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Abstract

This paper estimates a bivariate VAR-GARCH(1,1) model to examine linkages between food and energy prices. The adopted framework is suitable to analyse both mean and volatility spillovers, and also allows for possible parameter shifts resulting from four recent events, namely: 1) the 2006 food crisis, 2) the Brent oil bubble, 3) the introduction of the Renewable Fuel Standard (RFS) policy, and 4) the 2008 global financial crisis. The empirical findings suggest that there are significant linkages between food and both oil and ethanol prices. Further, the four events considered had mixed effects, the 2006 food crisis and 2008 financial crisis leading to the most significant shifts in the (volatility) spillovers between the price series considered.

JEL-Code: C320, F360, G150.

Keywords: energy and food prices, VAR-GARCH BEKK model, mean and volatility spillovers.

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1 Introduction

The relationship between energy and food prices has been analysed extensively in the literature. Their behaviour in terms of trends and volatilities appears to be rather similar. The recent crises in the period 2006-08 substantially affected these prices (e.g. wheat prices increased from \$3.8 to \$8.8 per bushel, and corn prices from \$2.6 to \$7). This sharp increase is a serious concern for the developing economies. According to the World Bank report (De Hoyos and Medvedev, 2009), the impact of the recent crises on global welfare was to lead between 75 and 160 million people into poverty. Furthermore, food-importing countries were exposed to political instability and internal conflicts. The higher price volatility has also generated additional uncertainty and had adverse effects on investment.

The links between energy and agricultural commodity prices were first analysed by Barnard (1983). The three-fold increase in the demand for bio-fuel in recent years has led to the introduction in the US in 2005 of the so-called the Renewable Fuel Standard (RFS) policy. This requires vehicles to use Methyl Tertiary Butyl Ether (MTBE) as an oxygenate added to gasoline to improve combustion and reduce harmful vehicle emissions. The MTBE ban is in effect in New York and Connecticut, states that had previously accounted for a total of 42 percent of national MTBE consumption. The RFS policy was approved in 2005 but was not enforced until June 2006. This new standard required motor fuels to contain a minimum amount of fuel coming from renewable sources, such as biomass (e.g., ethanol), solar power or wind energy. Since then, ethanol has been the only practical way to comply with the new standard. Therefore, in mid-2006, ethanol became the only available gasoline additive (Avalos, 2014). Abbott et al. (2009) described the link between food and fuel and argued that these two markets were historically independent until 2006, when ethanol usage became large enough to influence world energy prices. They calculated that bio-fuels and bio-fuel policy each accounted for a quarter of the total price increase in 2008, and RFS policies for a small percentage only. In addition, inflation and exchange rates also played an important role.

The higher demand for ethanol oil as a bio-fuel alternative to natural oil has led to more land being used for its production. The 'food versus fuel claim' posits that an increased demand for bio-fuel production may result in less land allocated to food production, which can lead to higher food prices. Bio-fuel production increased three-fold in the period 2006-2012. De Gorter et al. (2013) argued that food prices increased owing to RFS policies in rich countries only.

Most studies rely on standard supply and demand (e.g., Babcock, 2008) or equilibrium frameworks to model both fuel and food prices (e.g., Zhang et al„ 2014; and Serra et al., 2011b). These models have been criticised for not being sufficiently validated against historical data and are plagued by poor performance (Hertel and Beckman, 2011; Serra and Zilberman, 2013); in addition, equilibrium models mainly employ annual data, which is a clear limitation. For instance, Timilsina et al. (2011) developed a multi-country, multi-sector general equilibrium model and used recursive techniques to simulate various future oil price scenarios and assess the corresponding impact on bio-fuels production, agricultural output, land-use change and global food supply. One of the scenarios considered higher oil prices leading to an increase in bio-fuel price and a decrease in food supply. The effects of exchange rates have also been examined by other authors, such as Durvell et al. (2014), who estimated an error correction model for cereal, food and non-food consumer prices using monthly data and found that agriculture and food have a dominant role in Ethiopia's economy. Baquedano et al. (2014) also used a (single equation) error correction model to test for market cointegration and price transmission from macroeconomic factors to consumer prices for wheat, rice, maize, and sorghum in the major urban centres of a selected number of countries in Asia, Latin America, the Caribbean, and Sub-Saharan Africa. Their results confirm that open economies are more vulnerable to international shocks. Hochman (2014) adopted a multi-region framework dividing the world into regions, where demand for corn, rapeseed, rice, soybean, and wheat is shown to consist of demand food/feed, inventory, and (where applicable) bio-fuels. His results indicate that up to 25% of the price of corn can be affected by bio-fuel prices and up to 7% of the price of soybean by energy prices. He also examined the impact of shocks during periods when there are large inventories of food.

Very few papers examine the volatilities of energy and agricultural prices. For instance, Serra (2013) estimated volatilities to investigate the impact of bio-fuels on food and fuel prices up to 2013. Mcphail and Babcock (2012) showed that ethanol, RFS and the blend wall lead to more inelastic demand for both corn and gasoline, which makes both the corn and gasoline markets more susceptible to supply shocks and leads to greater price volatility. They also estimated supply and demand elasticities for the US corn, ethanol, and gasoline markets using a three-stage least squares approach to provide empirical evidence for their theoretical set-up. Further, they developed a stochastic partial equilibrium model that explicitly accounts for important sources of volatility in the corn-ethanol-gasoline links, including stochastic corn yields and crude oil prices. Babcock and Jacinto (2011) argued that only 8% of the increase in corn prices during the 2006-2009 period was the result of ethanol subsidies. They attributed the remainder to market forces and other factors, such as droughts, floods, a severe US recession, and two general commodity price surges. Ethanol policies, such as RFS, mandates and blend wall regulations, can affect the price variability of both corn and gasoline. Qiu et al. (2012) used a structural vector auto-regression (SVAR) model to show how supply/demand structural shocks affect food and fuel markets. Their results support the hypothesis that increased bio-fuel production may cause short-run food price increases but not long-run price shifts. However, agricultural products, such as corn, are affected by their own trade shocks. Their findings also suggest complementarity between ethanol and gasoline and the idea that demand and supply market forces are the main drivers of food price volatility.

The study of volatility can benefit from high frequency data both because high frequency volatility is easier to predict and because it has proven useful to forecast over longer horizons (Andersen et al., 2003). The most popular view is that the grain price boom from 2006 was the result of many factors, with bio-fuels being just one of them, and that bio-fuel policies account for only a fraction of the effects of bio-fuels (de Gorter et al., 2014). The food crisis caused the price of wheat, corn and soybeans to double between 2006 and mid-2008. Volatility issues and macro policies aimed at achieving more stable food and oil prices have become increasingly important (Wright and Parkash, 2011). Reviews of the literature investigating the economic impacts of bio-fuels have paid particular attention to structural models (Kretschmer and Peterson, 2010). Zhang et al. (2009), using weekly data, examined price volatility interactions between the US energy and food markets in the period 1989-2007 by estimating the BEKK model of Engle and Kroner (1995). Their results suggest that there is no relationship between fuel (ethanol, oil and gasoline) prices and agricultural commodity (corn and soybean) prices. However, they did not control for the 2006 food crisis and the 2005 MTBE policy.

Headey (2011) and Serra (2013) argued that previous research has generally relied on a specification of the variance-covariance matrix that does not allow for asymmetric impacts of price increases and decreases on volatility. They found that the high volatility persistence of commodity prices may be due to failing to account for structural breaks. Serra et al. (2011a) also used a standard BEKK model to analyze volatility interactions between crude oil, ethanol and sugarcane prices in Brazil using weekly prices during the 2000-2008 period. In a related study on the same topic Serra (2011) used semi-parametric MGARCH models. Both papers suggest that there is a relationship between sugar and energy prices. Wu et al. (2011) estimated a restricted asymmetric MGARCH model using US corn and oil prices from 1992 to 2009 to investigate volatility spillovers between oil and corn prices. They concluded that corn markets have become much more connected to crude oil markets after the implementation of the Energy Policy Act of 2005. Du et al. (2011) used futures market prices for crude oil, corn and wheat from 1998 to early 2009 to estimate stochastic volatility in these markets. The correlation coefficient between the crude oil and corn markets is found to increase from 0.07 to 0.34 after October 2009, while that between the crude oil and wheat markets increased from 0.09 to 0.27, indicating a much tighter linkage between crude oil and agriculture commodity markets in the second period. Trujillo-Barrera et al. (2012) estimated a similar model using futures prices for crude oil, ethanol and corn from 2006 to 2011, and identified volatility spillovers from the crude oil futures market to the ethanol and corn futures markets.

Nazlioglua et al. (2013) employed a univariate GARCH model and impulse responses to examine volatility transmission between world oil and selected world agricultural commodity prices (wheat, corn, soybeans, and sugar). They considered two sub-periods, before and after the food crisis, 01/01/1986 – 31/12/2005 and 01/01/2006 – 21/03/2011. Their causality-in-variance tests suggest that there is no transmission between oil and the agricultural commodity markets in the pre-crisis period, and no oil market volatility spillovers to the agricultural markets (with the exception of sugar during the post-crisis period).

Gardebroek and Hernandez (2013) examined oil, ethanol and corn prices in the US between 1997 and 2011 and used a multivariate GARCH approach to estimated interdependence and volatility spillovers across these markets. Their results indicate higher interaction between ethanol and corn markets in recent years and particularly after 2006, when ethanol became the sole alternative oxygenate for gasoline. However, they observed significant volatility spillovers only from corn to ethanol prices but not the reverse. They also did not find major cross-volatility effects from the oil to the corn markets. In another study using the univariate GARCH (1, 1) and EGARCH models, Wang and Zhang (2014) examined price volatility interactions between China's energy and bulk commodity markets between 2001 and 2010. They split the sample before and after 2007 and found that there is greater volatility clustering between the food and oil markets after the 2007 oil shock.

Olsen et al. (2014) used a univariate GARCH model for food prices only. They found evidence of different structural breaks for energy and food commodities (such as grains) respectively. The latter are more volatile than other commodities studied (metals) and display bidirectional (linear and non-linear) feedback effects vis-à-vis stock price indices. These findings suggest not only that shocks to commodity demand and supply may have an impact on aggregate price indices, but also that non-commodity shocks, as embodied in aggregate price indices, may affect commodity prices linearly and nonlinearly. Chen et al. (2014) identified in the crude oil market a structural break dated July 2004. Gorter et al. (2014) showed that grain prices have increased significantly since 2006 owing to several factors. Jebabli et al. (2014) focused on the recent financial crisis and its effects on volatility spillovers between food and energy prices. Fan and Xu (2011) stressed that the recent bubble in oil prices (2004-2008) and the resulting structural break should also be considered.

None of the papers mentioned above properly tested for and determined the dates of possible structural breaks in the energy-food prices volatility spillovers. The present study aims to fill this gap by examining the impact of well-known recent events on spillovers between food and energy prices in both the first (mean) and second (volatility) moments in the context of a VAR-GARCH model with a BEKK representation. Specifically, we consider the following four events: i) the food crisis, dated January 2006, analysed by Nazilogue et al. (2013); ii) the Brent oil bubble discussed by Fan and Xu (2011); iii) the June 2006 implementation of the RFS Policy discussed by Abott (2009), Avalos (2014) and de Gorter et al. (2013); and finally iv) the effect of the 2008 financial crisis (see Jebabli et al., 2014). The sample period goes from 1997 to 2014, and the series analysed are ethanol and Brent oil as energy prices, and corn, soybeans, sugar and wheat as food prices. The layout of the paper is as follows. Section 2 outlines the econometric model. Section 3 describes the data and presents the empirical findings. Section 4 summarises the main findings and offers some concluding remarks.

2 The Econometric Model

We model the joint process governing energy prices (oil and ethanol) and food prices (corn, soybeans, sugar and wheat) using a bi-variate VAR-GARCH(1,1) framework[1]. The model has the following specification:

$$\mathbf{x}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\gamma} y_{t-1} + \mathbf{u}_t \tag{1}$$

where $\mathbf{x}_t = (Energy_t, Food_t)$. The residual vector $\mathbf{u}_t = (e_{1,t}, e_{2,t})$ is bi-variate and normally distributed, $\mathbf{u}_t \mid I_{t-1} \sim (\mathbf{0}, H_t)$, with its corresponding conditional variance covariance matrix given by:

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{bmatrix} \tag{2}$$

The parameter vectors of the mean equation (1) are the constant $\boldsymbol{\alpha} = (\alpha_1, \alpha_2)$ and the autoregressive term $\boldsymbol{\beta} = (\beta_{11}, \beta_{12} + \beta_{12}^{*} + \beta_{12}^{**} + \beta_{12}^{***} + \beta_{12}^{****} \mid \beta_{21} + \beta_{21}^{*} + \beta_{21}^{**} + \beta_{21}^{***} + \beta_{21}^{****}, \beta_{22})$. We control for global stock market spillovers including the S&P 100 Index (y_t) in the mean equation (this effect is measured by the parameters $\boldsymbol{\gamma} = (\gamma_1 \mid \gamma_2))$). The parameter matrices for the variance Equation (2) are defined as C_0, which is restricted to be upper triangular, and two unrestricted matrices A_{11} and G_{11}.

To account for the possible effects of the recent crises, we include four dummy variables: the first (denoted by *) captures the 2006 food crisis (Nazlioglu et al., 2013); the second

[1] The model is based on the GARCH(1,1)-BEKK representation proposed by Engle and Kroner (1995).

(denoted by $**$), following Fan and Zu (2000), captures the oil crisis during the March 19, 2004 - June 6, 2008 period; the third (denoted by $***$) controls for the RFS policy implementation, June 2006, as suggested by Avalos (2014); and finally the fourth (denoted by $****$) corresponds to the 2008 global financial crisis (originating on 15 September 2008, i.e. on the day of the collapse of Lehman Brothers) as suggested by Jebabli et al. (2014). Therefore, the second moment will take the following form[2]:

$$H_t = C_0'C_0 + A_{11}' \begin{bmatrix} e_{1,t-1}^2 & e_{2,t-1}e_{1,t-1} \\ e_{1,t-1}e_{2,t-1} & e_{2,t-1}^2 \end{bmatrix} A_{11} + G_{11}' H_{t-1} G_{11} \tag{3}$$

where

$$\begin{aligned} A_{11} &= \begin{bmatrix} a_{11} & a_{12} + a_{12}^* + a_{12}^{**} + a_{12}^{****} + a_{12}^{****} \\ a_{21} + a_{21}^* + a_{21}^{**} + a_{21}^{***} + a_{21}^{****} & a_{22} \end{bmatrix}; \\ G_{11} &= \begin{bmatrix} g_{11} & g_{12} + g_{12}^* + g_{12}^{**} + g_{12}^{****} + g_{12}^{****} \\ g_{21} + g_{21}^* + g_{21}^{**} + g_{21}^{***} + g_{21}^{****} & g_{22} \end{bmatrix} \end{aligned}$$

Equation (3) models the dynamic process of H_t as a linear function of its own past values, H_{t-1}, and past values of the squared innovations $\left(e_{1,t-1}^2, e_{2,t-1}^2\right)$. The BEKK model guarantees by its construction that the covariance matrix in the system is positive definite. Given a sample of T observations, a vector of unknown parameters θ and a 2×1 vector of variables $\mathbf{x}_t$, the conditional density function for model (1) is:

$$f\left(\mathbf{x}_t | I_{t-1}; \theta\right) = (2\pi)^{-1} |H_t|^{-1/2} \exp\left(-\frac{\mathbf{u}_t' \left(H_t^{-1}\right) \mathbf{u}_t}{2}\right) \tag{4}$$

The log-likelihood function is:

$$L = \sum_{t=1}^{T} \log f\left(\mathbf{x}_t | I_{t-1}; \theta\right) \tag{5}$$

where θ is the vector of unknown parameters. The standard errors are calculated using the quasi-maximum likelihood methods of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals.

3 Empirical Analysis

3.1 Data

We use daily data (from Datastream and US Commodity Research Bureau for ethanol) for two energy price series (crude oil and ethanol) and four food price series (corn, soya bean, sugar and wheat) over the period 15/9/1997-25/7/2014, for a total of 4246 observations. Furthermore, as already mentioned, we control for stock market globalisation using a proxy

[2] Parameters (a_{21}) in Equation (3) measure the causality effect of variable 2 on variable 1, whereas $(a_{21} + a_{21}^*)$, $(a_{21} + a_{21}^{**})$, $(a_{21} + a_{21}^{***})$ and $(a_{21} + a_{21}^{****})$ measure the possible effect of the 2006 food crises, the 2004- 2008 oil bubble accumalation period, the mid 2006 RFS policy change, and the 2008 financial crisis, respectively.

for the global stock market index (US stock market index). We define daily returns as logarithmic differences of energy and food price indices.

Please Insert Tables 1-2 and Figure 1 about here

Figure 1 shows energy and food price changes. The recent literature has suggested several possible structural breaks affecting the spillovers between food and energy markets. Here we consider the four breaks mentioned above. The descriptive statistics presented in Table 1 concern the two sub-periods before and after the 2006 food crisis. Post-crisis volatilities are significantly higher for all commodity prices (but oil), and so are the standard deviations (especially in the case of ethanol: it increases to 0.19 from 0.09). All food prices (but sugar) reach a peak in the post-crisis sample. The mean values are rather similar. The increased volatility and larger extreme events (measured by maximum and minimum values) observed in the second sample affect, as one would expect, the Jarque-Bera statistics which indicate a larger departure from normality in the post- compared to the pre-crisis sample.[3]

The sample correlations, reported in Table 2, are positive for all energy and food prices in both subsamples, with the exception of that between ethanol and wheat (-0.003), which is very close to zero. Further, there is a positive correlation between US stock prices and all food and energy prices but oil and sugar in the pre-crisis sample and soybeans prices in the post-crisis sample.

3.2 Hypotheses Tested

We test for mean and volatility spillovers, by placing restrictions on the relevant parameters; specifically, we consider the following four sets of null hypotheses:

1. Tests of no spillovers from food to energy prices
$H_0$1a: Food $\rightarrow$ energy: $\beta_{12} = 0$
$H_0$1b: Food $\rightarrow$ energy after the first breakpoint: $\beta_{12}^{*} = 0$
$H_0$1c: Food $\rightarrow$ energy after the second breakpoint: $\beta_{12}^{**} = 0$
$H_0$1d: Food $\rightarrow$ energy after the third breakpoint: β_{12}^{***}
$H_0$1e: Food $\rightarrow$ energy after the fourth breakpoint: $\beta_{12}^{****} = 0$

2. Tests of no volatility spillovers from food to energy prices
$H_0$2a: Food $\rightarrow$ energy: $a_{21} = g_{21} = 0$
$H_0$2b: Food $\rightarrow$ energy after the first breakpoint: $a_{21}^{*} = g_{21}^{*} = 0$
$H_0$2c: Food $\rightarrow$ energy after the second breakpoint: $a_{21}^{**} = g_{21}^{**} = 0$
$H_0$2d: Food $\rightarrow$ energy after the third breakpoint: $a_{21}^{***} = g_{21}^{***} = 0$
$H_0$2e: Food $\rightarrow$ energy after the fourth breakpoint: $a_{21}^{****} = g_{21}^{****} = 0$

3. Tests of no spillovers from energy to food prices
$H_0$3a: Energy $\rightarrow$ food: $\beta_{21} = 0$
$H_0$3b: Energy $\rightarrow$ food after the first breakpoint: $\beta_{21}^{*} = 0$
$H_0$3c: Energy $\rightarrow$ food after the second breakpoint: $\beta_{21}^{**} = 0$

[3] Descriptive statistics for the remaining three breaks are available on request. They show a similar pattern with higher energy and food price volatilities in the second subsample.

$H_0$3d: Energy $\rightarrow$ food after the third breakpoint: β_{21}^{***}
$H_0$3e: Energy $\rightarrow$ food after the fourth breakpoint: $\beta_{21}^{****} = 0$

4. Tests of no volatility spillovers from energy to food prices
$H_0$4a: Energy $\rightarrow$ food: $a_{12} = g_{12} = 0$
$H_0$4b: Energy $\rightarrow$ food after the first breakpoint: $a_{12}^{*} = g_{12}^{*} = 0$
$H_0$4c: Energy $\rightarrow$ food after the second breakpoint: $a_{12}^{**} = g_{12}^{**} = 0$
$H_0$4d: Energy $\rightarrow$ food after the third breakpoint: $a_{12}^{***} = g_{12}^{***} = 0$
$H_0$4e: Energy $\rightarrow$ food after the fourth breakpoint: $a_{12}^{****} = g_{12}^{****} = 0$

3.3 Empirical Results

In order to test the adequacy of the models, Ljung–Box portmanteau tests were performed on the standardised and squared residuals. Overall, the results indicate that the VAR-GARCH(1,1) specification captures satisfactorily the persistence in returns and squared returns of all the series considered. Cross-market dependence in the conditional mean and variance vary in magnitude and sign across pairwise estimations. Note that the signs of cross-market volatilities are not relevant. The estimated VAR-GARCH(1,1) model with associated robust standard errors and likelihood function values are presented in Tables 3 to 7.

Please Insert Tables 3-7 about here

We select the optimal lag length of the mean equation using the Schwarz Information Criterion. The parameter estimates for the conditional means suggest statistically significant spillovers-in-mean at the standard 5% significance level. In particular, spillovers from energy prices, measured by b_{12}, have a significant impact on all food prices, with the exception of oil not affecting corn prices. Of the four breaks considered, the 2008 financial crisis, whose effect is measured by b_{12}^{****}, has the most significant impact on the pairwise causality-in-mean dynamics, with the exception of oil not affecting sugar and ethanol not affecting corn prices.

Concerning the conditional variance equations, the estimated "own-market" coefficients are statistically significant and the estimates of g_{11} suggest a high degree of persistence. The results reported in Tables 1 to 3 suggest the following. First, there are significant volatility spillovers from oil to food prices .The coefficient (in absolute value) is largest in the case of wheat (being equal to -0.371). The spillover effects increase after the oil price turbulence ($a_{21} + a_{21}^{**}$), in particular for corn (0.359). The effects of the 2008 financial crisis ($a_{21} + a_{21}^{****}$) are less clear, the coefficients increasing (in absolute value) in the cases of corn and ethanol, and decreasing in the case of soybeans, sugar and wheat, to $-0.037, 0.059$ and -0.189, respectively. Instead there is no evidence of volatility spillovers from ethanol to food prices. The effects of the introduction of the 2006 RFS policy ($a_{21} + a_{21}^{***}$) are mixed, leading to an increase in the coefficient in the cases of soybeans (0.013) and a decrease for sugar (-0.239). Overall, we find that spillovers running from the oil prices are bigger than those originating from ethanol for all food prices considered.

As for volatility linkages, there is evidence of spillovers from food to oil and ethanol prices. Also, they increase after the 2006 food crisis, whose effect is measured by a_{12}^{**}, from sugar and wheat to oil prices. On the contrary, the effects of the 2008 financial crisis ($a_{12} + a_{12}^{****}$)

on causality-in-variance from food to energy prices is statistically significant in all cases but soybeans to oil and wheat to ethanol prices. Also, the exogenous variable is statistically significant in all estimated models, indicating a positive γ_1 (US stock returns) effect, as one would expect.

Overall, our results are in line with those from previous studies and suggest strong linkages between food and energy markets. Despite being relatively mixed, they clearly show that the four breaks considered all had an effect on both mean and variance spillovers, with the 2006 food crisis and the 2008 financial crisis affecting in particular spillovers from oil to food prices, and the 2006 RFS policy having an impact mainly on the spillovers from ethanol to food prices.

4 Conclusions

This paper has investigated mean and volatility spillovers between energy (ethanol and oil) and four selected food (corn, soybeans, sugar and wheat) prices by estimating a VAR-GARCH model with a BEKK representation. Moreover, it has examined the possible effects of four recent events that might have resulted in shifts in the model parameters by including dummy variables in both the conditional mean and variance equations. The four breaks considered correspond to the following events: 1) the 2006 food crisis, 2) the Brent oil bubble, 3) the 2006 RFS policy implementation, and 4) the 2008 global financial crisis. The extensive dataset analysed, the focus on both first- and second- moment linkages and the incorporation of structural breaks into the multivariate GARCH specification all represent original contributions to the existing literature. To sum up, our findings confirm that food and energy prices are tightly interconnected, and also provide evidence that the recent turbulence in the world economy has affected their linkages, although no clear pattern emerges. Consequently, general policies aimed at stabilising key food prices cannot be formulated: the specific linkages between different markets need to be taken into account in order to devise appropriate policy measures.

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Table 1: Descriptive Statistics

	Corn	Ethanol	Oil	Soybeans	Stock	Sugar	Wheat
Whole Sample 15/9/1997-25/7/2014							
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.001	0.001	0.001	0.000	0.000
Maximum	0.248	0.253	0.135	0.073	0.110	0.142	0.225
Minimum	−0.261	−0.192	−0.136	−0.167	−0.095	−0.193	−0.202
Std. Dev.	0.022	0.015	0.022	0.017	0.013	0.023	0.021
Skewness	−0.235	−0.176	−0.064	−0.716	−0.215	−0.302	0.084
Kurtosis	19.117	0.949	6.091	9.125	10.49	6.717	13.251
Jarque-Bera	416.36	513.80	163.42	695.83	990.54	249.42	185.71
Observations	4221	4221	4221	4221	4221	4221	4221
Pre-Food Crisis 15/9/1997-31/12/2005							
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Maximum	0.091	0.115	0.130	0.065	0.056	0.142	0.084
Minimum	−0.102	−0.045	−0.136	−0.167	−0.071	−0.193	−0.023
Std. Dev.	0.018	0.009	0.024	0.016	0.012	0.021	0.015
Skewness	−0.148	1.443	−0.139	−0.910	−0.063	−0.250	−0.023
Kurtosis	6.562	21.646	5.172	12.452	5.911	6.694	6.874
Jarque-Bera	112.19	324.01	42.78	318.69	765.67	123.25	133.91
Observations	2165	2165	2165	2165	2165	2165	2165
Post-Food Crisis 1/1/2006-25/7/2014							
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Maximum	0.249	0.253	0.135	0.073	0.110	0.106	0.226
Minimum	−0.261	−0.192	−0.111	−0.127	−0.095	−0.130	−0.202
Std. Dev.	0.025	0.019	0.020	0.017	0.014	0.023	0.026
Skewness	−0.249	0.776	0.081	−0.564	−0.322	−0.381	0.107
Kurtosis	19.65	37.94	7.457	6.561	12.662	6.486	11.01
Jarque-Bera	234.92	421.2	174.19	115.54	808.94	197.01	554.89
Observations	2068	2068	2068	2068	2068	2068	2068

Note: Descriptive statistics for the whole sample 15/9/1997-25/7/2014, pre-food crisis 15/9/1997-31/12/2005, and post-food crisis sample 1/1/2006-25/7/2014. Numbers are rounded to the third decimal.

Table 2: Correlations

	Corn	Ethanol	Oil	Soybeans	Stock	Sugar	Wheat
				Whole Sample 15/9/1997-25/7/2014			
Corn	1.000	0.021	0.127	0.158	0.060	0.041	0.357
Ethanol	0.021	1.000	0.032	0.026	0.007	0.007	−0.001
Oil	0.126	0.033	1.000	0.046	0.067	0.050	0.111
Soya	0.158	0.026	0.046	1.000	0.011	0.038	0.146
Stock	0.060	0.007	0.067	0.011	1.000	0.077	0.016
Sugar	0.041	0.007	0.050	0.038	0.077	1.000	0.007
Wheat	0.357	−0.001	0.111	0.146	0.016	0.008	1.000
				Pre Food Crises 15/9/1997-31/12/2005			
Corn	1.000	0.023	0.029	0.304	0.028	0.056	0.226
Ethanol	0.023	1.000	0.057	0.028	0.015	0.018	0.009
Oil	0.029	0.057	1.000	0.041	−0.018	0.061	0.033
Soya	0.304	0.028	0.041	1.000	0.035	0.032	0.313
Stock	0.028	0.015	−0.018	0.035	1.000	−0.018	0.000
Sugar	0.056	0.018	0.061	0.032	−0.018	1.000	0.016
Wheat	0.226	0.009	0.033	0.313	0.000	0.016	1.000
				Post Food Crises 1/1/2006-25/7/2014			
Corn	1.000	0.022	0.226	0.062	0.080	0.031	0.415
Ethanol	0.022	1.000	0.025	0.027	0.004	0.002	−0.003
Oil	0.226	0.025	1.000	0.054	0.166	0.035	0.184
Soya	0.062	0.027	0.054	1.000	−0.009	0.045	0.058
Stock	0.080	0.004	0.166	−0.009	1.000	0.177	0.025
Sugar	0.031	0.002	0.035	0.045	0.177	1.000	0.002
Wheat	0.415	−0.003	0.184	0.058	0.025	0.002	1.000

TABLE 3: Estimated VAR-GARCH(1,1) model, Oil-Corn and Ethanol-Corn

	Oil => Corn		Eth. => Corn			Corn => Oil		Corn => Eth.	
					Conditional Mean				
	Coef.	p-value	Coef.	p-value		Coef.	p-value	Coef.	p-value
α_1	0.001	(0.171)	0.000	(0.710)	α_2	0.000	(0.596)	0.000	(0.994)
β_{11}	-0.019	(0.229)	0.225	(0.000)	β_{22}	-0.013	(0.510)	-0.022	(0.200)
β_{12}	0.003	(0.606)	0.053	(0.000)	β_{21}	-0.168	(0.000)	0.013	(0.294)
β_{12}^{*}	0.089	(0.093)	0.046	(0.475)	β_{21}^{*}	-0.089	(0.077)	0.049	(0.390)
β_{12}^{**}	-0.001	(0.889)	-0.062	(0.000)	β_{21}^{**}	0.001	(0.774)	0.021	(0.095)
β_{12}^{***}	0.054	(0.012)	0.065	(0.025)	β_{21}^{***}	-0.054	(0.062)	-0.006	(0.889)
β_{12}^{****}	0.027	(0.000)	-0.005	(0.292)	β_{21}^{****}	0.178	(0.000)	-0.051	(0.000)
γ_1	0.025	(0.231)	0.018	(0.303)	γ_2	0.023	(0.356)	0.045	(0.063)
					Conditional Variance				
c_{11}	0.003	(0.000)	0.003	(0.000)	c_{22}	0.008	(0.000)	0.013	(0.000)
c_{12}	-0.001	(0.000)	-0.002	(0.001)					
a_{11}	0.232	(0.000)	0.371	(0.000)	a_{22}	0.280	(0.000)	0.278	(0.000)
a_{21}	0.177	(0.000)	-0.006	(0.868)	a_{12}	-0.023	(0.207)	-0.313	(0.000)
a_{21}^{*}	-0.038	(0.002)	-0.040	(0.293)	a_{12}^{*}	-0.017	(0.700)	0.954	(0.000)
a_{21}^{**}	-0.189	(0.019)	-0.030	(0.680)	a_{12}^{**}	-0.097	(0.020)	-0.665	(0.000)
a_{21}^{***}	0.182	(0.000)	-0.003	(0.915)	a_{12}^{***}	0.078	(0.086)	-0.009	(0.854)
a_{21}^{****}	0.093	(0.000)	-0.064	(0.000)	a_{12}^{****}	-0.424	(0.000)	-0.541	(0.000)
g_{11}	0.964	(0.000)	-0.754	(0.000)	g_{22}	0.823	(0.000)	0.619	(0.000)
g_{21}	-0.116	(0.000)	0.169	(0.000)	g_{12}	-0.116	(0.000)	0.247	(0.000)
g_{21}^{*}	-0.038	(0.002)	-0.040	(0.293)	g_{12}^{*}	0.025	(0.000)	0.303	(0.000)
g_{21}^{**}	-0.189	(0.019)	-0.030	(0.680)	g_{12}^{**}	0.053	(0.219)	-0.261	(0.002)
g_{21}^{***}	0.182	(0.000)	-0.003	(0.915)	g_{12}^{***}	0.078	(0.086)	0.170	(0.000)
g_{21}^{****}	-0.275	(0.000)	0.129	(0.055)	g_{12}^{****}	0.093	(0.000)	-0.061	(0.000)
Log-lik		21004.985		23145.820					
$Q_{oil(10)}$	10.821								
$Q^2_{oil(10)}$	8.251								
$Q_{Eth.(10)}$			5.031						
$Q^2_{Eth.(10)}$			3.137						
$Q_{corn(10)}$	5.981		3.356						
$Q^2_{corn(10)}$	5.799		2.117						

Note: Standard errors (S.E.) are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals. Parameters not statistically significant at the 5% level are not reported. $Q_{(10)}$ and $Q^2_{(10)}$ are, respectively, the Ljung-Box test (1978) of significance of autocorrelations of ten lags in the standardized and standardized squared residuals. Parameters β_{21} and a_{12} measure the causality effect of oil (ethanol) on food commodities,. and the causality in variance effect, respectively The effects of the 1/1/2006, 20/3/2004, 6/6/2008 and 15/8/2004 crises are measured by $(\beta_{12}+\beta^{*}_{12})$, $(\beta_{12}+\beta^{**}_{12})$, $(\beta_{12}+\beta^{***}_{12})$ and $(\beta_{12}+\beta^{****}_{12})$, respectively. The same applies to the effects on food volatilities. The covariance stationary condition is satisfied by all the estimated models, all the eigenvalues of $A_{11}\otimes A_{11}+G_{11}\otimes G_{11}$ being less than one in modulus. Note that in the conditional variance equation, the sign of the parameters is not relevant. Numbers are rounded to the third decimal.

TABLE 4: Estimated VAR-GARCH(1,1) model, Oil-Soybean and Ethanol-Soybean

	Oil => Soybeans		Eth. => Soybeans			Soybeans => Oil		Soybeans => Eth.	
				Conditional Mean					
	Coef.	p-value	Coef.	p-value		Coef.	p-value	Coef.	p-value
α_1	0.001	(0.976)	0.190	(0.000)	α_2	0.000	(0.418)	-0.002	(0.006)
β_{11}	0.001	(0.976)	0.190	(0.000)	β_{22}	-0.114	(0.181)	0.114	(0.000)
β_{12}	0.068	(0.001)	0.112	(0.001)	β_{21}	-0.111	(0.000)	0.045	(0.456)
β_{12}^{*}	0.090	(0.380)	0.099	(0.042)	β_{21}^{*}	-0.082	(0.068)	-0.029	(0.911)
β_{12}^{**}	-0.036	(0.198)	0.043	(0.000)	β_{21}^{**}	0.012	(0.282)	-0.057	(0.341)
β_{12}^{***}	-0.085	(0.287)	0.039	(0.000)	β_{21}^{***}	-0.115	(0.230)	-0.511	(0.001)
β_{12}^{****}	0.082	(0.003)	0.042	(0.000)	β_{21}^{****}	0.126	(0.000)	0.190	(0.002)
γ_1	0.009	(0.699)	-0.010	(0.620)	γ_2	0.053	(0.300)	-0.118	(0.250)
				Conditional Variance					
c_{11}	0.017	(0.000)	0.007	(0.000)	c_{22}	0.060	(0.000)	0.057	(0.000)
c_{12}	-0.002	(0.754)	-0.002	(0.170)					
a_{11}	0.261	(0.032)	0.668	(0.000)	a_{22}	-0.010	(0.597)	0.272	(0.000)
a_{21}	0.046	(0.000)	0.017	(0.225)	a_{12}	0.207	(0.000)	0.230	0.00
a_{21}^{*}	0.037	(0.000)	0.004	(0.377)	a_{12}^{*}	0.036	(0.794)	-0.656	(0.000)
a_{21}^{**}	-0.001	(0.986)	-0.169	(0.000)	a_{12}^{**}	-0.003	(0.983)	-0.014	(0.896)
a_{21}^{***}	-0.078	(0.000)	0.013	(0.000)	a_{12}^{***}	0.027	(0.525)	0.295	(0.000)
a_{21}^{****}	-0.009	(0.000)	-0.030	(0.000)	a_{12}^{****}	-0.139	(0.369)	-0.309	(0.000)
g_{11}	0.023	(0.803)	-0.036	(0.239)	g_{22}	0.207	(0.000)	0.130	(0.000)
g_{21}	-0.248	(0.000)	0.023	(0.000)	g_{12}	-0.010	(0.597)	0.272	(0.000)
g_{21}^{*}	0.206	(0.000)	0.130	(0.000)	g_{12}^{*}	0.883	(0.012)	1.067	(0.000)
g_{21}^{**}	0.031	(0.397)	0.000	(0.959)	g_{12}^{**}	-1.309	(0.000)	-2.289	(0.896)
g_{21}^{***}	0.027	(0.263)	0.104	(0.000)	g_{12}^{***}	0.934	(0.008)	0.900	(0.000)
g_{21}^{****}	0.118	(0.000)	-0.109	(0.000)	g_{12}^{****}	1.032	(0.008)	2.084	(0.000)
Log-lik		22161.5		19087.61					
$Q_{Oil(10)}$	5.520								
$Q^2_{Oil(10)}$	8.052								
$Q_{Eth.(10)}$			4.453						
$Q^2_{Eth.(10)}$			2.137						
$Q_{Soy(10)}$	9.456		8.184						
$Q^2_{Soy(10)}$	10.859		7.120						

Note: See notes Table 3.

TABLE 5: Estimated VAR-GARCH(1,1) model, Oil-Sugar and Ethanol-Sugar

	Oil => Sugar		Eth. => Sugar			Sugar => Oil		Sugar => Eth.	
					Conditional Mean				
	Coef.	p-value	Coef.	p-value		Coef.	p-value	Coef.	p-value
α_1	0.001	(0.184)	0.000	(0.693)	α_2	0.001	(0.785)	0.000	(0.793)
β_{11}	-0.013	(0.427)	0.226	(0.000)	β_{22}	-0.082	(0.000)	-0.081	(0.000)
β_{12}	0.025	(0.013)	-0.059	(0.000)	β_{21}	0.057	(0.001)	-0.030	(0.374)
β_{12}^{*}	0.146	(0.002)	0.011	(0.819)	β_{21}^{*}	-0.148	(0.001)	-0.122	(0.001)
β_{12}^{**}	-0.001	(0.953)	0.030	(0.000)	β_{21}^{**}	0.060	(0.001)	0.097	(0.001)
β_{12}^{***}	-0.010	(0.788)	0.020	(0.382)	β_{21}^{***}	-0.010	(0.099)	-0.193	(0.001)
β_{12}^{****}	-0.007	(0.451)	0.041	(0.000)	β_{21}^{****}	-0.059	(0.000)	0.081	(0.001)
γ_1	0.031	(0.025)	0.006	(0.769)	γ_2	0.015	(0.569)	0.043	(0.072)
					Conditional Variance				
c_{11}	0.000	(0.628)	0.002	(0.007)	c_{22}	0.015	(0.000)	0.019	(0.000)
c_{12}	-0.009	(0.000)	-0.005	(0.001)					
a_{11}	0.187	(0.000)	0.338	(0.000)	a_{22}	0.381	(0.000)	0.378	(0.000)
a_{21}	0.097	(0.019)	-0.009	(0.669)	a_{12}	-0.122	(0.049)	0.072	(0.606)
a_{21}^{*}	0.011	(0.862)	0.035	(0.208)	a_{12}^{*}	0.154	(0.000)	0.213	(0.009)
a_{21}^{**}	-0.045	(0.642)	0.056	(0.210)	a_{12}^{**}	0.064	(0.650)	0.765	(0.000)
a_{21}^{***}	-0.088	(0.001)	-0.239	(0.002)	a_{12}^{***}	0.249	(0.000)	-0.911	(0.000)
a_{21}^{****}	-0.038	(0.773)	0.371	(0.000)	a_{12}^{****}	-0.367	(0.000)	0.700	(0.000)
g_{11}	0.981	(0.000)	-0.843	(0.000)	g_{22}	0.499	(0.000)	0.218	(0.026)
g_{21}	-0.223	(0.079)	-0.094	(0.000)	g_{12}	0.156	(0.008)	-0.208	(0.000)
g_{21}^{*}	-0.086	(0.370)	0.482	(0.000)	g_{12}^{*}	0.073	(0.420)	-0.006	(0.866)
g_{21}^{**}	0.187	(0.000)	0.003	(0.973)	g_{12}^{**}	-0.117	(0.279)	0.001	(0.994)
g_{21}^{***}	0.055	(0.164)	0.051	(0.004)	g_{12}^{***}	-0.084	(0.567)	0.081	(0.172)
g_{21}^{****}	0.275	(0.000)	-0.049	(0.000)	g_{12}^{****}	-0.119	(0.432)	0.231	(0.037)
Log-lik		20722.895		22793.120					
$Q_{Oil(10)}$	9.178								
$Q^2_{Oil(10)}$	8.123								
$Q_{Eth.(10)}$			3.241						
$Q^2_{Eth.(10)}$			3.255						
$Q_{Sugar(10)}$	5.740		8.837						
$Q^2_{Sugar(10)}$	6.588		2.312						

Note: See notes Table 3.

TABLE 6: Estimated VAR-GARCH(1,1) model, Oil-Wheat and Ethanol-Wheat

	Oil => Wheat		Eth. => Wheat			Wheat => Oil		Wheat => Eth.	
				Conditional Mean					
	Coef.	p-value	Coef.	p-value		Coef.	p-value	Coef.	p-value
α_1	0.001	(0.004)	0.000	(0.379)	α_2	0.000	(0.619)	0.000	(0.745)
β_{11}	-0.024	(0.107)	0.271	(0.000)	β_{22}	-0.049	(0.001)	-0.031	(0.648)
β_{12}	0.037	(0.000)	0.069	(0.000)	β_{21}	0.033	(0.000)	-0.130	(0.000)
β_{12}^{*}	-0.045	(0.450)	-0.037	(0.381)	β_{21}^{*}	-0.091	(0.291)	-0.135	(0.014)
β_{12}^{**}	-0.008	(0.227)	-0.110	(0.000)	β_{21}^{**}	0.047	(0.000)	0.099	(0.000)
β_{12}^{***}	-0.060	(0.000)	0.015	(0.460)	β_{21}^{***}	-0.126	(0.000)	-0.186	(0.000)
β_{12}^{****}	0.058	(0.000)	0.054	(0.000)	β_{21}^{****}	-0.080	(0.000)	0.106	(0.000)
γ_1	0.028	(0.122)	0.002	(0.842)	γ_2	0.008	(0.705)	-0.002	(0.918)
				Conditional Variance					
c_{11}	0.006	(0.000)	0.007	(0.001)	c_{22}	0.008	(0.000)	0.013	(0.000)
c_{12}	-0.004	(0.000)	0.000	(0.807)					
a_{11}	0.298	(0.000)	0.314	(0.000)	a_{22}	0.403	(0.000)	0.393	(0.000)
a_{21}	-0.371	(0.000)	-0.013	(0.653)	a_{12}	-0.057	(0.019)	0.016	(0.000)
a_{21}^{*}	0.146	(0.000)	-0.386	(0.000)	a_{12}^{*}	-0.078	(0.040)	0.244	(0.000)
a_{21}^{**}	0.134	(0.035)	0.386	(0.000)	a_{12}^{**}	0.084	(0.123)	-0.178	(0.227)
a_{21}^{***}	0.058	(0.000)	0.022	(0.547)	a_{12}^{***}	-0.174	(0.001)	-0.361	(0.000)
a_{21}^{****}	0.182	(0.000)	-0.206	(0.021)	a_{12}^{****}	-0.252	(0.001)	-0.052	(0.161)
g_{11}	0.867	(0.001)	0.388	(0.001)	g_{22}	0.403	(0.000)	0.393	(0.000)
g_{21}	0.794	(0.001)	0.027	(0.793)	g_{12}	-0.057	(0.019)	0.106	(0.000)
g_{21}^{*}	-0.381	(0.000)	0.609	(0.000)	g_{12}^{*}	-0.078	(0.040)	0.244	(0.000)
g_{21}^{**}	-0.113	(0.030)	-0.013	(0.574)	g_{12}^{**}	0.084	(0.123)	-0.178	(0.227)
g_{21}^{***}	0.176	(0.001)	0.037	(0.002)	g_{12}^{***}	-0.174	(0.001)	-0.361	(0.000)
g_{21}^{****}	-0.112	(0.005)	-0.043	(0.000)	g_{12}^{****}	-0.252	(0.001)	-0.052	(0.161)
Log-lik		21140.949		23212.603					
$Q_{Oil(10)}$	10.364								
$Q^2_{Oil(10)}$	6.475								
$Q_{Eth.(10)}$			9.446						
$Q^2_{Eth.(10)}$			4.076						
$Q_{Wheat(10)}$	2.804		7.179						
$Q^2_{Wheat(10)}$	7.757		4.719						

Note: See notes Table 3.

TABLE 7: Estimated VAR-GARCH(1,1) model, Ethanol-Oil

	Oil => Ethanol			Ethanol => Oil	
		Conditional Mean			
	Coef.	p-value		Coef.	p-value
α_1	0.001	(0.025)	α_2	0.000	(0.948)
β_{11}	0.011	(0.518)	β_{22}	0.261	(0.000)
β_{12}	0.120	(0.000)	β_{21}	-0.072	(0.000)
β_{12}^{*}	-0.047	(0.510)	β_{21}^{*}	0.085	(0.089)
β_{12}^{**}	0.082	(0.000)	β_{21}^{**}	0.012	(0.000)
β_{12}^{***}	-0.008	(0.825)	β_{21}^{***}	0.002	(0.946)
β_{12}^{****}	-0.162	(0.000)	β_{21}^{****}	0.052	(0.000)
γ_1	0.021	(0.401)	γ_2	0.007	(0.670)
		Conditional Variance			
c_{11}	0.014	(0.000)	c_{22}	0.005	(0.000)
c_{12}	-0.003	(0.000)			
a_{11}	0.309	(0.000)	a_{22}	0.362	(0.000)
a_{21}	0.082	(0.226)	a_{12}	-0.039	(0.102)
a_{21}^{*}	-0.854	(0.000)	a_{12}^{*}	0.077	(0.276)
a_{21}^{**}	0.238	(0.540)	a_{12}^{**}	0.032	(0.598)
a_{21}^{***}	0.751	(0.024)	a_{12}^{***}	-0.137	(0.029)
a_{21}^{****}	0.053	(0.856)	a_{12}^{****}	-0.020	(0.844)
g_{11}	-0.171	(0.134)	g_{22}	0.450	(0.000)
g_{21}	2.418	(0.000)	g_{12}	0.046	(0.000)
g_{21}^{*}	-1.256	(0.074)	g_{12}^{*}	0.393	(0.000)
g_{21}^{**}	-0.353	(0.008)	g_{12}^{**}	0.112	(0.002)
g_{21}^{***}	-0.286	(0.734)	g_{12}^{***}	0.199	(0.000)
g_{21}^{****}	-0.419	(0.001)	g_{12}^{****}	0.369	(0.004)
Log-lik		22781.373			
$Q_{Oil.(10)}$	4.745				
$Q^2_{Oil(10)}$	8.644				
$Q_{Eth.(10)}$	4.258				
$Q^2_{Eth.(10)}$	7.046				

Note: See notes Table 3.

Figure 1: Energy and Food Price Changes