the biofuels channel from the aggregate demand effect. Wang et al. [23] use the SVAR model to differentiate oil-related shocks, including oil supply, aggregate demand, and oil speculative demand shocks, and quantify their significance for the agricultural markets.

While most of the studies have focused on the effects of oil price fluctuations on agricultural commodity price changes, there has been virtually no systemic research that analyzes the impact of agricultural markets on crude oil prices. From a different perspective, we argue that the past global economic events not only change the nature of the agricultural sector but also of the energy market. Our primary objective is to compare the role of agricultural shocks with oil-specific shocks to emphasize that these changes have made shocks from the agricultural market one of the most significant predictors of crude oil price variations.

3. Methodology

The estimation of the causal relationships between agricultural commodities and crude oil can suffer from the problems of simultaneity and endogeneity. Theoretically, the causal relationship between the two variables can run in both directions. Baumeister and Kilian [9] have emphasized that the increasing use of machinery in agriculture can lead to the situation whereby the increase in demand for agricultural commodities will lead to an increase in the demand for crude oil. In response, VAR models have been widely used in the literature to deal with the problem of reverse causality. However, the outcomes of VAR models are subject to the ordering of the variables in the system. Therefore, we have decided to use the structural VAR model with the optimal ordering based on theory and in the previous literature.

On the other hand, both oil price and agricultural commodity prices are endogenous to the global business cycle, so that the inclusion of aggregate demand is necessary for the identification of the model. Moreover, Kilian [39] and Wang et al. [23] demonstrate that different oil market shocks have different impacts on oil price and agricultural commodity prices. Therefore, it is relevant to add alternative oil shocks in the model equations to examine which shocks are the most influential.

Consider the VAR(1) model in Equation (1):

$$z = (\Delta OIL_t, \Delta KI_t, \Delta OP_t, \Delta AGRI_t)' \tag{1}$$

where OIL_t denotes global oil production, KI_t is the Kilian index that captures the global demand for industrial commodities, OP_t is the price of Brent crude oil, and $AGRI_t$ represents the prices of agricultural commodities. The variables are expressed in logarithms, and ϵ_t is the error term that represents the shocks corresponding to each equation. The variables are non-stationary in levels, but become stationary after transformation to first differences.

The VAR(1) model with contemporaneous terms for each of the four variables can be represented in Equations (2)–(5), as follows:

$$\Delta OIL_t = b_{10} - b_{12}\Delta KI_t - b_{13}\Delta OP_t - b_{14}\Delta AGRI_t + B_{oil}z_{t-1} + \varepsilon_t^{Oil\ supply\ shock} \tag{2}$$

$$\Delta KI_t = b_{20} - b_{21}\Delta OIL_t - b_{23}\Delta OP_t - b_{24}\Delta AGRI_t + B_{ki}z_{t-1} + \varepsilon_t^{Aggregate\ demand\ shock} \tag{3}$$

$$\Delta OP_t = b_{30} - b_{31}\Delta OIL_t - b_{32}\Delta KI_t - b_{34}\Delta AGRI_t + B_{op}z_{t-1} + \varepsilon_t^{Oil\ specific\ demand\ shocks} \tag{4}$$

$$\Delta AGRI_t = b_{40} - b_{41}\Delta OIL_t - b_{42}\Delta KI_t - b_{43}\Delta OP_t + B_{agri}z_{t-1} + \varepsilon_t^{\text{Agriculture specific shocks}} \tag{5}$$

where B_{oil}, B_{ki}, B_{op} and B_{agri} represent the vectors of coefficients for z_{t-1} in each equation. Moving the contemporaneous terms to the left-hand side of Equations (2)–(5), the structural form of the VAR system is given in compact form in Equations (6)–(8), where the elements refer respectively to Equations (2)–(5), as follows:

$$Az_t = b + Bz_{t-1} + \varepsilon_t \tag{6}$$

where

$$A = \begin{bmatrix} 1 & b_{12} & b_{13} & b_{14} \\ b_{21} & 1 & b_{23} & b_{24} \\ b_{31} & b_{32} & 1 & b_{34} \\ b_{41} & b_{42} & b_{43} & 1 \end{bmatrix} \tag{7}$$

and

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^{Oil\ supply\ shock} \\ \varepsilon_t^{Aggregate\ demand\ shock} \\ \varepsilon_t^{Oil\ specific\ demand\ shocks} \\ \varepsilon_t^{Agricultural\ shocks} \end{bmatrix} \tag{8}$$

A more general model, VAR(p), that includes additional information from previous periods can be written in Equation (9) as:

$$Az_t = b + \sum_{i=1}^{p} B_i z_{t-p} + \varepsilon_t \tag{9}$$

where the order of p in the model with additional lags on all the variables is chosen by using the Akaike information criterion (AIC). It is assumed that the shocks are serially and mutually uncorrelated. Moreover, variables have different degrees of exogeneity. Following Kilian [39], it is assumed that oil production ΔOIL_t has the highest degree of exogeneity, so that it can only be affected by its own oil supply shocks. In particular, it is assumed that changes in aggregate demand, oil price and agricultural prices cannot affect oil production contemporaneously ($b_{12} = b_{13} = 0$), which means that global oil production is inelastic to shocks from other markets within time period t. The parametric restriction means that global oil production is inelastic to shocks from other markets within time period t.

Wang et al. [23] have stated three possible explanations regarding this assumption. First, world oil supply changes are often triggered by internal political events in major oil exporting countries (OPEC) which are exogenous to the world fluctuations in the short-term. Second, oil production is capital intensive and, therefore, has a high cost of adjusting its capacity according to the short-term fluctuations in world demand [39]. Third, oil exporting countries often have sluggish reactions to short-term demand due to the high uncertainty in the oil market.

Moreover, Ramcharran [40] argues that OPEC and non-OPEC countries may have different reactions to oil price shocks. On the one hand, OPEC countries are likely to decrease their oil supplies when oil price increases, due to the target revenue objective. On the other hand, due to competition objective, non-OPEC countries may increase their oil supplies, given the rise in oil price. Therefore, the impact of oil price surges on world crude oil supply is ambiguous.

Recent studies that are related to the demand and supply of oil in Europe include scenarios concerned with public energy research, development expenditures, financing energy innovation in Europe (see Bointner, Pezzutto, and Sparber [41], and financing innovations for renewable energy transition in Europe (see Bointner et al. [42]).

Oil production can also respond to changes in global oil demand, but the response only arises after observing oil price trends for extended periods [43]. Furthermore, global economic activity ΔKI_t responds to innovations in oil supply and its own aggregate demand shocks. It is widely believed that changes in oil prices cannot affect global economic activity within the same calendar month [39]. Therefore, it is assumed that $b_{23} = 0$.

For the last assumption, oil production, global economic activity and precautionary demand for oil are often treated as predetermined with respect to agricultural commodity prices, so it assumed that $b_{14} = b_{24} = b_{34} = 0$. Following Kilian [19], oil price ΔOP_t is affected by oil production, global economic activity and its own precautionary innovations. Agricultural commodity prices have the lowest degree of exogeneity and are dependent on shocks from other variables and their own shocks. Innovations in agricultural markets may arise from both the supply side (such as weather impacts or natural disasters [43]) or the demand side (such as consumer preferences [44]).

According to the above assumptions, the specification of the matrix A of the parameters in Equation (7) is now given in Equation (10) as:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 \\ b_{41} & b_{42} & b_{43} & 1 \end{bmatrix} \tag{10}$$

The reduced form of Equation (10) can be obtained by multiplying both sides by the matrix A^{-1}, which is given in Equations (11) and (12), where the random error term in Equation (11) is given in Equation (12), as:

$$z_t = \beta + \sum_{i}^{p} \gamma_i z_{t-i} + \epsilon_t \tag{11}$$

where

$$\epsilon_t = \begin{bmatrix} \epsilon_t^{\Delta OIL} \\ \epsilon_t^{\Delta KI} \\ \epsilon_t^{\Delta OP} \\ \epsilon_t^{\Delta AGRI} \end{bmatrix} = A^{-1}\varepsilon_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21} & 1 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & 1 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{42} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{Oil\ supply\ shock} \\ \varepsilon_{Aggregate\ demand\ shock} \\ \varepsilon_{Oil-specific\ demand\ shock} \\ \varepsilon_{Agricultural\ shocks} \end{bmatrix} \tag{12}$$

A similar specification can be found in Wang et al. [23].

After estimating the parameters in the SVAR model, we used the cumulative impulse response functions (IRF) to measure the responses of oil prices and agricultural commodity prices to changes in the other three variables. Ideally, the impulse response function will measure the reaction of the system to changes in one variable, given that there are no shocks in the other variables. However, in the reduced form VAR, variables are contemporaneously correlated, such that it is not possible to isolate the impact of specific variables [22].

In order to orthogonalize the impact of the shocks, we used the Cholesky scheme which imposes zero restrictions on contemporaneous terms. The restrictions are based on economic theory, which states that variables in the vector z_t cannot have contemporaneously causal effects on those variables that have been ordered beforehand. The IRF illustrates the size, statistical significance and the persistence of such impacts. The Granger non-causality test was calculated to reveal the causal directional relationships among the variables. The forecasting error variance decomposition was used to examine the relative importance of each type of shock to variations in agricultural commodity prices.

4. Data and Tests

This section will evaluate the food-energy nexus to investigate the impact of oil price shocks on agricultural commodity prices, and vice-versa, from January 2000–July 2018. The monthly spot prices of 15 commodities are used, including Brent crude oil, biofuel-related agricultural commodities (namely, corn, sugarcane, soybeans, wheat, coconut oil, palm oil, palm kernel oil, and soybean oil), and other agricultural commodities (specifically, barley, cocoa, coffee, cotton, rice and tea). The commodity prices are obtained from the World Bank Commodity Price Data (the Pink Sheet) (http://www.worldbank.org/en/research/commodity-markets). In order to ensure consistency, the nominal prices are deflated by the US CPI, which is obtained from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/CPALTT01USM661S).

Following Chiu et al. [14], we divide the full sample into three sub-samples, namely January 2000–July 2006, August 2006–April 2013, and May 2013–July 2018. The breaks are the results of unit root tests with two structural breaks for the corn series [45,46]. Corn is chosen to determine the structural breaks as it is one of the most important inputs for biofuels, which helps to connect the food-energy nexus (see [29,30]). Furthermore, July 2006 is also very close to the date when the Energy Policy Act of 2005 was implemented in May 2006. The new renewable fuel standard requires a minimum amount of fuel arising from renewable sources, which increases the demand for ethanol (or bio-ethanol) and, therefore, for corn and other biofuel-related agricultural commodities [9,13]. Table 1 shows the descriptive statistics for the crude oil and agricultural commodity prices expressed in logarithms. The mean prices and volatility of most agricultural commodity prices during the second period are larger than those in the other two periods, which add further support to the examination of three sub-sample periods.

Table 1. Data description.

January 2000–July 2006						
Variable	**Mean**	**SD**	**Max**	**Min**	**Skewness**	**Kurtosis**
Brent	2.715	0.321	3.401	2.156	0.591	2.331
Corn	3.791	0.098	4.072	3.581	0.605	3.407
Sugar	5.586	0.067	5.714	5.470	0.127	1.945
Soybeans	4.683	0.156	5.203	4.448	0.970	4.192
Wheat	4.157	0.124	4.460	3.925	0.290	2.668
Coconut oil	5.369	0.240	5.779	4.893	−0.256	2.048
Palm oil	5.146	0.182	5.490	4.689	−0.688	3.169
Palm kernel oil	5.356	0.252	5.767	4.836	−0.348	1.997
Soybean oil	5.350	0.214	5.718	4.921	−0.373	2.023
Barley	3.764	0.121	4.011	3.548	0.300	2.205
Cocoa	6.439	0.238	6.931	6.029	−0.144	2.376
Coffee	6.654	0.234	7.147	6.303	0.475	1.875
Cotton	6.296	0.160	6.628	5.941	0.041	2.408
Rice	4.582	0.159	4.853	4.335	0.378	1.739
Tea	6.605	0.102	6.885	6.437	1.010	3.155

Table 1. *Cont.*

August 2006–April 2013						
Variable	**Mean**	**SD**	**Max**	**Min**	**Skewness**	**Kurtosis**
Brent	3.472	0.263	3.920	2.785	−0.600	2.788
Corn	4.380	0.259	4.788	3.853	0.036	1.552
Sugar	5.291	0.245	5.708	4.975	0.396	1.576
Soybeans	5.172	0.200	5.502	4.652	−0.636	2.827
Wheat	4.613	0.220	5.134	4.091	0.043	2.300
Coconut oil	5.966	0.322	6.731	5.490	0.497	2.232
Palm oil	5.775	0.243	6.178	5.240	−0.302	2.279
Palm kernel oil	5.932	0.342	6.748	5.317	0.273	2.348
Soybean oil	5.967	0.218	6.367	5.499	−0.187	2.085
Barley	4.211	0.227	4.556	3.676	−0.445	2.156
Cocoa	6.857	0.198	7.197	6.437	−0.160	2.030
Coffee	7.226	0.257	7.797	6.891	0.782	2.423
Cotton	6.536	0.318	7.534	6.087	1.380	4.666
Rice	5.229	0.237	5.856	4.794	−0.163	3.040
Tea	6.881	0.145	7.094	6.567	−0.705	2.247
May 2013–July 2018						
Variable	**Mean**	**SD**	**Max**	**Min**	**Skewness**	**Kurtosis**
Brent	3.103	0.369	3.673	2.367	0.298	1.906
Corn	4.097	0.175	4.661	3.897	1.534	5.216
Sugar	4.893	0.097	5.060	4.761	0.618	1.879
Soybeans	5.011	0.137	5.331	4.825	0.804	2.482
Wheat	4.294	0.266	4.757	3.874	0.362	1.827
Coconut oil	6.081	0.197	6.475	5.684	−0.126	2.291
Palm oil	5.444	0.188	5.816	5.092	0.344	2.226
Palm kernel oil	5.920	0.196	6.377	5.556	0.230	2.165
Soybean oil	5.601	0.158	5.943	5.364	0.690	2.229
Barley	3.748	0.252	4.410	3.421	0.813	3.095
Cocoa	6.819	0.190	7.059	6.457	−0.581	1.872
Coffee	7.090	0.164	7.452	6.850	0.634	2.506
Cotton	6.413	0.117	6.615	6.214	0.072	1.674
Rice	4.953	0.098	5.263	4.819	0.956	4.001
Tea	6.881	0.073	7.004	6.685	−0.472	2.993

Following Wang et al. [23], oil price shocks are separated into different sources, including oil supply shocks, oil demand shocks from aggregate demand, and other oil demand shocks that are either precautionary or speculative in nature. World crude oil production is collected from the US Energy Information Administration, while the Kilian index is used as a proxy for global real economic activity (see [39]). This paper uses the updated version of the index, which has been corrected by Kilian [47] and can be found at the following website: (https://sites.google.com/site/lkilian2019/research/data-sets).

Tests for stationarity are conducted to avoid the problem of spurious regression that can arise when the series are non-stationary, and ordinary least squares estimation is used to draw statistical inferences. We perform the usual augmented Dickey and Fuller (ADF) [48] unit root test with one structural break Zivot and Andrews (ZA) [49], as well as the unit root test with two structural breaks Clemente Montanes Reyes (In this paper, the innovative outlier model is used.) (CMR) [45,46]. The null hypothesis of the unit root test is that the time series contains a unit root and hence is non-stationary. For the ADF test, the optimal lag length is based on the Akaike information criterion.

The conventional augmented Dickey and Fuller [48] test may yield misleading results if the time series contains structural breaks. Even when accounting for a structural break, the results of the unit root test based on Zivot and Andrews [49] can still have low power if the time series contains two structural breaks. Therefore, we perform the unit root test with two structural breaks, based on the tests suggested by Perron and Vogelsang [45] and Clemente et al. [46]. The results of the tests show that the null hypothesis of non-stationarity cannot be rejected for most of the time series. (In this paper, the innovative outlier model is used.) However, it is clear from Table 2 that, according to the three tests, most of the time series are found to be stationary in first differences.

Table 2. Unit root tests.

	ADF	ZA		CMR	
Levels					
	Level	**T-Stat**	**Break in**	**Mint t**	**Break in**
Oil production	−1.415	−3.654; −2.853; −3.746	Intercept (2008m8); Trend (2012m8); Both Intercept and Trend (2003m1)	−5.269	2003m6; 2015m1
Kilian's index	−2.419	−3.939; −3.598; −4.649	Intercept (2010m6); Trend (2004m8); Both Intercept and Trend (2008m9)	−4.336	2003m1; 2010m4
Brent	−2.028	−4.384; −3.339; −3.895	Intercept (2014m7); Trend (2011m3); Both Intercept and Trend (2014m10)	−4.31	2004m11; 2014m8
Corn	−1.964	−3.957; −3.785; −4.702	Intercept (2013m7); Trend (2012m2); Both Intercept and Trend (2010m7)	−4.366	2006m7; 2013m4
Sugar	−0.577	−4.162; −3.398; −6.192 ***	Intercept (2008m10); Trend (2004m1); Both Intercept and Trend (2008m10)	−6.159 **	2008m8; 2014m7
Soybeans	−2.211	−4.352; −4.259 *; −4.569	Intercept (2014m3); Trend (2012m3); Both Intercept and Trend (2007m5)	−4.547	2007m3; 2014m1
Wheat	−2.373	−4.272; −3.54; −4.045	Intercept (2014m6); Trend (2011m5); Both Intercept and Trend (2010m7)	−5.041	2007m4; 2014m11
Coconut oil	−1.973	−4.081; −3.953; −4.309	Intercept (2012m2); Trend (2010m12); Both Intercept and Trend (2012m2)	−4.479	2001m9; 2006m8
Palm oil	−1.981	−3.591; −4.157*; −4.282	Intercept (2014m4); Trend (2011m1); Both Intercept and Trend (2010m8)	−4.828	2006m5; 2014m2
Palm kernel oil	−2.379	−5.156 **; −5.001 ***; −5.461 **	Intercept (2012m5); Trend (2010m12); Both Intercept and Trend (2012m5)	−5.02	2001m9; 2006m8
Soybean oil	−1.729	−2.734; −3.337; −3.515	Intercept (2013m2); Trend (2010m12); Both Intercept and Trend (2007m4)	−4.253	2006m8; 2014m3
Barley	−2.111	−3.897; −3.089; −3.38	Intercept (2014m6); Trend (2011m10); Both Intercept and Trend (2009m10)	−4.864	2006m8; 2014m4
Cocoa	−2.381	−3.016; −3.043; −3.376	Intercept (2006m11); Trend (2009m11); Both Intercept and Trend (2007m12)	−4.215	2006m9; 2016m7
Coffee	−1.734	−3.394; −4.25 *; −4.418	Intercept (2004m9); Trend (2011m1); Both Intercept and Trend (2012m2)	−3.929	2004m7; 2008m11
Cotton	−2.916**	−4.042; −3.566; −4.451	Intercept (2009m4); Trend (2010m12); Both Intercept and Trend (2010m8)	−5.505 **	2010m7; 2011m2
Rice	−1.721	−3.757; −4.688 **; −7.314 ***	Intercept (2013m5); Trend (2009m3); Both Intercept and Trend (2008m2)	−5.024	2007m9; 2013m3
Tea	−2.057	−4.577; −3.545; −4.546	Intercept (2007m4); Trend (2010m11); Both Intercept and Trend (2009m1)	−5.227	2007m2; 2009m1
First Differences					
	ADF	**ZA**		**CMR**	
		T-Stat	**Break in**	**Mint t**	**Break in**
Oil production	−10.075 ***	−13.275 ***; −13.138 ***; −13.26 ***	Intercept (2005m6); Trend (2008m10); Both Trend and Intercept (2005m6)	−4.392	2001m5; 2003m11
Kilian's index	−7.114 ***	−9.049 ***; −8.758 ***; −9.045 ***	Intercept (2008m6); Trend (2015m3); Both Trend and Intercept (2008m6)	−8.687 **	2008m8; 2008m10
Brent	−9.310 ***	−12.351 ***; −12.236 ***; −12.469 ***	Intercept (2008m7); Trend (2015m9); Both Trend and Intercept (2014m7)	−8.07 **	2008m8; 2008m11
Corn	−9.030 ***	−11.998 ***; −11.799 ***; −12.007 ***	Intercept (2012m8); Trend (2006m11); Both Trend and Intercept (2008m7)	−8.05 **	2008m9; 2012m6
Sugar	−10.415 ***	−13.043 ***; −12.621 ***; −13.028 ***	Intercept(2008m5); Trend (2009m11); Both Trend and Intercept (2008m5)	−9.035 **	2008m9, 2009m9
Soybeans	−6.035 ***	−6.85 ***; −6.687 ***; −7.061 ***	Intercept (2008m7); Trend(2003m1); Both Trend and Intercept (2004m4)	−7.445 **	2008m9; 2012m6
Wheat	−9.775 ***	−12.097 ***; −11.87 ***; −12.078 ***	Intercept (2008m4); Trend (2015m9); Both Trend and Intercept (2008m4)	−6.991 **	2010m5; 2011m1
Coconut oil	−4.706 ***	−5.538 ***; −5.328 ***; −5.521 **	Intercept (2011m3); Trend (2015m10); Both Trend and Intercept (2011m3)	−5.855 **	2008m6; 2008m10
Palm oil	−6.291 ***	−6.01 ***; −5.86 ***; −6.122 ***	Intercept (2008m4); Trend (2003m1); Both Trend and Intercept (2008m4)	−4.898	2008m6; 2008m9
Palm kernel oil	−6.024 ***	−6.634 ***; −6.443 ***; −6.612 ***	Intercept (2011m3); Trend (2002m12); Both Trend and Intercept (2011m3)	−7.422 **	2008m6; 2008m10
Soybean oil	−5.485 ***	−5.771 ***; −5.475 ***; −5.832 ***	Intercept (2008m7); Trend (2003m1); Both Trend and Intercept (2008m4)	−6.959 **	2008m6; 2008m11
Barley	−8.509 ***	−10.003 ***; −9.899 ***; −10.159 ***	Intercept (2008m8); Trend (2015m9); Both Trend and Intercept(2013m6)	−4.353	2008m6; 2008m11
Cocoa	−10.286***	−13.425 ***; −13.242 ***; −13.707 ***	Intercept(2002m11); Trend(2003m7); Both Trend and Intercept (2002m10)	−13.755 **	2002m8; 2008m9
Coffee	−9.155***	−12.96 ***; −12.96 ***; −13.249 ***	Intercept (2011m5); Trend (2002m10); Both Trend and Intercept (2005m4)	−4.345	2013m12; 2014m2
Cotton	−6.787 ***	−9.475 ***; −8.802 ***; −9.59 ***	Intercept (2011m4); Trend (2014m9); Both Trend and Intercept (2011m4)	−6.423 **	2010m6; 2011m1
Rice	−8.534***	−10.051 ***; −9.522 ***; −10.391 ***	Intercept (2008m5); Trend (2003m2); Both Trend and Intercept (2008m5)	−12.366 **	2007m12; 2008m3
Tea	−14.410***	−14.588 ***; −14.48 ***; −14.623 ***	Intercept (2009m10); Trend (2007m7); Both Trend and Intercept (2009m10)	−4.266	2008m10; 2009m8

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

Non-stationary time series may appear to be co-moving, despite there being no long-run equilibrium relationship among them. In order to test for the long-run relationship among agricultural commodity and oil prices, the cointegration test with a structural break is calculated, according to the procedures suggested in Gregory and Hansen [50]. If there exists cointegration among the variables, a model that includes an error correction term should be used instead of a VAR model. We perform the cointegration test with a structural break for each of the three sub-samples given by January 2000–July 2006, August 2006–April 2013, and May 2013–July 2018. The cointegration test has three test statistics, namely ADF, Z_t and Z_a, and three specifications, namely a break in the constant term (C model), breaks in the constant and trend (C/T model) or breaks in the constant and slope (C/S model).

Table 3 shows no clear indications that there exist long-run relationships among the variables at the 5% significance level during the first period. In the second period, the ADF and Z_t statistics reject the null hypothesis of no cointegration, while Z_a fails to reject the null hypothesis of no cointegration for corn, sugar, and barley. For the other agricultural commodity prices, the three test statistics fail to find any cointegration at the 5% significance level, except for rice when using the Z_t statistic with the constant and slope specifications. In the third period, only corn is indicative of cointegration for the ADF and Z_t statistics, while for most of the other cases the test statistics cannot reject the null hypothesis at the 5% significance level.

Therefore, the structural VAR model will be used to analyze the dynamic relationship between oil and agricultural commodity prices. Before considering the impulse response functions (the analysis is based on the cumulative orthogonalized impulse response functions.) we calculate some diagnostic tests to check the stability condition and the assumption that the SVAR residuals are not autocorrelated. The diagnostic tests show that the model is stable and that there is no indication of model misspecification. The structural breaks of the commodity prices can be found in Figure 1. The optimal lag length for the individual subsample periods is determined according to the Akaike information vriterion. The significance level used for the impulse response functions is set at 5%.

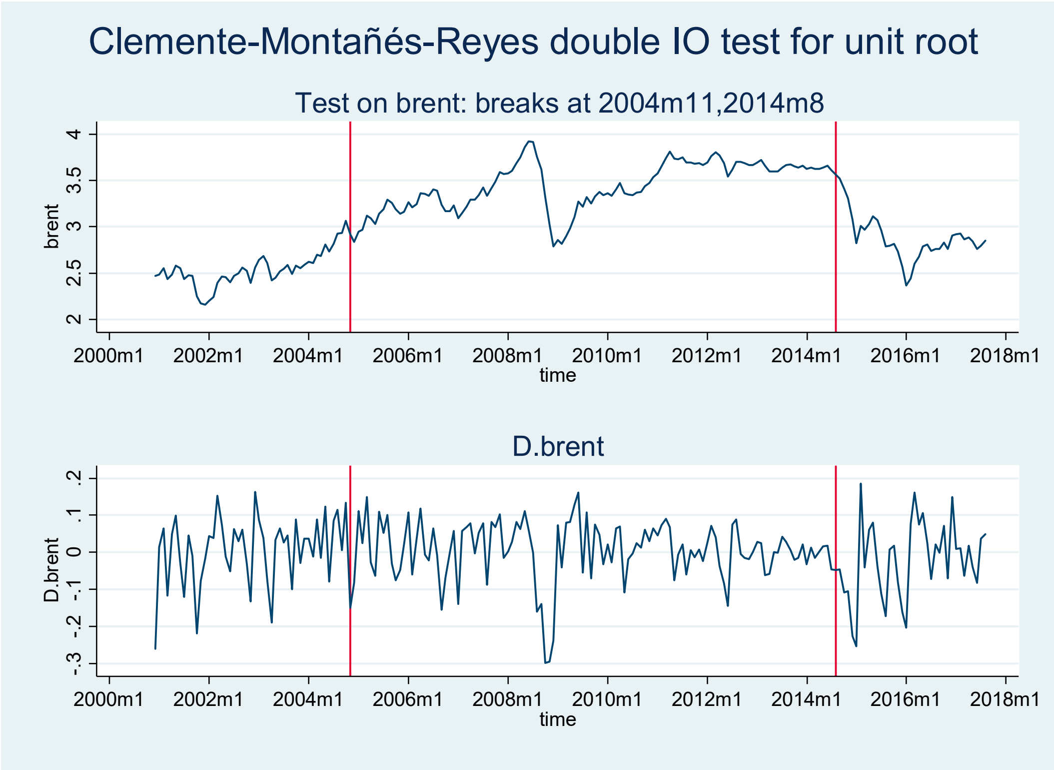
Table 3. Cointegration test with a structural break.

First Period									
	ADF*Test			**Zt*Test**			**Za*Test**		
Model	**C**	**C/T**	**C/S**	**C**	**C/T**	**C/S**	**C**	**C/T**	**C/S**
Corn	−4.067	−5.702 **	−4.076	−4.216	−4.885	−4.204	−24.249	−32.949	−25.295
Sugar	−5.233 *	−5.204	−5.475	−5.051 *	−5.345 *	−5.412	−33.597	−37.511	−41.555
Soybeans	−4.451	−4.655	−5.01	−4.286	−4.521	−4.285	−25.269	−28.814	−27.719
Wheat	−4.244	−4.729	−4.034	−3.86	−4.43	−3.899	−20.177	−22.993	−22.369
Coconut oil	−4.329	−4.672	−4.292	−4.429	−4.893	−5.077	−25.751	−29.578	−36.886
Palm oil	−4.501	−4.69	−4.615	−4.648	−4.798	−4.782	−31.435	−33.816	−34.678
Palm kernel oil	−3.982	−4.722	−4.223	−4.104	−4.648	−4.945	−23.401	−28.443	−36.89
Soybean oil	−5.022 *	−5.032	−4.241	−4.273	−4.293	−4.529	−27.775	−27.555	−31.79
Barley	−5.158 *	−5.322	−5.647	−4.595	−4.716	−4.538	−31.032	−31.722	−29.661
Cocoa	−4.852	−4.731	−4.923	−4.985	−4.898	−5.007	−37.523	−35.73	−37.902
Coffee	−5.114 *	−5.492 *	−5.104	−4.37	−4.966	−4.499	−23	−33.257	−31.572
Cotton	−4.213	−4.669	−5.026	−4.125	−4.725	−4.896	−26.629	−34.303	−34.407
Rice	−5.149 *	−5.128	−5.355	−4.628	−4.634	−4.846	−23.312	−25.365	−31.592
Tea	−4.531	−5.248	−4.866	−4.647	−5.282	−5.468	−36.007	−42.911	−43.026
Second Period									
	ADF*Test			**Z_t*Test**			**Z_a*Test**		
Model	**C**	**C/T**	**C/S**	**C**	**C/T**	**C/S**	**C**	**C/T**	**C/S**
Corn	−5.509 **	−5.277	−5.396	−6.313 ***	−5.662 **	−6.132 **	−37.361	−33.266	−36.95
Sugar	−5.94 ***	−5.819 **	−6.024 **	−5.439 **	−5.932 **	−6.095 **	−41.353	−49.522	−50.463
Soybeans	−4.213	−4.142	−5.196	−5.126 *	−4.653	−5.524	−25.678	−25.131	−33.702
Wheat	−4.124	−4.319	−5.103	−4.6	−4.405	−4.922	−25.258	−25.923	−34.275
Coconut oil	−4.44	−4.452	−4.361	−4.232	−4.158	−4.252	−20.99	−22.344	−25.25
Palm oil	−4.939	−4.645	−4.997	−4.975	−4.541	−4.79	−23.895	−23.312	−24.359
Palm kernel oil	−4.897	−4.906	−4.764	−3.979	−3.794	−4.288	−22.027	−20.622	−25.223
Soybean oil	−4.333	−4.486	−4.66	−5.143 *	−5.326	−5.743	−24.325	−28.028	−29.396
Barley	−6.406 ***	−5.962 **	−7.803 ***	−6.251 ***	−5.907 **	−6.237 **	−36.852	−42.682	−41.976
Cocoa	−5.091 *	−5.217	−5.12	−4.881	−5.031	−5.355	−33.844	−35.234	−35.184

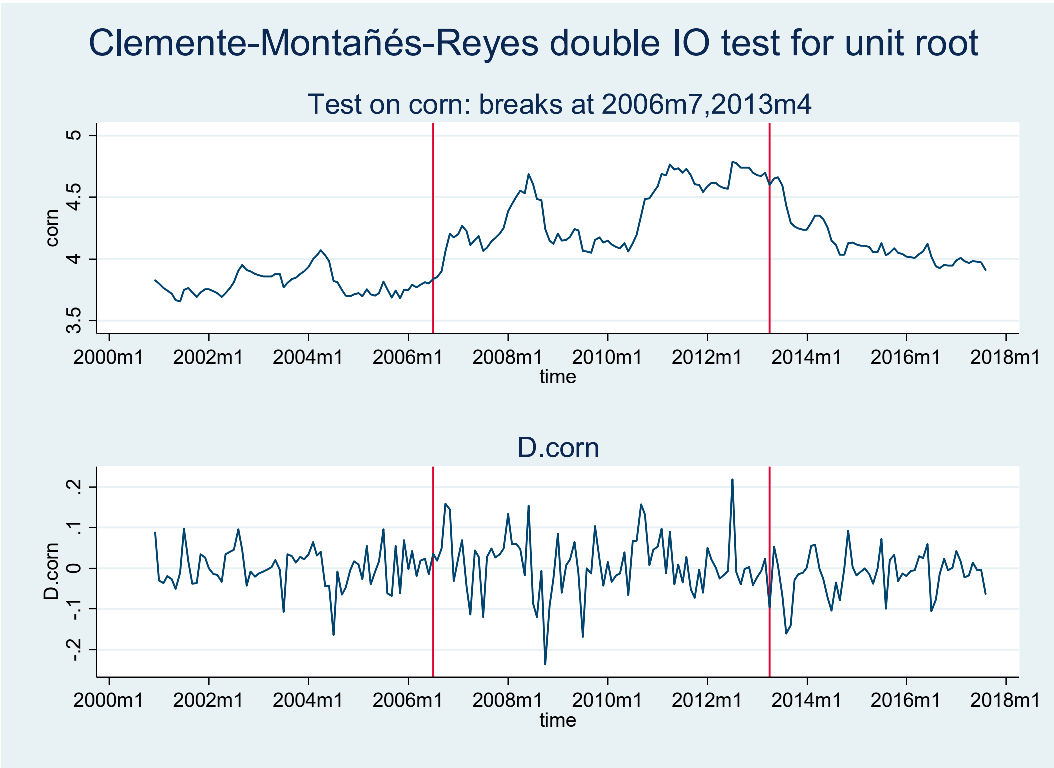
Table 3. *Cont.*

Coffee	−4.058	−3.394	−4.769	−4.083	−3.415	−5.027	−26.195	−21.5	−36.09
Cotton	−3.939	−3.652	−4.451	−4.17	−3.807	−4.371	−24.519	−20.969	−27.441
Rice	−4.581	−5.099	−5.667	−4.431	−4.789	−6.784 ***	−27.063	−32.792	−47.299
Tea	−4.806	−5.214	−5.533	−4.881	−5.152	−5.568	−37.077	−39.977	−44.11
Third Period									
	ADF*test			**Z_t*test**			**Z_a*test**		
Model	**C**	**C/T**	**C/S**	**C**	**C/T**	**C/S**	**C**	**C/T**	**C/S**
Corn	−6.09 ***	−6.158 ***	−6.46 **	−4.762	−4.765	−6.013 **	−28.253	−27.232	−46.448
Sugar	−4.238	−4.347	−4.283	−4.175	−4.22	−4.239	−21.802	−22.314	−22.004
Soybeans	−5.003	−5.505 *	−5.734	−4.847	−5.17	−5.645	−33.115	−36.889	−41.341
Wheat	−4.595	−4.737	−4.709	−4.441	−4.659	−4.561	−25.547	−29.926	−29.319
Coconut oil	−3.056	−3.211	−4.001	−3.022	−3.238	−3.826	−18.289	−19.887	−26.202
Palm oil	−3.872	−4.402	−4.866	−3.837	−4.237	−4.421	−21.874	−28.046	−30.517
Palm kernel oil	−4.759	−5.014	−5.458	−3.974	−3.994	−4.062	−17.343	−19.42	−21.349
Soybean oil	−5.261 *	−5.251	−4.92	−4.436	−4.627	−4.556	−24.541	−29.801	−31.283
Barley	−4.172	−4.449	−5.659	−4.061	−4.233	−4.834	−26.237	−26.257	−32.037
Cocoa	−4.952	−4.95	−4.9	−4.452	−4.638	−4.711	−28.409	−30.311	−31.881
Coffee	−3.941	−4.031	−4.592	−3.738	−3.892	−4.585	−21.45	−22.973	−31.257
Cotton	−4.936	−4.636	−4.76	−4.302	−4.867	−4.462	−24.727	−33.309	−29.298
Rice	−5.353 **	−5.357 *	−5.254	−4.763	−4.764	−4.769	−27.068	−28.014	−29.973
Tea	−4.499	−4.798	−6.026 **	−4.403	−4.463	−4.894	−25.135	−26.476	−34.366

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

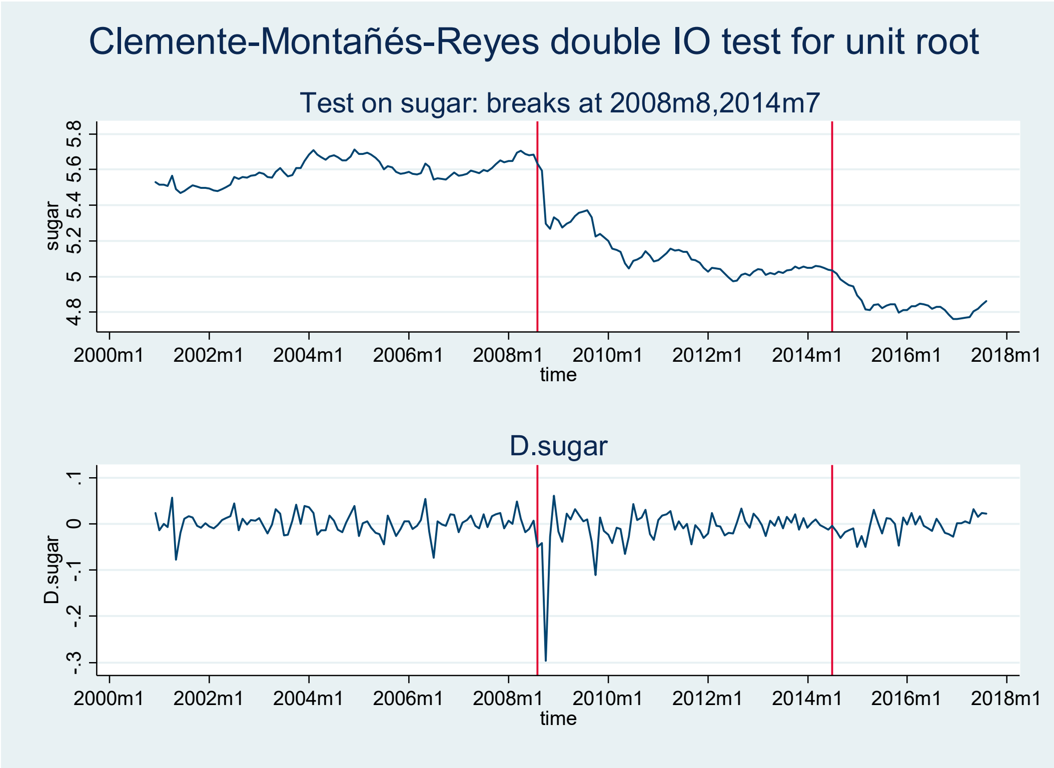


Brent

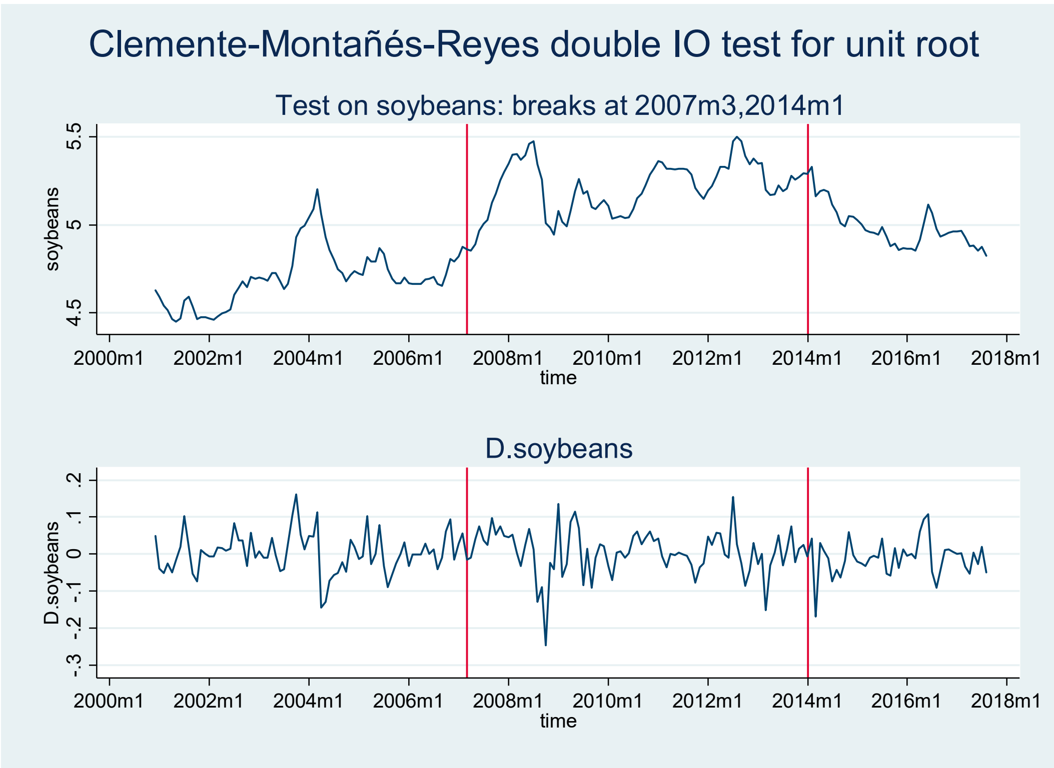


Corn

Figure 1. *Cont.*

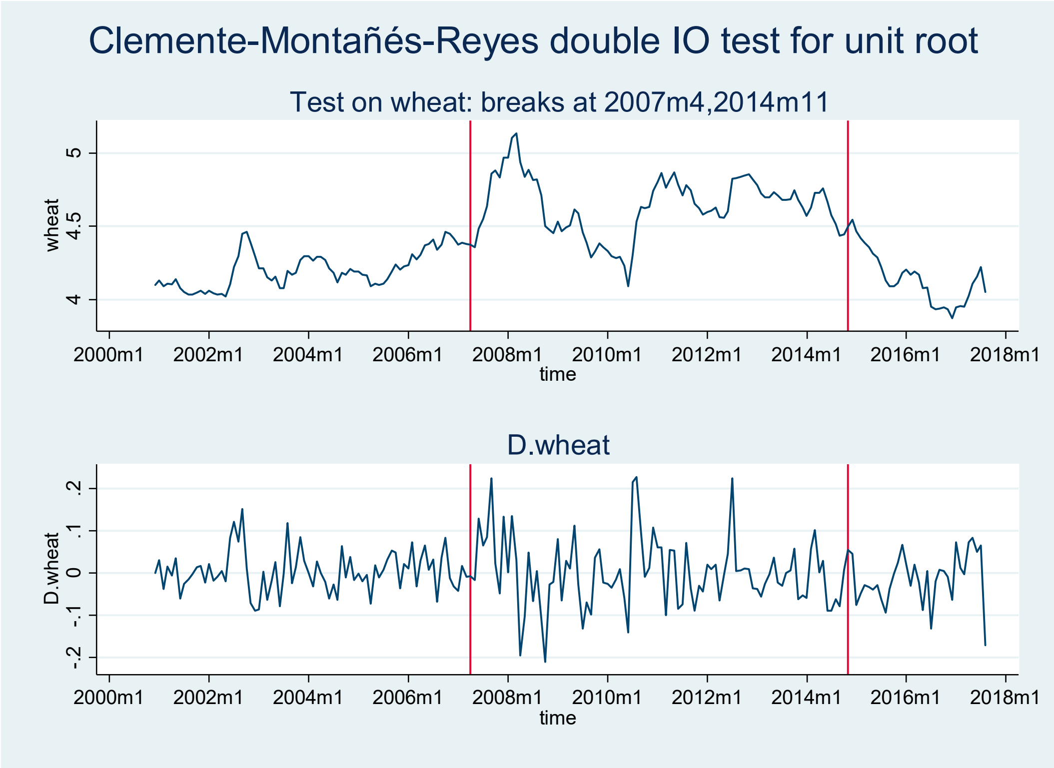


Sugar

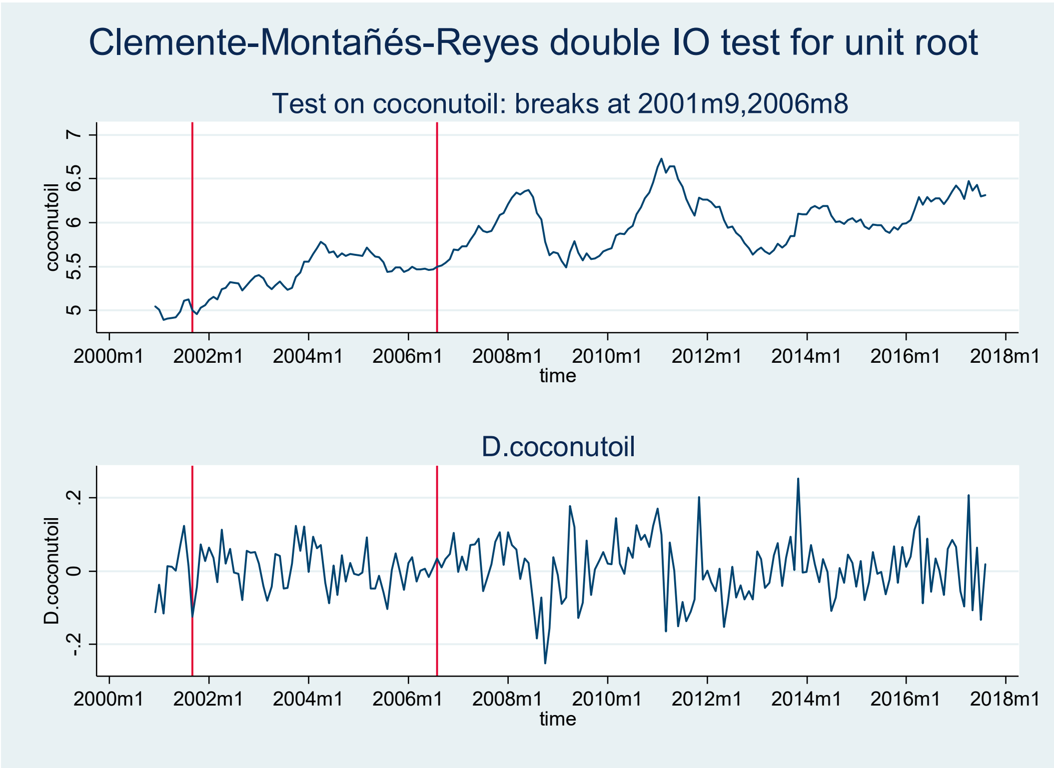


Soybeans

Figure 1. *Cont.*

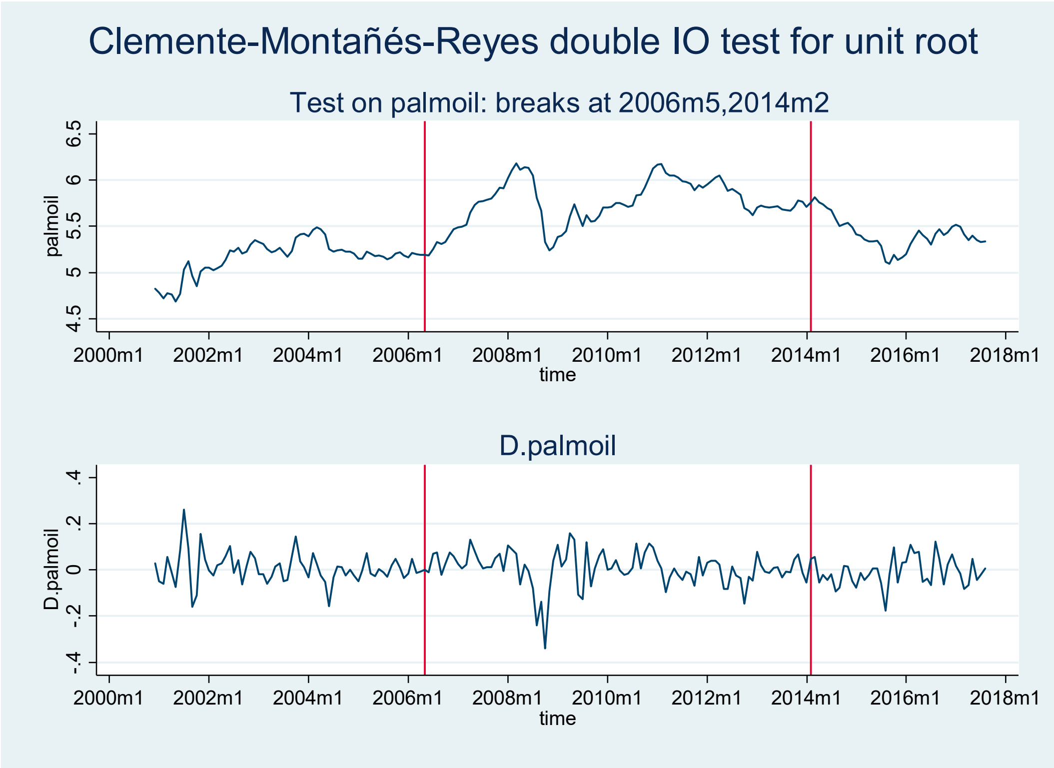


Wheat

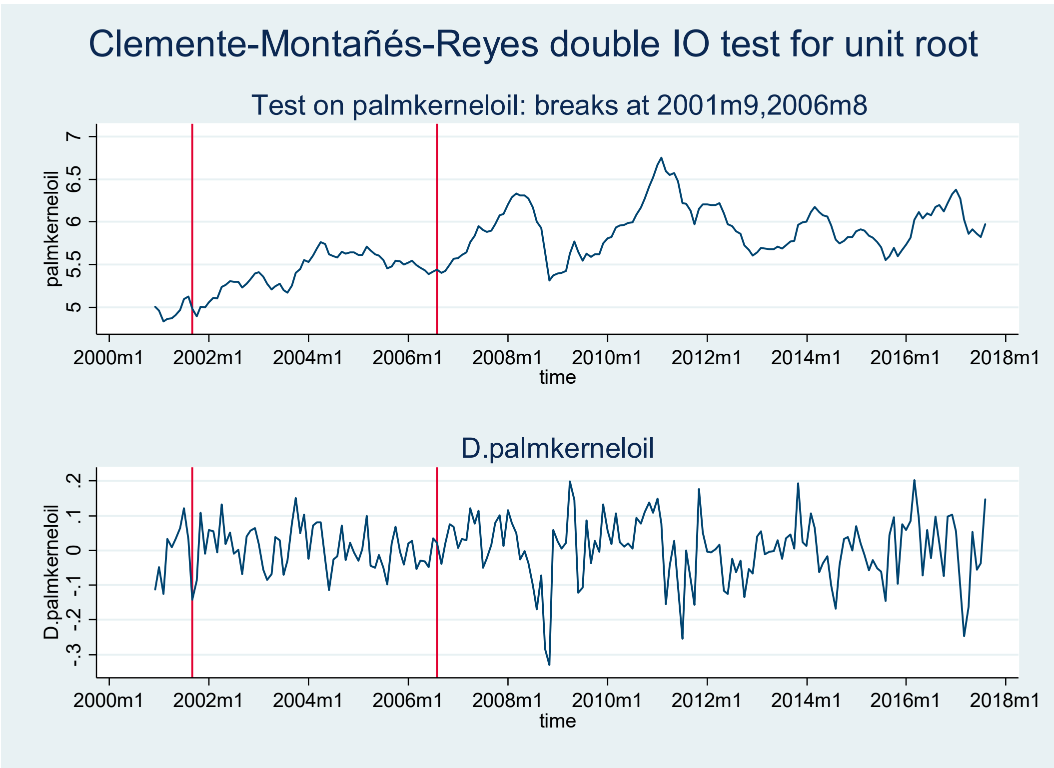


Coconut oil

Figure 1. *Cont.*

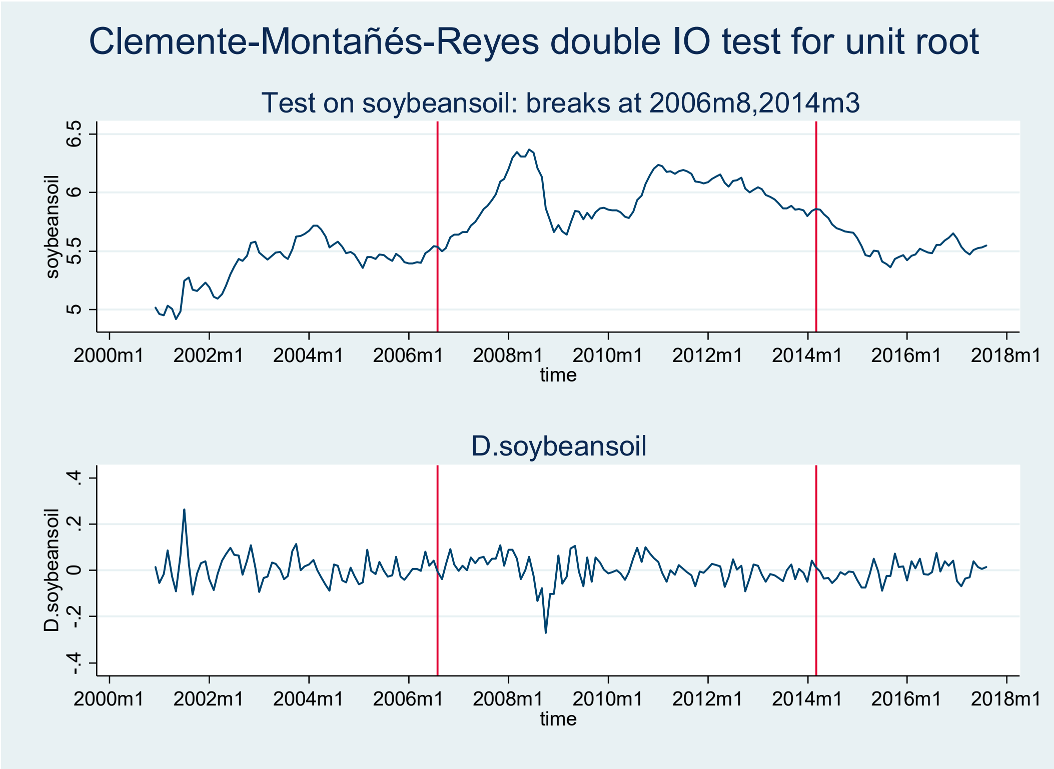


Palm oil

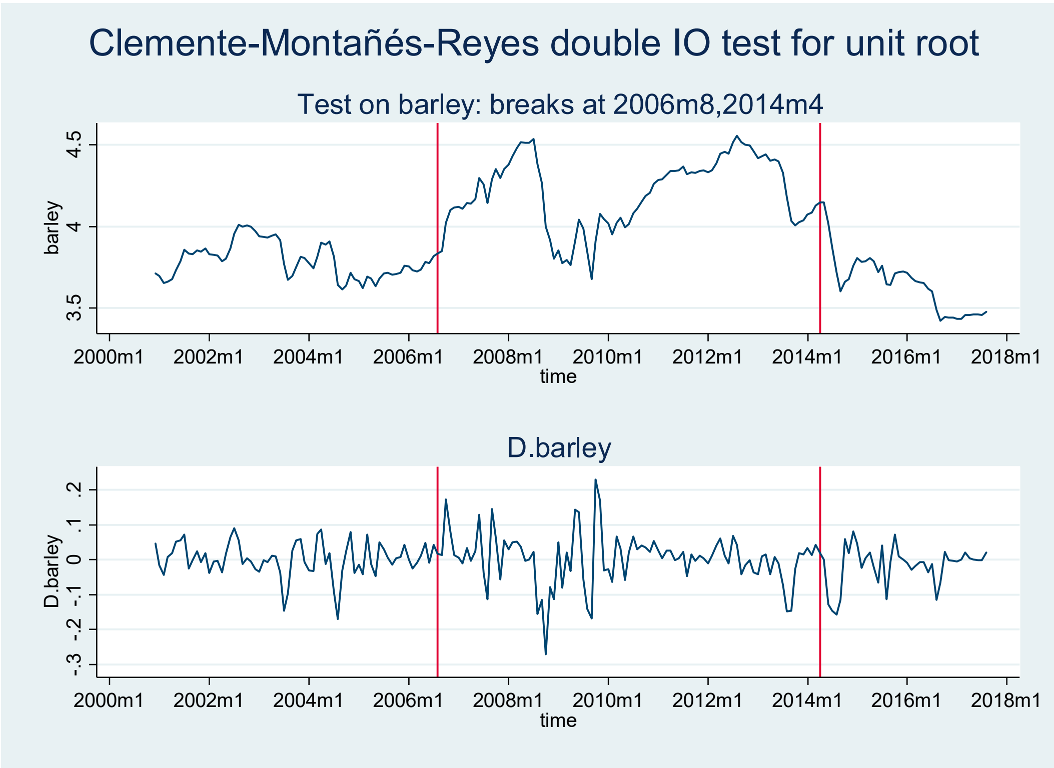


Palmkernel oil

Figure 1. *Cont.*

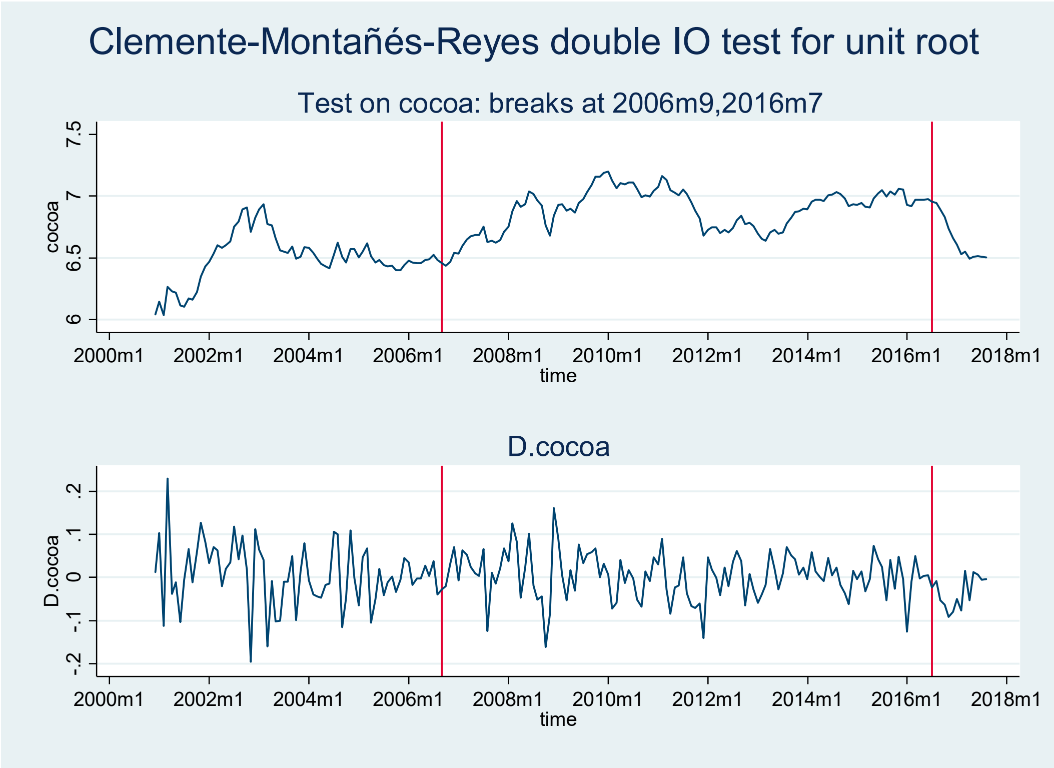


Soybean oil

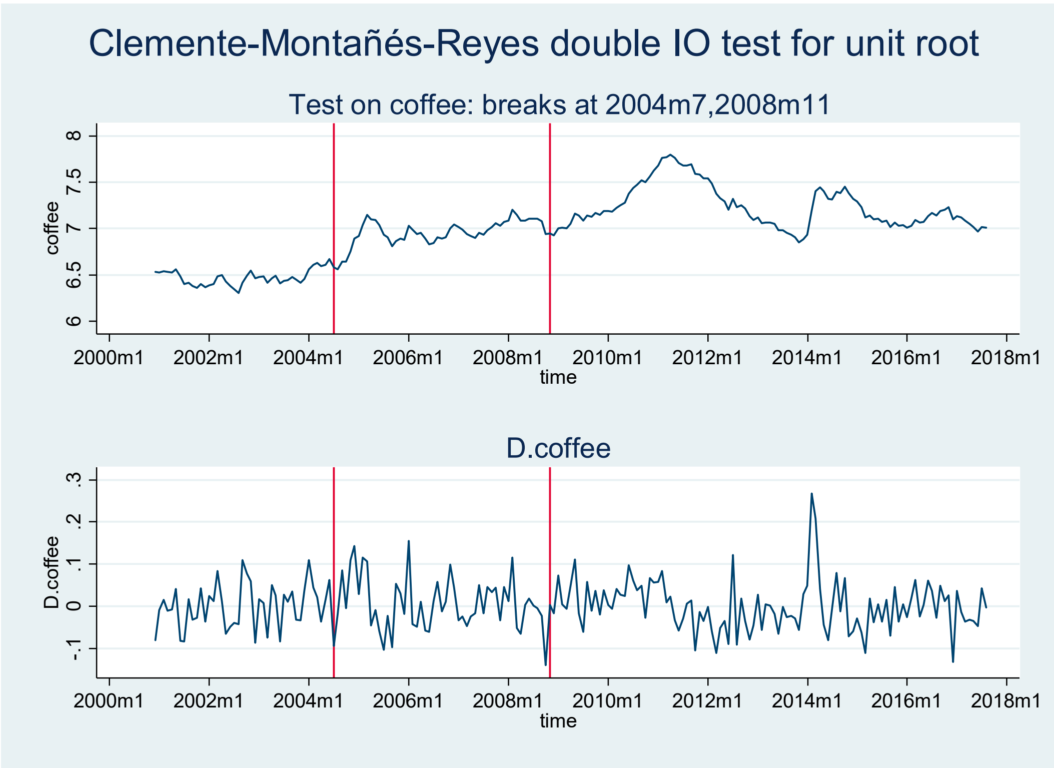


Barley

Figure 1. *Cont.*

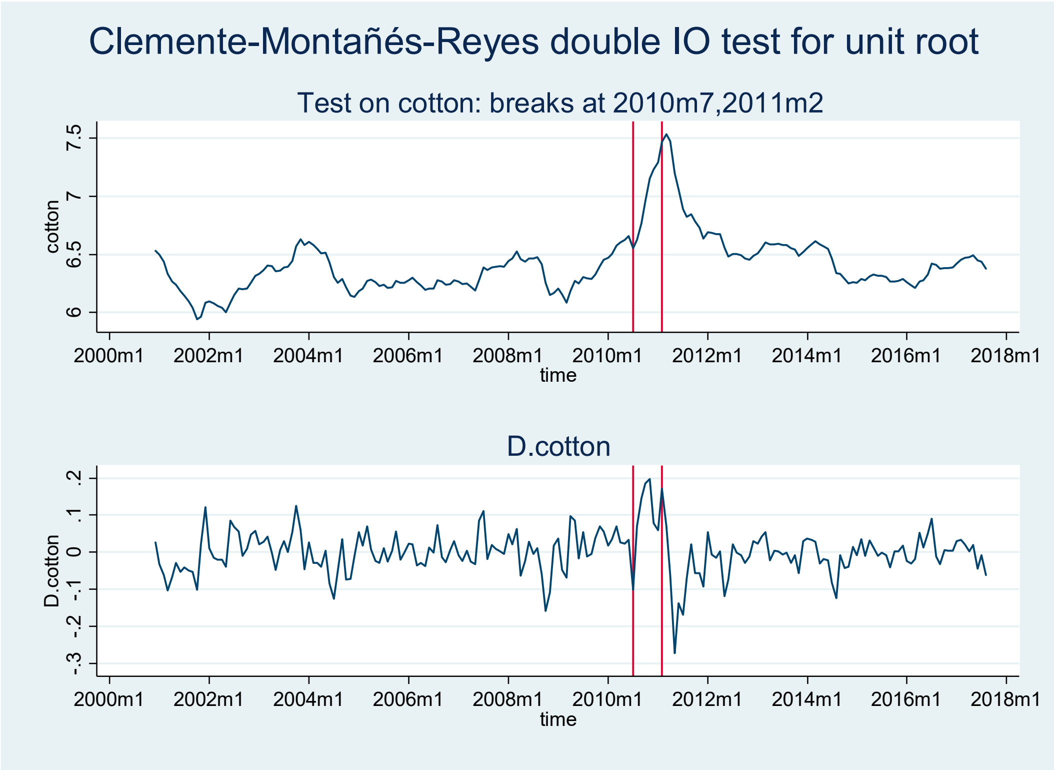


Cocoa

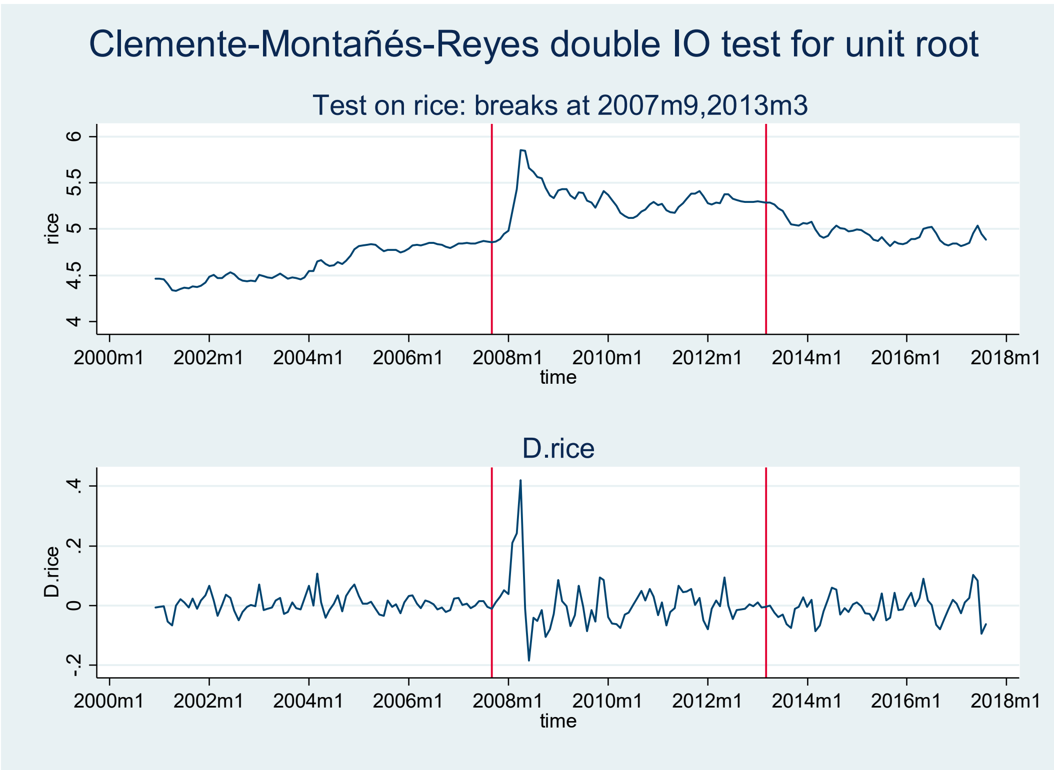


Coffee

Figure 1. *Cont.*

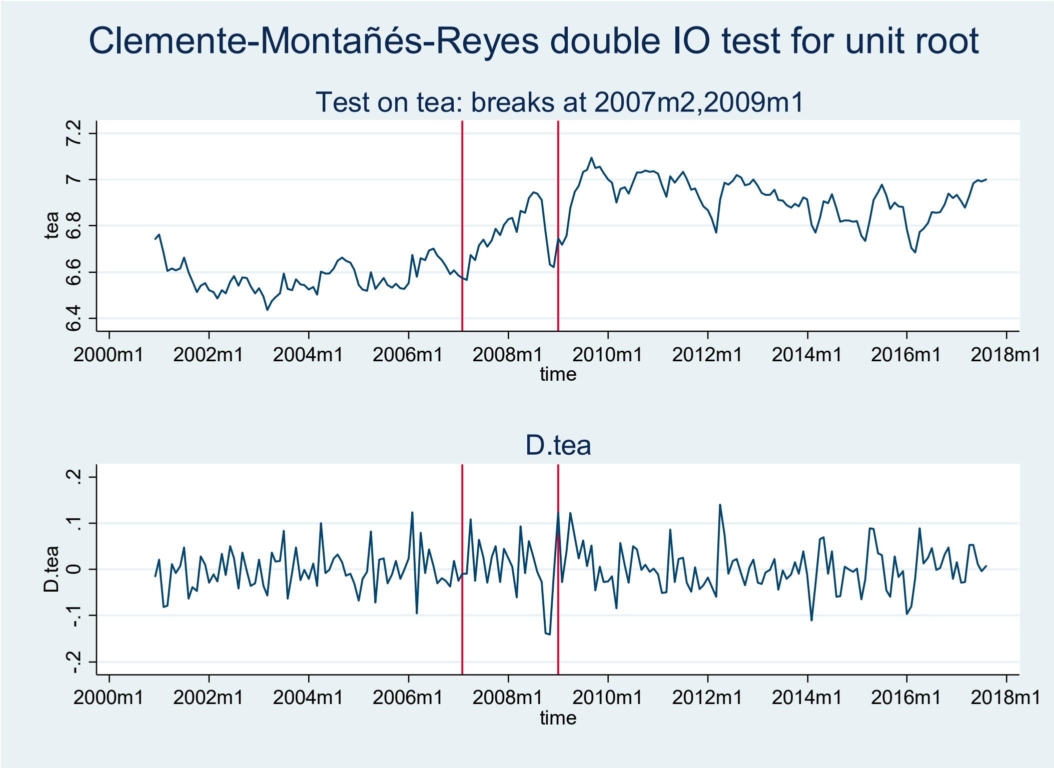


Cotton



Rice

Figure 1. *Cont.*



Tea

Figure 1. Commodity price series and their breakpoints.

5. Empirical Results

5.1. Responses of Agricultural Commodity Prices to Oil Shocks

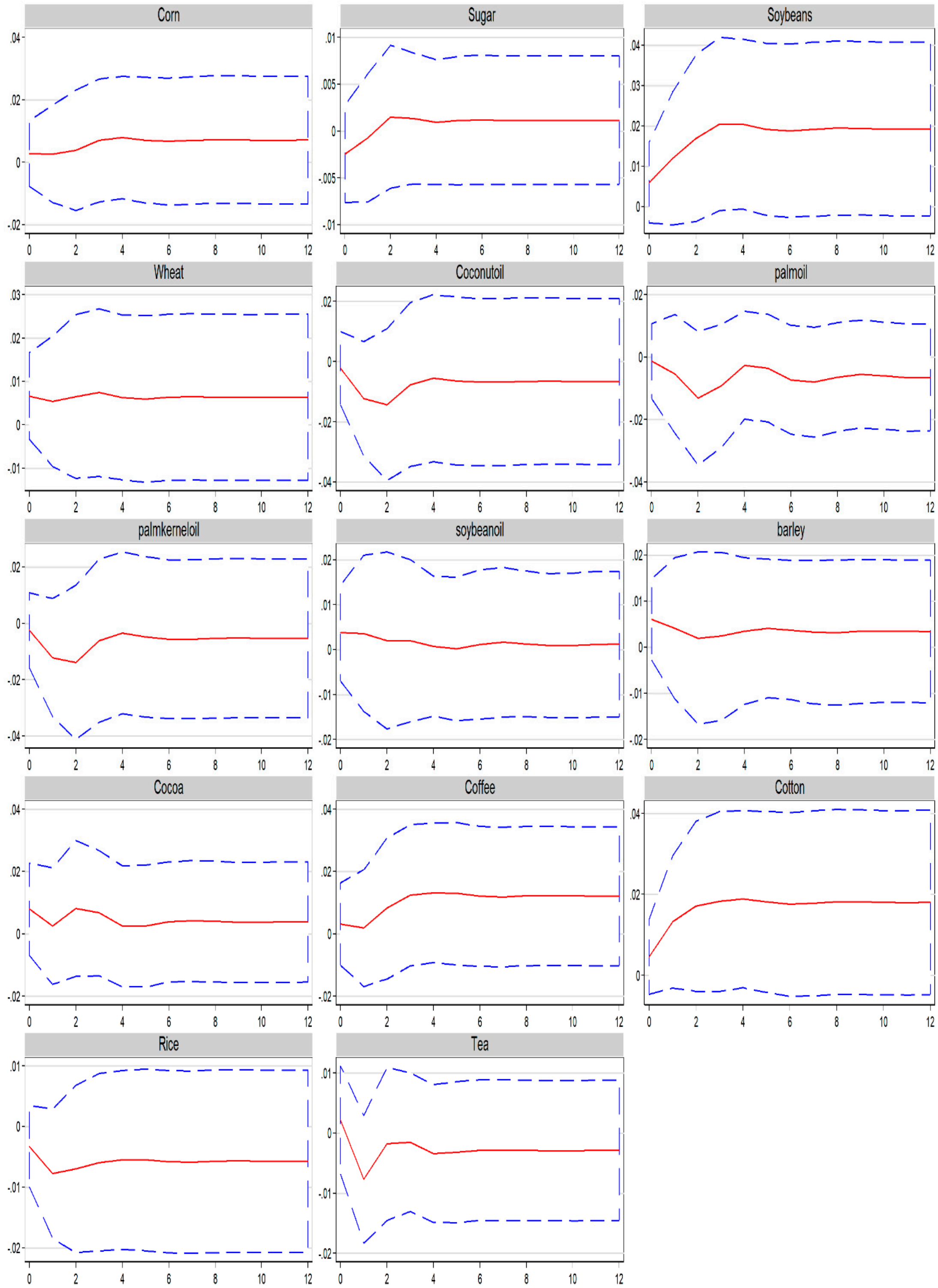
Figure 2 shows that oil supply shocks do not have significant impacts on any agricultural commodity returns for all three periods under investigation. According to Wang et al. [23], such outcomes reflect the fact that oil supply shocks have little impact on crude oil prices.

Figure 3 shows the responses of agricultural commodity prices to aggregate demand shocks. During the first period, it can be seen that the aggregate demand shock has significant effects on 4 of 14 commodities (soybeans, coconut oil, palm oil, and palm kernel oil). The effects on soybeans, coconut oil, and palm kernel oil are highly significant and persistent, even after 12 months, while the effect on palm oil becomes marginally significant after six months. For the other eight agricultural commodities, the impact of aggregate demand shock is insignificant.

During the second period, the responses of 3 of 14 commodities (sugar, barley, and tea) are significant, but the response of sugar becomes marginally significant after six months. The effects on other agricultural commodity prices are statistically insignificant.

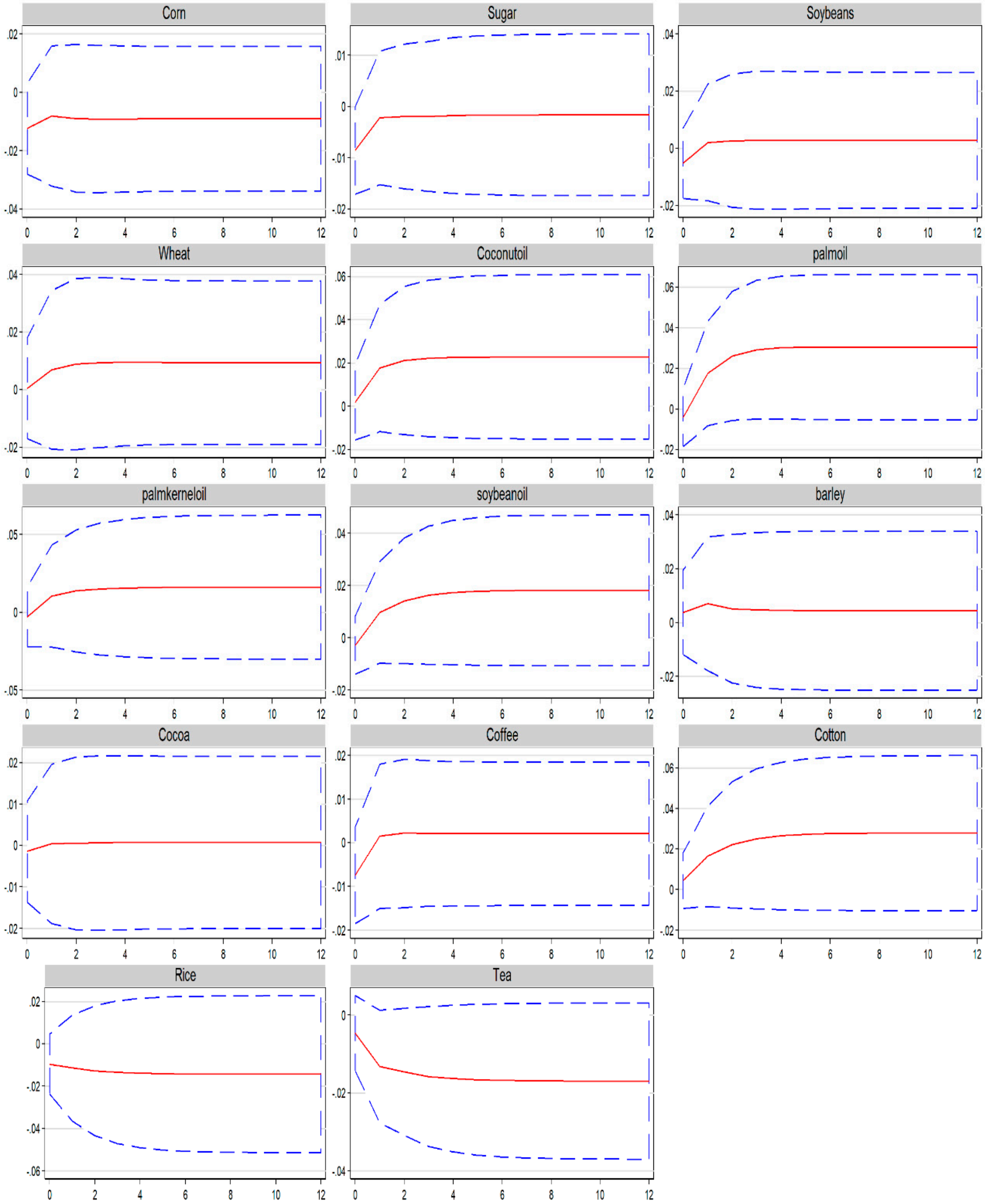
During the third period, the impact of aggregate demand shocks loses its significance in every case. Overall, we observe that the impacts of aggregate demand become weaker in the second period, which is similar to the outcomes mentioned in Wang et al. [23]. On the other hand, by increasing the number of agricultural commodities, our results show that the effects of aggregate demand on agricultural commodity returns are not as strong as suggested in Wang et al. [23].

Various sub-periods are considered in this paper to evaluate the robustness of the findings. These sub-periods cover the normal period, the global financial crisis period, and post-crisis period. Figure 2 presents the accumulated responses of agricultural price returns (vertical axis) to oil supply shocks (horizontal axis) in Period 1, from January 2000–July 2006, in Period 2, from August 2006–April 2013, and in Period 3, from May 2013–July 2018.



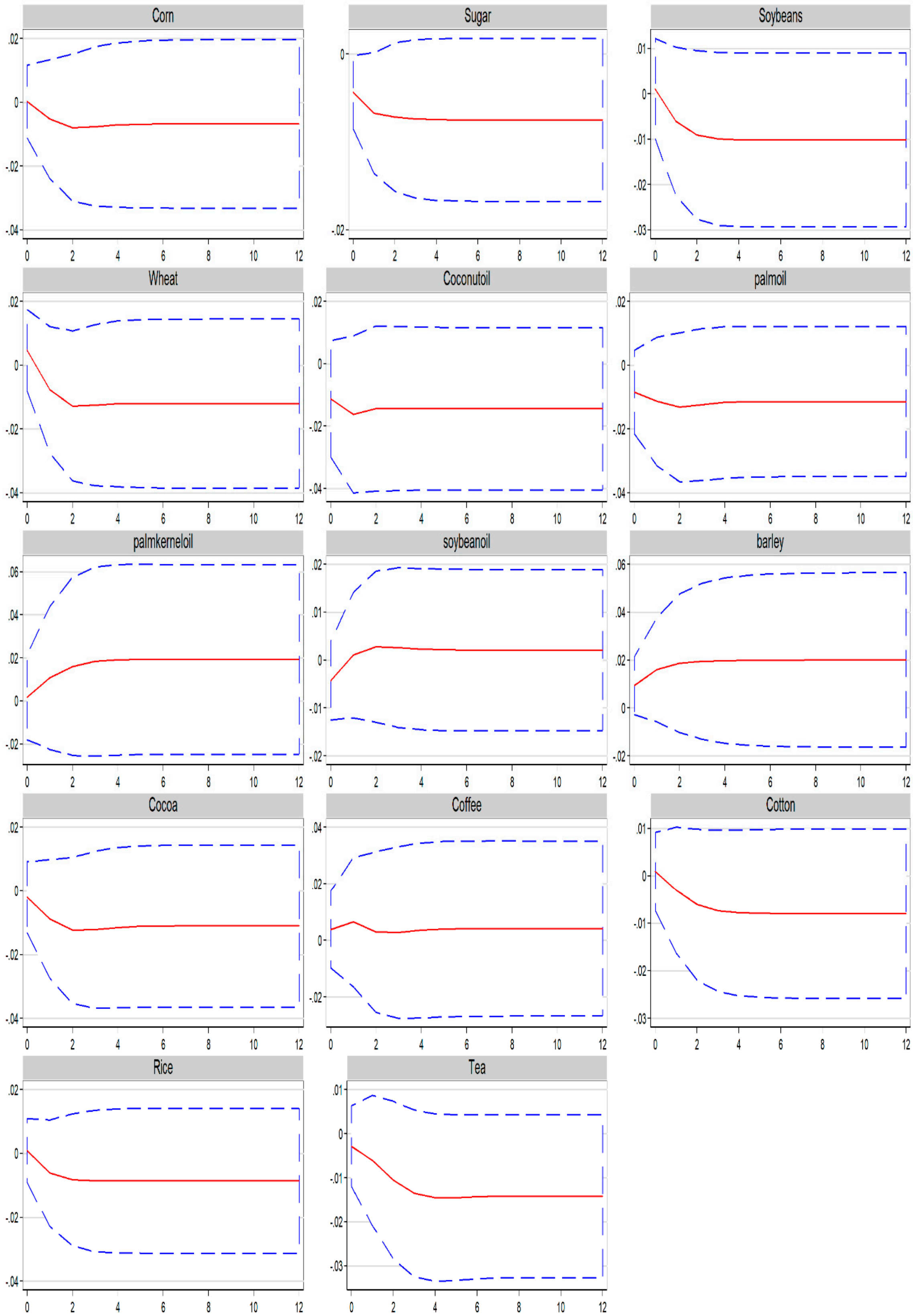
Period 1: 2000m1–2006m7

Figure 2. *Cont.*



Period 2: 2006m8–2013m4

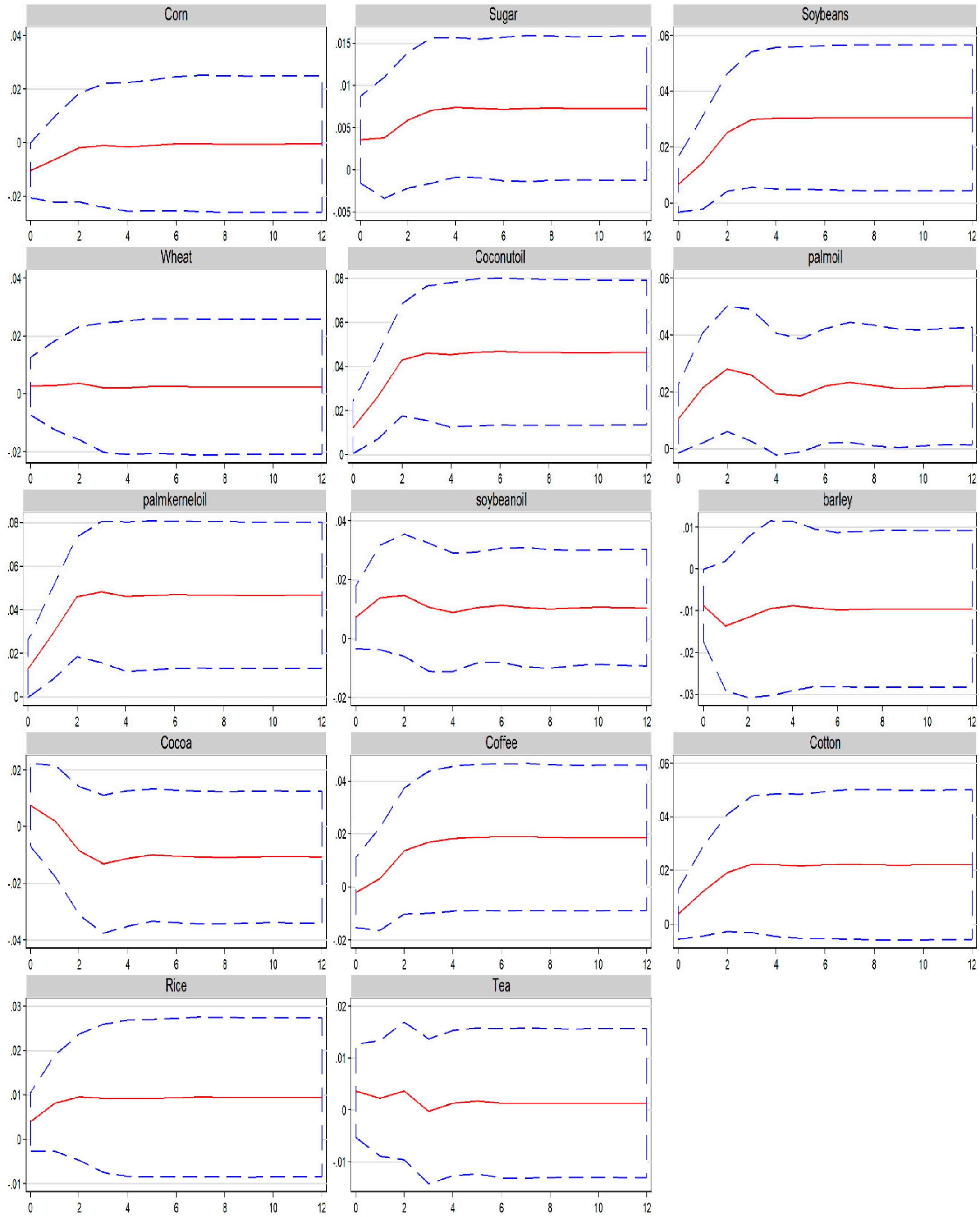
Figure 2. *Cont.*



Period 3: 2013m5–2018m7

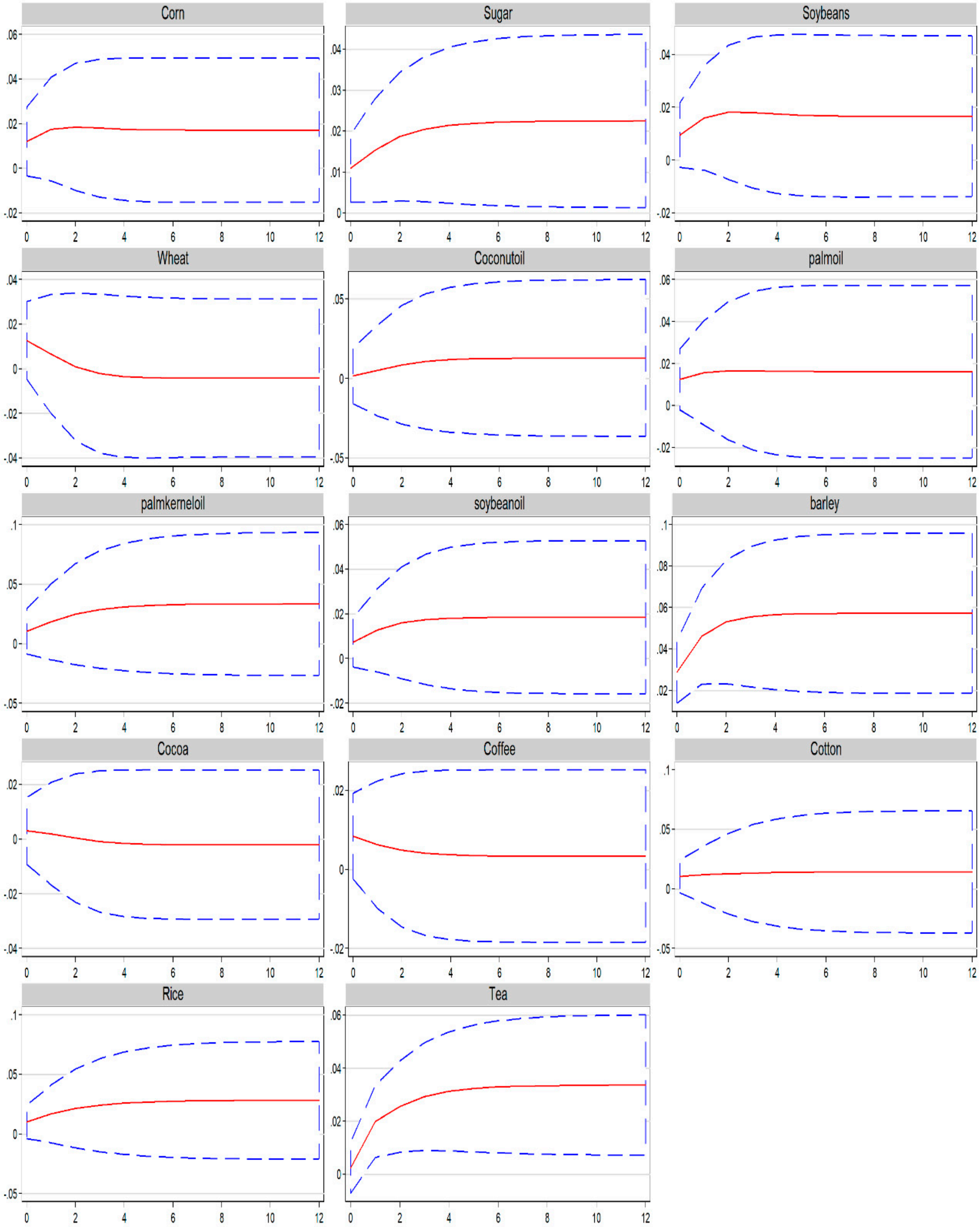
Figure 2. Accumulated responses of agricultural price returns to oil supply shocks.

Figure 3 shows the accumulated responses of agricultural commodity price returns (vertical axis) to aggregate demand shocks (horizontal axis) in Period 1, January 2000–July 2006, in Period 2, from August 2006–April 2013, and in Period 3, from May 2013–July 2018.



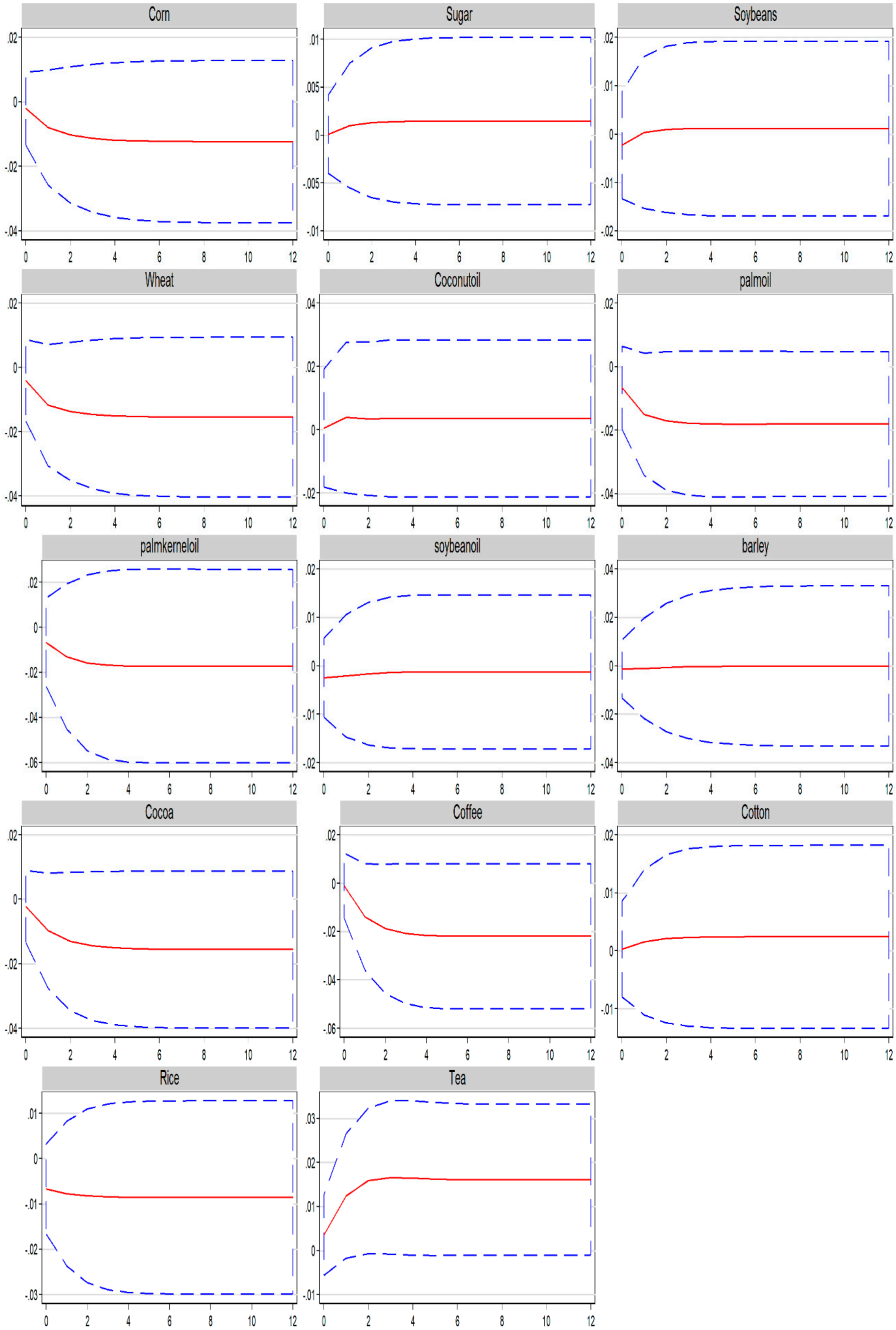
Period 1: 2000m1–2006m7

Figure 3. *Cont.*



Period 2: 2006m8–2013m4

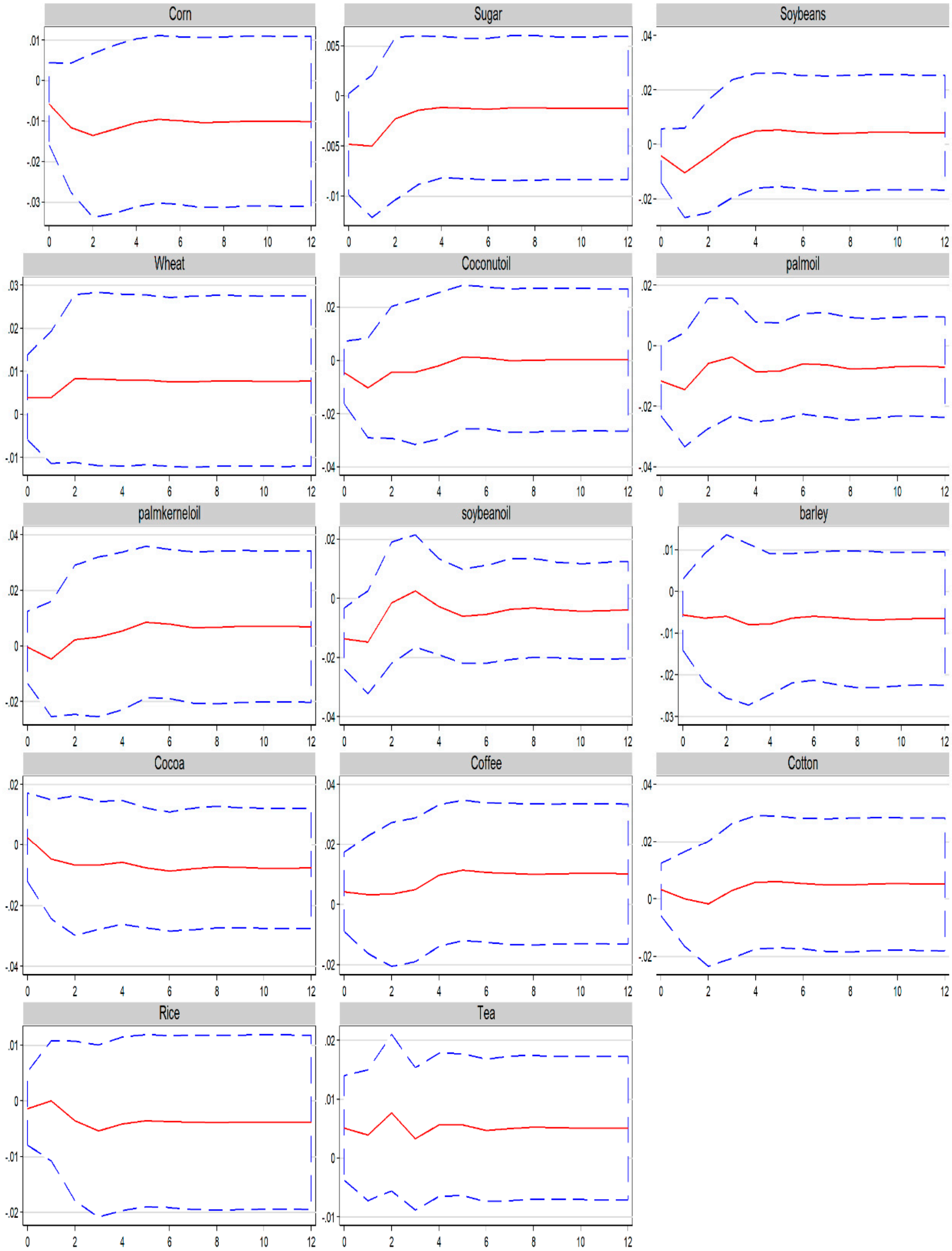
Figure 3. *Cont.*



Period 3: 2013m5–2018m7

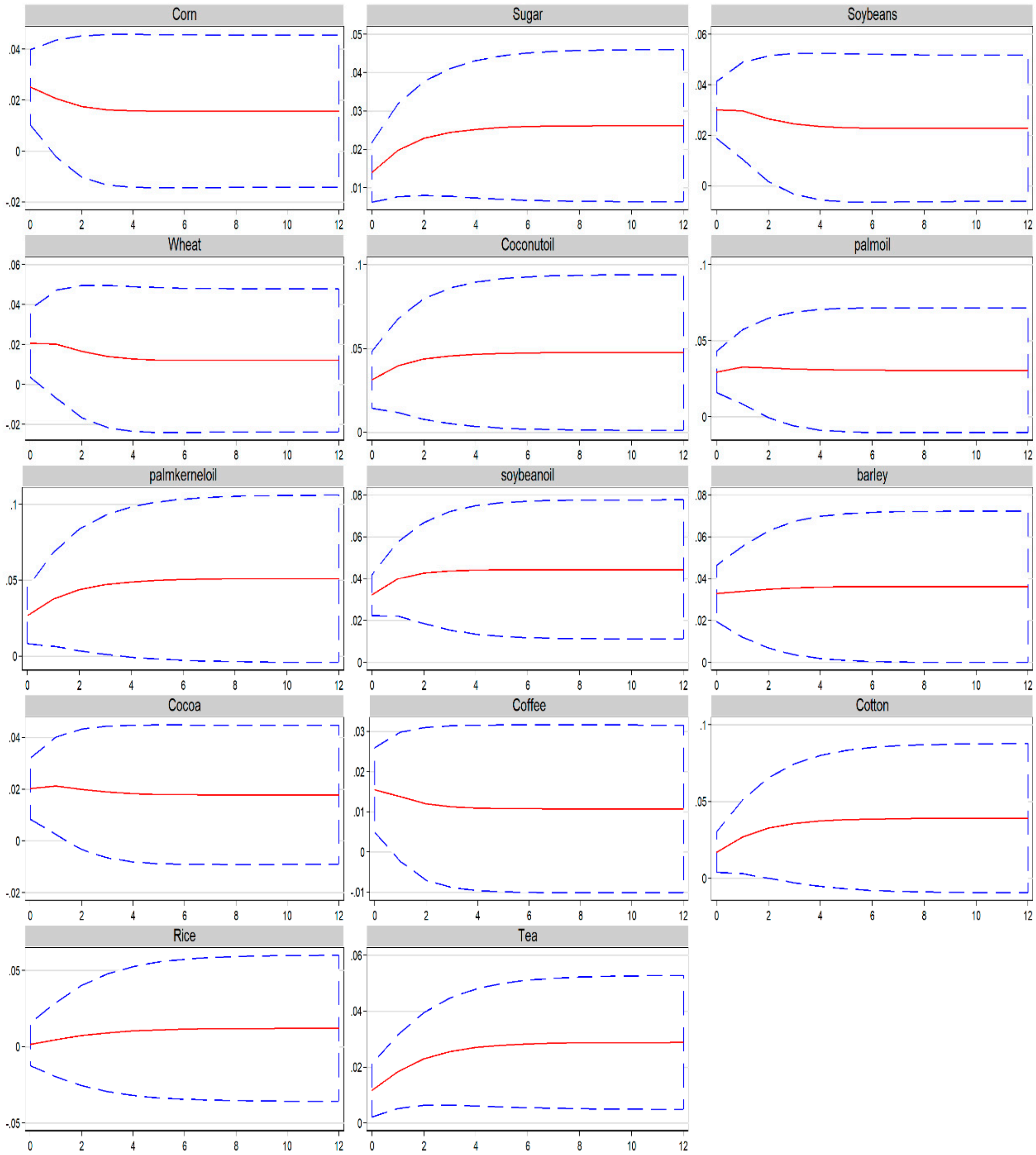
Figure 3. Accumulated responses of agricultural commodity price returns to aggregate demand shocks.

Figure 4 shows the accumulated responses of agricultural commodity price returns (vertical axis) to other oil-specific shocks (horizontal axis) in Period 1, January 2000–July 2006, in Period 2, from August 2006–April 2013, and in Period 3, from May 2013–July 2018.



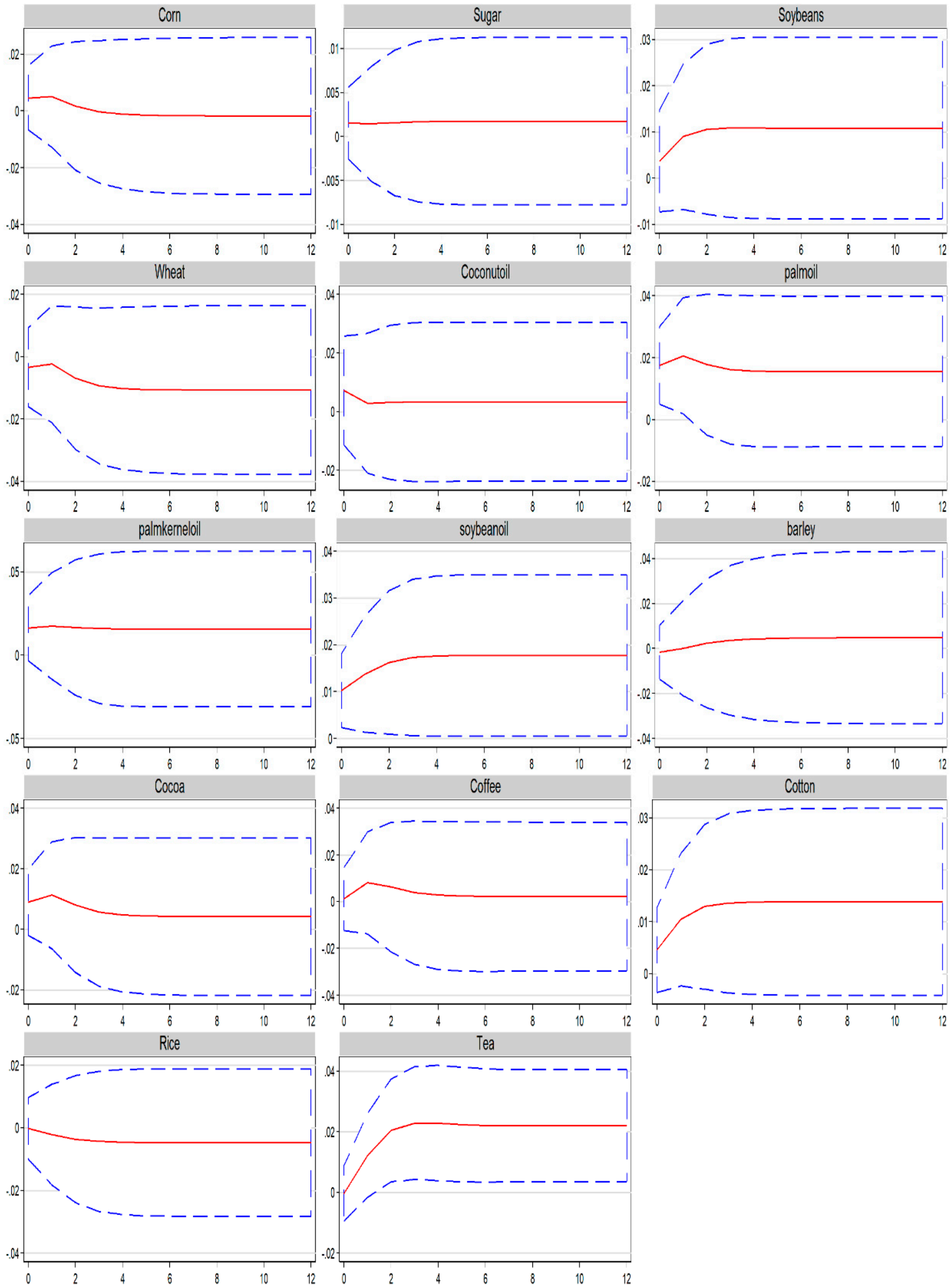
Period 1: 2000m1–2006m7

Figure 4. *Cont.*



Period 2: 2006m8–2013m4

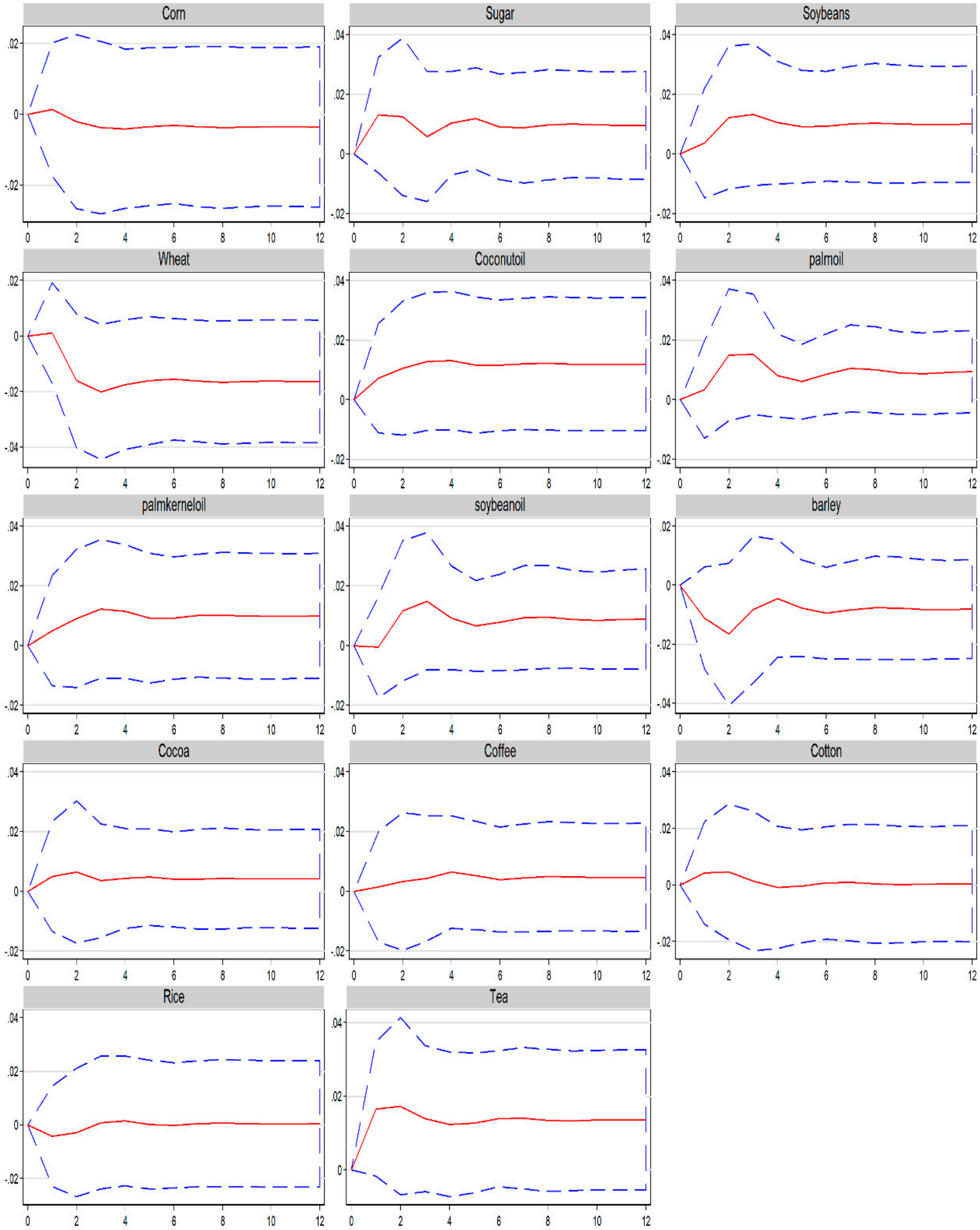
Figure 4. *Cont.*



Period 3: 2013m5–2018m7

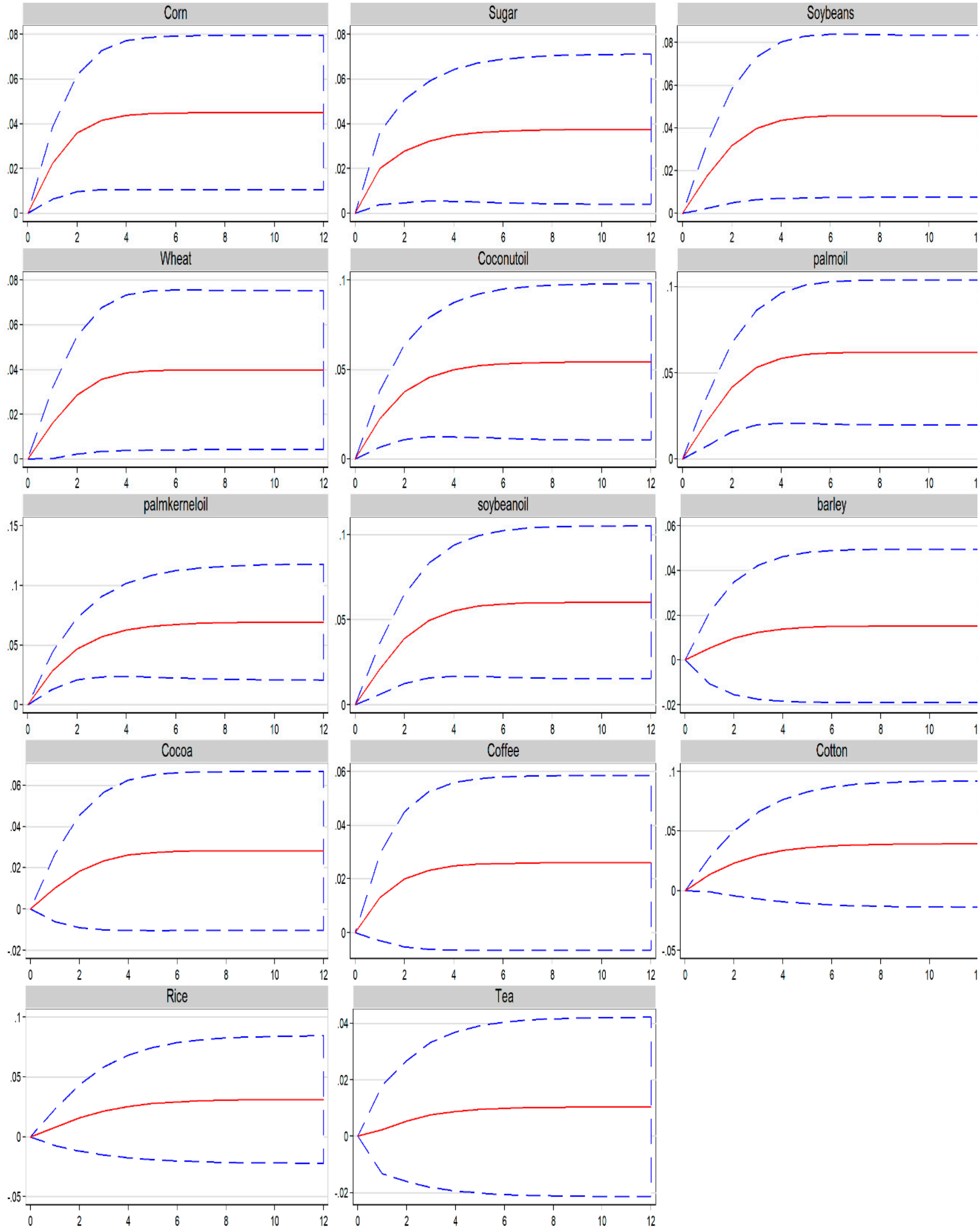
Figure 4. Accumulated responses of agricultural commodity price returns to other oil-specific shocks.

Figure 5 shows the accumulated responses of oil price returns (vertical axis) to agricultural commodity price shocks (horizontal axis) in Period 1, January 2000–July 2006, in Period 2, from August 2006–April 2013, and in Period 3, from May 2013–July 2018.



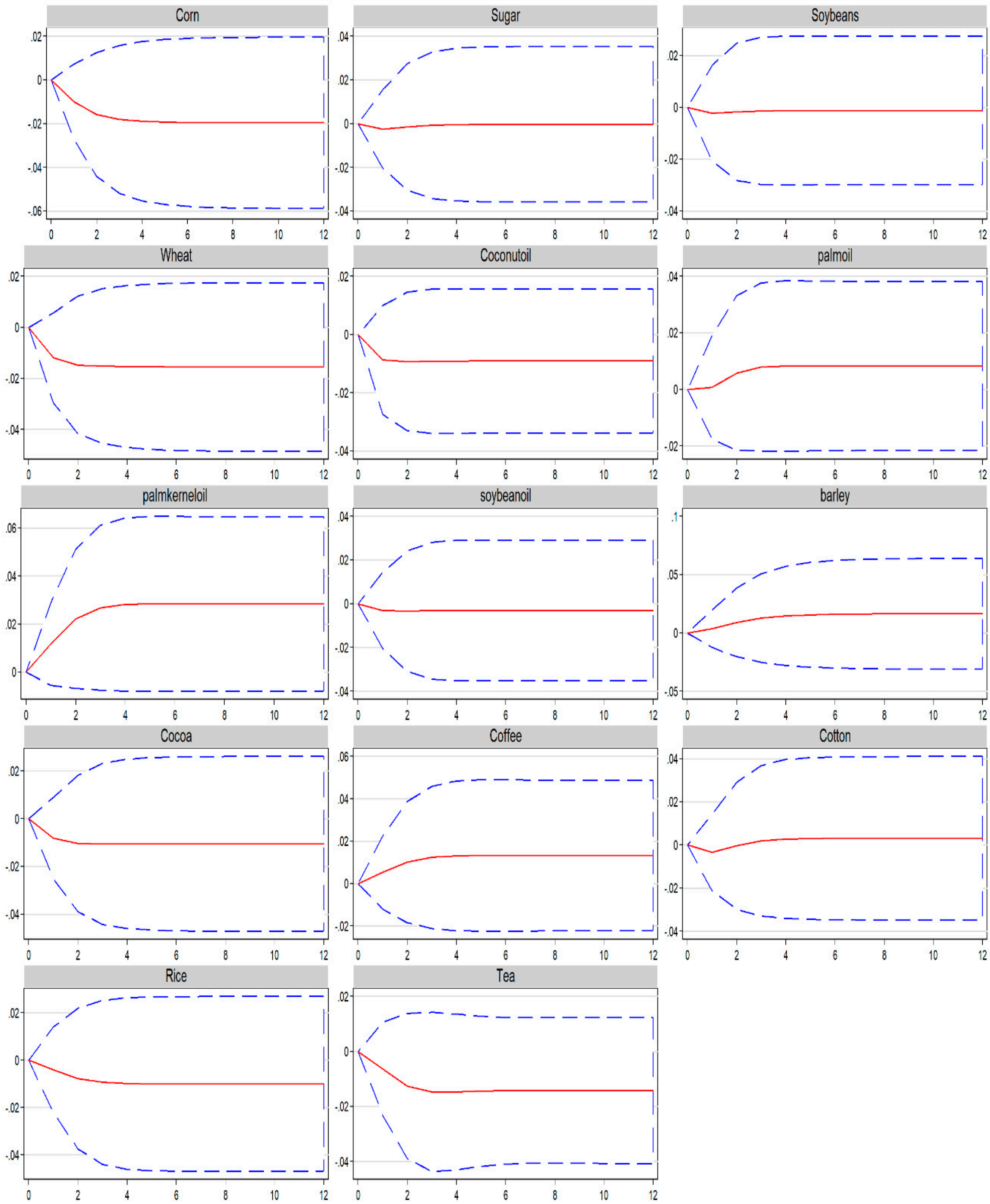
Period 1: 2000m1–2006m7

Figure 5. *Cont.*



Period 2: 2006m8–2013m4

Figure 5. *Cont.*



Period 3: 2013m5–2018m7

Figure 5. Accumulated responses of oil price returns to agricultural commodity price shocks.

Figure 3 shows the responses of agricultural commodity returns to other oil-specific shocks, besides oil supply and aggregate demand shocks. During the first period, impacts of other oil demand shocks are statistically insignificant for every agricultural commodity. The situation changes dramatically during the second period, where oil-specific demand shocks trigger a positive response of every agricultural commodity, except for the rice case. However, the degree of impact varies for different commodities. The impacts on six commodities (namely, corn, wheat, palm oil, cocoa, coffee, and cotton prices) are significant, but only last for two months or less.

The responses of four commodities (namely, soybeans, coconut oil, palm kernel oil, and barley) last from two to six months. The impacts on soybean oil and tea are highly significant and persistent, even after 12 months. The effects on sugar are also statistically significant, but the magnitudes are relatively small compared with the other agricultural commodities. The effects on vegetable oils are relatively large, ranging from 0.04%–0.05%, while the impacts on other commodities are approximately 0.02%.

In general, the responses of most agricultural commodities are significant for the first months, but become marginally significant or statistically insignificant in latter months, except for the cases of soybean oil and tea. During the third period, most agricultural commodity prices do not respond to oil-specific demand shocks, except for palm oil, soybean oil, and tea. However, the impacts on palm oil and soybean oil are only significant in the first few months. The impact on tea is significant and persistent, though the magnitude of the impact is much weaker.

It is shown in the outcomes of the model that the agricultural commodity prices react differently to various oil-related shocks, which is associated with how the shocks impact oil price. According to Kilian [19,39] and Wang et al. [23], the demand-related shocks are more influential to oil price than supply shocks because disruptions of oil supply from one geography region may be substituted by supply expansion from other regions, which makes the global production less sensitive to regional shocks.

On the other hand, although the political events in major oil-producing countries may not have a large effect on global oil supply, these events can still trigger oil price response through increasing precautionary demand [39]. This phenomenon further suggests the relative importance of demand-related oil shocks to oil price and agricultural commodity prices.

5.2. Responses of Crude Oil Price to Agricultural Shocks

The existing literature raises a serious issue as to why co-movements only occur during the second period. Some authors have argued that the popularization of biofuels after 2006 is responsible for the linkages between the agricultural and oil markets becoming more intense. This paper has found evidence for the reverse causality from agricultural commodity prices to crude oil prices during the second period. Figure 4 shows the response of crude oil prices to the agricultural commodity price shocks. In the first period, oil prices show no response to the agricultural commodity price shocks, but the situation changes sharply in the second period. During the first few months, the responses are positive and increasing in magnitude for some agricultural commodities.

In addition, only certain commodities have significant impacts on oil prices, including corn, sugar, soybeans, wheat and vegetable oils (namely, coconut oil, palm oil, palm kernel oil, and soybean oil). The impacts of these commodities increase in size for the first four months and thereafter remain constant. The proportions of the effects are relatively large, at approximately 0.04–0.05%. Moreover, the significance of the effects does not fade over time but last over the horizon of 12 months. Such effects cannot be found for other agricultural commodities, including barley, cocoa, coffee, cotton, rice, and tea. However, the impacts of agricultural markets on oil prices disappear completely during the third period. In some cases, oil prices have negative responses to agricultural commodity price increases (such as for corn, wheat, coconut oil, cocoa, rice, and tea), although such effects are not always significant.

There are two possible explanations as to why agricultural shocks can exert an influence on oil price. First, the agricultural sector has become more reliant on machinery in recent years, which may increase the global demand for crude oil. The increasing demand for crude oil in the agricultural sector, accompanied by the expansion of food consumption due to economic growth, may lead to the situation that changes in demand of agricultural commodities may trigger fluctuations in the oil market. Second, the demand for agricultural commodities does not only include the demand for food consumption but also the demand for biofuel, owing to new energy policies. The second explanation is more likely to explain why only those agricultural commodities that are closely related to biofuel production are more likely to trigger responses in oil price returns.

5.3. Granger Causality Tests

The Granger causality tests are calculated after fitting the data to the SVAR model. Table 4 shows the results of the tests for the three sample periods. For the period January 2000–July 2006, it is not possible to determine any causal relationship between agricultural commodity and oil prices. For the period August 2006–March 2013, there are Granger causal relationships from some agricultural commodity prices to oil prices. In particular, the null hypothesis that corn and vegetable oil prices, such as coconut oil, palm oil, palm kernel oil, and soybean oil, cannot Granger-cause Brent price is strongly rejected at the 1% significance level. Similarly, sugar, soybeans, and wheat prices are found to Granger-cause oil prices at the 5% significance level. Cotton prices can also Granger-cause oil prices, but only at the 10% significance level.

Table 4. Granger causality tests.

Direction of Causality	2000m1–2006m7	2006m8–2013m4	2013m5–2018m7
Corn → Brent	0.19	7.79 ***	1.3
Brent → Corn	0.96	1.91	0.04
Sugar → Brent	1.64	6.12 **	0.07
Brent → Sugar	0.39	0.6	0.07
Soybeans → Brent	1.13	5.24 **	0.05
Brent → Soybeans	2.84	4.33 **	0.91
Wheat → Brent	3.18	4.1 **	1.79
Brent → Wheat	0.83	0.56	0.07
Coconut Oil → Brent	1.04	8.18 ***	0.84
Brent → Coconut Oil	3.4	0.11	0.18
Palm oil → Brent	2.11	9.61 ***	0.01
Brent → Palm oil	0.89	2.91*	0
Palm kernel oil → Brent	0.71	14.07 ***	1.81
Brent → Palm kernel oil	2.84	0.001	0.27
Soybean oil → Brent	1.89	7.89 ***	0.11
Brent → Soybean oil	3.47	2.11	0.07
Barley → Brent	1.85	0.44	0.19
Brent → Barley	0.25	0.53	0.21
Cocoa → Brent	0.41	1.52	0.88
Brent → Cocoa	0.97	0.59	0.01
Coffee → Brent	0.19	2.57	0.36
Brent → Coffee	0.15	0.76	1.05
Cotton → Brent	0.14	3.37 *	0.15
Brent → Cotton	1.5	0.01	1.47
Rice → Brent	0.25	1.05	0.19
Brent → Rice	1.75	0.11	0.16
Tea → Brent	3.66	0.09	0.54
Brent → Tea	1.24	2.02	8.76 ***

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

It is also observed that there are some Granger causal relationships in the reverse direction from oil prices to agricultural commodity prices. For example, Brent crude oil prices can Granger-cause soybeans prices at the 5% significance level. Oil prices can also Granger-cause palm oil prices, but only at the 10% significance level. Overall, it is observed that soybean and palm oil prices have bi-directional Granger causal relationships with crude oil prices. For the third period, the null hypothesis that agricultural commodity prices do not Granger-cause oil prices cannot be rejected for each and every commodity under investigation, and the same pattern can be found in the reverse direction, except for tea. During the third period, the null hypothesis that oil prices do not Granger-cause tea prices is strongly rejected at the 1% significance level.

These observations are shown in Tables 5 and 6, which show the percentage of contributions to oil price variations for horizons of one month and 12 months, respectively.

Table 5. Percentage contributions to oil price variations for a horizon of one month.

	Oil Supply Shock	Aggregate Demand Shock	Other Oil-Specific Demand Shocks	Agricultural Price Shock
2000m1–2006m7				
Corn	0.38	2.20	97.42	0.00
Sugar	0.50	1.80	97.69	0.00
Soybeans	0.49	2.47	97.04	0.00
Wheat	0.22	3.94	95.83	0.00
Coconut oil	0.20	2.57	97.23	0.00
Palm oil	0.45	2.66	96.90	0.00
Palm kernel oil	0.25	2.48	97.27	0.00
Soybean oil	0.44	2.30	97.25	0.00
Barley	0.74	2.04	97.22	0.00
Cocoa	0.47	1.86	97.67	0.00
Coffee	0.34	2.04	97.62	0.00
Cotton	0.56	1.88	97.56	0.00
Rice	0.46	2.30	97.24	0.00
Tea	0.73	3.22	96.05	0.00
2006m8–2013m4				
	Oil Supply Shock	**Aggregate Demand Shock**	**Other Oil-Specific Demand Shocks**	**Agricultural Price Shock**
Corn	0.20	6.47	93.33	0.00
Sugar	0.30	5.99	93.71	0.00
Soybeans	0.00	6.17	93.83	0.00
Wheat	0.01	5.97	94.02	0.00
Coconut oil	0.00	6.55	93.45	0.00
Palm oil	0.01	4.05	95.94	0.00
Palm kernel oil	0.00	6.34	93.66	0.00
Soybean oil	0.07	4.75	95.18	0.00
Barley	0.02	7.83	92.15	0.00
Cocoa	0.00	7.27	92.73	0.00
Coffee	0.00	7.75	92.25	0.00
Cotton	0.15	8.86	90.99	0.00
Rice	0.03	7.59	92.38	0.00
Tea	0.02	8.13	91.85	0.00
2013m5–2018m7				
	Oil Supply Shock	**Aggregate Demand Shock**	**Other Oil-Demand Shocks**	**Agricultural Price Shock**
Corn	6.83	0.23	92.94	0.00
Sugar	6.86	0.74	92.40	0.00
Soybeans	6.77	0.71	92.52	0.00
Wheat	7.65	0.33	92.02	0.00
Coconut oil	6.89	0.71	92.40	0.00
Palm oil	6.82	0.69	92.49	0.00
Palm kernel oil	5.59	0.78	93.62	0.00
Soybean oil	6.81	0.67	92.52	0.00
Barley	6.42	0.84	92.74	0.00
Cocoa	7.22	1.10	91.68	0.00
Coffee	6.48	0.63	92.90	0.00
Cotton	7.79	0.16	92.05	0.00
Rice	6.62	0.57	92.81	0.00
Tea	6.25	0.56	93.19	0.00

Table 6. Percentage contributions to oil price variations for a horizon of 12 months.

	Oil Supply Shock	Aggregate Demand Shock	Other Oil-Demand Shocks	Agricultural Price Shock
2000m1–2006m7				
Corn	3.15	4.19	92.47	0.20
Sugar	2.71	3.78	90.78	2.74
Soybeans	3.43	4.11	91.31	1.15
Wheat	2.98	5.27	87.92	3.84
Coconut oil	2.90	4.35	91.70	1.05
Palm oil	3.04	3.98	90.10	2.88
Palm kernel oil	2.97	4.22	92.00	0.81
Soybean oil	3.12	3.83	90.37	2.69
Barley	2.98	3.71	90.23	3.09
Cocoa	3.15	3.81	92.55	0.49
Coffee	3.00	3.97	92.73	0.29
Cotton	3.15	3.89	92.71	0.25
Rice	3.13	4.22	92.14	0.52
Tea	3.26	5.09	87.28	4.37
2006m8–2013m4				
	Oil Supply Shock	**Aggregate Demand Shock**	**Other Oil-Demand Shocks**	**Agricultural Price Shock**
Corn	0.21	13.95	76.48	9.36
Sugar	0.80	13.77	79.07	6.37
Soybeans	0.21	13.29	78.80	7.70
Wheat	0.18	12.45	81.18	6.18
Coconut oil	0.33	13.27	75.70	10.70
Palm oil	1.50	8.95	75.96	13.60
Palm kernel oil	0.34	12.38	70.26	17.02
Soybean oil	0.62	10.30	77.10	11.98
Barley	0.15	16.16	82.93	0.76
Cocoa	0.22	14.63	82.50	2.66
Coffee	0.19	15.82	80.97	3.01
Cotton	0.64	16.61	78.32	4.43
Rice	0.18	15.09	82.37	2.37
Tea	0.24	16.26	83.21	0.28
2013m5–2018m7				
	Oil Supply Shock	**Aggregate Demand Shock**	**Other Oil-Demand Shocks**	**Agricultural Price Shock**
Corn	19.68	0.44	77.91	1.96
Sugar	19.82	1.00	79.07	0.10
Soybeans	19.72	0.98	79.22	0.07
Wheat	20.30	0.60	76.98	2.12
Coconut oil	19.87	0.94	78.11	1.08
Palm oil	19.42	0.96	79.19	0.43
Palm kernel oil	17.04	1.02	78.11	3.82
Soybean oil	19.94	0.97	78.96	0.13
Barley	18.77	1.16	79.21	0.86
Cocoa	20.11	1.45	77.45	1.00
Coffee	19.26	0.88	79.06	0.80
Cotton	20.54	0.38	78.68	0.40
Rice	19.37	0.81	79.35	0.46
Tea	18.31	0.97	79.55	1.18

5.4. Variance Decomposition

In order to verify how the shocks to agricultural markets contribute to the variance of crude oil prices, we use the variance decomposition technique, which evaluates the relative importance of each shock to oil prices. Tables 5 and 6 reveal the decomposition results for the time horizon of one month and 12 months, respectively. The outcomes show that the shocks to oil prices are primarily affected by themselves. However, the contribution of other sources of shocks, namely oil supply shocks, aggregate demand shocks, and agricultural commodity price shocks, become larger at the time horizon of 12 months. In fact, they become increasingly more important in the second and third periods as compared with the first period, while the importance of oil price shocks tends to be reduced over time. In particular, the proportion of oil price shocks ranges from 87.28–92.73% at the forecast length of 12 months during the first period. However, the shocks only contribute lower proportions of 70.26–83.21% and 76.98–79.55% during the second and third periods, respectively.

Among the other shocks, agricultural commodity price shocks are least important in explaining oil price variations, except for the period August 2006–April 2013 at the time horizon of 12 months. In this period, the shocks from agricultural markets were more important to oil price variations than oil supply shocks. For example, agricultural commodity prices explain around 0.28–17.02% of oil price variations, while this proportion is approximately less than 2% for oil supply shocks.

Among agricultural markets, it is observed that there are commodities which are more important to oil price variations than the others. In particular, shocks from the corn, sugar, soybeans, wheat, coconut oil, palm oil, palm kernel oil, and soybean oil markets contribute more to oil price variations than do the barley, cocoa, coffee, cotton, rice, and tea markets. Shocks from the first group contribute 6.37–17.02%, while shocks from the second group contribute only 0.28–4.43% to oil price variations. It is worth noting that, during this period, vegetable oils, such as palm oil, palm kernel oil, and soybean oil, can somewhat surprisingly explain a higher proportion of crude oil price variations than can aggregate demand shocks.

5.5. Discussion

The relationship between the agricultural and oil markets may reflect an increase in aggregate demand. By applying the structural VAR model and the Kilian index, Wang et al. [23] filter out the impacts of the business cycle to isolate the true effects of oil price shocks on agricultural commodity prices. Following Wang et al. [23], it has been found that the impact of oil price shocks on agricultural commodity prices becomes stronger after the US Government decided to increase the mandated amount of biofuels in energy consumption. The policy increased the substitutability between oil and biofuels, thereby transmitting an increase from oil prices to agricultural commodity prices.

Moreover, the transmission from oil prices to agricultural commodity prices can occur because of increases in agricultural production costs. The agricultural sector in large producing countries, such as China, has become more capital intensive in recent years, which increases the dependency of agricultural commodity prices on crude oil price [51]. On the other hand, it may be argued that agricultural markets are more likely to be affected by their own shocks, such as climate change or increases in tariff and export restriction.

However, it has been shown that supply shocks have a limited impact on agricultural commodity prices due to stocking behavior of the local government [43]. Wang et al. [23] also show that the contributions of agricultural shocks to variations of agricultural commodity prices have been reduced largely after the food crisis. Therefore, there are reasons to believe that shocks from energy markets have become one of the most influential factors in the agricultural markets.

Considering reverse causality, the same procedure can be applied to disentangle the impacts of agricultural shocks from aggregate demand shocks. It has been found that oil prices react to agricultural commodity price shocks after the biofuel mandated policy was issued. Such effects cannot be found prior to the mandated policy act. However, there are many reasons that may lead to such reactions, such as the increasing usage of machinery mentioned above, as well as the popularization of biofuels.

The empirical results from the impulse response functions, Granger causality tests, and variance decomposition analysis all point to the heterogeneity of oil price responses to agricultural commodity prices for different commodities. Different commodities may affect oil prices through different channels. For the commodities that are less likely to be a factor in biofuel production, these commodities primarily affect oil prices because of the increasing use of machinery in agricultural activities. For other commodities that are more likely to be a factor in biofuel production, the effects should be stronger because there are additional effects through the biofuel channel. Therefore, the identification of the causal relationship between energy and food can be determined by identifying the heterogeneity of oil price responses to different agricultural commodity prices.

According to our results, agricultural shocks cannot trigger the response of crude oil price during the first period. However, only agricultural commodities which are more likely to be the input of biofuel production can affect oil price during the second period. The results suggest that the expansion of biofuel production is likely to be the cause of the vulnerability of crude oil prices to agricultural commodity price fluctuations.

Originally, the purpose of biofuel production was to reduce the dependency on fossil fuels and increase the total global energy supply. However, the first-generation biofuel has a critical shortcoming. The production of biofuel requires several types of resources, including energy itself. On the other hand, biofuel has been criticized for having low energy return on investment (EROI) [52,53], which means that the amount of energy generated from biofuel may not be significantly larger than the quantity required to produce. This might create a loop where an oil price increase incentivizes subsidies for biofuel production which, in turn, increases demand for more agricultural production.

Furthermore, the mechanization of the agricultural sector has made crude oil one of the most important input factors in the production and distribution process. Therefore, an increase in agricultural production may add to energy demand, which increases crude oil prices and eventually leads to the negation of the original purpose of biofuel, which is to replace crude oil as the main energy source.

6. Concluding Remarks

In this paper, we have replicated the results in Wang et al. [23] and related research using an extended sample period from January 2000–July 2018. The impulse response functions confirm the empirical findings that not all oil shocks contribute the same effect on agricultural price fluctuations. In particular, oil supply shocks play an insignificant role in explaining agricultural commodity prices in all subsamples. It was observed that the effects of aggregate demand shocks on the agricultural market are not as strong as suggested in Wang et al. [23] when the number of commodities was increased. The shocks only have significant impacts on four commodities in the first period, and on three commodities in the second period of the 14 commodities considered. During the period 2006m8–2013m4, oil-specific demand shocks had significant impacts on almost all agricultural commodity prices, which is in sharp contrast to the situation in the first and third periods. The empirical findings show that the crude oil market plays a major role in explaining fluctuation in agricultural markets during this period.

Furthermore, the influences of agricultural shocks on oil prices were investigated after controlling for aggregate demand shocks. Using the impulse response function, it was shown that the shocks do not have any significant impacts on oil prices during the first period. However, the situation changed sharply in the second period, where more than one-half of the agricultural commodity prices were found to trigger significant responses in oil prices. Moreover, the same commodities could also Granger-cause oil prices in the same period. These new empirical findings cannot be found in the period before the implementation of the energy policy act. It was also observed that the commodities that have an impact on oil price are not arbitrary as these commodities are likely to be used as inputs for biofuels, as suggested in the literature.

The difference between this article and Wang et al. [23], except for the extended sample period, is that we have considered the reverse direction of causality to show that shocks from the agricultural market can have an impact on oil prices. In addition, we have also used a wider range of agricultural commodities than in the previous study. Owing to the application of various statistical techniques, such as Granger causality tests, impulse response functions, and variance decomposition, we are able to separate the list into two groups of commodities that have different relationships with crude oil prices.

As the size of the biofuel market becomes larger, the possibility that shocks from the agricultural and energy markets can influence each other also increases. The implications of the empirical results in this paper for public policy are two-fold. First, the results show that the agricultural sector is vulnerable to the fluctuations in the oil market, which is relatively volatile. This might make maintaining food security a more challenging task. Thus, policymakers should consider a balance between biofuel expansion objectives and sustainable food crop supply. Land and other agricultural resources should be strategically distributed so that governments can maintain food security and develop bioenergy at the same time.

On the other hand, the expansion of agricultural mechanization and biofuel production have also made oil prices vulnerable to agricultural commodity prices. The world may become more dependent on fossil fuels, owing to biofuels, if production technology is not sufficiently cost-effective. Therefore, policymakers need to develop new biofuels, such that the production process is less dependent on crude oil.

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