The 2017 Annual Meeting, Southern Agricultural Economics Association

Mobile, Alabama February 4-7, 2017

VOLATILITY SPILLOVER BETWEEN OIL PRICES, US DOLLAR EXCHANGE RATES AND INTERNATIONAL AGRICULTURAL COMMODITIES PRICES

SIMA SIAMI - NAMINI AND DARREN HUDSON

January 18, 2017

Abstract

Crude Oil prices are thought to have direct and indirect effect through the exchange rate on the international agricultural commodities prices. The aim of this paper is to examine the interdependence relationship between crude oil futures prices, US dollar exchange rate, and international agricultural commodities prices, including corn (maize), sorghum, wheat, sugar, coconut oil, fishmeal, olive oil, palm oil, groundnut oil, groundnuts, rapeseed oil, soybean meal, soybean oil, soybeans, and sunflower prices. Using autoregressive (AR) model with an exponential generalized autoregressive conditional heteroskedasticity (EGARCH), namely AR-EGARCH model, we describe mean and variance equation in EGARCH model and then extract GARCH variance time series to investigate the volatility spillover from crude oil returns and US dollar exchange rate to the international agricultural commodities returns. To this end, the vector auto-regression (VAR) and vector error correction model (VECM) Granger causality approach, generalized and accumulated impulse-response analysis for identification of the short run and long run interrelationships are applied to the monthly data spanning from Jan 1986 to Nov 2015. The generalized and accumulated impulse response analysis suggests the volatility of international agricultural commodities prices do not significantly react to the volatility of crude oil price and the volatility of exchange rate shocks in the short run for the pre-crisis time period. But, they are significant for the post-crisis time period. The long run causality analysis reveals that the volatility of crude oil prices and appreciation/depreciation of the US dollar exchange rate are transmitted to the international agricultural commodities prices for the post-crisis time period. Also, crude oil returns volatility does affect the US dollar exchange rate volatility for the post-crisis time period which in turn affects the volatility of the international agricultural commodities returns through changes in prices.

Key words: Volatility Spillover, Agricultural commodities returns, EGARCH Model.

---

[1]. Graduate Research Assistant and Larry Combest Endowed Chair in Agricultural Competitiveness, respectively, Department of Agricultural and Applied Economics, Texas Tech University.

Introduction

Before beginning the world food crisis in 2006, the effect of exchange rates and monetary policies on the international agricultural commodities prices have attracted much attention of previous studies (Schuh, 1974; Frankel, 1986; Saghaian, Reed, & Marchant, 2002; Cho et al. 2005). Schuh (1974) debates that US macroeconomic policies could influence the value of US dollar exchange rate, which in turn impacts the competitiveness of US agricultural commodities in the global markets through changes is prices. Cho et al. (2005) investigate the linkage between changes in real exchange rates and changes in relative agricultural commodities prices, and the relationship between inflation rate and changes in relative agricultural prices for different time periods. Using monthly data covering Jan 1974 to Dec 2002, they find that long run changes in real exchange rates have a significant negative correlation with the long run changes in relative agricultural prices. Furthermore, inflation rate significantly affects changes in the relative agricultural prices in the short run.

The period since 2006 has been noticeable instability in all global markets, including international agricultural commodities markets because of volatility in oil prices, and then most discussion of recent studies has focused on the direct effect of oil price volatility on agricultural commodities prices. In fact, for the period 2006 to 2015, international agricultural commodities prices have changed considerably, and influenced by major factors such as increasing use of biofuels in developing countries, devaluation of the US dollar exchange rates, supply shocks in major producing regions, strong variability in crude oil prices, and the development of the biofuel industry in the United States. The latter factors have been emerging linkages between price volatility in energy and agricultural markets.

Review of related literature show that most of them try to analyze the impact of crude oil prices on the agricultural commodity prices using different methods for a specific time periods, although the results are mixed and limited based on research study assumption. In this regard, several research studies just analyze the impact of oil price on agricultural commodities markets using vector auto-regression (VAR) model or vector error correction model (VECM). On the other hand, there are a few research studies that analyze the volatility spillover from oil prices to agricultural commodities prices using generalized autoregressive conditional heteroskedasticity (GARCH) model. But, almost none of them don't consider to analyze the volatility transmission from crude oil prices and US dollar exchange rates to the volatility of the international agricultural commodities prices in general, and commodity food prices using GARCH and VECM model. The question is what is the impact of crude oil volatility and the impact of US dollar exchange rates volatility on the volatility of international agricultural commodities? What are the volatility transmission patterns from crude oil prices and US dollar exchange prices to the international agricultural commodities prices before and after beginning the global food crisis in 2006? As crude oil prices are thought to have direct and indirect effect through the exchange rate on the international agricultural commodities prices and then on commodity food prices, which direct and indirect effect exists and dominate in pre- and post-crisis time period? Is there any causal effect between the volatility of crude oil prices and US dollar exchange rates volatility with the volatility of the international agricultural commodities prices for pre- and post-crisis time?

The main purpose of this study is to identify whether volatility in crude oil prices and US dollar exchange rates have any causal effect on the volatility in international agricultural commodities prices, including corn, sorghum, wheat, sugar, coconut oil, fishmeal, olive oil, palm oil, peanut oil, groundnuts, rapeseed oil, soybean meal, soybean oil, soybeans, and sunflower oil. The three first goods are the main crops used as inputs in production of biofuels and the other commodities are main agricultural products for food in the world. To investigate volatility spillover between energy and agricultural markets, our empirical analysis is conducted for two time periods, including the pre-crisis time period from Jan 1986 to Dec 2005, and the post-crisis time period from Jan 2006 to Nov 2015. Our empirical results provide evidence on volatility spillover from crude oil prices and US dollar exchange rate to the volatility of the international agricultural commodities prices in the post-crisis period, implying that global agricultural commodity markets have become more integrated with energy markets after the world food crisis.

The present study aims to examine the volatility spillover between crude oil prices and the international agricultural commodities prices in both the first (mean) and second (volatility) moments in the context of an AR-EGARCH model. Also, we use VAR model for generalized and accumulated impulse-response functions and analyzing Granger causality between variables in our study. Using a vector error correction model (VECM), we estimate the short run and long run relationship to find the degree of price transmission, and to estimate the corresponding short run error correction model to gain insight into the short run adjustment toward the long run price relationship.

The layout of this paper is structured as follows. In the next section, we discuss the debate on the presence of volatility spillovers from oil prices and exchange rates to agricultural commodities prices based on empirical literature review. In section 3, we present the data and some descriptive statistics. Section 4 describes the econometric model while Section 5 presents the results. Finally, Section 6 concludes.

Literature Review

While a considerable body of research has demonstrated the relationship between crude oil prices, exchange rates and agricultural commodity prices, nevertheless we need to investigate whether the influence of price volatility in the crude oil market is expanding to agricultural commodity price volatility. Also, exchange rates are a major variable in determining domestic prices for agricultural commodities, and the quantities of goods domestically produced, consumed, and traded. Over the past decade, the oil price volatility has coincided with a closer link between oil prices and asset prices, including exchange rates. Then, crude oil prices are thought to have indirect effect through the exchange rate on global agricultural commodity prices. In this section, we briefly have a survey of results related to the present study.

Yu et al. (2006) examine the dynamic relationship between crude oil prices and vegetable oils used in biodiesel production including soybean, sunflower, rapeseed, and palm oil. Using weekly data for the period of Jan 1999 to Mar 2006, they find a long run co-integration relationship between vegetable oils and crude oil prices, but the impact of crude oil prices on vegetable oils prices is not significant.

Baffes (2007) analyze how crude oil prices spill over the prices of some international commodities. He finds that the pass-through of crude oil price changes to the overall non-energy commodity index, the fertilizer index, agriculture and metals are 0.16, 0.33, 0.17 and 0.11, respectively. In the other study, Baffes (2010) re-examine this relationship at a more disaggregated level, and conclude the highest pass-through of oil price changes to the fertilizer index followed by agriculture. Campiche et al. (2007) examine the co-variability between crude oil prices and agricultural commodities prices, including corn, sorghum, sugar, soybeans, soybean oil, and palm oil, for the period 2003 to 2007. Using VECM model to determine whether there is an increasing tendency for price changes in petroleum to correspond to price changes in agricultural commodities, they find that there are no co-integration relationships between crude oil prices and agricultural commodities prices during the 2003-2005. But, the findings show that corn and soybean prices are co-integrated with crude oil prices for the period 2006 to 2007.

Hudson et al. (2009) examine the co-integration relationship between oil, exchange rates, and several agricultural commodities prices, including corn, soybeans, soybean oil, cotton, and wheat for the period Jan 2000 to Sept 2008. They find that agricultural commodities prices are related to oil for corn, cotton, and soybeans with exception of wheat. Also, exchange rate has a major role in connection between prices over time.

Frank and Garcia (2010) estimate the linkage between several agricultural grains, livestock commodities, oil and exchange rates using weekly cash data from 1998 to 2009. They use VAR and VECM approach and identify a structural break in mid-2006 between two time periods. The results show that the effect of own lags in the agricultural commodity prices are larger/smaller than the effect of the exchange rate and crude oil prices for the first/second time period in the study. Saghaian (2010) identify the link between energy and commodity prices using time-series analysis and Granger causality supplemented by a directed graph theory modeling approach. The results show that although there is a strong correlation between oil and agricultural commodity prices, including corn, soybeans, and wheat, but the evidence for a causal link from oil to agricultural commodity prices is mixed. Busse et al. (2010) investigate vertical price transmission in the biodiesel supply chain in Germany by focusing on the connections between prices of rapeseed oil, soybeans oil, biodiesel and crude oil. They find a strong impact of crude oil price on biodiesel prices, and a considerable impact of biodiesel prices on rapeseed oil prices. Zhang et al. (2010) analyze short run and long run relationship between prices of fuel and agricultural commodities. They find that there is no direct long run relation between fuel prices and agricultural commodity prices, but there is only direct short run relationship.

Alom et al. (2011) investigate volatility spillovers from international oil prices to food markets in selected Asia and Pacific countries. Using VAR and GARCH models for the period 1995-2010, they find positive correlations between food and oil volatilities. Volatility spillovers from oil to domestic markets are larger for recent periods. Serra (2011) analyze the volatility spillover between crude oil, ethanol and sugar prices in Brazil. The results show that there are strong volatility relationships between the prices. The finding indicate that crude oil and sugar market shocks cause an increase in the volatility of the ethanol price. In a different study, Serra et al. (2011) analyze the price linkages and transmission patterns in the US ethanol industry and find that there exists a long run relationship between the prices of ethanol, corn, oil and gasoline as well as strong links between energy and food prices. Du, Yu, and Hayes (2011) investigate the spillover of crude oil prices to agricultural commodity prices using stochastic volatility models and weekly crude oil, corn, and wheat futures prices during the period of Nov 1998 and Jan 2009. The results show that there is no evidence of spillover for the first period sample until 2006. For the second period sample from Oct 2006 to Jan 2009, the results indicate significant volatility spillover from the crude oil market to the corn market.

Kaltalioglu and Soytas (2011) investigate the volatility spillover between oil, food consumption item, and agricultural raw material price indexes using the Cheung-Ng approach for the period Jan 1980 to April 2008. The results show that variation in crude oil prices does not Granger cause the variance in food and agricultural raw material prices.

Nazlioglu and Soytas (2012) examine the dynamic relationship between crude oil prices and agricultural commodity prices using panel co-integration and Granger causality methods. The results show that there is evidence on the causal relationship between crude oil prices and agricultural commodity prices. In other study, Nazlioglu et al (2013) examine volatility transmission from crude oil prices to several agricultural commodity prices, including wheat, corn, sugar, and soybean. They use impulse response techniques and causality in variance by dividing daily data from Jan 1986 to March 2011 into pre- and post-crisis time period. They find that there is no shock transmission from crude oil prices to agricultural commodities prices for the post-crisis time period. Trujillo-Barrera et al. (2012) examine the volatility spillovers between crude oil, corn and ethanol markets in the United States with weekly futures for the period 2006-2011. The multivariate GARCH model shows volatility transmission from crude oil to corn and ethanol markets and volatility spillovers from the corn to the ethanol market, but there is no evidence of volatility spillovers from ethanol to corn. Hassouneh et al. (2012) examine the transmission patterns between food and energy prices in Spain. The results show that there is a long run relationship between biodiesel, sunflower and crude oil prices. Also, biodiesel adjusts to deviations from long run relationship and sunflower oil prices are influenced by energy prices. Kristoufek et al. (2012) analyze the existence of any relationship between biodiesel, ethanol and related fuels and commodity prices in the United States and Germany. The results show that although biofuel is affected by food and fuel prices, biofuel prices has a limited capacity in the determination of food prices.

Balcilar et al. (2014) investigates causality between oil prices and the prices of agricultural commodities in South Africa. They use daily data over the period April 19, 2005 to July 31, 2014 for oil prices and agricultural commodities, including soybeans, wheat, sunflower and corn. The effect of oil prices on agricultural commodity prices varies across the different quantiles of the conditional distribution, and due to nonlinear dependence between oil prices and agricultural commodity prices, Granger causality provides misleading results. Rezitis (2014) examines the relationship between crude oil prices, US dollar exchange rates, thirty of the international agricultural commodities prices, and five fertilizer prices using panel data approach over the period June 1983 to June 2013. The results indicate that crude oil prices and US dollar exchange rates affect the international world agricultural commodities prices. The findings support the bidirectional panel causality between crude oil prices and international agricultural commodities prices; between exchange rate and international agricultural commodities prices, and between crude oil and exchange rates.

Cabrera and Schulz (2015) investigate price and volatility risk originating in linkages between energy and agricultural commodity prices in Germany using GARCH models and quantify the volatility and correlation risk structure. They find that prices move together in the long run and preserve the equilibrium, whilst correlations are mostly positive with persistent market shocks. In fact, concerns about biodiesel being the cause of high and volatile agricultural commodity prices is unjustified. Al-Maadid et al. (2015) estimate a bivariate VAR-GARCH (1,1) model to examine relationship between food and energy prices. They analyze both mean and volatility spillovers for possible parameter shifts resulting from the 2006 food crisis, the Brent oil bubble, the introduction of the Renewable Fuel Standard (RFS) policy, and the 2008 global financial crisis. The findings confirm the existence significant linkages between food and oil and ethanol prices. Also, the 2006 food crisis and the 2008 global financial crisis leading to the most significant shifts in the volatility spillovers between food and energy prices.

In line with related literature, this study investigates the volatility spillover from crude oil and exchange rates to the volatility of selected international agricultural commodities prices, which in turn affects the food price index.

Two Main Factors Driving the International Agricultural Commodities Prices

International agricultural commodities prices rose strongly during the last decade, peaking sharply in 2008. There are many micro and macro popular factors to explain the recent decade trends in international agricultural commodities prices, including strong global growth (especially from China and India), easy monetary policy (as reflected in low real interest rates or expected inflation), a speculative bubble (resulting from bandwagon expectations), and risk (possibly resulting from geopolitical uncertainties) (Frankel & Rose, 2009). These factors have contributed to increase almost all commodities prices together during much of last decade and peaked in 2008. These factors include weather shocks, policies to promote use of biofuels that increased demand for maize and vegetable oils; depreciation of the US dollar exchange rate; long run economic growth in some of developing countries like China that increase prices for petroleum and fertilizer of the resource - intensive nature of their economic growth and led to increase demand for other commodities prices.

Based on the above explanations it should be evident why agricultural commodities prices are becoming increasingly correlated with oil prices. Figure 1 shows monthly data trends for commodity food price index includes cereal, vegetable oils, meat, seafood, sugar, bananas, and oranges price indices, and oil price index during the period from Jan 1992 to Nov 2015. The recession of 2008 drove price down briefly. Most agricultural commodity markets are characterized by a high degree of volatility. To explain briefly the reasons behind it, we just need to explore that agricultural output varies from time to time because of some natural shocks like weather. Also, demand and supply elasticity is relatively low with respect to price, and supply cannot respond much to prices in the short run, and it can respond to price changes with a lag, and this can cause cyclical adjustments which in turn add an extra degree of variability to the markets concerned.

[Insert Figure 1]

We can briefly explain the volatility of oil prices to the volatility of corn price as an example. Figure 2 shows monthly data trends for corn price and oil price index during the period from Jan 1992 to Nov 2015. For the period since the end of 2006, US oil and corn prices moves in the same direction that the wave travels. This occurred because of increasing ethanol's share in US corn demand, increasing energy's share in crop costs of production, and the treatment of all commodities as a unified asset class in commodity index funds.

[Insert Figure 2]

As mentioned above, a variety of reasons have increased agricultural commodities prices, including increased ethanol production, income-led increases in food demand in Asia, supply disruptions in Europe and Australia, and a weak dollar. Figure 3 shows monthly data trends for commodity food price index and US dollar exchange rate during the period from Jan 1992 to Nov 2015. In general, US prices rise with a weak dollar because of the terms of trade which shows the relationship between export prices and import prices. If the currency of a major export competitor strengthens relative to the dollar, then the demand for US exports rises even if the currency of the buyer does not change relative to the dollar. Figure 3 presents that US dollar exchange rate has fallen substantially from its peak value in 2001 and 2002. But most of the decrease occurred before the run-up in agricultural commodities prices.

[Insert Figure 3]

Data

We employ daily data on futures prices for light sweet crude oil (Cushing, Oklahoma) from the New York Mercantile Exchange (NYMEX) and turned it into monthly data. We also collect monthly data for international agricultural commodities prices by cereals group including maize (corn), sorghum, wheat, sugar; and vegetable oils and protein meal group including coconut oil, fishmeal, olive oil, palm oil, groundnut oil, groundnuts, rapeseed oil, soybean meal, soybean oil, soybeans, sunflower oil. All monthly data for international agricultural commodities prices are retrieved from index Mundi website. The period considered spans from 1986:01 to 2015:11. The natural logarithms of the variables are arranged in monthly data. The return series are calculated based on difference between the log price at time t and the log of price in time t-1, and used in the empirical analysis. Regarding the returns estimation, there are both theoretical and empirical reasons for preferring logarithmic returns (Strong, 1992). In theory, logarithmic returns are more easily managed when linking together sub-period returns to form returns over long intervals. But in empirical, logarithmic returns are more likely to be normally distributed and so conform to the assumptions of the standard statistical techniques.

As we mentioned earlier, there is some debate as to whether the international agricultural commodities prices are not responsive to the oil prices until 2006, but because of the world's food price crisis for the period 2006 to 2008, we have observed higher correlation between oil and international agricultural commodities prices since 2006 (Campiche et al., 2007). Therefore, following some types of research studies, we consider two time periods in our study, including the pre-crisis period spanning from 1 Jan 1986 to 31 Dec 2005, and the post-crisis period from 1 Jan 2006 to 30 Nov 2015.

It should be pointed out that most international agricultural commodities are traded in US dollar. Then exchange rate volatility have repercussions for the volatility of international prices of agricultural commodities. We use exchange rate data, measured as a trade weighted US dollar index in terms of major currencies, was obtained from the Federal Reserve Economic Data database. A more detailed description of the data is presented in Table 1.

[Insert Table 1]

Table 2 represents the descriptive statistics for both time periods. The mean and the volatility of the returns in the post-crisis period are higher than those in the pre-crisis period. Also, the mean, and standard deviation of the oil returns are greater than those of the international agricultural commodity returns in the pre-crisis period (except olive oil and sugar for mean, and rapeseed oil for standard deviation).

In the post-crisis period, standard deviation of the oil returns is substantially higher than those of the international agricultural commodities returns (except sunflower oil). Also, standard deviation of the international agricultural commodity returns in the post-crisis period are higher than those in the pre-crisis period (except groundnuts and rapeseed oil). It is expected since the oil price surge in the post-crisis period, increases the derived demand for the agricultural commodities such as corn and soybeans which are used in biofuels production which in turn leads to a substantial rise in the prices of those agricultural commodities. In the post-crisis, corn prices exhibit relatively higher average return, and higher unconditional volatility compared to wheat.

The skewness and kurtosis coefficients reveal all prices exhibit high peakness and fat tailedness relative to a normal distribution. The international agricultural commodities return including wheat, sugar, fishmeal, olive oil, groundnut oil, and sunflower oil have high probability of rising prices due to their positive skewness. Distributions with kurtosis greater than 3 are said to be leptokurtic. The excess kurtosis, which is the kurtosis minus 3, show leptokurtic for all variables and it confirms that Student's t-distribution is more adequate in conditional variance estimation of our model. The Jarque-Bera statistic reject normality in all cases (except for trade weighted US dollar index in the pre-crisis period).

It should be pointed out that all variables at first difference (for log return series) were found to be stationarity at either 1% or 5% levels for both Augmented Dickey - Fuller (ADF) and Philips - Perron (PP) unit root tests[2].

[Insert Table 2]

Table 3 illustrates that the correlation between the oil price volatility and the international agricultural commodities returns dramatically has increased in the post-crisis time period compared to the pre-crisis time period. The results of descriptive analysis indicate that the volatility of oil prices can affect the volatility of the international agricultural commodities prices, and it is very important among policy-makers**.**

[Insert Table 3]

[2]. The results are not reported in this paper, but are available upon request.

Methods

Related literature review show how crude oil prices, exchange rates, and agricultural commodities prices are interrelated together and changed over time. In this study, we extract the conditional volatility of all variables in our study using the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model proposed by Nelson (1991) to capture the asymmetric impact of shocks on volatilities and to avoid imposing non-negativity restrictions on the values of the GARCH parameters to be estimated (Nelson & Cao 1992).

In the EGARCH model, to capture volatility in oil and agricultural commodities markets consider the following mean return equation:

(1) $R_{i,t} = \alpha_0 + \sum_{i=1}^{r} \alpha_i \, R_{i,t-i} + \varepsilon_{i,t}$

Where $R_{i,t}$ is the return of price index i between time t and time t-1, $\varepsilon_{i,t}$ is the error term for the return on index *i* at time *t*, with mean zero and conditional variance of $\sigma_{j,t}^2$. We specify the mean return equation using autoregressive (AR) models. The autocorrelation and partial autocorrelation functions are considered and residuals from the mean equations are tested for whiteness using the Ljung-Box statistics to determine the lag length for each return series. It was found that 2 and 3 lags are optimal lag lengths for return series to yield uncorrelated residuals for the pre- and post-crisis time periods, respectively. The conditional variance, $\sigma_{j,t}^2$, depicted as GARCH process that is an asymmetric function of lagged disturbances $\varepsilon_{i,t-1}$:

(2) $ln\sigma_{j,t}^2 = \omega_j + \alpha_i |z_{j,t-1}| + \gamma_i z_{j,t-1} + \beta_j \ln\sigma_{j,t-1}^2$

(3) $z_{j,t-1} = \frac{\varepsilon_{i,t-1}}{\sqrt{\sigma_{j,t-1}^2}}$

where $z_{j,t}$ is the standardized residual. Then in EGARCH model, the variance is conditional on its past values as well as a function of $z_{j,t-1}$. The parameter γ_i allows for this ARCH effect to be asymmetric. A statistically significant γ_i indicates that an asymmetric effect exists. It is a real parameter, such that $\gamma_i < 0$ when negative returns have a greater impact on future volatility than positive returns. Due to the volatility specification in terms of the logarithmic transformation, there are no restrictions on the parameters to ensure positive variance. The persistence of volatility implied is measured by $\sum \beta_i < 1$, and a sufficient condition for stationarity and finite kurtosis is $|\beta_i| < 1$.

We use the univariate EGARCH model to test for volatility spillover from the oil prices and US dollar exchange rates to the international agricultural commodities prices. In this regard, we apply two approaches to test the volatility spillover between variables. We can employ the squared residuals from the mean-conditional variance formulation for crude oil prices and for US dollar exchange rates as our two exogenous variables in the conditional variance equation for the international agricultural commodities prices (Hamao et al., 1990; Theodossiou & Lee, 1993). To illustrate it, consider the following equation

(4) $ln\sigma_{j,t}^2 = \omega_j + \alpha_i|z_{j,t-1}| + \gamma_i z_{j,t-1} + \beta_j \ln\sigma_{j,t-1}^2 + alnOILPresid_{j,t}^2 + blnTWEXresid_{j,t}^2$

where $OILPresid_{j,t}^2$ and $TWEXresid_{j,t}^2$ are the squared residuals from the mean-conditional variance formulation for crude oil prices and US dollar exchange rates, respectively. This is our first approach to investigate the volatility effect from crude oil price and US dollar exchange rate to the international agricultural commodities prices in our study.

As our second approach in the present study, we can make GARCH variance series from variance equation (2) for all variables, and then construct VAR models for both the pre- and post-crisis time periods to analyze what extend the volatility of the international agricultural commodities returns respond to a shock in oil and US dollar exchange rate volatility in short run. In this regard, the generalized and accumulated impulse-response functions[3] are derived from the VAR models, and, we investigate VAR Granger causality between variables. Finally, using VECM model, we investigate the short run and long run granger causality between the volatility of variables (or GARCH variance series from variance equation) in the present study.

Results

In this section, we present the empirical results of our model for the sample period of 1986m01 to 2005m12 (pre-crisis time period) and for the sample period of 2006m01 to 2015m11 (post-crisis time period) for our two approaches that we mentioned it in methods section.

The Results of EGARCH Model and VAR Granger - Causality

This section briefly represents the results for variance equations of the EGARCH model estimations for both pre- and post-crisis periods[4]. First, we compute the squared returns for time series and test for evidence heteroscedasticity and volatility clustering as our two precondition for applying EGARCH Model. The reason for using the square returns come from the fact that we can't reject the hypothesis that the average of the monthly returns is different

---

[3]. The accumulated impulse response function is the cumulative sum of the impulse response function.
[4]. As we extract the volatility of the variables from the variance equation in AR-EGARCH model, then the mean equation results are not reported in this paper, but are available upon request.

from zero. If we assume that the mean is zero, then the unconditional variance can be approximately by the squared returns of our monthly data. The clustering of volatility can be easily observed from the squared returns trend for both pre- and post-crisis periods (Figure 4. in Appendix).

[Insert Figure 4]

We find heteroscedasticity for time series by calculating the autocorrelation (AC) and partial autocorrelation (PAC), and by performing the Ljung-Box Q-statistics. Table 4 presents the results of the volatility estimation through univariate EGARCH Modeling in terms of variance equation for both pre-and post-crisis time periods, and most equations were determined to be best fit by AR-EGARCH (1,1). As shown in Table 4, the ARCH parameter (α_i) and the GARCH parameter (β_i) appear to be high differences across two time periods. The degree of volatility persistence, β_i is statistically significant for all variables except soybean oil in the pre-crisis period. Also, the ARCH parameters, α_i is statistically significant for all variable except soybeans in the post-crisis time period. The absolute value of the degree of volatility persistence, namely $|\beta_i|$, have increased for corn, sorghum, sugar, coconut, groundnut oil, rapeseed oil, soybean meal, soybean oil, soybeans, sunflower in the post-crisis time period. Also, the absolute value of the ARCH parameter, namely $|\alpha_i|$, have increased for corn, wheat, olive oil, palm oil, groundnut oil, rapeseed oil, soybean meal, and sunflower oil for the post-crisis time period.

A high ARCH parameter implies high short run volatility, whilst a high GARCH parameters indicate high long run volatility. The results from the EGARCH model estimations clearly show that the volatility processes of the commodities return in question is dominated by the ARCH and GARCH effect for two time periods, but the impact of ARCH and GRACH effect have increased for the post-crisis than pre-crisis time period. In the other words, more autoregressive persistence in the post-crisis time period suggest high long run volatility in the agricultural commodities returns, and is the same for ARCH effect. By the way, both strong effect show the high short run and high long run volatility in agricultural commodities returns in the post-crisis time period.

The asymmetric effect parameter, γ_i, is significant for all agricultural commodities prices except soybean oil for pre-crisis time period. Overall, a negative return (or shocks) for the asymmetric effect parameter, γ_i, show a greater impact on future volatility than positive returns (shocks), and a positive sign show that a positive shock does have a high impact on future volatility than negative shocks. In the other words, the significant positive and negative asymmetric does not have the same effects, and positive shock increases volatility more than a negative shock. For example, soybean oil has a non-significant negative and significant positive return for the pre- and post-crisis period, respectively. It means that soybean oil returns have affected by positive shocks in the pre- and post-crisis time period, because its negative asymmetric for the pre-crisis time period is not significant. Also, corn has a significant negative and positive return for the pre- and post-crisis period, respectively. It means, that corn has a significant negative shock for the pre-crisis period, but significant positive shock for the recent years. As shown in Table 4, crude oil and US dollar exchange rate have significant positive returns for both time periods.

[Insert Table 4]

After determining the volatility processes of the commodities returns in this study, we now focus on investigating whether there are volatility spillovers between the crude oil prices, US dollar exchange rates, and international agricultural commodities prices. As we mentioned in before section, we use two different approaches to investigate the volatility spillover. As a first approach in this study, we estimate variance equation with considering the recent squared residuals from the mean-conditional variance formulation of the crude oil returns and US dollar exchange rate as an exogenous variable in the conditional variance equation for all international agricultural commodities returns. The results of the univariate AR-EGARCH model testing volatility spillover are presented in terms of variance equation in Table 5[5]. As shown in Table 5, there is a significant volatility spillover from crude oil returns to the international agricultural commodities returns for both time periods; with exception of corn, sugar, coconut oil, palm oil, groundnut oil, rapeseed oil, soybean meal, soybean oil, and soybeans in the pre-crisis time period; also with exception of corn, and sugar for the post-crisis time period. It means that the most volatility of international agricultural commodities returns are affected by the volatility of the crude oil returns for the post-crisis time period. The magnitude of the spillover coefficient varies from -0.0037 for rapeseed oil to 0.3012 for fishmeal in the pre-crisis time period, and from -0.0726 for fishmeal to 0.2309 for soybean oil in the post-crisis time period. Also, there is a significant volatility spillover from US dollar exchange rate to the international agricultural commodities returns; with exception of corn, sugar, olive oil, palm oil, groundnut oil, soybean oil, soybeans, and sunflower oil in the pre-crisis time period; also with exception of corn, wheat, sugar, fishmeal, palm oil, soybean meal, soybean oil, soybeans for the post-

[5]. The mean equation results are not reported in this paper, but are available upon request.

crisis time period. It means that US dollar exchange rate volatility strongly does affect the volatility of international agricultural commodities returns in pre-crisis time period than post-crisis time period, but almost the volatility of international agricultural commodities returns is highly affected by the volatility of crude oil returns for the post-crisis time period.

[Insert Table 5]

As a second approach, we use a VAR model and Granger causality test to investigate the volatility spillover from crude oil returns and US dollar exchange rate to all international agricultural commodities returns in the present study. The Johansen co-integration test show that there is a long run relationship between variables[6]. Using Schwarz information criterion (SC), we find two lags for constructing our VAR model.

Table 6 presents the results of VAR Granger causality tests. The results for the pre-crisis time period show that there is no Granger causality between the volatility of crude oil returns to the volatility of the international agricultural commodities returns except for sorghum (unidirectional), coconut oil (unidirectional), palm oil (unidirectional), rapeseed oil (bidirectional), and a unidirectional volatility of soybean oil to crude oil returns. The results for the post-crisis time period show that there is no Granger causality between the volatility of crude oil returns to the volatility of the international agricultural commodities returns except for coconut oil (unidirectional), soybean meal (bidirectional), soybean oil (bidirectional), soybeans (bidirectional), and a unidirectional volatility of wheat and rapeseed oil to the volatility of crude oil returns.

[Insert Table 6]

Also, there is no Granger causality from the volatility of US dollar exchange rate to volatility of the international agricultural commodities returns except for rapeseed oil (unidirectional), and from the coconut oil, fishmeal, soybeans (all are unidirectional) to the volatility of US dollar exchange for the pre-crisis time period. For the post-crisis time period, there is no Granger causality from the volatility of US dollar exchange rate to the volatility of international agricultural commodities returns, but we have unidirectional Granger causality from coconut oil, palm oil, rapeseed oil, soybean meal, soybean oil, soybeans to the volatility of US dollar exchange rate.

The impulse response functions for one standard deviation shock to the crude oil returns volatility and US dollar volatility are presented in Figure 5 and Figure 6 for pre-crisis time

---

[6]. The results of the Johansen co-integration test have not reported in this paper, but are available upon request.

period, respectively. The results show that impulse response functions are not significant for pre-crisis time period, but they are significant for post-crisis time period (Figure 7 and Figure 8, respectively). It means, a shock in the volatility of crude oil returns is not transmitted to the volatility of the international agricultural commodities returns in the short run for pre-crisis time period, but they are transmitted for the post-crisis time period.

[Insert Figure 5], [Insert Figure 6], [Insert Figure 7], [Insert Figure 8]

We can test it by calculating the cumulative effects of the right hand lagged variables of VAR model. Table 7 presents the results of the cumulative effects of the right hand lagged variables of the VAR model and their corresponding F-statistics in bracket and P-values in parenthesis for all variables.

[Insert Table 7]

The results show almost the same pattern for the cumulative impulse response functions for one standard deviation shock to the oil returns volatility and US dollar volatility in the pre-crisis time period which are presented in Figure 9 and Figure 10. But the cumulative impulse response functions for one standard deviation shock to the crude oil returns volatility and US dollar volatility are significant for the post-crisis time period which are presented in Figure 11 and Figure 12, respectively.

[Insert Figure 9], [Insert Figure 10], [Insert Figure 11], [Insert Figure 12]

The Results of VECM Model

Table 8 presents the short run and long run Granger causality tests based on VECM model for pre- and post-crisis time period. As shown in this table, there is no short run Granger causality from crude oil return volatility to the volatility of the international agricultural commodities returns in the pre-crisis time period with exception of coconut oil (bidirectional) and palm oil (unidirectional), and except for coconut oil, groundnuts, soybeans (all unidirectional), palm oil and soybean oil (both bidirectional) for the post-crisis time period. It means, that the volatility of the international agricultural commodities returns does strongly affect by the volatility of crude oil returns in the short run, and it support our results for the existence of high ARCH effect in the post-crisis time period. Also, there is unidirectional short run Granger causality from sorghum, fishmeal, groundnuts, rapeseed oil, soybean meal to the crude oil returns volatility in the pre-crisis time period. There is unidirectional short run Granger causality from wheat rapeseed oil to the crude oil returns volatility in the post-crisis time series.

The results in Table 8 show that there is no short run Granger causality from US dollar exchange rate volatility to the volatility of the international agricultural commodities returns in the pre-crisis time period with exception of coconut oil (unidirectional), soybean meal (unidirectional), and except for coconut oil (unidirectional), palm oil (bidirectional), groundnuts (bidirectional) for the post-crisis time series. Also, there is unidirectional short run Granger causality from the volatility of fishmeal to the US dollar exchange rates volatility in the pre-crisis time period. There is unidirectional short run Granger causality from the volatility of sugar, palm oil groundnut oil, groundnut, soybean meal, soybean oil, and soybeans to the US dollar exchange rate in the post-crisis time series. Then the results support us before findings about the existence of highly ARCH effect for the post-crisis time period. One of the interesting results show that there is short run Granger causality from crude oil return volatility to the US dollar exchange rate volatility for the post-crisis time period.

In addition, the F-statistic values for long run causality (the ECT coefficient) are statistically significant for the international agricultural commodities returns with exception of palm oil in the pre-crisis time period, and with exception of corn, sorghum, wheat, sugar, fishmeal, rapeseed oil, soybean meal, soybean oil, and sunflower oil for the post-crisis time period. The results support our before finding about the existence of high GARCH effect for both time periods. Furthermore, the joint test (for jointly short run and long run relationships) indicates that there is a strong causality between crude oil returns volatility and all international agricultural commodities returns volatility for the pre-crisis time period. But, there is no causality between them in the post-crisis time with exception of coconut oil, palm oil, groundnuts, soybean meal, soybean oil, and soybeans. Also, the joint test indicates that there is a strong causality between US dollar exchange rates volatility and international agricultural commodities returns volatility with exception of palm oil for the pre-crisis time period, and with exception of corn, sugar, fishmeal, olive oil, groundnut oil, rapeseed oil, soybean meal, soybean oil, and sunflower oil in the post-crisis time period. This result support us before findings about that the crude oil returns volatility (compare to US dollar exchange rate volatility) does strongly affect the volatility of the international agricultural commodities returns for the post-crisis time period.

[Insert Table 8]

Conclusion

In this paper, we examine the relationship between crude oil returns and UD dollar exchange volatility and the volatility in the international agricultural commodities prices using monthly price series for NYMEX light sweet crude oil futures prices, US dollar exchange rates, and international agricultural commodities prices, including corn (maize), sorghum, wheat, sugar, coconut oil, fishmeal, olive oil, palm oil, groundnut oil, groundnuts, rapeseed oil, soybean meal, soybean oil, soybeans, and sunflower prices. All selected international agricultural commodities are related to food price index, and the results can help food policy makers take steps to improve food security policy. The exponential GARCH model or EGARCH model was used to capture spillovers across commodities returns, and then we extracted GARCH variance series as a measure for volatility of all variables in the present study. The results show that the volatility of the international agricultural commodities returns is dominated by the ARCH and GARCH effect for two time periods, but the impact of ARCH and GRACH effect have increased for the post-crisis compared to the pre-crisis time period.

We capture the effect of crude oil return and US dollar exchange rate volatility in variance equation, and the results show that there is significant relationship between volatility of both crude oil returns and US dollar exchange rate to the international agricultural commodities returns, simultaneously. For example, the crude oil returns volatility and US dollar exchange rate volatility are significant for sorghum, wheat, fishmeal, groundnuts in the pre-crisis time period, and for sorghum, coconut oil, olive oil, groundnut oil, groundnuts, rapeseed oil, and sunflower oil in the post-crisis time period. The results show that most volatility of international agricultural commodities returns are affected by the volatility of the crude oil returns for the post-crisis time period. Also, the volatility of US dollar exchange rate affects the international agricultural commodities returns for both pre- and post-crisis time periods.

We construct VAR models to obtain impulse responses, and the cumulative effects of the right-hand lagged variables of the VAR model and VAR Granger causality tests between the variables under consideration. The results show that there is no Granger causality between the volatility of crude oil returns to the volatility of the international agricultural commodities returns except for sorghum, coconut oil, palm oil, rapeseed oil in the pre-crisis time period, and except for coconut oil, soybean meal, soybean oil, soybeans in the post-crisis time period.

The general and the cumulative impulse response functions confirm that none of the impulse response functions are significant in pre-crisis time periods, but they are significant for the post-crisis time periods. The empirical results of the impulse responses and the cumulative effects indicate that the greatest response of each variable is attributed to itself, and the responses of the international agricultural commodities returns volatility to crude oil returns volatility and US dollar exchange rate volatility are positive and negative, respectively.

The results of VECM model support us before findings that there is significant ARCH (or short run) effect and GARCH (or long run) effect between the crude oil returns volatility and US dollar exchange rate volatility and the volatility of the international agricultural commodities returns. The ECT coefficient as a measure of long run relationship between variables in VECM model are statistically significant except for palm oil in the pre-crisis time period, and except for corn, sorghum, wheat, sugar, fishmeal, rapeseed oil, soybean meal, soybean oil, and sunflower oil for the post-crisis time period. The joint test show that there is a strong causality between crude oil returns volatility and all international agricultural commodities returns volatility for the pre-crisis time period. But, there is no causality between them in the post-crisis time with exception of coconut oil, palm oil, groundnuts, soybean meal, soybean oil, and soybeans.

Finally, the results of the present study show that the crude oil returns volatility does strongly affect the volatility of the international agricultural commodities returns in the post-crisis time period, and the crude oil returns volatility does affect the volatility of the US dollar exchange rate which in turn impacts the volatility of the international agricultural commodities returns through changes in the prices.

References

[1] Al-Maadid, A., and Caporale, G. M., Spagnolo, F., and Spagnolo, N. (2015). Spillovers between Food and Energy Prices and Structural Breaks. DIW Berlin. Discussion papers 1466.

[2] Bollerslev, T., (1987). A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *Review of Economics and Statistics 69,* 542-547.

[3] Bakhat, M. and Würzburg, K., (2013). Price Relationships of Crude Oil and Food Commodities, Economics for Energy, *Alcoa Foundation*, WP FA06/2013.

[4] Balcilar, M., Chang, S., Gupta, R., Kasongo, V., and Kyei, C., (2014). The Relationship between Oil and Agricultural Commodity Prices: A Quantile Causality Approach, Department of Economics, University of Pretoria.

[5] Baffes, J., (2011). The Energy/Non-Energy Price Link: Channels, Issues, and Implications. In Piot-Lepetit, I. ed., Methods to Analyze Agricultural Commodity Price Volatility, New York: *Springer,* 31–44.

[6] Campiche, J., H. Bryant, J. Richardson, and Outlaw. J., (2007). Examining the Evolving Correspondence between Petroleum Prices and Agricultural Commodity Prices. Paper

presented at the American Agricultural Economics Association Annual Meeting, Portland, OR, and July 29 - Aug 1, 2007.

[7] Cho, G., Kim, M. and Koo, W. W. (2005). Macro Effects on Agricultural Prices in Different Time Horizons, Department of Agribusiness and Applied Economics North Dakota State University. Paper prepared for presentation at the American Agricultural Economics Association Meeting, Providence, Rhode Island, and July 24-27, 2005.

[8] Cabrera, B. L., and Schulz, F., (2015). Volatility Linkages between Energy and Agricultural Commodity Prices, *Energy Economics 54,* 190-203.

[9] Du, X., Yu, C. L., and Hayes. D. J. (2011). Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis. *Energy Economics 33,* 497–503.

[10] Frank, J. and Garcia, P. (2010). How Strong are the Linkages among Agricultural, Oil, and Exchange Rate Markets? Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management St. Louis, Missouri, April 19-20, 2010.

[11] Frankel, J. A. and Rose, A. K. (2009). Determinants of Agricultural and Mineral Commodity Prices. Reserve Bank of Australia.

[12] Hafner, C. M., and Herwartz, H. (2006). A Lagrange Multiplier Test for Causality in Variance, *Economics Letters 93,* 137-141.

[13] Hamao, Y., Masulis, R., and Ng, N., (1990). Correlations in Price Changes and Volatility across International Stock Markets. *Review of Financial Studies 3,* 281-307.

[14] Harri, A. and Husdon, D. (2009). Mean and Variance Dynamics between Agricultural Commodity Prices and Crude Oil Prices and Implications for Hedging. In the Economics of Alternative Energy Sources and Globalization: The Road Ahead Meeting, Orlando, FL, 2009.

[15] Hudson, D., and K. Coble. (1999). Harvest Contract Price Volatility in Cotton. *The Journal of Futures Markets 19,* 717-33.

[16] Hudson, D., and T. Hanson. (1999). an Examination of Farm/Processor Price Spreads in Catfish Markets. *Aquaculture Economics and Management 3,* 222-27.

[17] Harri, A., Nalley, L., and Hudson, D. (2009). The Relationship between Oil, Exchange Rates, and Commodities Prices, *Journal of Agricultural and Applied Economics,* 41(2), 501–510.

[18] Buguk, C., Hudson, D., and Hanson, T. (2003). Price Volatility Spillover in Agricultural Markets: An Examination of U.S. Catfish Markets. *Journal of Agricultural and Resource Economics 28(1),* 86-99.

[19] Kaltalioglu, M., and Soytas, U., (2011). Volatility Spillover from Oil to Food and Agricultural Raw Material Markets, *Modern Economy 2,* 71-76.

[20] Kristoufek, L., Janda, K., Zilberman, D. (2012). Correlations between Biofuels and Related Commodities before and during the Food Crisis: A Taxonomy Perspective, *Energy Economics 34(5),* 1380–1391.

[21] Lambert P, and Laurent S., (2001). Modeling Financial Time Series Using GARCH-Type Models with a Skewed Student Distribution for the Innovations, Working Paper, university de Liege.

[22] Liefert, W., and Persaud, S. (2009). The Transmission of Exchange Rate Changes to Agricultural Prices, United States Department of Agriculture, Economic Research Report 76.

[23] Manera, M., Nicolini, M., and Vignati, I., (2013). Financial Speculation in Energy and Agriculture Futures Markets: A Multivariate GARCH Approach. The Quarterly *Journal of the IAEE's Energy Economics Education Foundation 34/3.*

[24] Manera, M., Nicolini, M., and Vignati, I. (2013). Futures Price Volatility in Commodities Markets: The Role of Short Term vs Long Term Speculation. Università di Pavia, Department of Economics and Management, DEM Working Paper Series 42.

[25] Nazlioglu, S., Erdem, C., and Soytas, U., (2013). Volatility Spillover between Oil and Agricultural Commodity Markets, *Energy Economics 36,* 658-665.

[26] Nazlioglou, S., U. Soytas. (2012). Oil Price, Agricultural Commodity Prices, and the Dollar: A Panel Co-integration and Causality Analysis, *Energy Economics 34,* 1098-1104.

[27] Ng, A. (2000). Volatility Spillover Effects from Japan and the US to the Pacific-Basin. *Journal of International Money and Finance 19,* 207–233.

[28] Robert S. Pindyck, R. S., and Julio J. Rotemberg, J. J., (1990). The Excess Co-Movement of Commodity Prices. *The Economic Journal 100(403),* 1173-1189.

[29] Rezitis, A. N. (2014). The Relationship between Agricultural Commodity Prices, Crude Oil Prices and US Dollar Exchange Rates: A Panel VAR Approach and Causality Analysis, *International Journal of Applied Economics (Forthcoming).*

[30] Schuh, G. E. (1974). The Exchange Rate and U.S. Agriculture. *American Journal of Agricultural Economics 56,* 1-13.

[31] Sayed H., Saghaian, S. H., Reed, M. R., and Marchant, M. A. (2002). Monetary Impacts and Overshooting of Agricultural Prices in an Open Economy, *American Journal of Agricultural Economics 84, 90-103*.

[32] Serra, T. (2011). Volatility Spillovers between Food and Energy Markets: A Semi-Parametric Approach, *Energy Economics*, forthcoming.

[33] Saghaian, S. H. (2010). The Impact of the Oil Sector on Commodity Prices: Correlation or Causation? *Journal of Agricultural and Applied Economics 42(3),* 477-485.

[34] Serra, T., D. Zilberman, Gil, J. M., and Goodwin, B. K. (2011). Nonlinearities in the US Corn-Ethanol-Oil-Gasoline Price System, *Agricultural Economics 42,* 35-45.

[35] Sayed H. and Saghaian, S. H. (2010). The Impact of the Oil Sector on Commodity Prices: Correlation or Causation? *Journal of Agricultural and Applied Economics 42(3),* 477-485.

[36] Saucedo, A., Brümmer, B., and Jaghdani, T. J. (2015). The Dynamic Pattern of Volatility Spillovers between Oil and Agricultural markets, Scientific Paper 8, ULYSSES Understanding and coping with food markets volatility towards more stable World and EU food Systems, Seventh Framework Program.

[37] Setiawan, K., and Maekawa, K., (2014). Estimation of Vector Error Correction Model with GARCH Errors: MONTE CARLO Simulation and Application, *Econ Papers 7002*.

[38] Strong, N., (1992). Modeling Abnormal Returns: A Review Article, *Journal of Business Finance and Accounting 19(4),* 533–553.

[39] Trujillo-Barrera, A., Mallory, M. and Garcia, P. (2012). Volatility Spillovers in the U.S. Crude Oil, Corn, and Ethanol Markets. *Journal of Agricultural and Resource Economics 37(2),* 247–262.

[40] Theodossiou, P. and Lee, U., (1993). Mean and Volatility Spillovers across Major National Stock Markets: Further Empirical Evidence. *Journal of Financial Research 16,* 337-350.

[41] Yu, Tun-Hsiang, D.A. Bessler, and Fuller. S., (2006). Co-integration and Causality Analysis of World Vegetable Oil and Crude Oil Prices. Paper presented at the American Agricultural Economics Association Annual Meeting, Long Beach, CA, and July 23–26, 2006.

Appendix A

Table 1.

Data Description

Data	**Description**
CORN	Maize (corn), U.S. No. 2 Yellow, FOB Gulf of Mexico, U.S. price, US Dollars per metric ton
SORG	Sorghum (US), no. 2 milo yellow, f.o.b. Gulf ports, US Dollars per Metric Ton
WHET	Wheat, No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico, US Dollars per Metric Ton
SUGA	Sugar; Free Market, Coffee Sugar and Cocoa Exchange (CSCE) contract no.11 nearest future position, US cents per Pound
COCO	Coconut oil (Philippines/Indonesia), bulk, c.i.f. Rotterdam, US Dollars per Metric Ton
FISH	Fishmeal, Peru Fish meal/pellets 65% protein, CIF, US Dollars per Metric Ton
OLIO	Olive Oil, extra virgin less than 1% free fatty acid, ex-tanker price U.K., US Dollars per Metric Ton
PALO	Palm oil, Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US Dollars per Metric Ton
PEAO	Groundnut oil/peanut oil (any origin), c.i.f. Rotterdam, US Dollars per Metric Ton
GRON	Groundnuts (peanuts), 40/50 (40 to 50 count per ounce), cif Argentina, US Dollars per Metric Ton
RAPO	Rapeseed Oil; Crude, fob Rotterdam, US Dollars per Metric Ton
SOYM	Soybean Meal, Chicago Soybean Meal Futures (first contract forward) Minimum 48 percent protein, US Dollars per Metric Ton
SOYO	Soybean Oil; Chicago Soybean Oil Futures (first contract forward) exchange approved grades, US Dollars per Metric Ton
SOYB	Soybeans, U.S. soybeans, Chicago Soybean futures contract (first contract forward) No. 2 yellow and par, US Dollars per Metric Ton
SUNF	Sunflower Oil, US export price from Gulf of Mexico, US Dollars per Metric Ton
OILP	Crude Oil (Light-Sweet, Cushing, Oklahoma), Cushing, OK Crude Oil Future Contract 1 (US Dollars per Barrel)
TWEX	Trade Weighted U.S. Dollar Index: Major Currencies, Index Mar 1973=100, Monthly

Table 2.

Descriptive statistics

Pre-crisis	**CORN**	**SORG**	**WHET**	**SUGA**	**COCO**	**FISH**	**OLIO**	**PALO**	**PEAO**	**GRON**	**RAPO**	**SOYM**	**SOYO**	**SOYB**	**SUNF**	**OILP**	**TWEX**
Mean	-0.0001	-7.5E-05	0.0009	0.0044	0.0015	0.0018	0.0040	0.0011	0.0012	0.0002	0.0023	0.0009	0.0001	0.0003	0.0024	0.0039	-0.0014
Std. Dev.	0.0544	0.0579	0.0514	0.0830	0.0747	0.0461	0.0449	0.0747	0.0474	0.0755	0.0884	0.0598	0.0532	0.0525	0.0607	0.0842	0.0169
Skewness	-0.3977	0.3102	0.1459	0.1077	0.7550	-1.0064	0.0153	0.2497	0.4747	-0.0486	0.8303	-0.2944	0.2889	0.1107	0.7938	-0.5575	-0.1961
Kurtosis	8.4131	8.7125	3.8687	3.4970	5.2372	9.1884	10.272	4.3158	6.9247	11.812	16.025	7.5524	3.1544	6.9206	5.9418	6.0682	2.8908
Jarque-Bera	298.1	328.80	8.3638	2.9224	72.555	421.73	526.66	19.725	162.37	773.38	1716.9	209.84	3.5635	153.56	111.28	93.875	1.6518
Excess Kurtosis	5.4131	5.7125	0.8687	0.4970	2.2372	6.1884	7.2720	1.3158	3.9247	8.812	13.025	4.5524	0.1544	3.9206	2.9418	3.0682	-0.1092
Post-crisis	**CORN**	**SORG**	**WHET**	**SUGA**	**COCO**	**FISH**	**OLIO**	**PALO**	**PEAO**	**GRON**	**RAPO**	**SOYM**	**SOYO**	**SOYB**	**SUNF**	**OILP**	**TWEX**
Mean	0.0040	0.0049	-0.0003	0.0005	0.0058	0.0060	-0.0011	0.0026	0.0025	0.0076	9.2E-05	0.0035	0.0023	0.0032	-.00008	-0.0027	0.0007
Std. Dev.	0.0703	0.0808	0.0798	0.0792	0.0814	0.0545	0.0457	0.0782	0.0647	0.0554	0.0546	0.0697	0.0594	0.0642	0.1014	0.0917	0.0176
Skewness	-0.1236	-0.1120	0.2227	0.2260	-0.1502	0.8736	0.8503	-0.7276	0.6413	0.0927	-0.0838	-0.1119	-0.6892	-0.6603	2.6437	-1.0135	0.3760
Kurtosis	4.5398	4.7503	4.5356	3.1543	3.9278	6.2606	5.6122	5.5062	8.3675	5.0451	4.9057	3.4346	5.1329	4.9731	24.158	4.7751	3.8750
Jarque-Bera	12.059	15.439	12.676	1.1313	4.7166	67.855	48.176	41.646	151.00	20.909	18.147	1.1854	31.981	27.952	2358.4	35.999	6.6016
Excess Kurtosis	1.5398	1.7503	1.5356	0.1543	0.9278	3.2606	2.6122	2.5062	5.3675	2.0451	1.9057	0.4346	2.1329	1.9731	21.158	1.7751	0.8750

Table 3.

Correlation Matrix [Pre-Crisis Time Period]

	CORN	**SORG**	**WHET**	**SUGA**	**COCO**	**FISH**	**OLIO**	**PALO**	**PEAO**	**GRON**	**RAPO**	**SOYM**	**SOYO**	**SOYB**	**SUNF**	**TWEX**	**OILP**
CORN	1																
SORG	0.8230	1															
WHET	0.4505	0.5174	1														
SUGA	0.1488	0.1338	0.1601	1													
COCO	0.2132	0.1715	0.1998	0.0751	1												
FISH	-0.0590	-0.0676	0.0198	0.0710	-0.1032	1											
OLIO	-0.0396	-0.0592	0.0125	-0.0978	0.0169	0.1787	1										
PALO	0.2422	0.2242	0.1702	0.1348	0.6468	0.0369	-0.0393	1									
PEAO	0.1684	0.1515	-0.0378	0.1739	0.1142	-0.0485	-0.0703	0.1309	1								
GRON	-0.0600	-0.0275	-0.0946	0.0190	0.0022	-0.1183	0.0400	-0.0174	0.2826	1							
RAPO	0.0742	-0.0360	0.1002	0.1657	0.1623	0.1934	0.0776	0.2490	0.1618	-0.0551	1						
SOYM	0.4286	0.3816	0.2637	0.0224	0.1115	-0.0105	0.0268	0.0883	0.0734	0.0016	0.0635	1					
SOYO	0.5315	0.4803	0.2715	0.1282	0.3941	0.0292	-0.0721	0.6552	0.2405	-0.0415	0.2187	0.3980	1				
SOYB	0.5731	0.5022	0.2906	0.0567	0.2398	0.0024	-0.0249	0.3186	0.1336	0.0028	0.1329	0.8749	0.7039	1			
SUNF	0.3589	0.3002	0.1865	0.1869	0.3857	-0.0033	-0.0138	0.5082	0.3279	0.0598	0.2366	0.1499	0.5960	0.3515	1		
TWEX	0.1155	0.1797	0.0337	-0.0464	0.0075	-0.2856	-0.4600	-0.0585	0.1331	-0.0615	-0.1705	-0.0551	0.0191	-0.0399	0.0516	1	
OILP	-0.0907	-0.0739	-0.0451	-0.0880	-0.0322	-0.0116	0.1585	0.0085	0.0864	0.1576	-0.0567	-0.0060	-0.0802	-0.0314	-0.0700	-0.0828	1

Correlation coefficient are for log return series.

Table 3 (Cont.)

Correlation Matrix [Post-Crisis Time Period]

	CORN	**SORG**	**WHET**	**SUGA**	**COCO**	**FISH**	**OLIO**	**PALO**	**PEAO**	**GRON**	**RAPO**	**SOYM**	**SOYO**	**SOYB**	**SUNF**	**TWEX**	**OILP**
CORN	1																
SORG	0.6763	1															
WHET	0.5391	0.3842	1														
SUGA	0.2639	0.2401	0.2850	1													
COCO	0.4363	0.3252	0.3259	0.1445	1												
FISH	0.1254	0.0633	0.0229	-0.0047	0.0766	1											
OLIO	0.0016	0.0649	0.0401	0.0155	0.1218	0.0282	1										
PALO	0.4665	0.3366	0.3967	0.2468	0.7365	0.1061	0.0487	1									
PEAO	0.1956	0.1261	0.0932	-0.0052	0.2466	0.0881	0.0075	0.2292	1								
GRON	0.2283	0.2976	0.1568	-0.0137	0.2770	0.0941	0.1919	0.1728	0.2372	1							
RAPO	0.4548	0.3282	0.4297	0.2389	0.5415	0.1500	0.1783	0.5602	0.3973	0.3523	1						
SOYM	0.6347	0.3186	0.5109	0.2380	0.3479	0.0144	-0.0073	0.4469	0.1416	0.0707	0.4171	1					
SOYO	0.6346	0.5040	0.5170	0.3370	0.6270	0.1052	0.1382	0.8240	0.3052	0.2571	0.6965	0.6027	1				
SOYB	0.7114	0.4528	0.5666	0.3037	0.4920	0.0643	0.0342	0.6261	0.2143	0.1751	0.5604	0.9183	0.8244	1			
SUNF	0.2849	0.1669	0.0534	-0.0076	0.2429	0.1073	0.0656	0.1818	0.2773	0.0973	0.3869	0.1738	0.2670	0.2170	1		
TWEX	-0.2754	-0.2092	-0.3196	-0.2892	-0.3904	-0.2390	-0.4475	-0.4261	-0.0888	-0.2058	-0.5605	-0.2498	-0.5115	-0.3730	-0.2488	1	
OILP	0.2767	0.1559	0.2101	0.1999	0.3674	0.1313	0.2054	0.4318	0.2837	0.1370	0.5296	0.2623	0.5432	0.3697	0.2936	-0.5543	1

Correlation coefficient are for log return series.

Table 4.

Results for variance equation

Pre-crisis	CORN	SORG	WHET	SUGA	COCO	FISH	OLIO	PALO	PEAO	GRON	RAPO	SOYM	SOYO	SOYB	SUNF	OILP	TWEX
ω	-7.8057	-2.6271	-5.3372	-4.6337	-4.2804	-13.975	-2.2220	-2.4991	-7.3024	-0.9277	-0.6240	-2.9734	-12.205	-15.094	-5.0241	-1.5558	-2.5317
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.3444	-1.1647	-0.8914	1.8792	-1.0426	4.7247	-0.6022	-0.4399	-1.3388	86.1437	-0.5989	-0.3805	0.4313	1.9244	-0.3721	-0.5645	-0.4561
	(0.0200)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0159)	(0.0000)	(0.0191)	(0.0000)	(0.0010)	(0.0058)	(0.0000)	(0.0039)	(0.0000)	(0.0000)
γ	-0.2149	1.2731	1.2835	-0.7684	0.9197	-3.5317	0.6783	0.6042	1.7934	-68.798	0.2766	0.4446	-0.0435	0.2172	0.7784	0.4859	0.1773
	(0.0986)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0347)	(0.0000)	(0.0002)	(0.7536)	(0.0014)	(0.0000)	(0.0000)	(0.0005)
β	0.3635	0.7236	0.5199	0.6347	0.5292	-0.1822	0.8133	0.7432	0.3976	0.8956	0.9169	0.7262	-0.0817	-0.2642	0.5503	0.8161	0.8230
	(0.0266)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7360)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Post-crisis	**CORN**	**SORG**	**WHET**	**SUGA**	**COCO**	**FISH**	**OLIO**	**PALO**	**PEAO**	**GRON**	**RAPO**	**SOYM**	**SOYO**	**SOYB**	**SUNF**	**OILP**	**TWEX**
ω	-3.1704	-1.0511	-8.3547	-18,362	-1.2491	0.0016	-10.153	-11.613	-3.9850	-11.079	-2.0248	-19.543	-1.3043	-16.627	-0.1611	-4.0560	-30.853
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0017)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0027)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-1.0937	-0.5012	-1.5841	1.1744	-0.7841	-0.4881	-0.6670	-2.2534	-2.0953	-3.3564	1.5053	-1.0001	-0.3558	0.3599	4.1602	-0.6242	-0.8457
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0135)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0249)	(0.1285)	(0.0000)	(0.0046)	(0.0000)
γ	0.6050	-0.1046	1.5922	-0.6142	0.8558	0.1625	1.6369	2.1929	2.5613	3.1471	-0.9218	0.3225	0.7169	-0.5898	-4.6418	1.1693	0.5046
	(0.0000)	(0.0068)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0078)	(0.0000)	(0.0087)	(0.0000)	(0.0000)	(0.0000)
β	0.6285	0.8481	-0.0177	-0.7013	0.8563	0.1682	0.1716	-0.2607	0.6397	-0.1667	0.9043	-0.9900	0.8758	-0.5467	0.9718	0.5178	-0.9527
	(0.0000)	(0.0000)	(0.0116)	(0.0000)	(0.0000)	(0.0004)	(0.0782)	(0.0012)	(0.0000)	(0.0403)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0000)	(0.0000)	(0.0000)

Table 5.

Results for variance equation

Pre-crisis	CORN	SORG	WHET	SUGA	COCO	FISH	OLIO	PALO	PEAO	GRON	RAPO	SOYM	SOYO	SOYB	SUNF
ω	-8.5010	-9.1376	-3.4908	-5.0159	-4.3159	-9.3139	-12.061	-2.7808	-7.1369	-1.6163	-5.3827	-1.5303	-11.232	-14.928	-6.3133
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.6278)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.2754	0.2441	-0.9957	1.7600	-1.0215	5.0702	-0.6199	-0.4418	-1.2785	14.0424	-3.4473	-0.2084	0.5366	1.9533	-0.4719
	(0.0845)	(0.3517)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0028)	(0.0138)	(0.0000)	(0.1860)	(0.8654)	(0.0184)	(0.0043)	(0.0000)	(0.0048)
γ	-0.1491	-0.0510	1.2269	-0.6650	0.8995	-2.2547	0.7155	0.6195	1.7054	-12.378	4.9996	0.2316	-0.0282	0.2165	0.9200
	(0.2974)	(0.7855)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0003)	(0.0000)	(0.1951)	(0.8624)	(0.0116)	(0.8472)	(0.0016)	(0.0000)
β	0.2956	0.0105	0.6811	0.5853	0.5257	0.4059	0.0573	0.7192	0.4133	0.8928	0.0972	0.8560	0.0087	-0.2489	0.4298
	(0.0531)	(0.9325)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5649)	(0.0000)	(0.0000)	(0.0000)	(0.6261)	(0.0000)	(0.9649)	(0.0000)	(0.0000)
a	-0.0229	-0.1274	0.0456	-0.0174	-0.0163	0.3012	0.1449	0.0049	0.0048	0.0543	-0.0037	0.0056	-0.0336	-0.0296	-0.0384
	(0.1387)	(0.0000)	(0.0002)	(0.3555)	(0.1736)	(0.0000)	(0.0000)	(0.5718)	(0.6531)	(0.0037)	(0.9042)	(0.5878)	(0.2748)	(0.1536)	(0.0060)
b	-0.0095	-0.0935	-0.0091	-0.0088	0.01077	0.0083	-0.0018	0.0048	-0.0023	0.0465	-0.0509	-0.0129	0.0004	0.0025	-0.0019
	(0.4018)	(0.0000)	(0.0000)	(0.4222)	(0.0023)	(0.0039)	(0.8888)	(0.1237)	(0.7855)	(0.0000)	(0.0000)	(0.0000)	(0.9562)	(0.7074)	(0.7852)
Post-crisis	**CORN**	**SORG**	**WHET**	**SUGA**	**COCO**	**FISH**	**OLIO**	**PALO**	**PEAO**	**GRON**	**RAPO**	**SOYM**	**SOYO**	**SOYB**	**SUNF**
ω	-5.4839	-2.1589	-8.4093	-1.0450	-6.0688	-0.4962	-10.117	-8.3140	-0.4178	-8.4399	-11.945	-11.089	-11.408	-13.482	-9.4934
	(0.0000)	(0.0000)	(0.0000)	(0.0233)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-1.1478	-0.7224	-1.4686	-9.3694	-1.6401	-0.3311	-0.6588	-1.5894	-1.9668	-2.2815	2.1631	0.2335	1.0844	0.1733	9.5442
	(0.0015)	(0.0000)	(0.0000)	(0.8747)	(0.0000)	(0.0000)	(0.0204)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5556)	(0.0000)	(0.6390)	(0.0671)
γ	1.0909	-0.7611	1.4407	36.9697	1.4951	-0.2957	1.6172	1.7419	2.3632	1.9475	-1.6458	-0.6513	-0.4491	-0.3963	-8.1266
	(0.0034)	(0.0000)	(0.0000)	(0.5179)	(0.0000)	(0.0093)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0218)	(0.0809)	(0.1199)
β	0.4425	0.7197	0.0015	0.4624	0.35026	0.9267	0.2041	0.1445	0.9284	0.0941	0.1207	-0.0385	0.1014	-0.2152	0.2954
	(0.0000)	(0.0000)	(0.8085)	(0.0027)	(0.0003)	(0.0000)	(0.0072)	(0.0000)	(0.0000)	(0.2886)	(0.2234)	(0.8407)	(0.4330)	(0.1678)	(0.0000)
a	0.0531	0.0975	0.1131	0.0698	0.0497	-0.0726	0.2188	0.1181	0.1883	0.0964	0.2194	0.1347	0.2309	0.1444	1.0486
	(0.2028)	(0.0000)	(0.0008)	(0.1753)	(0.0980)	(0.0001)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0003)	(0.0031)	(0.0000)	(0.0180)	(0.0000)
b	0.0907	0.0304	-0.0722	0.0688	0.0917	0.0022	-0.1894	0.0480	-0.2479	-0.1859	-0.1542	0.0322	-0.0394	0.0521	0.2239
	(0.1143)	(0.0375)	(0.1223)	(0.3638)	(0.0698)	(0.9515)	(0.0100)	(0.4151)	(0.0000)	(0.0000)	(0.0157)	(0.6957)	(0.4369)	(0.4409)	(0.0000)

Table 6.

The results of VAR Granger causality tests

Pre-Crisis				**Post-Crisis**			
Null Hypothesis	Chi-Sq (Prob.)	Null Hypothesis	Chi-Sq (Prob.)	Null Hypothesis	Chi-Sq (Prob.)	Null Hypothesis	Chi-Sq (Prob.)
OILP $\nrightarrow$ CORN	0.3467 (0.8408)	TWEX $\nrightarrow$ CORN	0.1535 (0.9261)	OILP $\nrightarrow$ CORN	1.0187 (0.6009)	TWEX $\nrightarrow$ CORN	1.7977 (0.4070)
CORN $\nrightarrow$ OILP	3.3181 (0.1903)	CORN $\nrightarrow$ TWEX	1.6344 (0.4416)	CORN $\nrightarrow$ OILP	1.2134 (0.5451)	CORN $\nrightarrow$ TWEX	3.8145 (0.1485)
OILP $\rightarrow$ SORG	4.8844 (0.0870)	TWEX $\nrightarrow$ CORN	0.4384 (0.8031)	OILP $\nrightarrow$ SORG	0.3075 (0.8575)	TWEX $\nrightarrow$ CORN	1.2201 (0.5433)
SORG $\nrightarrow$ OILP	3.9471 (0.1390)	CORN $\nrightarrow$ TWEX	2.5387 (0.2810)	SORG $\nrightarrow$ OILP	4.1189 (0.1275)	CORN $\nrightarrow$ TWEX	3.2594 (0.1960)
OILP $\nrightarrow$ WHET	0.0170 (0.9915)	TWEX $\nrightarrow$ WHET	1.0393 (0.5947)	OILP $\nrightarrow$ WHET	0.2181 (0.8967)	TWEX $\nrightarrow$ WHET	0.3626 (0.8342)
WHET $\nrightarrow$ OILP	1.4383 (0.4872)	WHET $\nrightarrow$ TWEX	1.3031 (0.5212)	WHET $\rightarrow$ OILP	5.5798 (0.0614)	WHET $\nrightarrow$ TWEX	1.7947 (0.4077)
OILP $\nrightarrow$ SUGA	0.3851 (0.8249)	TWEX $\nrightarrow$ SUGA	2.5914 (0.2737)	OILP $\nrightarrow$ SUGA	3.9061 (0.1418)	TWEX $\nrightarrow$ SUGA	2.8863 (0.2362)
SUGA $\nrightarrow$ OILP	0.8720 (0.6466)	SUGA $\nrightarrow$ TWEX	0.0708 (0.9652)	SUGA $\nrightarrow$ OILP	0.1696 (0.9187)	SUGA $\nrightarrow$ TWEX	0.3650 (0.8332)
OILP $\rightarrow$ COCO	7.2333 (0.0269)	TWEX $\nrightarrow$ COCO	0.9349 (0.6266)	OILP $\rightarrow$ COCO	6.7075 (0.0350)	TWEX $\nrightarrow$ COCO	1.3341 (0.5132)
COCO $\nrightarrow$ OILP	0.0930 (0.9546)	COCO $\rightarrow$ TWEX	5.1642 (0.0756)	COCO $\nrightarrow$ OILP	0.3111 (0.8559)	COCO $\rightarrow$ TWEX	11.8200 (0.0027)
OILP $\nrightarrow$ FISH	0.8056 (0.6684)	TWEX $\nrightarrow$ FISH	3.0202 (0.2209)	OILP $\nrightarrow$ FISH	0.0113 (0.9943)	TWEX $\nrightarrow$ FISH	0.1938 (0.9077)
FISH $\nrightarrow$ OILP	1.1994 (0.5490)	FISH $\rightarrow$ TWEX	4.8642 (0.0879)	FISH $\nrightarrow$ OILP	0.2540 (0.8807)	FISH $\nrightarrow$ TWEX	0.4258 (0.8082)
OILP $\nrightarrow$ OLIO	0.9506 (0.6217)	TWEX $\nrightarrow$ OLIO	1.1847 (0.5530)	OILP $\nrightarrow$ OLIO	0.9629 (0.6179)	TWEX $\nrightarrow$ OLIO	1.3323 (0.5137)
OLIO $\nrightarrow$ OILP	0.0137 (0.9931)	OLIO $\nrightarrow$ TWEX	2.4818 (0.2891)	OLIO $\nrightarrow$ OILP	0.9214 (0.6308)	OLIO $\nrightarrow$ TWEX	2.5444 (0.2802)
OILP $\rightarrow$ PALO	13.0868 (0.0014)	TWEX $\nrightarrow$ PALO	1.0684 (0.5861)	OILP $\nrightarrow$ PALO	1.5303 (0.4653)	TWEX $\nrightarrow$ PALO	3.1776 (0.2042)
PALO $\nrightarrow$ OILP	3.7042 (0.1569)	PALO $\nrightarrow$ TWEX	2.7283 (0.2556)	PALO $\nrightarrow$ OILP	0.5131 (0.7737)	PALO $\rightarrow$ TWEX	9.5938 (0.0083)

$\nrightarrow$ *Means does not Granger Causality.*

Table 6 (Cont.)

Pre-Crisis				Post-Crisis			
Null Hypothesis	Chi-Sq (Prob.)	Null Hypothesis	Chi-Sq (Prob.)	Null Hypothesis	Chi-Sq (Prob.)	Null Hypothesis	Chi-Sq (Prob.)
OILP $\nrightarrow$ PEAO	1.4472 (0.4850)	TWEX $\nrightarrow$ PEAO	1.5473 (0.4613)	OILP $\nrightarrow$ PEAO	0.3132 (0.8550)	TWEX $\nrightarrow$ PEAO	0.6716 (0.7148)
PEAO $\nrightarrow$ OILP	1.0584 (0.5891)	PEAO $\nrightarrow$ TWEX	1.5247 (0.4666)	PEAO $\nrightarrow$ OILP	0.9769 (0.6136)	PEAO $\nrightarrow$ TWEX	0.6804 (0.7116)
OILP $\nrightarrow$ GRON	3.7078 (0.1566)	TWEX $\nrightarrow$ GRON	0.8121 (0.6663)	OILP $\nrightarrow$ GRON	0.4471 (0.7997)	TWEX $\nrightarrow$ GRON	1.0537 (0.5905)
GRON $\nrightarrow$ OILP	2.5740 (0.2761)	GRON $\nrightarrow$ TWEX	1.4128 (0.4934)	GRON $\nrightarrow$ OILP	1.1971 (0.5496)	GRON $\nrightarrow$ TWEX	0.2446 (0.8849)
OILP $\rightarrow$ RAPO	32.4428 (0.0000)	TWEX $\rightarrow$ RAPO	7.5830 (0.0226)	OILP $\nrightarrow$ RAPO	0.5973 (0.7418)	TWEX $\nrightarrow$ RAPO	0.6041 (0.7393)
RAPO $\rightarrow$ OILP	15.7186 (0.0004)	RAPO $\nrightarrow$ TWEX	0.3580 (0.8361)	RAPO $\rightarrow$ OILP	36.0679 (0.0000)	RAPO $\rightarrow$ TWEX	6.1323 (0.0466)
OILP $\nrightarrow$ SOYM	0.5558 (0.7574)	TWEX $\nrightarrow$ SOYM	0.8614 (0.6500)	OILP $\rightarrow$ SOYM	5.5629 (0.0619)	TWEX $\nrightarrow$ SOYM	2.5672 (0.2770)
SOYM $\nrightarrow$ OILP	4.3259 (0.1150)	SOYM $\nrightarrow$ TWEX	0.1751 (0.9162)	SOYM $\rightarrow$ OILP	7.3198 (0.0257)	SOYM $\rightarrow$ TWEX	4.9385 (0.0846)
OILP $\nrightarrow$ SOYO	0.2777 (0.8704)	TWEX $\nrightarrow$ SOYO	0.1236 (0.9400)	OILP $\rightarrow$ SOYO	11.3600 (0.0034)	TWEX $\nrightarrow$ SOYO	2.7597 (0.2516)
SOYO $\rightarrow$ OILP	6.2477 (0.0440)	SOYO $\nrightarrow$ TWEX	2.2596 (0.3231)	SOYO $\rightarrow$ OILP	13.9035 (0.0010)	SOYO $\rightarrow$ TWEX	115.3627 (0.0000)
OILP $\nrightarrow$ SOYB	1.2196 (0.5434)	TWEX $\nrightarrow$ SOYB	0.0813 (0.9602)	OILP $\rightarrow$ SOYB	10.3221 (0.0057)	TWEX $\nrightarrow$ SOYB	2.2089 (0.3314)
SOYB $\nrightarrow$ OILP	3.0141 (0.2216)	SOYB $\rightarrow$ TWEX	8.3418 (0.0154)	SOYB $\rightarrow$ OILP	5.7604 (0.0561)	SOYB $\rightarrow$ TWEX	11.2742 (0.0036)
OILP $\nrightarrow$ SUNF	0.1512 (0.9272)	TWEX $\nrightarrow$ SUNF	1.00125 (0.6062)	OILP $\nrightarrow$ SUNF	0.0586 (0.9711)	TWEX $\nrightarrow$ SUNF	0.0065 (0.9967)
SUNF $\nrightarrow$ OILP	0.8733 (0.6462)	SUNF $\nrightarrow$ TWEX	3.6516 (0.1611)	SUNF $\nrightarrow$ OILP	0.5589 (0.7562)	SUNF $\nrightarrow$ TWEX	0.1352 (0.9347)

$\nrightarrow$ *Means does not Granger Causality.*

Table 7. The Results of the Cumulative Effect of the Independent Variables of the VAR Model *F-statistics in [] and P-value in ()*

Pre-Crisis				Post-Crisis			
	CORN	**OILP**	**TWEX**		**CORN**	**OILP**	**TWEX**
CORN	0.0589 [0.4228] (0.5162)	0.0032 [0.0058] (0.9394)	-2.7474 [0.0141] (0.9057)	CORN	0.8373 [252.4334] (0.0000)	0.0052 [0.4336] (0.5117)	-38.5927 [1.6320] (0.2042)
OILP	-0.0904 [2.3508] (0.1266)	0.8179 [880.6884] (0.0000)	-22.1787 [2.1704] (0.1421)	OILP	0.3678 [0.1671] (0.6836)	0.1728 [1.6136] (0.2067)	1490.0956 [8.3425] (0.0047)
TWEX	-3.34E-05 [0.0956] (0.7574)	-1.2E-05 [0.0502] (0.8229)	0.9215 [1116.252] (0.0000)	TWEX	-0.0004 [1.8335] (0.1786)	0.0003 [50.1681] (0.0000)	-0.6182 [14.9524] (0.0002)
	SORG	**OILP**	**TWEX**		**SORG**	**OILP**	**TWEX**
SORG	0.2270 [7.0094] (0.0087)	0.1304 [3.5409] (0.0611)	18.5707 [0.2465] (0.6200)	SORG	0.9174 [564.7856] (0.0000)	0.0096 [0.30744] (0.5804)	-67.6282 [1.1184] (0.2926)
OILP	-0.0637 [5.3839] (0.0671)	0.8267 [871.7987] (0.0009)	-19.2714 [1.6271] (0.2034)	OILP	0.6161 [4.0868] (0.0457)	0.1249 [0.8260] (0.3654)	1653.0874 [10.7223] (.0014)
TWEX	-7.3E-06 [0.0135] (0.9076)	-8.9E-06 [0.0282] (0.8660)	0.9215 [1109.689] (0.0000)	TWEX	-0.0001 [2.1244] (0.1450)	0.0003 [46.8271] (0.0000)	-0.5901 [13.5201] (0.0004)
	WHET	**OILP**	**TWEX**		**WHET**	**OILP**	**TWEX**
WHET	0.1842 [4.8067] (0.0294)	-0.0098 [0.0170] (0.8963)	-9.8332 [0.0568] (0.8118)	WHET	0.3600 [8.4499] (0.0044)	-0.0151 [0.1486] (0.7007)	15.4722 [0.0113] (0.9156)
OILP	0.0044 [0.0201] (0.8875)	0.8184 [874.0791] (0.0000)	-22.0929 [2.1332] (0.1455)	OILP	0.2758 [0.4139] (0.5213)	0.1376 [1.0303] (0.3123)	1695.0885 [11.3006] (0.001)
TWEX	-1.7E-05 [0.0864] (0.7690)	-1.2E-05 [0.0628] (0.8023)	0.9212 [1112.369] (0.0000)	TWEX	0.0002 [1.6201] (0.2057)	0.0003 [41.9383] (0.0000)	-0.5344 [10.8300] (0.0013)
	SUGA	**OILP**	**TWEX**		**SUGA**	**OILP**	**TWEX**
SUGA	0.0232 [0.0636] (0.8010)	-1.5589 [0.3698] (0.5437)	1406.256 [0.9953] (0.3195)	SUGA	0.2934 [4.2999] (0.0405)	-0.0570 [3.8977] (0.0509)	168.1889 [2.5012] (0.1167)
OILP	-0.0008 [0.5970] (0.4405)	0.8171 [867.6228] (0.0000)	-20.5711 [1.8190] (0.1788)	OILP	-0.2635 [0.1536] (0.6959)	0.1817 [1.7544] (0.1881)	1480.1566 [8.5852] (0.0041)
TWEX	1.67E-07 [0.0083] (0.9272)	-1.2E-05 [0.0536] (0.8175)	0.9209 [1090.379] (0.0000)	TWEX	2.88E-05 [0.0183] (0.8926)	0.0003 [45.3315] (0.0000)	-0.5561 [12.0643] (0.0007)
	COCO	**OILP**	**TWEX**		**COCO**	**OILP**	**TWEX**
COCO	0.6792 [144.4770] (0.0000)	0.1008 [7.2105] (0.0078)	4.2196 [0.0484] (0.8261)	COCO	0.8634 [263.6105] (0.0000)	-0.0109 [1.0836] (0.3002)	-42.3835 [1.0758] (0.3019)
OILP	0.0078 [0.0274] (0.8680)	0.8157 [680.5846] (0.0000)	-23.1980 [2.1014] (0.1485)	OILP	-0.2979 [0.1859] (0.6672)	01764 [1.6503] (0.2017)	1491.4273 [7.8912] (0.0059)
TWEX	0.0002 [4.7668] (0.0300)	-6.9E-05 [1.4977] (0.2223)	0.9031 [977.1119] (0.0000)	TWEX	0.0004 [3.43905] (0.0664)	0.0003 [46.3801] (0.0000)	-0.5296 [10.9381] (0.0013)
	FISH	**OILP**	**TWEX**		**FISH**	**OILP**	**TWEX**
FISH	0.4104 [20.0987] (0.0000)	-10.6316 [0.0505] (0.8224)	45843.38 [2.9818] (0.0856)	FISH	0.4214 [16.6886] (0.0001)	-0.0009 [0.0004] (0.9843)	-82.3985 [0.1937] (0.6607)
OILP	1.68E-05 [0.0976] (0.7550)	0.8188 [873.0400] (0.0000)	-22.2696 [2.0507] (0.01535)	OILP	0.0860 [0.0945] (0.7591)	0.1798 [1.7292] (0.1913)	1468.3781 [8.3639] (0.0046)
TWEX	1.867E-07 [3,6954] (0.0558)	-7.1E-06 [0.0198] (0.8881)	0.9107 [1045.593] (0.0000)	TWEX	-5.095E-05 [0.3375] (0.561)	0.0003 [47.7594] (0.0000)	-0.5675 [12.7233] (0.0005)
	OLIO	**OILP**	**TWEX**		**OLIO**	**OILP**	**TWEX**
OLIO	0.2444 [8.2274] (0.0045)	-0.0145 [0.8056] (0.3704)	-8.9379 [1.0281] (0.3117)	OLIO	-0.0596 [0.1879] (0.6655)	0.0341 [0.8358] (0.3627)	-158.0375 [1.3012] (0.2565)
OILP	0.0072 [0.0023] (0.9612)	0.8181 [860.0487] (0.0000)	-21.9712 [2.0724] (0.1514)	OILP	-0.1177 [0.0545] (0.8158)	0.1756 [1.6487] (0.2019)	1487.5178 [8.5772] (0.0042)
TWEX	0.0002 [0.4719] (0.4928)	-9E-06 [0.0321] (0.8580)	0.9234 [1110.691] (0.0000)	TWEX	-0.0002 [1.1055] (0.2954)	0.0003 [49.4359] (0.0000)	-0.5684 [12.9262] (0.0005)

Table 7 (Cont.)

Pre-Crisis				Post-Crisis			
	PALO	**OILP**	**TWEX**		**PALO**	**OILP**	**TWEX**
PALO	0.7253 [194.6725] (0.0000)	-0.0521 [0.7002] (0.4036)	26.1170 [0.5459] (0.4608)	PALO	-0.3223 [4.8158] (0.0303)	0.0123 [0.2441] (0.6222)	74.4663 [0.6426] (0.4245)
OILP	0.0021 [0.0086] (0.9261)	0.8145 [871.1194] (0.0000)	-23.4448 [2.2360] (0.1362)	OILP	0.4656 [0.3070] (0.5806)	0.1422 [0.9942] (0.3209)	1590.4838 [8.9579] (0.0034)
TWEX	4.61E-05 [1.1897] (0.2765)	-9E-06 [0.0296] (0.8636)	0.9137 [1014.888] (0.0000)	TWEX	-0.0001 [0.3321] (0.5657)	0.0003 [39.5039] (0.0000)	-0.4385 [7.3339] (0.0079)
	PEAO	**OILP**	**TWEX**		**PEAO**	**OILP**	**TWEX**
PEAO	0.0365 [0.1616] (0.6881)	-0.1571 [1.3032] (0.2548)	59.8147 [0.6314] (0.4277)	PEAO	0.01504 [0.0127] (0.9104)	0.6753 [0.0735] (0.7869)	-5823.509 [0.3916] (0.5328)
OILP	-0.0149 [0.6638] (0.4160)	0.8164 [865.1056] (0.0000)	-21.2563 [1.9603] (0.1628)	OILP	-0.0028 [0.1609] (0.6891)	0.1685 [1.5540] (0.2152)	1509.5852 [8.9405] (0.0034)
TWEX	-3.4E-05 [1.0265] (0.3120)	-1.6E-05 [0.0939] (0.7595)	0.9239 [1113.894] (0.0000)	TWEX	1.072E-06 [0.2206] (0.6395)	0.0003 [46.2264] (0.0000)	-0.5438 [11.5411] (0.0010)
	GRON	**OILP**	**TWEX**		**GRON**	**OILP**	**TWEX**
GRON	0.2813 [12.2249] (0.0006)	39585.98 [2.6358] (0.1059)	-7789771 [0.3395] (0.5607)	GRON	-0.0359 [0.0744] (0.7856)	-0.01024 [0.4466] (0.5053)	44.62968 [0.6126] (0.4355)
OILP	1.392E-07 [2.3333] (0.1280)	0.81667 [874.5106] (0.0000)	-20.429372 [1.8202] (0.1786)	OILP	-1.0155 [0.7652] (0.3836)	0.1802 [1.7789] (0.1851)	1463.42 [8.4562] (0.0044)
TWEX	-7.06E-11 [0.1781] (0.6734)	-1.07E-05 [0.0444] (0.8332)	0.921523 [1105.914] (0.0000)	TWEX	0.0001 [0.1438] (0.7053)	0.0003 [46.4679] (0.0000)	-0.5571 [12.1282] (0.0005)
	RAPO	**OILP**	**TWEX**		**RAPO**	**OILP**	**TWEX**
RAPO	0.7083 [403.4042] (0.0000)	0.5522 [31.0141] (0.0000)	123.7266 [7.5634] (0.0064)	RAPO	0.5627 [28.0972] (0.0000)	0.0115 [0.1388] (0.7102)	-67.8154 [0.3387] (0.5618)
OILP	-0.0442 [12.4919] (0.0005)	0.8511 [586.5187] (0.0000)	-4.7805 [0.08988] (0.7646)	OILP	1.8417 [20.5501] (0.0000)	0.1956 [2.7446] (0.1005)	972.9851 [4.7605] (0.0313)
TWEX	-1.396E-05 [0.3509] (0.5542)	-3.33E-05 [0.2545] (0.6144)	0.914343 [924.6510] (0.0000)	TWEX	0.0003 [3.2667] (0.0735)	0.0003 [46.0568] (0.0000)	-0.5510 [12.0189] (0.0008)
	SOYM	**OILP**	**TWEX**		**SOYM**	**OILP**	**TWEX**
SOYM	0.7268 [222.9279] (0.0000)	-0.0059 [0.2272] (0.6340)	-1.1736 [0.0297] (0.8633)	SOYM	0.2361 [2.5824] (0.1110)	0.0136 [0.3019] (0.5838)	-142.4506 [2.4006] (0.1242)
OILP	0.1556 [2.0852] (0.1501)	0.8168 [880.8755] (0.0000)	-19.6024 [1.6918] (0.1947)	OILP	1.5078 [3.6370] (0.0591)	0.2367 [3.1466] (0.0789)	1245.4345 [6.3362] (0.0133)
TWEX	-7.32E-05 [0.1357] (0.7129)	-1.12E-05 [0.0488] (0.8253)	0.9208 [1100.328] (0.0000)	TWEX	0.0004 [2.2287] (0.1384)	0.0003 [43.9236] (0.0000)	-0.5471 [11.9435] (0.0008)
	SOYO	**OILP**	**TWEX**		**SOYO**	**OILP**	**TWEX**
SOYO	-0.0621 [0.4066] (0.5244)	0.0076 [0.1635] (0.6863)	3.23312 [0.0994] (0.7529)	SOYO	0.8275 [23.6846] (0.0000)	-0.0782 [11.2198] (0.0011)	143.9212 [2.3416] (0.1289)
OILP	-0.2132 [2.2446] (0.1355)	0.8207 [894.9116] (0.0000)	-20.6405 [1.8979] (0.1697)	OILP	3.8730 [10.8847] (0.0013)	-0.1891 [1.3769] (0.2432)	766.181 [1.3924] (0.2406)
TWEX	-4.1E-05 [0.0242] (0.8764)	-7.7E-06 [0.0234] (0.8786)	0.921769 [1116.634] (0.0000)	TWEX	0.0011 [16.3205] (0.0001)	0.0001 [10.8956] (0.0013)	-0.2784 [3.3480] (0.0700)
	SOYB	**OILP**	**TWEX**		**SOYB**	**OILP**	**TWEX**
SOYB	-0.0103 [0.0119] (0.9132)	--7.336 [0.0983] (0.7542)	-2295.3280 [0.0379] (0.8456)	SOYB	-09266 [29.3711] (0.0000)	0.0125 [8.4581] (0.0044)	10.6241 [0.3842] (0.5367)
OILP	-1.53E-05 [0.0157] (0.9004)	0.8073 [719.7180] (0.0000)	-23.7599 [2.4622] (0.1180)	OILP	-9.9504 [3.5169] (0.0634)	01509 [1.2869] (0.2591)	1947.125 [13.3998] (0.0004)
TWEX	-4.5069 [4.1890] (0.0418)	-1.49E-05 [0.0756] (0.7836)	0.9226 [1135.135] (0.0000)	TWEX	-0.0037 [5.2754] (0.0236)	0.0003 [46.76402] (0.0000)	-0.3633 [4.8587] (0.0275)
	SUNF	**OILP**	**TWEX**		**SUNF**	**OILP**	**TWEX**
SUNF	0.0022 [0.0005] (0.9816)	-0.5951 [0.0028] (0.9574)	6061.454 [0.9808] (0.3230)	SUNF	0.9189 [15840.41] (0.0000)	0.1351 [0.0382] (0.8455)	-151.0653 [0.0035] (0.9531)
OILP	-0.0002 [0.7139] (0.3990)	0.8182 [871.6031] (0.0000)	-20.5511 [1.8192] (0.1787)	OILP	-0.0002 [0.0273] (0.8691)	0.1695 [1.5624] (0.2140)	1472.9989 [8.5886] (0.0041)
TWEX	4.977E-07 [1.3930] (0.2391)	-1.02E-05 [0.0408] (0.8400)	0.917575 [1101.580] (0.0000)	TWEX	1E-07 [0.0487] (0.8258)	0.0003 [46.2794] (0.0000)	-0.5577 [12.2335] (0.0007)

***.** *F-statistics in [] and P-value in ().*

Table 8. The Short- and Long-run Granger - Causality Tests Based on VECM Model

Dependent Variable	Pre-crisis time period							Post-crisis time period						
	Short - run			Long - run	Joint (Short - run/Long - run)			Short - run			Long - run	Joint (Short - run/Long - run)		
	CORN	OILP	TWEX	ECT (-1)	CORN, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	CORN	OILP	TWEX	ECT (-1)	CORN, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
CORN	-	0.2006	0.2679	73.1480	66.0629	24.3970	24.7116	-	0.9330	0.8034	1.5283	0.5202	0.6383	1.0302
	(-)	(0.818)	(0.7652)	(0.0000)	(0.0000)	(0.00000)	(0.0000)	(-)	(0.3966)	(0.4505)	(0.2191)	(0.6693)	(0.5920)	(0.3824)
OILP	2.2544	-	0.7935	1.0651	1.6825	0.6678	0.9082	0.4387	-	0.9118	0.1213	0.3308	6.9838	7.0491
	(0.1073)	(-)	(0.4535)	(0.3032)	(0.1716)	(0.5726)	(0.4378)	(0.6460)	(-)	(0.4050)	(0.7283)	(0.8031)	(0.0002)	(0.0002)
TWEX	0.4182	0.2434	-	0.5971	0.7446	0.3480	0.2692	0.4434	4.589	-	43.5071	14.9200	54.2719	115.7575
	(0.6587)	(0.7841)	(-)	(0.4405)	(0.5265)	(0.7906)	(0.8455)	(0.6430)	(0.0123)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	SORG	OILP	TWEX	ECT (-1)	SORG, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	SORG	OILP	TWEX	ECT (-1)	GRON, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
SORG	-	0.4389	0.1129	40.9117	50.2659	13.7439	13.8273	-	0.3859	0.9676	0.2869	0.4584	0.3012	0.8056
	(-)	(0.6453)	(0.8932)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.6808)	(0.3833)	(0.5933)	(0.7119)	(0.8245)	(0.4934)
OILP	6.1250	-	0.7513	19.8690	7.0393	6.9999	7.1699	1.4388	-	0.6349	0.4172	1.0921	6.4762	7.4746
	(0.0026)	(-)	(0.4729)	(0.0000)	(0.0002)	(0.0002)	(0.0001)	(0.2418)	(-)	(0.5319)	(0.5197)	(0.3558)	(0.0005)	(0.0001)
TWEX	0.3901	0.2044	-	0.5536	1.0169	0.3056	0.2721	0.3075	4.3215	-	43.5730	14.9508	51.3866	118.7929
	(0.6775)	(0.8153)	(-)	(0.4576)	(0.3859)	(0.8213)	(0.8455)	(0.7359)	(0.0157)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	WHET	OILP	TWEX	ECT (-1)	WHET, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	WHET	OILP	TWEX	ECT (-1)	RAPO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
WHET	-	0.3171	0.7012	65.4116	49.9114	21.8829	22.6327	-	0.4681	1.0243	0.3523	19.6089	0.4293	0.6894
	(-)	(0.7285)	(0.4970)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.6275)	(0.3636)	(0.5541)	(0.0000)	(0.7324)	(0.5605)
OILP	1.8211	-	0.6262	1.9771	1.2151	1.0116	1.1206	3.1197	-	4.1331	0.6759	2.3856	7.3173	9.0423
	(0.1642)	(-)	(0.5355)	(0.1611)	(0.3050)	(0.3883)	(0.3415)	(0.0482)	(-)	(0.0187)	(0.4128)	(0.0732)	(0.0002)	(0.0000)
TWEX	1.0628	0.3136	-	1.4410	1.1336	0.6812	0.5653	1.1154	8.9139	-	39.3456	15.95267	47.8581	118.7024
	(0.3472)	(0.7311)	(-)	(0.2312)	(0.3362)	(0.5643)	(0.6384)	(0.3316)	(0.0003)	(-)	(0.0009)	(0.0000)	(0.0000)	(0.0000)
	SUGA	OILP	TWEX	ECT (-1)	SUGA, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	SUGA	OILP	TWEX	ECT (-1)	SOYM, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
SUGA	-	0.4489	0.6389	72.1298	69.4433	25.293	25.6154	-	1.2046	0.9136	0.9748	51.2254	0.8089	0.6264
	(-)	(0.6389)	(0.5029)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.3039)	(0.4042)	(0.3257)	(0.0000)	(0.4916)	(0.5995)
OILP	1.1829	-	0.6515	2.7002	1.0581	1.2331	1.2848	0.3120	-	2.5034	0.1866	0.2286	6.8236	6.7763
	(0.3082)	(-)	(0.5222)	(0.1017)	(0.3677)	(0.2985)	(0.2804)	(0.7326)	(-)	(0.0866)	(0.6671)	(0.8762)	(0.0003)	(0.0003)
TWEX	0.7628	0.2774	-	0.7321	0.5089	0.4253	0.3018	9.7240	6.9290	-	50.2813	18.2776	49.9565	130.2357
	(0.4675)	(0.7580)	(-)	(0.3931)	(0.6765)	(0.7350)	(0.8240)	(0.0001)	(0.0015)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

**. All figures are the calculated F statistics, P-values in ().*

Table 8 (Cont.)

Dependent Variable	Pre-crisis time period							Post-crisis time period						
	Short - run			Long - run	Joint (Short - run/Long - run)			Short - run			Long - run	Joint (Short - run/Long - run)		
	COCO	OILP	TWEX	ECT (-1)	COCO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	COCO	OILP	TWEX	ECT (-1)	COCO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
COCO	-	3.6292	2.3893	5.0356	7.8608	4.4575	3.0416	-	5.5840	3.2347	4.0005	1.8554	5.6286	2.1815
	(-)	(0.0281)	(0.0940)	(0.0258)	(0.0000)	(0.0046)	(0.0298)	(-)	(0.0049)	(0.0433)	(0.0479)	(0.1416)	(0.0013)	(0.0945)
OILP	8.1966	-	1.2022	45.8053	17.0933	15,7855	15.7537	0.2200	-	0.4882	0.3939	0.2629	6.2572	6.3897
	(0.0004)	(-)	(0.3024)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8028)	(-)	(0.6151)	(0.5316)	(0.8520)	(0.0006)	(0.0005)
TWEX	0.2601	0.1425	-	4.5159	2.1672	1.6500	1.5458	2.3105	3.3176	-	38.5196	17.5622	41.9001	123.2396
	(0.7712)	(0.8673)	(-)	(0.0347)	(0.0927)	(0.1787)	(0.2035)	(0.1042)	(0.0400)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	FISH	OILP	TWEX	ECT (-1)	FISH, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	FISH	OILP	TWEX	ECT (-1)	FISH, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
FISH	-	0.6838	0.2471	15.6697	93.5938	5.6808	5.5024	-	0.2531	0.2433	0.4237	7.4621	0.2359	0.1833
	(-)	(0.5057)	(0.7812)	(0.0001)	(0.0000)	(0.0000)	(0.0012)	(-)	(0.77690	(0.7844)	(0.5165)	(0.0001)	(0.8711)	(0.9075)
OILP	12.9995	-	1.4148	31.5972	11.8752	10.8522	11.0049	0.2917	-	1.5100	0.0014	0.2035	6.6035	6.9885
	(0.0000)	(-)	(0.2451)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7476)	(-)	(0.2257)	(0.9698)	(0.8937)	(0.0004)	(0.0002)
TWEX	4.6909	0.1849	-	8.7295	3.6523	3.0238	2.9625	0.5229	5.5839	-	42.4432	14.2175	53.4708	114.7432
	(0.0101)	(0.8313)	(-)	(0.0035)	(0.0133)	(0.0305)	(0.0330)	(0.5943)	(0.0050)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	OLIO	OILP	TWEX	ECT (-1)	OLIO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	OLIO	OILP	TWEX	ECT (-1)	OLIO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
OLIO	-	0.3333	0.3457	42.7196	52.5252	14.3346	14.2597	-	0.8708	2.0427	4.2908	19.2794	1.5667	1.6927
	(-)	(0.7168)	(0.7081)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.4216)	(0.1348)	(0.0408)	(0.0000)	(0.2018)	(0.1731)
OILP	2.2482	-	0.7354	7.3784	2.4856	2.8050	2.8534	0.4363	-	2.0669	0.0314	0.3674	6.6398	7.4638
	(0.1079)	(-)	(0.4804)	(0.0071)	(0.6150)	(0.0406)	(0.0381)	(0.6476)	(-)	(0.1317)	(0.8597)	(0.7767)	(0.0004)	(0.0001)
TWEX	0.7535	0.2804	-	0.0463	0.6561	0.2008	0.0560	1.4649	5.3705	-	38.7249	13.6804	52.4402	108.2511
	(0.4719)	(0.7557)	(-)	(0.8298)	(0.5799)	(0.8957)	(0.9825)	(0.2358)	(0.0060)	(-)	(0.0000)	(0.0000)	(0.0009)	(0.0000)
	PALO	OILP	TWEX	ECT (-1)	PALO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	PALO	OILP	TWEX	ECT (-1)	PALO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
PALO	-	7.4991	0.2932	0.6596	11.6401	5.1567	0.4466	-	12.2824	13.5203	25.5905	52.754	9.5238	10.7446
	(-)	(0.0007)	(0.7462)	(0.4175)	(0.0000)	(0.0018)	(0.7199)	(-)	(0.00000	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
OILP	1.2901	-	1.2703	47.1432	16.8192	15.8378	16.3256	5.4933	-	0.6017	13.6102	4.6115	11.8842	11.43911
	(0.2773)	(-)	(0.2827)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0054)	(-)	(0.5497)	(0.0004)	(0.0045)	(0.0000)	(0.0000)
TWEX	1.5859	0.4100	-	1.3889	1.6455	0.7602	0.4793	2.8199	21.9594	-	0.1926	4.2368	31.9866	79.6942
	(0.2070)	(0.6641)	(-)	(0.2398)	(0.1797)	(0.5175)	(0.6969)	(0.0641)	(0.0000)	(-)	(0.6616)	(0.0072)	(0.0000)	(0.0000)

*. *All figures are the calculated F statistics, P-values in ().*

Table 8 (Cont.)

Dependent Variable	Pre-crisis time period							Post-crisis time period						
	Short - run			Long - run	Joint (Short - run/Long - run)			Short - run			Long - run	Joint (Short - run/Long - run)		
	PEAO	OILP	TWEX	ECT (-1)	PEAO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	PEAO	OILP	TWEX	ECT (-1)	PEAO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
PEAO	-	0.6746	0.4598	78.7071	68.1484	26.2999	27.1511	-	1.0038	0.6832	2.6243	16.9389	1.0238	1.0705
	(-)	(0.5103)	(0.6320)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.3699)	(0.5072)	(0.1082)	(0.0000)	(0.3851)	(0.3648)
OILP	0.9193	-	0.6541	1.2914	0.7826	0.7751	0.8743	0.4542	-	3.0635	0.4051	0.3724	6.9905	7.3232
	(0.4003)	(-)	(0.5209)	(0.2570)	(0.5047)	(0.5090)	(0.4551)	(0.6362)	(-)	(0.0508)	(0.5258)	(0.7731)	(0.0002)	(0.0002)
TWEX	0.1042	0.2255	-	1.3675	0.6759	0.5946	0.4850	4.3443	8.1617	-	35.7184	12.5054	49.5076	110.4059
	(0.9011)	(0.7983)	(-)	(0.2435)	(0.5676)	(0.6191)	(0.6930)	(0.0153)	(0.0005)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	GRON	OILP	TWEX	ECT (-1)	GRON, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	GRON	OILP	TWEX	ECT (-1)	GRON, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
GRON	-	0.6381	1.1389	50.4111	38.2156	17.5481	17.4710	-	3.7183	5.7303	13.8496	21.3388	5.2244	4.7558
	(-)	(0.5293)	(0.3220)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.0275)	(0.0043)	(0.0003)	(0.0000)	(0.0021)	(0.0037)
OILP	5.6331	-	0.6510	23.4548	7.9545	8.2581	8.2505	1.0596	-	8.1792	3.2088	1.4154	7.8914	8.1609
	(0.0041)	(-)	(0.5225)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3502)	(-)	(0.0005)	(0.0761)	(0.2423)	(0.0001)	(0.0001)
TWEX	0.6676	0.0536	-	0.3713	0.6817	0.1640	0.1609	9.2382	19.2959	-	27.8823	9.8370	44.4130	104.5522
	(0.5139)	(0.9478)	(-)	(0.5429)	(0.5640)	(0.9205)	(0.9225)	(0.0002)	(0.0000)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	RAPO	OILP	TWEX	ECT (-1)	RAPO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	RAPO	OILP	TWEX	ECT (-1)	RAPO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
RAPO	-	2.7994	0.5977	90.4273	37.9654	39.9424	30.4541	-	0.7924	0.0477	0.1892	13.3843	0.6178	0.2208
	(-)	(0.0630)	(0.5509)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.4554)	(0.9534)	(0.6645)	(0.0000)	(0.6049)	(0.8817)
OILP	13.2788	-	0.6838	74.2218	24.8385	25.1558	25.2651	19.6586	-	6.5279	3.9398	14.2378	4.9517	6.9524
	(0.0000)	(-)	(0.5057)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.0021)	(0.0497)	(0.0000)	(0.0030)	(0.0003)
TWEX	0.1466	0.2292	-	0.1248	0.3753	0.1772	0.0868	0.5407	11.5501	-	46.8006	18.5979	55.2814	122.6377
	(0.8637)	(0.7953)	(-)	(0.7242)	(0.7708)	(0.9118)	(0.9672)	(0.5839)	(0.0000)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	SOYM	OILP	TWEX	ECT (-1)	SOYM, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	SOYM	OILP	TWEX	ECT (-1)	SOYM, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
SOYM	-	0.0136	2.7218	4.3037	4.2486	1.4378	3.4471	-	0.8882	2.0672	0.2447	56.2519	2.1809	1.6334
	(-)	(0.9865)	(0.0679)	(0.0392)	(0.0000)	(0.2325)	(0.0175)	(-)	(0.4144)	(0.1316)	(0.6218)	(0.0000)	(0.0945)	(0.1860)
OILP	5.9387	-	1.2030	44.9726	16.0257	15.3292	15.5631	1.4936	-	2.7079	0.4752	2.3770	5.6716	5.2784
	(0.0031)	(-)	(0.3022)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2292)	(-)	(0.0712)	(0.4921)	(0.0740)	(0.0012)	(0.0020)
TWEX	0.6281	0.1293	-	0.2822	0.5743	0.1803	0.1438	10.1169	5.7134	-	43.5545	15.5579	49.8871	108.6068
	(0.5345)	(0.8787)	(-)	(0.5958)	(0.6325)	(0.9096)	(0.9355)	(0.0001)	(0.0044)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

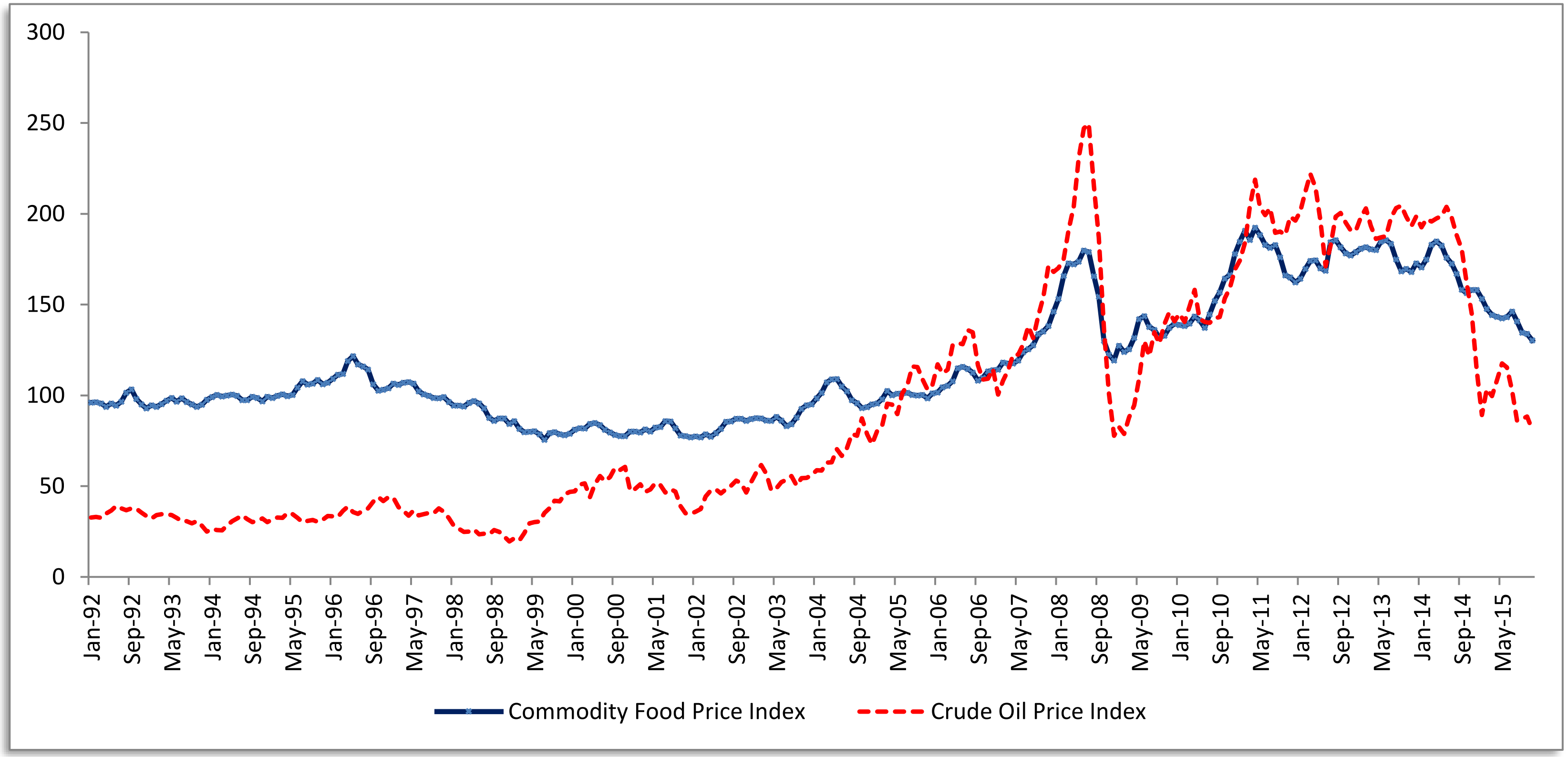
**. All figures are the calculated F statistics, P-values in ().*

Table 8 (Cont.)

Dependent Variable	Pre-crisis time period							Post-crisis time period						
	Short - run			Long - run	Joint (Short - run/Long - run)			Short - run			Long - run	Joint (Short - run/Long - run)		
	SOYO	OILP	TWEX	ECT (-1)	SOYO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	SOYO	OILP	TWEX	ECT (-1)	SOYO, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
SOYO	-	0.6128	0.0982	91.4751	87.0938	31.6226	30.5781	-	4.3361	0.2818	0.0018	0.0507	3.4342	1.0722
	(-)	(0.5428)	(0.9065)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.01550	(0.7550)	(0.9660)	(0.9848)	(0.0196)	(0.3642)
OILP	0.6748	-	0.5417	0.1035	2.1659	0.3794	0.3987	9.7830	-	0.2605	0.9647	6.6373	13.5490	1.1582
	(0.5102)	(-)	(0.5825)	(0.7480)	(0.0929)	(0.7679)	(0.7540)	(0.0001)	(-)	(0.7711)	(0.3282)	(0.0004)	(0.0000)	(0.3293)
TWEX	1.0124	0.2273	-	0.3110	1.1073	0.2482	0.1648	39.2384	9.4285	-	40.6895	76.9363	18.3564	173.5960
	(0.3650)	(0.7969)	(-)	(0.5776)	(0.3469)	(0.8625)	(0.9200)	(0.0000)	(0.0002)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	SOYB	OILP	TWEX	ECT (-1)	SOYB, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	SOYB	OILP	TWEX	ECT (-1)	SOYB, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
SOYB	-	0.8773	0.6653	74.3442	72.6670	25.3441	25.6702	-	2.3532	0.9115	87.7552	96.0823	38.982	31.9786
	(-)	(0.4173)	(0.5151)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.1000)	(0.4050)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
OILP	1.8805	-	1.2993	1.5359	2.1323	0.8102	1.3382	1.0167	-	10.5620	0.0007	2.1722	6.8352	7.0926
	(0.1549)	(-)	(0.2748)	(0.2165)	(0.0970)	(0.4894)	(0.2627)	(0.3653)	(-)	(0.0001)	(0.9792)	(0.0956)	(0.0003)	(0.0002)
TWEX	0.1327	0.1787	-	3.8683	2.8367	1.4064	1.3831	5.5914	18.4157	-	23.0716	10.6337	44.7650	59.3574
	(0.8758)	(0.8364)	(-)	(0.0504)	(0.0389)	(0.2417)	(0.2487)	(0.0049)	(0.0000)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	SUNF	OILP	TWEX	ECT (-1)	SUNF, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)	SUNF	OILP	TWEX	ECT (-1)	SUNF, ECT (-1)	OILP, ECT (-1)	TWEX, ECT (-1)
SUNF	-	1.0400	0.6545	76.4976	74.1049	25.9647	25.9128	-	0.0095	0.0123	0.0659	86.4565	0.0376	0.0482
	(-)	(0.3551)	(0.5207)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.9905)	(0.9877)	(0.7979)	(0.0000)	(0.9902)	(0.9859)
OILP	0.3133	-	0.6291	0.0016	0.3649	0.3441	0.4194	0.1573	-	2.1533	0.0911	0.1339	6.3410	7.0390
	(0.7313)	(-)	(0.5340)	(0.9677)	(0.7783)	(0.7935)	(0.7392)	(0.8546)	(-)	(0.1211)	(0.7634)	(0.9396)	(0.0003)	(0.0002)
TWEX	2.0456	0.1498	-	1.2385	1.36606	0.5237	0.4917	1.7745	6.5284	-	44.8418	16.0649	55.6073	122.1656
	(0.1317)	(0.8609)	(-)	(0.2669)	(0.2540)	(0.6664)	(0.6883)	(0.1745)	(0.0021)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

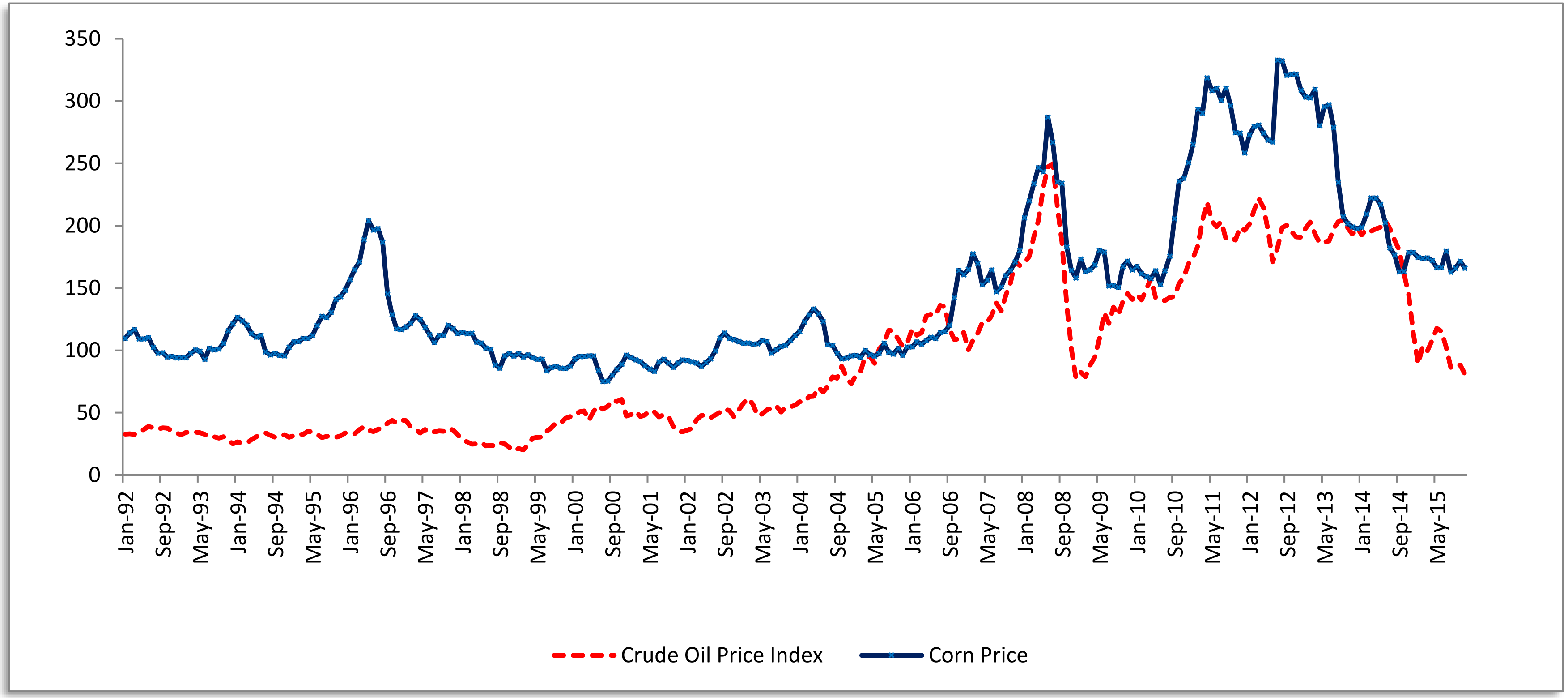
**. All figures are the calculated F statistics, P-values in ().*

Figure 1. Commodity Food Price Index vs. Oil price Index, 1992m01-2015m11



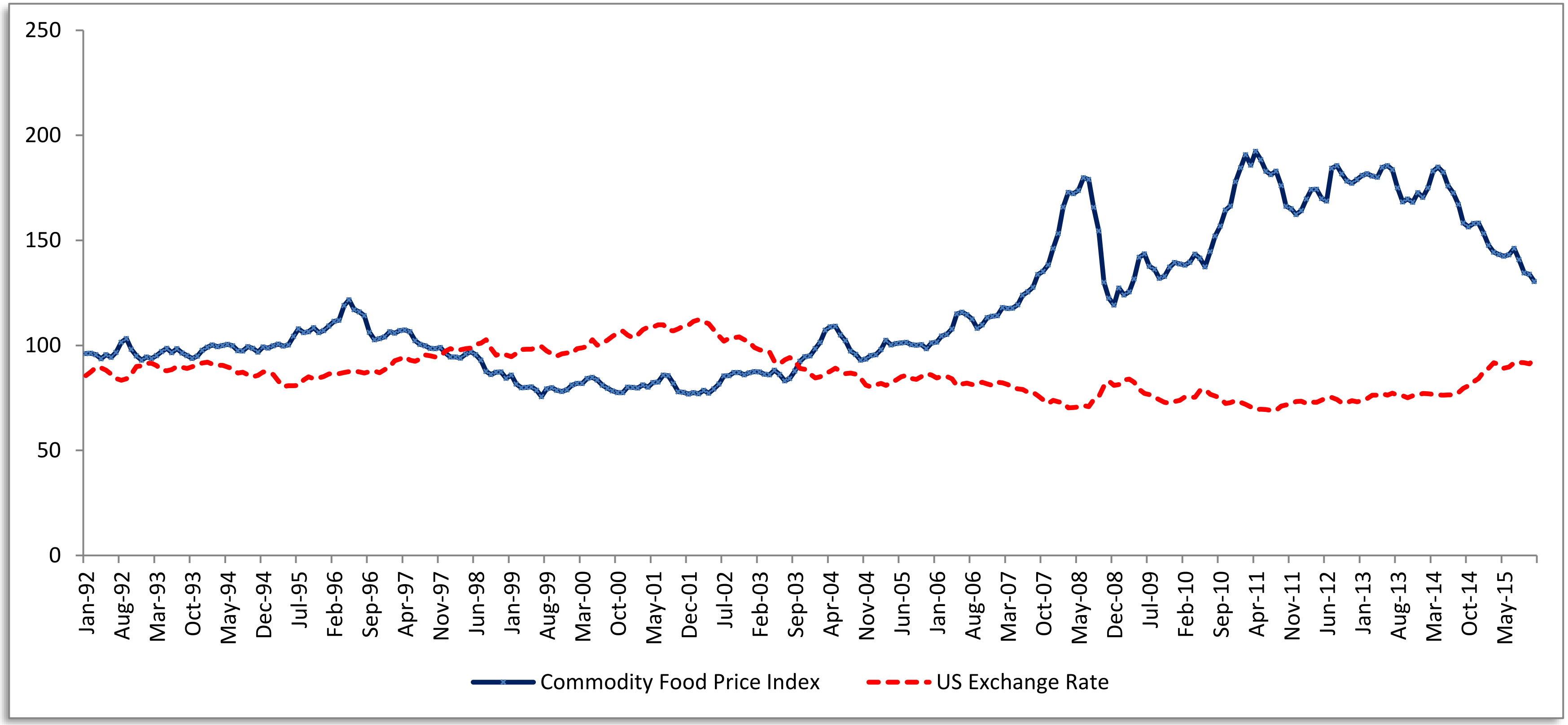
Source: www.indexmundi.com

Figure 2. Corn Price vs. Oil price Index, 1992m01-2015m11



Source: www.indexmundi.com

Figure 3. Commodity Food Price Index vs. US Dollar Exchange Rate 1992m01-2015m11



Source: www.indexmundi.com, https://research.stlouisfed.org

Figure 4. The Clustering of Volatility from the Squared Returns Trend [for Pre-Crisis Time Period]

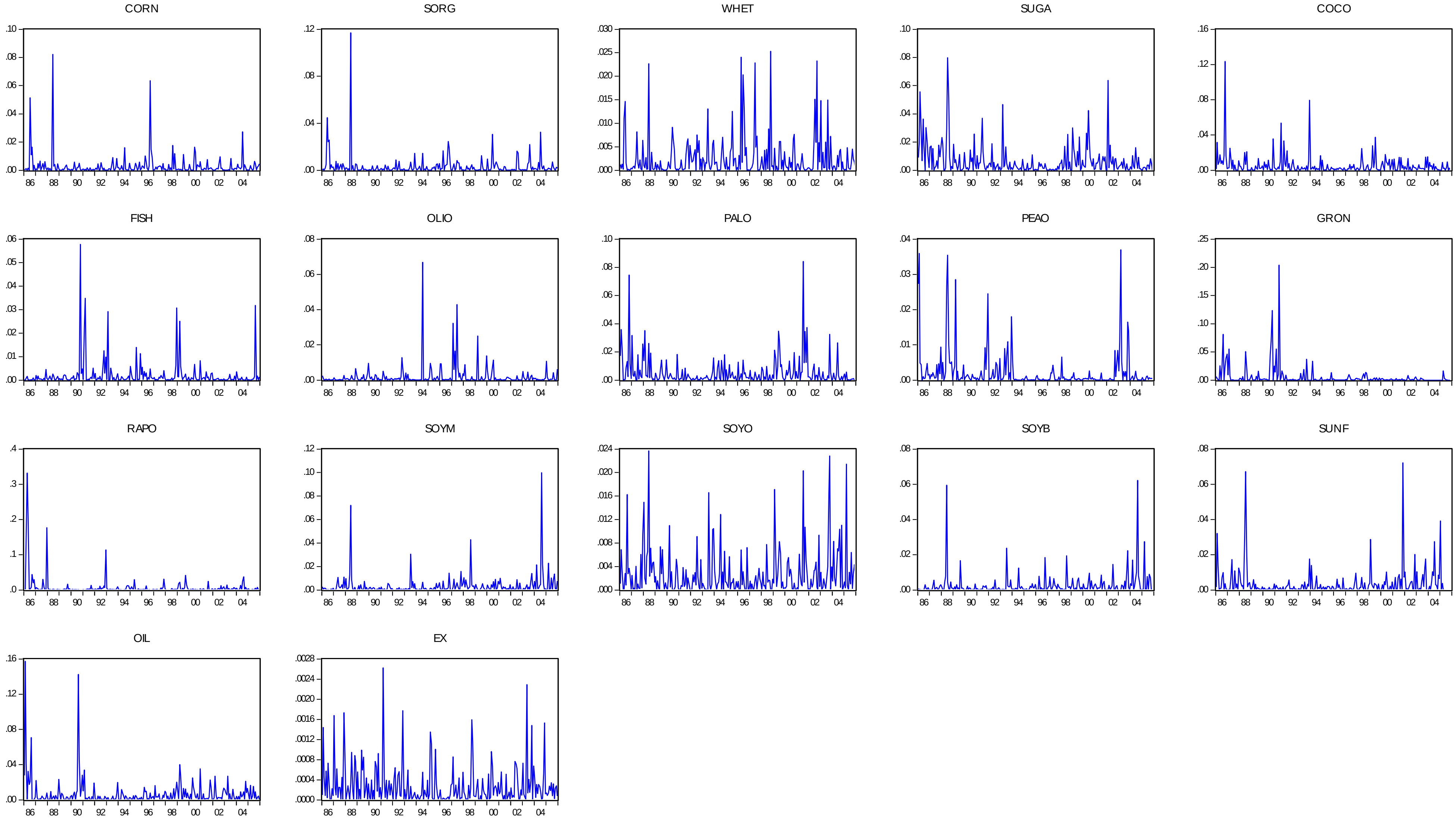


Figure 4 (Cont.) – [for Post-Crisis Time Period]

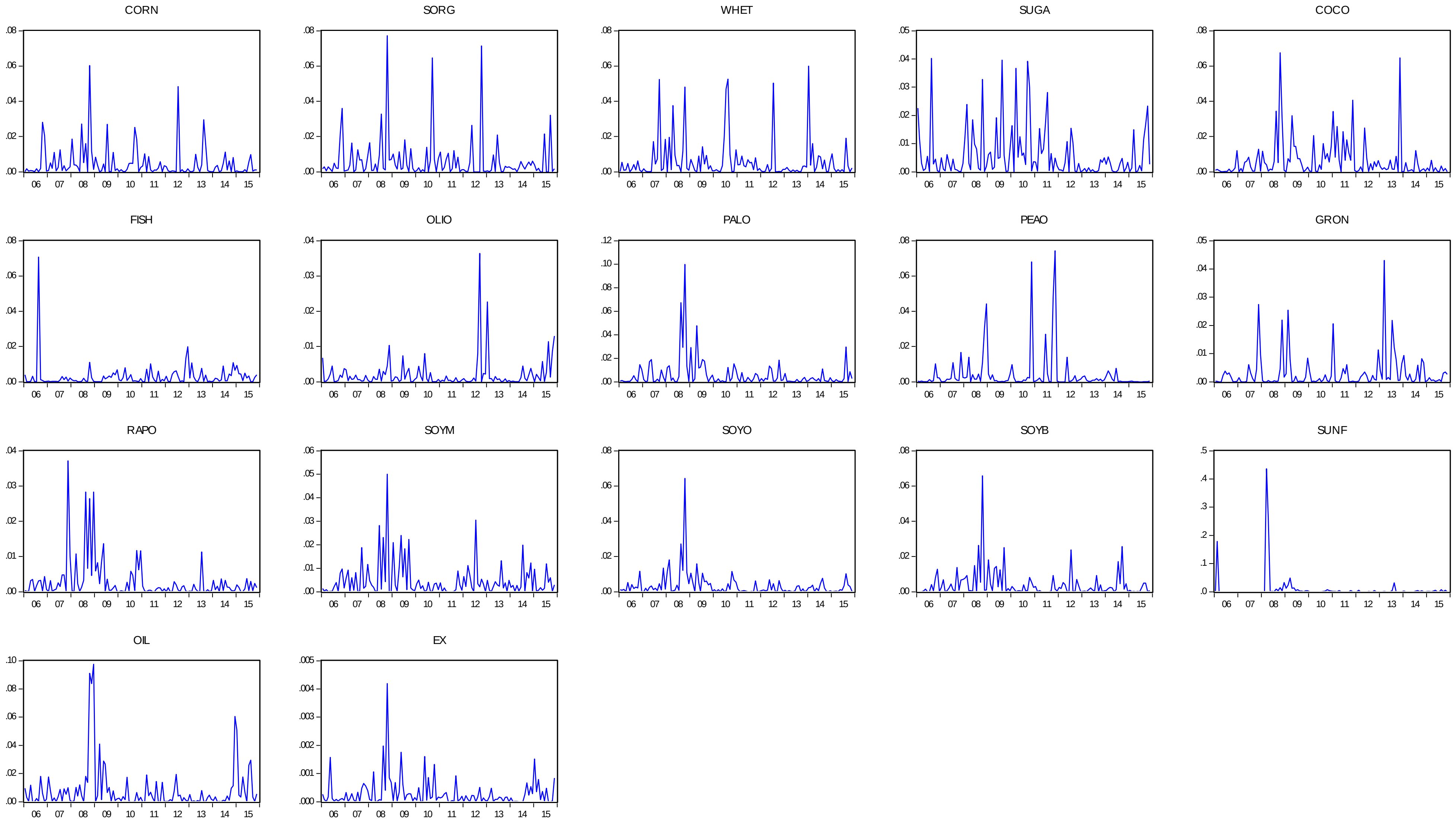


Figure 5. Generalized Impulse - Response functions for the Pre-Crisis Time Period Due to One Unit Shock in Crude Oil Volatility

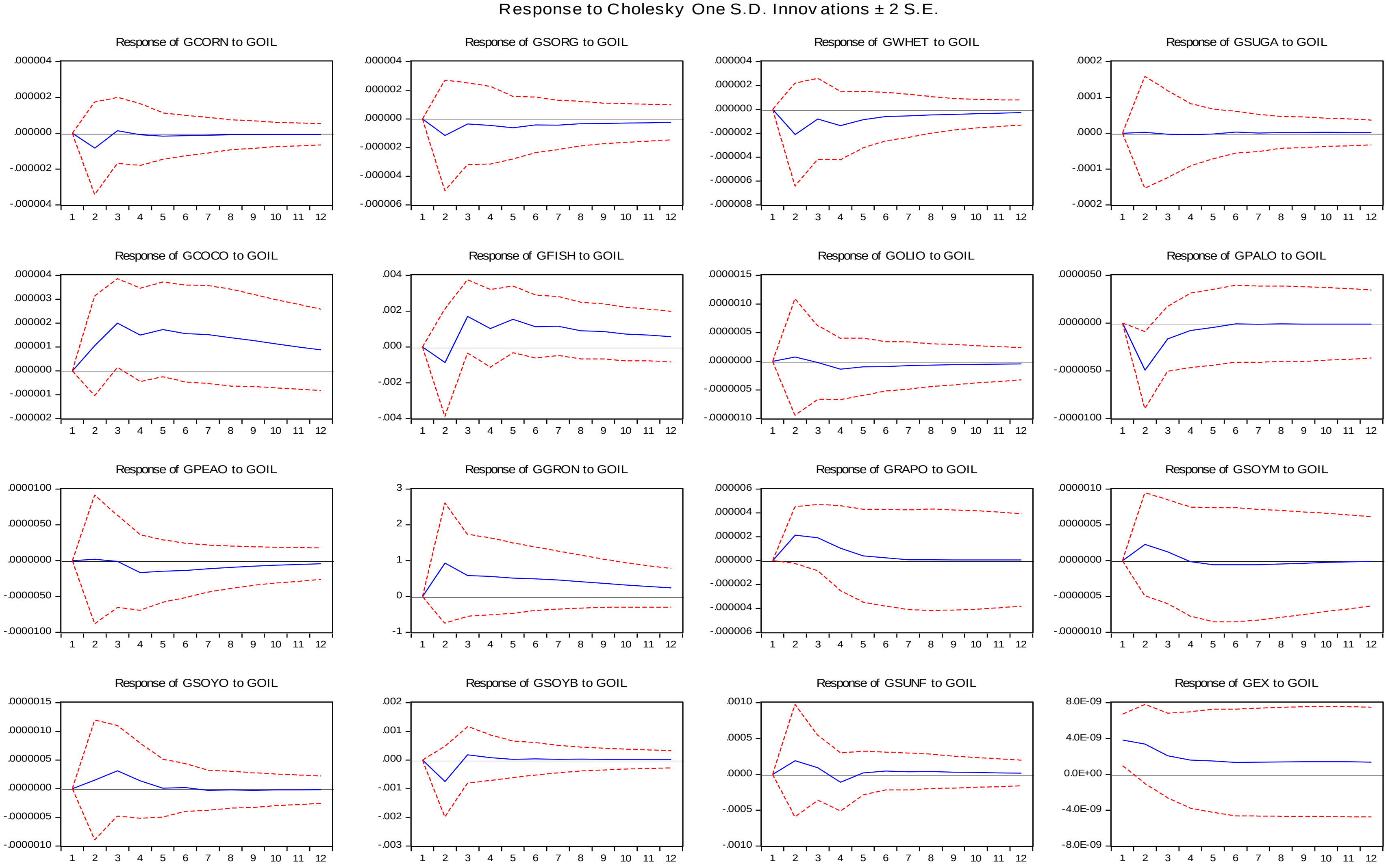


Figure 6. Generalized Impulse - Response Functions for the Pre-Crisis Time Period

Due to One Unit Shock in US dollar Exchange Rate Volatility

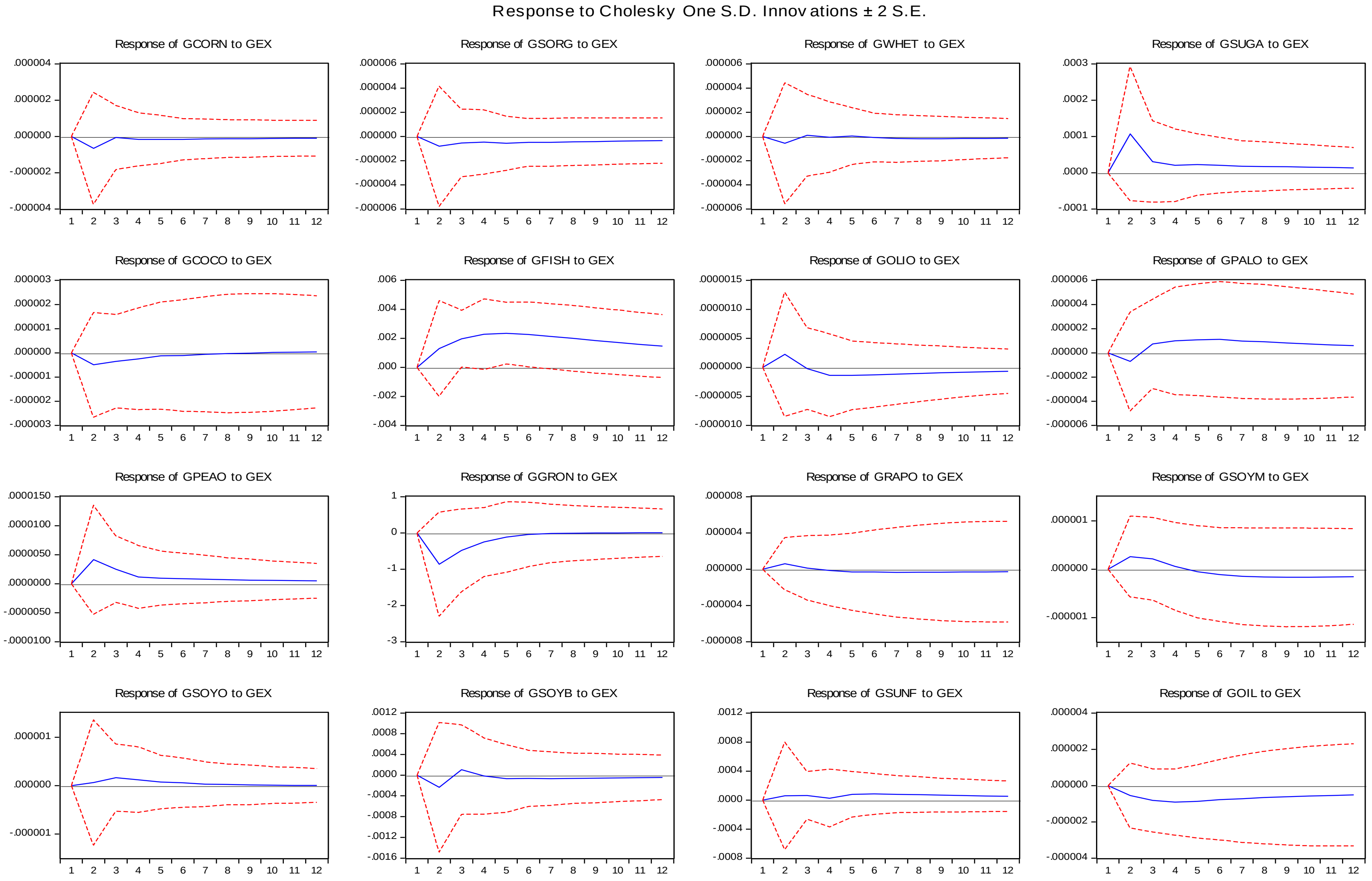


Figure 7. Generalized Impulse - Response Functions for the Post-Crisis Time Period Due to One Unit Shock in Crude Oil Volatility

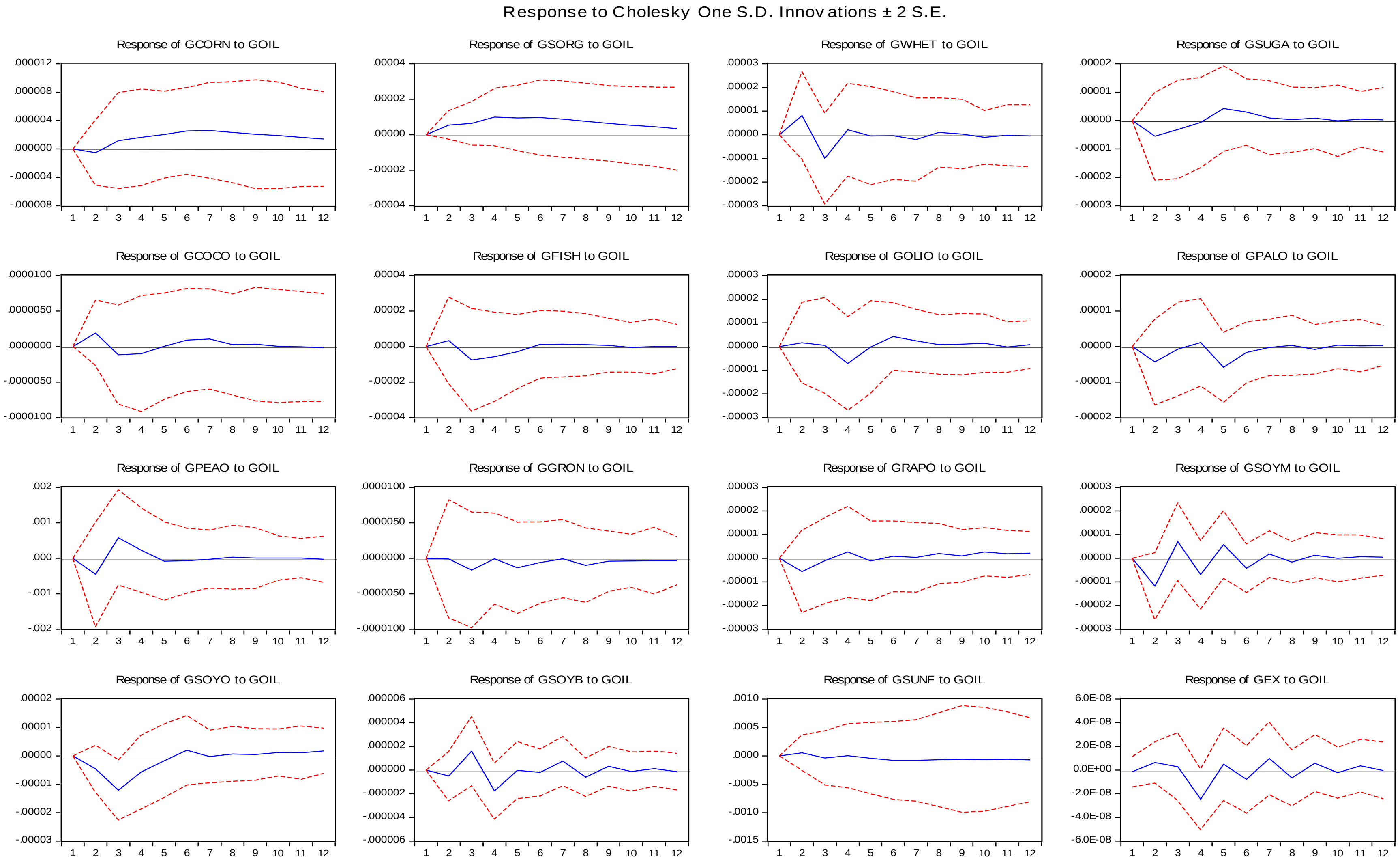


Figure 8. Generalized Impulse - Response Functions for the Post-Crisis Time Period Due to One Unit Shock in US Dollar Exchange Rate Volatility

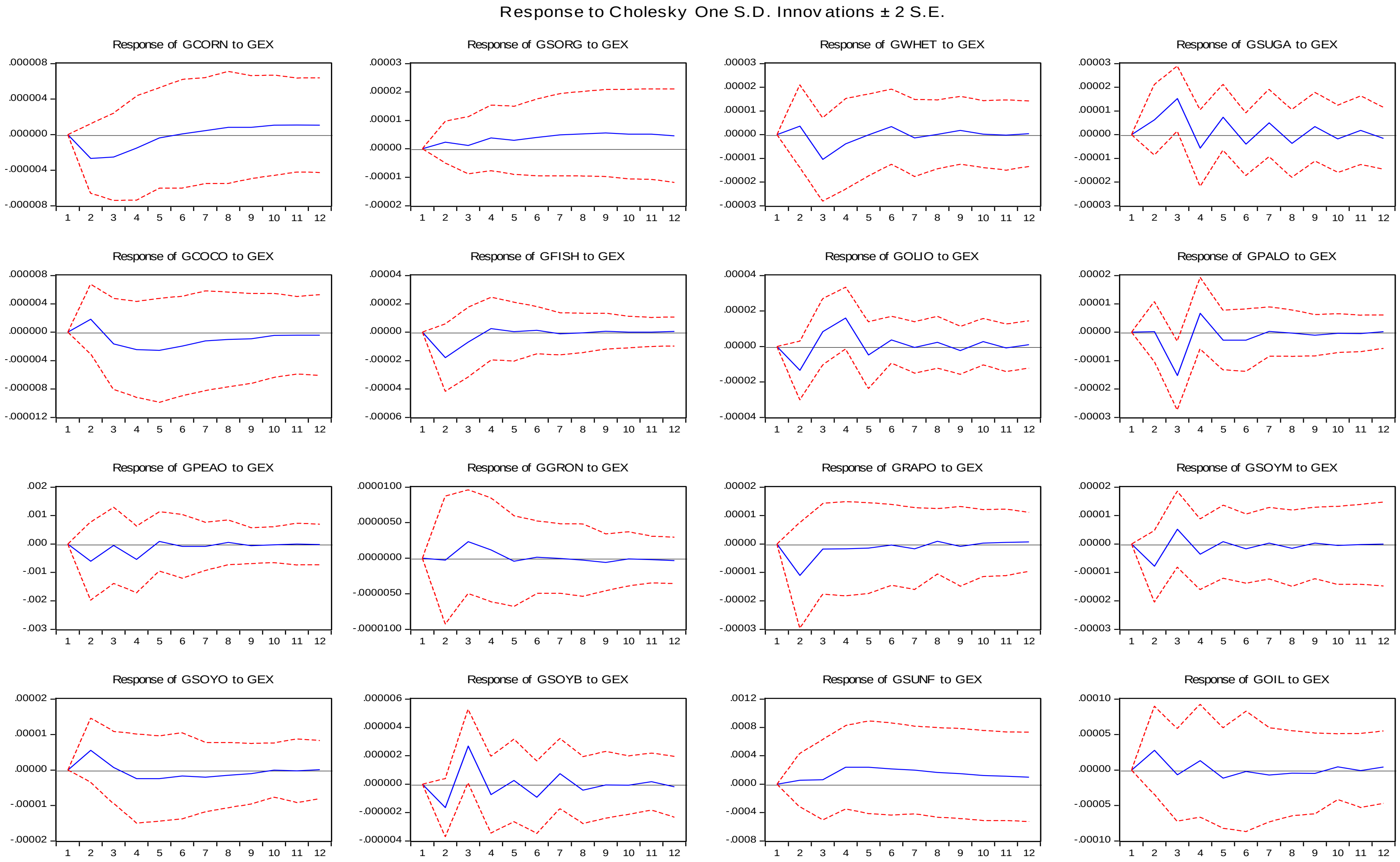


Figure 9. Accumulated Impulse - Response Functions for the Pre-Crisis Time Period Due to One Unit Shock in Crude Oil Returns Volatility

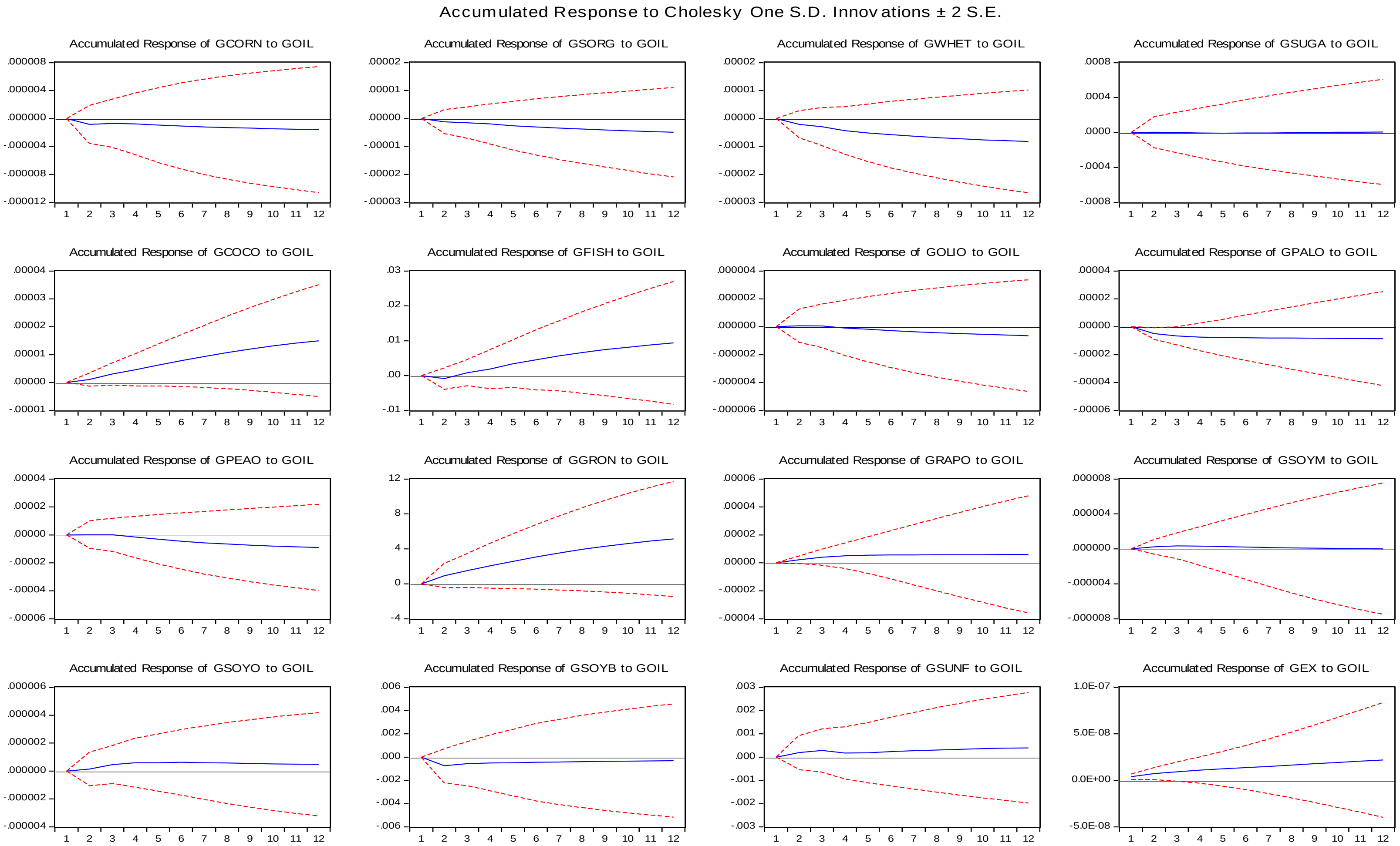


Figure 10. Accumulated Impulse - Response Functions for the Pre-Crisis Time Period Due to One Unit Shock in US Dollar Exchange Rate Volatility

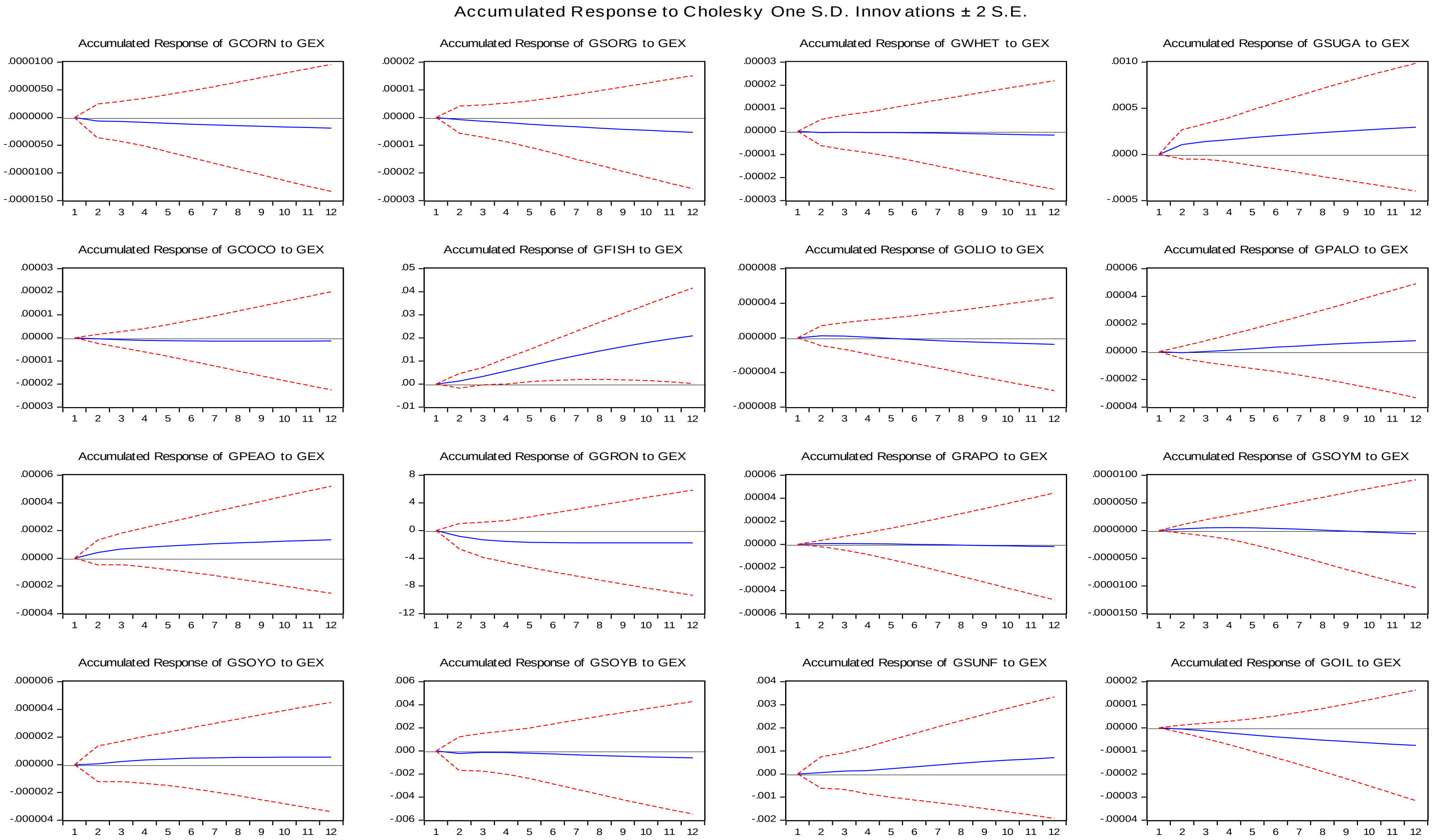


Figure 11. Accumulated Impulse - Response Functions for the Post-Crisis Time Period Due to One Unit Shock in Crude Oil Returns Volatility

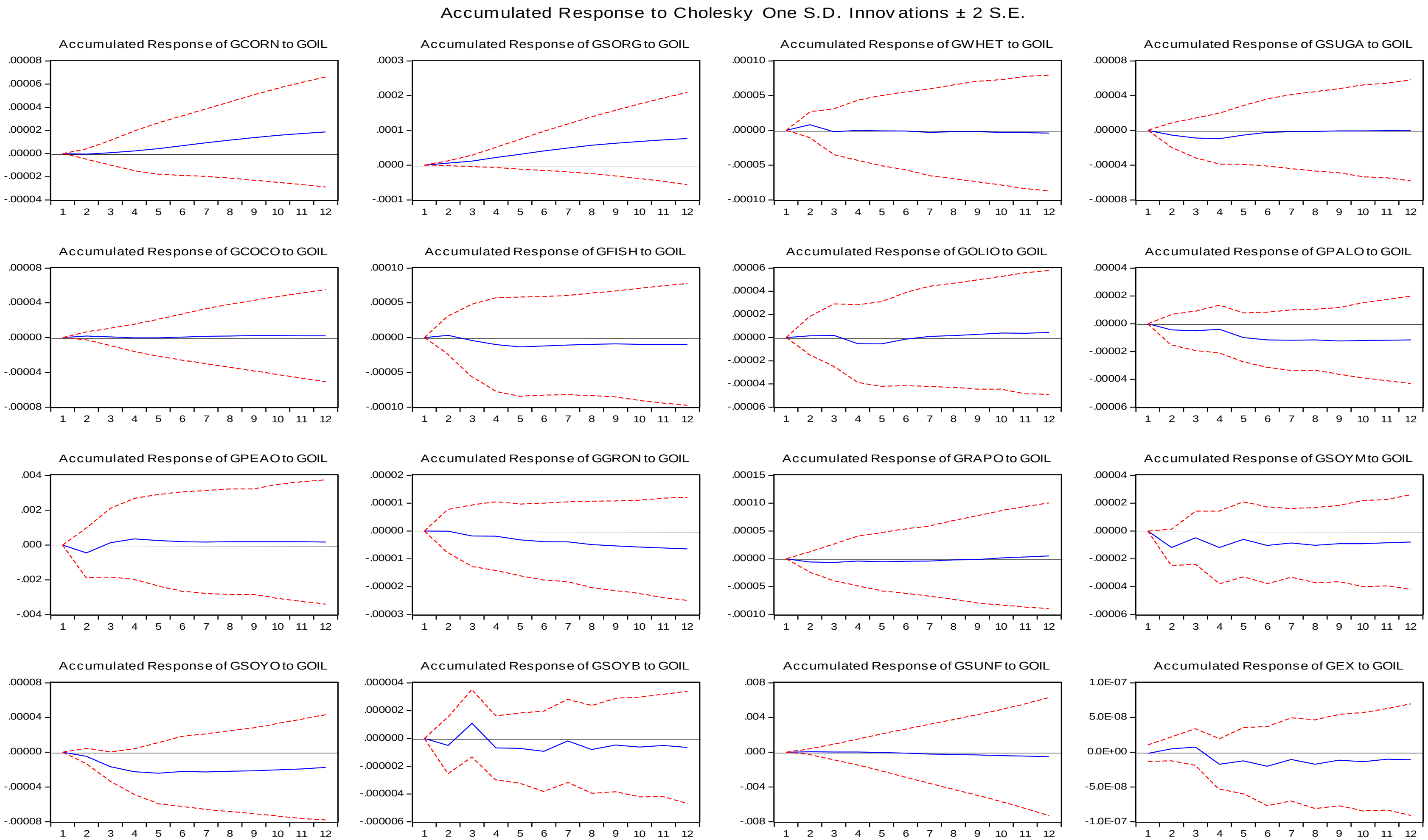


Figure 12. Accumulated Impulse - Response Functions for the Post-Crisis Time Period Due to One Unit Shock in US Dollar Exchange Rate Volatility