Spillover effects of World oil prices on food prices: evidence for Asia and Pacific countries

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ABSTRACT

This study investigates the mean and volatility spillover effects of World oil prices on food prices for selected Asia and Pacific countries including Australia, New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand. The research employs vector autoregression (VAR) and GARCH-family models using daily observations for the 2 January1995 to 30 April 2010 period, splitting the data into two subsamples 1995-2001 and 2002-2010. The major empirical findings of the study are as follows. World oil prices positively influence food prices of the selected countries both in mean and in volatility, though the magnitudes of effects differ from country to country for different time periods. The effects are found mostly in the short run but not in the long run. Stronger mean and volatility spillover effects are found for the more recent subsample period suggesting increasing interdependence between World oil and Asia Pacific food markets in recent times. In terms of mean spillover effects net food importer countries' food price show stronger effects to the shocks, whereas in terms of volatility spillover effects no distinction in absorbing the World oil shocks can be made between exporters and importers. The findings suggest that oil prices should be taken into consideration in policy preparation and forecasting purposes for food prices.

Keywords: Oil price; food price; mean; volatility; spillover

1. Introduction

The skyrocketing trend of world oil and food prices in recent years has attracted the attention of concerned observers. The nexus between these two prices is now well documented in both media and academic literature for different reasons and recent surging of these prices also added additional attention to the analysts of governments, international and private research organizations(Abott *et al.*, 2009). Hence, the impact of oil prices on food prices has been studied from different viewpoints. It is believed that food prices are immensely influenced by world oil prices because agriculture is traditionally energy intensive and thus oil prices have direct linkage with agricultural commodity prices. When oil price increases agricultural input prices also increase, ultimately triggering the agricultural commodity price hikes (Hanson *et al.*, 1993; Nazlioglu and Soytas, 2010).

One of the many reasons for the rise in food prices is the increase in petroleum prices. A number of studies have focused on the causes of food price hike emphasising the factors related to petroleum usage and price; for example, increased demand for bio-fuel as an alternative of conventional fossil fuel has been identified as one of the factors of the food price surge (Headey and Fan, 2008; Mitchell, 2008; Rosegrant *et al.*, 2008). Few other studies also show that increases in oil and metal prices lead the jump in food prices (Radetzki, 2006; Headey and Fan, 2008; Du *et al.*, 2010).

A few studies have dealt with the analysis of spillover effects of oil price on food prices. Baffes (2007) examined the effect of oil prices on 35 internationally traded primary commodity prices including food and found that the fertilizer price index has shown highest pass through of any agricultural commodity. Alghalith (2010) pointed out that in an oil exporting country like Trinidad and Tobago the food price is largely influenced by higher oil prices. Du *et al.* (2010) applying a Bayesian econometric analysis documented evidence of volatility spillovers among crude oil, corn and wheat markets. In the same line Esmaeili and Shokoohi (2011), using principal component analysis, argued that the oil price index has an influence on the food price index . Relationships between oil and food prices were also modelled by Chen *et al.* (2010), documenting that global grain prices for corn, soybean and wheat are significantly influenced by the changes in crude oil prices. The impact of crude oil prices on vegetable oil price is found to be positive as discussed in Abdel and Arshad (2008).

Despite having extensive evidence of positive relationships between oil and agricultural commodity prices some studies concluded that there is no significant influence of oil prices on food prices.For example, Nazlioglu and Soytas (2010) revealed in the case of Turkey that oil prices do not have any direct or indirect impact on agricultural commodity prices. Yu *et al.* (2006) by applying cointegration approach to World crude oil prices and a set of edible oil prices concluded that World oil price does not exert any influence on edible oil prices. Kaltalioglu and Soytas (2009) also reports similar results that World oil prices do not have any significant influence on World food prices and agricultural raw materials prices. In a study in the context of China's corn, soybean, and pork prices for the period of January 2000 to October 2007 Zhang and Reed (2008) maintained that World crude oil prices are not the factors predominately contributing to the recent surging of selected agricultural commodity prices.

However, to the best of our knowledge, there is a dearth of studies of the impact of World oil prices on food prices using a *daily* data set in the style of financial asset modelling with regard to mean and volatility spillover effects. This seems to be particularly true in the context of Asia and Pacific countries. This topic, however, warrants the attention of researchers now, not only due to its importance for social well being, but also because of the fact that food prices, particularly food commodity future prices, are gaining popular positions in the portfolios of fund managers much as crude oil prices have (Robles *et al.*, 2009; Gilbert, 2010). Hence, the objective of the current study is to explore the mean and volatility spillover effects of World oil prices on food prices in the context of a set of Asia and Pacific countries namely Australia, New Zealand, Korea, Singapore, Hong Kong, Taiwan, India and Thailand. The study area is a combination of both net food exporters and importers with a common feature of their net oil importer status. Australia, New Zealand, India and Thailand are regarded as net food exporter countries. Hence the empirical findings w permit inferences about similarities and differences in terms of the effects of oil price shocks.

The remainder of the paper is structured as follows. The next section outlines the sources of data obtained and the statistical properties of both oil and food price data. Section 3 delineates the methodology used along with the model framework for both univariate and multivariate analysis. Section 4 reports results and discusses the main empirical findings while the last section concludes the paper.

2. Data and their properties

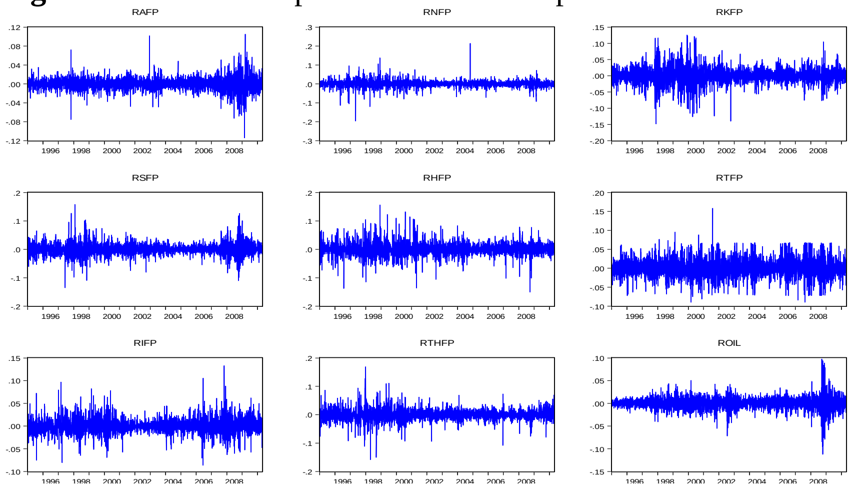
This study uses daily oil and food producer price indices for January 1995 to April 2010 provided by DataStream. The sample period is chosen based on the availability of data for all required series. For oil world integrated series (OP) and for food prices integrated food producer price indices for Australia (AFP), New Zealand (NFP), Korea (KFP), Singapore (SFP), Hong Kong (HFP), Taiwan (TFP), India (IFP) and Thailand (THFP) are chosen. Food price increases experienced sharp growth after 2001 and so we examine the effects of oil prices on food prices in three different time periods, by estimating models in distinct time periods, namely full sample January 1995 to April 2010, early subsample from January 1995 to December 2001 and latest subsample from January 2002 to April 2010. As a consequence 4,000 observations for full sample, 1,824 observations for the early subsample and 2,087 observations for the latest subsample are utilized.

Table 1 depicts summary statistics of food and oil prices over the full sample period. The measure of volatility, standard deviation, is high for all of the price series which basically tells about the high volatility of food and oil prices. All price series are positively skewed except the New Zealand food price index. That means all other series have long right tail and New Zealand food price index has long left tail. The values of kurtosis are close to three in all cases except New Zealand implying distributions are more peaked than normal. None of the series shows any evidence of a normal distribution because the Jarque-Bera statistics reject the null hypothesis of normality at any level of significance for every series of data. The LB Q-stat indicates high evidence of autocorrelation and non-constant variances. The lower panel of Table 1 displays the properties of returns series. Returns series are calculated by using standard logarithmic technique $\boldsymbol{R_t = ln(P_t/P_{t-1})}$ where P_t is the price for current day while P_{t-1} represents price for the previous day. Returns series seem to have the typical characteristics of financial variables which can be seen in Figure 1. Figure 1 shows that returns for both oil and food price follow volatility clustering. The evidence of long left tails can be seen for the food price returns of Australia and Korea along with international oil prices. Excess kurtosis is greater than 3 in all cases. The existence of standard deviations greater than mean returns, non normality, and evidence of autocorrelation clearly suggest the data o be analyzed by GARCH type models. Returns series are used for estimation purposes within the framework of univariate and multivariate GARCH models. From the summary statistics it seems evident that oil and food prices display features associated with financial characteristics such as volatility clustering, long tails and leptokurtosis.

Table 1 Statistical properties of data

	Prices								
	AFP	NFP	KFP	SFP	HFP	TFP	IFP	THFP	OP
Mean	976.71	451.26	385.75	474.17	168.94	284.35	1078.30	550.57	1387.06
Median	895.33	483.45	333.69	418.97	116.65	234.69	899.30	561.64	1100.81
Maximum	1905.49	744.57	871.13	1007.11	625.34	695.64	2989.23	1190.86	3336.58
Minimum	477.21	206.46	124.31	117.19	33.39	116.25	254.14	176.56	501.41
Std. Dev.	363.04	129.65	180.13	218.31	132.94	135.55	630.13	171.32	658.94
Skewness	0.636	-0.244	0.595	0.526	1.460	0.866	0.833	0.370	0.844
Kurtosis	2.31	1.86	2.09	1.98	4.45	2.67	2.95	3.35	2.66
J-B	348.54	254.97	373.57	355.22	1776.97	518.42	463.56	112.01	493.92
Prob.	0.0000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LBQ(15)	59377	58556	58548	58996	58363	58330	58470	57112	59157
Obs.	4000	4000	4000	4000	4000	4000	4000	4000	4000
	Returns								
	RAFP	RNFP	RKFP	RSFP	RHFP	RTFP	RIFP	RTHFP	ROP
Mean (%)	0.0001	-6.78E-06	0.0002	0.0001	0.0004	0.0002	0.0004	0.0001	0.0003
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0008
Maximum	0.0105	0.2138	0.1251	0.1576	0.1556	0.1583	0.1391	0.1687	0.0975
Minimum	-0.1138	-0.1967	-0.1481	-0.1352	-0.1505	-0.0898	-0.0862	-0.1580	-0.1123
Std. Dev. (%)	0.0123	0.0160	0.0232	0.0193	0.0209	0.0225	0.0156	0.0186	0.0130
Skewness	-0.0455	0.0782	-0.0691	0.2547	0.1131	0.1113	0.3936	0.0234	-0.4214
Kurtosis	11.071	23.414	7.710	9.486	9.265	5.002	8.148	11.871	11.9545
J-B	10856	69445	3699	7053	6550	676	4520	1311	11.954
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LBQ(15)	44.60	14.89	70.17	34.15	21.77	36.57	44.85	62.23	111.83
Obs.	3999	3999	39999	3999	3999	3999	3999	3999	3999

Figure 1 Oil and food price returns for the period 1995 to 2010



3. Methodology

3.1 Methods for modelling mean spillover effects of oil prices on food prices

With a view to check mean spillover effects of World oil prices to food prices this study employs bi-variate vector autoregression (VAR) method of analysis originally developed by Sims (1980). In the VAR approach to analysing interrelationships among variables the two main procedures are Granger causality tests and innovation accounting such as impulse response analyses and forecast error variance decompositions. Estimated VAR results are analyzed with the help of Granger causality tests, variance decomposition and impulse response analysis. A typical VAR model having p lags can be expressed succinctly in matrix notation as follows:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + \dots\dots\dots + A_p X_{t-p} + \varepsilon_t \tag{1}$$

Where X_t is a *n x 1* vector of endogenous variables, A_0 is a *n x 1* vector of constants, A_i are *n x n* matrices of parameters and ε_t is a zero mean white noise vector of *n x n* variance-covariance matrices.

Granger causality shows whether lagged values of one variable help to predict another variable. "A variable y_t is said to Granger-cause x_t, if x_t can be predicted with greater accuracy by using past values of the y_t variable rather than not using such past values, all other terms remaining unchanged (Granger, 1969)". Letting y_t and x_t, be two stationary variables with zero means, a simple causal model can be written in the following VAR form:

$$y_t = \alpha_1 + \sum_{j=1}^{m} a_j x_{t-j} + \sum_{j=1}^{m} b_j y_{t-j} + \varepsilon_t \tag{2}$$

$$x_t = \alpha_2 + \sum_{j=1}^{m} c_j y_{t-j} + \sum_{j=1}^{m} d_j x_{t-j} + \eta_t \tag{3}$$

Where ε_t and η_t are assumed as uncorrelated white noise series, i.e. $E(\varepsilon_\tau\, \varepsilon_\sigma) = 0 = E(\eta_\tau\, \eta_\sigma),\ s \neq t$. If a_j is statistically different from zero and b_j is not statistically different from zero then we say x_t Granger-causes y_t. Similarly, y_t is Granger-causing x_t if some c_j is statistically different from zero. If both parameters are statistically different from zero there will have bidirectional causality or it is said to have feedback relationship between them, and if neither of them is statistically different from zero we infer that x_t and y_t are independent of each other.

Assuming that invertability conditions hold we can consider the VMA (Vector moving average) representation of the bivariate VAR model for the impulse response functions.

$$\begin{bmatrix} FP_t \\ OP_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \sum_{i}^{\infty} \begin{pmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{pmatrix} \begin{bmatrix} e_{1,t-i} \\ e_{2,t-i} \end{bmatrix} \tag{4}$$

The parameters in the $\phi_{jk}(i)$ may be used to generate the numerical effects of errors' shocks on the time path of endogenous variables. In the proposed case, there would be two possible shocks to the system and therefore, there will be four impulse response functions (IRFs), which will be presented in graphical form.

In the bivariate setting the m step forecast error for x_t series can be expressed as

$$\begin{aligned} x_{t+m} - E_t(x_{t+m}) = & a_{11}(0)e_{xt+m} + a_{11}(1)e_{xt+m-1} + \dots\dots\dots\dots + a_{11}(m-1)e_{xt+1} \\ & + a_{12}(0)e_{yt+m} + a_{12}(1)e_{yt+m-1} + \dots\dots\dots + a_{12}(m-1)e_{yt+1} \end{aligned} \tag{5}$$

where x_t is a column vector of variables.

Taking the variance $\sigma_x(m)^2$ of this m step forecast error gives:

$$\begin{aligned} \sigma_x(m)^2 = & \sigma_x^2\left[a_{11}(0)^2 + \dots\dots\dots\dots\dots + a_{11}(m-1)^2\right] \\ & + \sigma_y^2\left[a_{12}(0)^2 + \dots\dots\dots\dots\dots + a_{12}(m-1)^2\right] \end{aligned} \tag{6}$$

The first part of the right hand side of the above equation shows the variance due to the shocks to x_t and second part measures the effect to the y_t series.

3.2 Methods for volatility spillover effects of oil prices on food prices

In order to examine the volatility spillover effects of international oil prices on the food prices of selected Asian and Pacific countries we use univariate GARCH models. The estimation procedure involves several stages. First of all we estimate different GARCH models of oil price volatility for different time periods. Models are estimated under the set of different linear and nonlinear GARCH models and the best fit model is selected based on the information criteria and forecasting capabilities. Over the full sample period the Exponential GARCH (EGARCH) model developed by Nelson (1991) fits data better than other models. For the early subsample the Component GARCH (CGARCH) model developed by Engle and Lee (1993) better captures volatility characteristics than other models, and over the latest subsample the Power ARCH (PARCH) model provided by Ding *et al.* (1993) outperforms other models.

In the second stage we obtain conditional variances (CV) out of these models to incorporate them into the variance equations of food price returns models. In the final stage we estimate several ARMA (p,q)-GARCH(1,1) models for all food price series incorporating CVs in variance equations in line with Liu and Pan (1997) Lin and Tamvakis (2001) Engle *et al. (2002)* Hammoudeh *et al*.(2003) and chose best models based on the information criteria and forecasting ability. In this stage simple GARCH models provided by Bollerslev (1986), Threshold GARCH (TGARCH) developed by Glosten *et al.* (1993), EGARCH, PARCH and CGARCH models are found to be good fit for different food price series in different time periods.

The models we estimated for the purpose of volatility spillover effects are discussed briefly in the following two sections.

3.2.1 Volatility models for oil price

As stated earlier for oil price volatility, EGARCH, CGARCH and PARCH models are found to be good fit for three different time periods. For full sample, oil price is estimated by ARMA (p,q)-EGARCH (1, 1) model. The model can be specified as follows:

Mean equation:

$$ROIL_t = \beta_1 + \beta_2 ROIL_{t-i} + \beta_4 e_{t-i} + \varepsilon_t \quad (7)$$

$$\varepsilon_t \sim iid(0, h_t)$$

Variance equation:

$$\log h_t = \gamma_0 + \gamma_1 \left| \frac{e_{t-1}}{h_{t-1}} \right| - \gamma_2 \frac{e_{t-1}}{h_{t-1}} + \gamma_3 \log h_{t-1} \quad (8)$$

Where the parameter γ_1 captures the magnitude of conditional shocks on the conditional variance, γ_2 measures leverage effects (if $\gamma_2 < 0$ then negative shocks give rise to higher volatility than positive shocks and vice versa), γ_3 measures persistency of any shocks to volatility and should be less than 1 to reflect the stationarity of the returns series.

For the 1995 to 2001 sample period the symmetric ARMA (p,q)-CGARCH (1, 1) model seems be suited to capture the financial characteristics. The model can be written as follows:

Mean equation:

$$ROIL_t = \beta_1 + \beta_2 ROIL_{t-i} + \beta_4 e_{t-i} + \varepsilon_t \quad (9)$$

$$\varepsilon_t \sim iid(0, h_t)$$

Variance equations:

$$q_t = \gamma_0 + \gamma_1(q_{t-1} - \gamma_0) + \gamma_2(e_{t-1}^2 - h_{t-1})$$
$$h_t = q_t + \gamma_4(e_{t-1}^2 - q_{t-1}) + \gamma_5(h_{t-1} - q_{t-1}) \qquad (10)$$

Where q_t is the permanent component, $(e_{t-1}^2 - h_{t-1})$ serves as the driving force for the time dependent movement of the permanent component and $(h_{t-1} - q_{t-1})$ represents the transitory component of the conditional variance. The parameter γ_4 measures asymmetry of leverage effects and the sum of parameters γ_3 and γ_5 measures the transitory shock persistence, while γ_1 measures the long run persistency derived from the shock to a permanent component given by γ_2.

For the period January 2002 to April 2010 PGARCH (1, 1) model is selected as follows:

$$ROIL_t = \beta_1 + \beta_2 ROIL_{t-i} + \beta_3 e_{t-i} + \varepsilon_t$$

$$\varepsilon_t \sim iid(0, h_t)$$

$$(\sqrt{h_t})^{\gamma_4} = \gamma_0 + \gamma_1(|e_{t-1}| - \gamma_2 e_{t-1})^{\gamma_4} + \gamma_3(\sqrt{h_{t-1}})^{\gamma_4} \qquad (11)$$

where $\sqrt{h_t}$ is conditional standard deviation and γ_4 is power term which is determined within the model, γ_1 and γ_3 are ARCH and GARCH parameters, while γ_2 parameter captures leverage effects or asymmetry. Based on the value of the power term this model can take the form of various ARCH/GARCH models. If γ_4=2 it becomes TGARCH model and when γ_4=2 and γ_2=0 it becomes GARCH(1,1) model.

3.2.2 Volatility spillover models for food prices

As stated earlier different volatility models qualify to be estimated for different food price models across time periods. Conditional variance equations of the ARMA (p,q)-GARCH models for GARCH, TGARCH, EGARCH, PARCH and symmetric and asymmetric CGARCH models estimated are presented below. ARMA orders are set by Box-Jenkins methodology (Box and Jenkins, 1976). Conditional mean equations are not shown because the interest is on conditional variance equations only. The parameters (γ_s) associated with $roilh_{t-1}$ in each case measures the volatility spillover effects from World oil prices to food prices of the selected countries.

Conditional variance equation of GARCH (1, 1) model:

$$h_t = \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_3 h_{t-1} + \gamma_4 roilh_{t-1} \tag{12}$$

Conditional variance equation of TGARCH (1, 1) model:

$$h_t = \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_2 e_{t-1}^2 d_{t-1} + \gamma_3 h_{t-1} + \gamma_4 oilh_{t-1} \tag{13}$$

Conditional variance equation of EGARCH (1, 1) model:

$$\log h_t = \gamma_0 + \gamma_1 \left| \frac{e_{t-1}}{h_{t-1}} \right| - \gamma_2 \frac{e_{t-1}}{h_{t-1}} + \gamma_3 \log h_{t-1} + \gamma_4 oilh_{t-1} \tag{14}$$

Conditional variance equation of PGARCH (1, 1) model:

$$(\sqrt{h_t})^{\gamma_5} = \gamma_0 + \gamma_1 (|e_{t-1}| - \gamma_2 e_{t-1})^{\gamma_5} + \gamma_3 (\sqrt{h_{t-1}})^{\gamma_5} + \gamma_4 Oilh_{t-1} \tag{15}$$

Conditional variance equations of symmetric CGARCH model with spillover parameter in permanent equation:

$$\begin{aligned} q_t &= \gamma_0 + \gamma_1 (q_{t-1} - \gamma_0) + \gamma_2 (e_{t-1}^2 - h_{t-1}) + \gamma_3 oilh_{t-1} \\ h_t &= q_t + \gamma_4 (e_{t-1}^2 - q_{t-1}) + \gamma_5 (h_{t-1} - q_{t-1}) \end{aligned} \tag{16}$$

Conditional variance equations of symmetric CGARCH model with spillover parameter in transitory equation:

$$\begin{aligned} q_t &= \gamma_0 + \gamma_1 (q_{t-1} - \gamma_0) + \gamma_2 (e_{t-1}^2 - h_{t-1}) \\ h_t &= q_t + \gamma_3 (e_{t-1}^2 - q_{t-1}) + \gamma_4 (h_{t-1} - q_{t-1}) + \gamma_5 oilh_{t-1} \end{aligned} \tag{17}$$

Conditional variance equations of asymmetric CGARCH (1, 1) with spillover parameter in permanent equation:

$$\begin{aligned} q_t &= \gamma_0 + \gamma_1 (q_{t-1} - \gamma_0) + \gamma_2 (e_{t-1}^2 - h_{t-1}) + \gamma_3 oilh_{t-1} \\ h_t &= q_t + \gamma_4 (e_{t-1}^2 - q_{t-1}) + \gamma_5 (e_{t-1}^2 - q_{t-1}) d_{t-1} + \gamma_6 (h_{t-1} - q_{t-1}) \end{aligned} \tag{18}$$

Conditional variance equations of asymmetric CGARCH (1, 1) with spillover parameter in transitory equation:

$$\begin{aligned} q_t &= \gamma_0 + \gamma_1 (q_{t-1} - \gamma_0) + \gamma_2 (e_{t-1}^2 - h_{t-1}) \\ h_t &= q_t + \gamma_3 (e_{t-1}^2 - q_{t-1}) + \gamma_4 (e_{t-1}^2 - q_{t-1}) d_{t-1} + \gamma_5 (h_{t-1} - q_{t-1}) + \gamma_6 oilh_{t-1} \end{aligned} \tag{19}$$

In each case to avoid the possible violation of normality models are estimated by using generalized error distribution (GED).

3.3 Methods for robustness analysis

In order to check robustness of the results to be obtained for mean and volatility spillover effects from World oil prices to food prices of the concerned countries we use multivariate GARCH (MGARCH) models, in particular, bivariate BEEK (Baba, Engle, Kroner and Kraft) type model proposed by Engle and Kroner (1995) is employed. To be specific, we develop model in line with Higgs and Worthington (2004) and Lee (2009). The model consists of conditional mean and variance equations. The conditional mean returns equation we develop for each of the food price model can be written as:

$$R_t = \rho + AR_{t-1} + \varepsilon_t \tag{20}$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t)$$

where R_t is an *n x 1* vector of daily food/oil price returns at time t for each market, ρ is an *n x 1* vector of constants, ε_t is a *n x 1* vector of innovation for each market at time *t* with its corresponding *n* x *n* conditional variance and covariance matrix, H_t and the elements of a_{ij} of the matrix *A* are the measures of the degree of mean return spillover effects across food and oil markets, specifically, the estimates of the elements of the matrix A offer measures for own lagged and cross mean spillovers.

The variance equation in the BEKK representation for MGARCH model can be written as:

$$H_t = C'C + B'\varepsilon_{t-1}\varepsilon'_{t-1}B + G'H_{t-1}G \tag{21}$$

where $c_{i,j}$ are elements of *n* x *n* symmetric C matrix of constants; $b_{i,j}$, the elements of *n* x *n* symmetric *B* matrix, measure the degree of lagged and cross innovation from market *i* to market j and the elements $g_{i,j}$ of the n x n symmetric G matrix signifies the persistence of conditional volatility between market i and j.

The equation in (21) can be written in its simple form for the bi-variate BEKK model as:

$$H_t = C'C + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} + \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}' H_{t-1} \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} \qquad (22)$$

In equation (22) b_{21} measures the volatility spillover from oil market to food market and b_{12} represents the volatility spillover from food market to oil market, g_{21} indicates volatility persistence effects from oil market to food market and g_{12} shows the volatility persistence effects from food market to oil market. For possible violation of normality we estimate models using Bollerslev and Wooldridge (1992) robust standard errors.

4. Empirical Results

4.1 Mean spillover effects from oil prices to food prices

In order to examine the effects of shocks to oil prices on food prices at mean level, bivariate VAR models pairing oil price to each country's food prices are estimated for each of the series covered in the study. Augmented Dickey Fuller (ADF) tests results in Table 2 show that all price series are nonstationary levels while they are stationary in first differences, hence integrated of order 1 (Dickey and Fuller, 1979).

Table 2 Results Unit root test

	1995-2010		1995-2001		2002-2010	
	Level	First diff.	Level	First diff.	Level	First diff.
OP	-1.2181	-45.1538[a]	-1.7616	-32.8788[a]	-1.3622	-41.0669[a]
AFP	-1.4532	-68.2317[a]	-1.5527	-43.5495[a]	-1.3927	-50.7298[a]
NFP	-1.6695	-62.1734[a]	-0.5725	-32.4212[a]	-1.1077	-45.3704[a]
KFP	-1.4040	-60.4630[a]	-1.9086	-26.6785[a]	-1.5674	-47.0544[a]
SFP	-0.6752	-62.0449[a]	-0.8843	-42.1481[a]	-0.6603	-45.6006[a]
HFP	1.8033	-58.4303[a]	-1.2995	-42.98297[a]	0.7765	-42.6141[a]
TFP	-1.3745	-45.8658[a]	-1.2781	-39.9285[a]	-1.1804	-34.7303[a]
IFP	0.4328	-58.7985[a]	-0.7288	-39.9593[a]	-0.2242	-43.3031[a]
THFP	0.1118	-62.5226[a]	-1.6312	-39.79405[a]	0.5766	-48.2952[a]

Notes: The values are t statistics and [a], [b], [c] indicate 1%, 5% and 10% significance level respectively

However, according to the Johansen (1988) cointegration testing procedure, in no instance is the food price series cointegrated with world oil prices at any level of significance. These results are not produced here for brevity purpose but are available from the author. Although oil and food price indices do not show any long run linear combination (consistent with Zhang *et al.*(2010)p), the Pearsonian correlation coefficients amongst the series are significant, being greater than 0.5 . about or greater than 0.50 in each case for full sample period (see Table 3). For the early and recent subsamples the correlation coefficients differ from full sample results. Based on the positive correlations in all cases except two exceptions in the early subsample, it can be concluded that though oil and food prices do not exhibit any long run relationship there might have short run relationship between them. The significant lagging and leading relationship along with nonstationary properties suggest using bivariate VAR regression models with first differenced series. With a view to estimating the VAR models, optimal lag lengths are selected based on the lowest values of information criteria e.g. LR, FPE, AIC, SC and HQ supported by at least 3 criteria values which are used for Granger causality tests. For each model we select the lag length indicated by three of the five criteria employed. As can be seen in Table 4 for most models optimal lag length is 8 with the exception of New Zealand and Thai models. For these two models optimal lag lengths are 3 and 5 respectively.

Table 3 Correlation between oil and food prices

1995-2010	AFP	NFP	KFP	SFP	HFP	TFP	IFP	THFP	OP
OP	0.801	0.543	0.904	0.489	0.794	0.674	0.887	0.497	1.000
1995-2001									
OP	0.6463	0.7255	0.3838	-0.7928	-0.7199	0.1337	0.8501	0.1306	1.00
2002-2010									
OP	0.5942	0.2062	0.9446	0.9046	0.8067	0.8393	0.8363	0.0925	1.000

Table 4 Optimal lag length

Models	LR	FPE	AIC	SC	HQ
AFP OP	8	8	8	2	3
NFP OP	5	3	3	2	3
KFP OP	8	8	8	2	3
SFP OP	8	8	8	2	3
HFP OP	8	8	8	3	3
TFP OP	8	8	8	2	3
IFP OP	8	8	8	2	4
THFP OP	5	5	5	2	3

Based on the optimal lag length the models are estimated accordingly in the unrestricted VAR form and we do not report the results of VAR models in the paper because associated tool kits explain results more than VAR coefficients. The results of Granger causality tests, variance decompositions and impulse response functions are illustrated in the following sections.

4.1.1 Granger causality test results

Table 5 reports Granger causality test results. The second, third and fourth column lists Chi-square statistics with p-values in parentheses for the period of 1995-2010, 1995-2001 and

2002-2010 respectively. It is clear from estimated chi-square statistics that future food prices can be predicted with lagged values of themselves and international oil prices. International oil prices and food prices of all countries show unidirectional causal relationship from oil to food prices except Australia across all three sample/subsamples. In the case of Australia and India a bidirectional causal relationship can be observed for full sample period. Although it seems there is bidirectional causal relationship between oil and Indian food prices the Chi square statistics from oil to food is statistically significant at 1% level of significance while from food to oil it is statistically significant only at 10% level of significance. For the two subsamples no evidence of bidirectional causal relationship appears for India, or for Australia for the subsample of 1995-2001. These results imply weak causality evidence from food prices to oil price. Based on the analysis above, it can be inferred that there is significant evidence of unidirectional mean spillover from oil prices to food prices in the Asia-pacific region.

Table 5 Results of Granger causality test for food and oil prices

Null hypotheses	1995-2010	1995-2001	2002-2010
OP does not Granger cause AFP	125.7587[a] (0.0000)	55.09729[a] (0.0000)	77.54047[a] (0.0000)
AFP does not Granger cause OP	57.45922[a] (0.0000)	9.544899 (0.2159)	30.15450[a] (0.0000)
OP does not Granger cause NFP	60.70656[a] (0.0000)	9.313342[b] (0.0254)	54.87965[a] (0.0000)
NFP does not Granger cause OP	3.33546 (0.3427)	2.857248 (0.4142)	5.667793 (0.1289)
OP does not Granger cause KFP	87.53245[a] (0.0000)	9.373401 (0.1536)	78.61508[a] (0.0000)
KFP does not Granger cause OP	8.888258 (0.3518)	20.77351[a] (0.0020)	8.617526 (0.1253)
OP does not Granger cause SFP	197.3285[a] (0.0000)	10.92196[b] (0.0122)	171.2682[a] (0.0000)
SFP does not Granger cause OP	10.14783 (0.2548)	1.241693 (0.7430)	19.51118[b] (0.0124)
OP does not Granger cause HFP	282.2730[a] (0.0000)	12.60525[b] (0.0274)	169.1262[a] (0.0000)
HFP does not Granger cause OP	12.55834 (0.1280)	8.680473 (0.1225)	2.266800 (0.5189)
OP does not Granger cause TFP	93.83193[a] (0.0000)	17.07319[a] (0.0007)	60.68194[a] (0.0000)
TFP does not Granger cause OP	12.99043 (0.1122)	2.244068 (0.5233)	10.42649 (0.2364)
OP does not Granger cause IFP	45.10794[a] (0.0000)	28.33284[a] (0.0002)	29.40450[a] (0.0000)
IFP does not Granger cause OP	16.86679[c] (0.0315)	8.301984 (0.3067)	3.365326 (0.4986)
OP does not Granger cause THFP	22.58338[a] (0.0004)	8.103010[c] (0.0879)	15.58669[a] (0.0004)
THFP does not Granger cause OP	4.268140 (0.5115)	2.613111 (0.6245)	3.927047 (0.1404)

Notes: The values are chi-square statistics and values in parentheses are p-values and [a], [b], [c] indicate 1%, 5% and 10% significance level respectively

4.1.2 Analysis of forecast error variance decomposition

The generated variance decomposition functions for 10, 20 and 30 day horizon are displayed in Table 6 over the full and two subsample periods. Over the full sample period all the price series receive considerable innovation effects from oil price changes. Shocks to oil prices contribute 5.5 percent to the variation of Australian food price chnages for 10 day horizon while the effects decrease gradually over the horizons. The contribution of oil price shocks to New Zealand food price change is 2.8 percent and the effects for Korea, Singapore, Hong Kong, Taiwan, India and Thailand are 8.52, 20.11, 18.21, 7.31, 7.16 and 3.49 percent respectively over 10 day period and the effects persist over 30 day horizon. Food importer countries show more volatility in prices than food exporter countries. Estimated values for the early subsample period shows negligible variation in food prices of each country due to the shocks in oil price changes while latest period data shows relatively high responsiveness of food price changes than the early subsample. This implies that oil and food markets are more interdependent in the recent periods than any other times in the past. Although the magnitudes of the sources of variation due to the oil price shocks are low there is a significant variation in food price in the recent time and the trend remains the same.

Table 6 Variance decomposition (%) of food prices for horizon 10, 20 and 30 days

	Periods	1995-2010(OP)	1995-2001(OP)	2002-2010(OP)
AUSFP	10	5.5199	0.6599	1.8454
	20	1.8625	0.3609	1.5906
	30	1.6721	0.2503	1.3528
NZFP	10	2.8164	0.4663	2.2728
	20	1.5599	0.7652	2.4586
	30	1.6195	1.1233	2.5836
KORFP	10	8.5244	1.0450	5.9672
	20	4.5631	1.2185	7.4944
	30	5.2781	1.2805	8.4889
SINFP	10	20.1125	0.1925	7.9498
	20	6.6162	0.1099	8.4112
	30	6.9563	0.1650	8.0272
HKFP	10	18.2119	0.3391	2.7374
	20	7.5751	0.2399	2.3556
	30	7.9745	0.1718	2.0402
TWNFP	10	7.3127	0.7893	2.1691
	20	2.0419	0.7510	2.9954
	30	2.3279	0.6934	3.4838
INFP	10	7.1694	0.2611	2.4671
	20	3.0392	0.5742	2.8066
	30	3.1728	1.2641	2.8729
THFP	10	3.4928	0.1496	0.7087
	20	1.4455	0.2458	0.6884
	30	1.5534	1.2641	0.6383

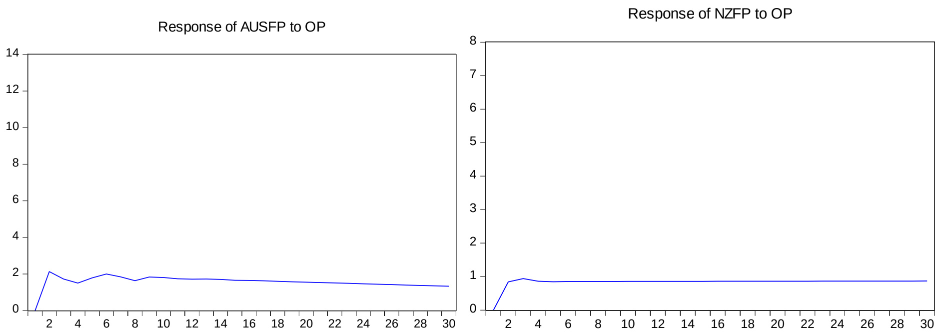
Overall analysis of variance decomposition shows that oil prices contribute to the sources of food price volatility but the magnitude differs for food importing and food exporting countries. In food importing countries of Korea, Singapore, Hong Kong and Taiwan the contribution of oil prices to sources of volatility is higher than in food exporting countries of

Australia and New Zealand. Moreover, the magnitudes differ across time periods and in recent time period food and oil markets found to be more interdependent. This is because food production is getting more technology intensive, depending more on oil. The results of variance decomposition support the results of Granger causality tests that oil prices help prediction of food prices.

4.1.3 Impulse response analysis

The impulse response functions of food prices to oil price shocks are exhibited in Figures 2-4 over three time periods for a horizon of 30 days. Figure 2 depicts the responses over the full sample period. The impulse response of the Australian food price changes to international oil shows that oil price shock positively affects Australian food prices in day 1 and persists for a long time though the magnitude diminishes over time. The magnitude is around 3 percent. It can also be seen in Figure 3 that in thirty days the effect of shock does not disappear. New Zealand food prices also positively respond to the oil price shock and the effects of shocks stay stable for 30 days and longer with a magnitude of more than 1 percent. The Korean, Singapore, Hong Kong and Taiwan food prices also positively respond to the oil price shocks and the effects of shocks increases over time although the size of the effects are different. Consistent with New Zealand the effects of shocks to the Indian and Thai food prices are positive and keep stable over the period. Similar patterns can be seen in the net food exporter countries except Australia and this is also applicable among net importer countries.

Figure 2 Impulse response functions of food prices to a Cholesky one standard deviation to oil price shock over the period 1995-2010.



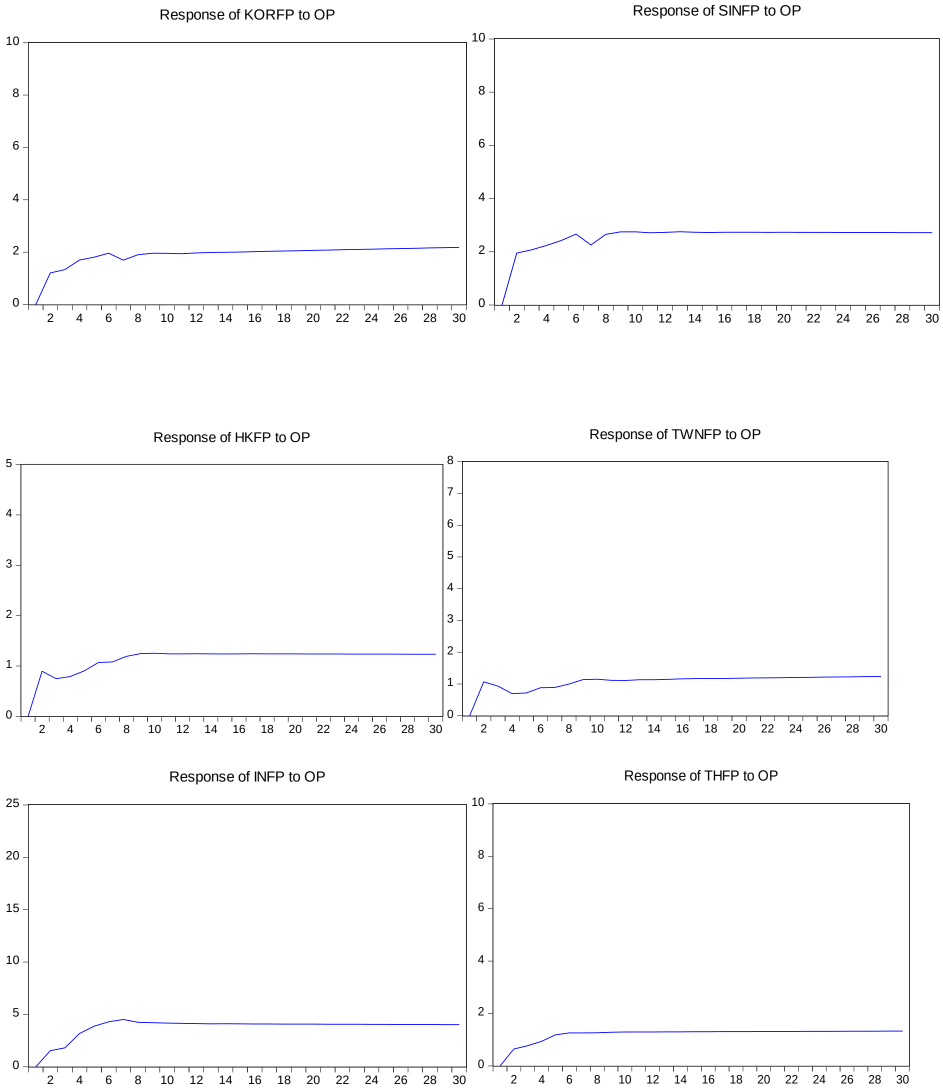


Figure 3 displays responsiveness of food prices to international oil prices over the period of 1995-2001. Similar to variance decomposition results positive short-lived responses of food prices to oil price shocks can be viewed. Excepting New Zealand, Korea and Thailand in all other cases the effects of shocks die out quickly. In the Australian and Indian food market prices respond positively at around 2 percent at day 1 while it dies out rapidly in a week. In Singapore market the effects remain about 2 weeks and in Hong Kong it remains about four weeks. In the case of New Zealand and Thailand the effects increases gradually and decreases after a long period while it remains stable for 30 days and then dies out in Korean case.

Figure 3 Impulse response functions of food prices to a Cholesky one standard deviation to oil price shock over the period 1995-2001

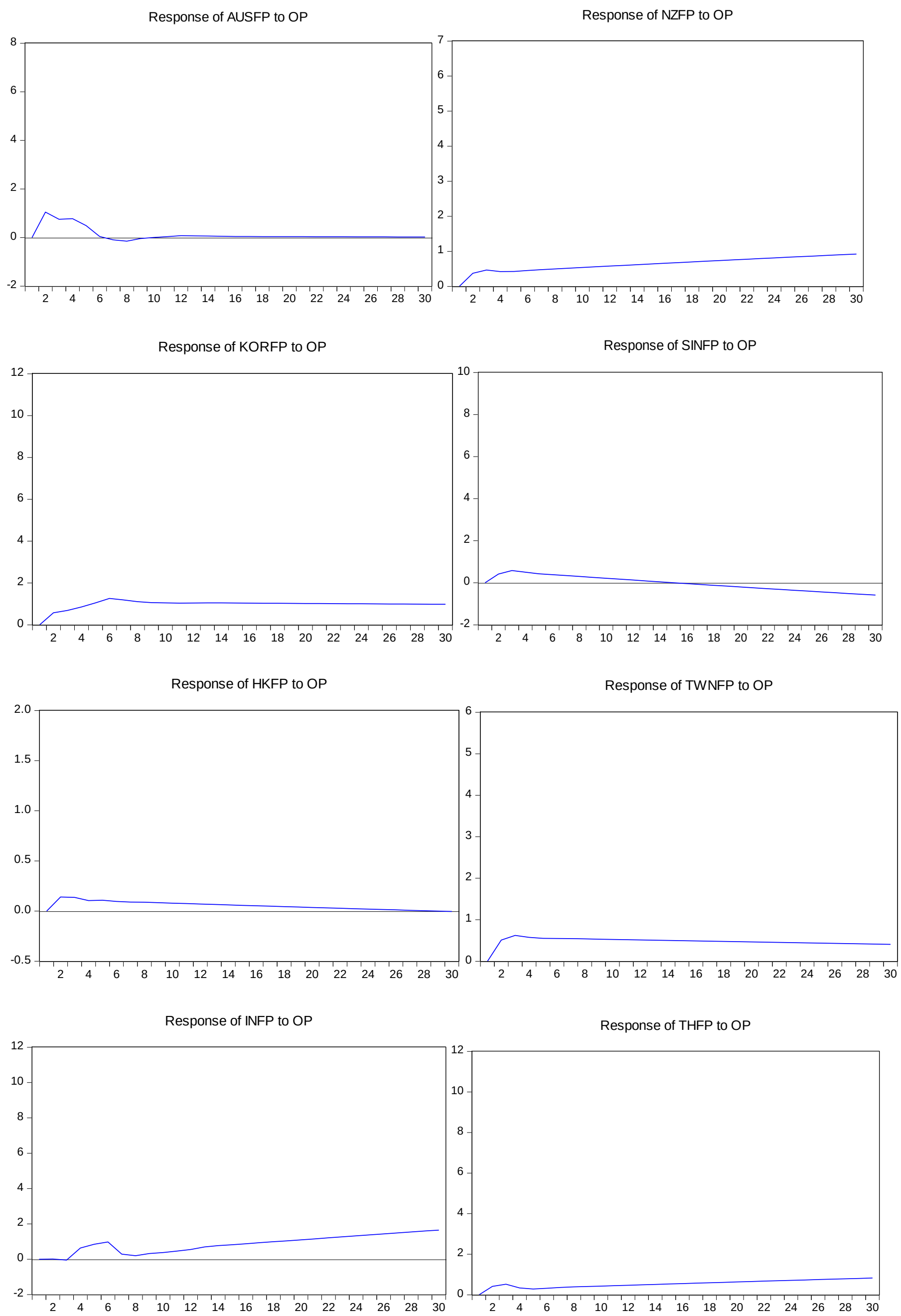
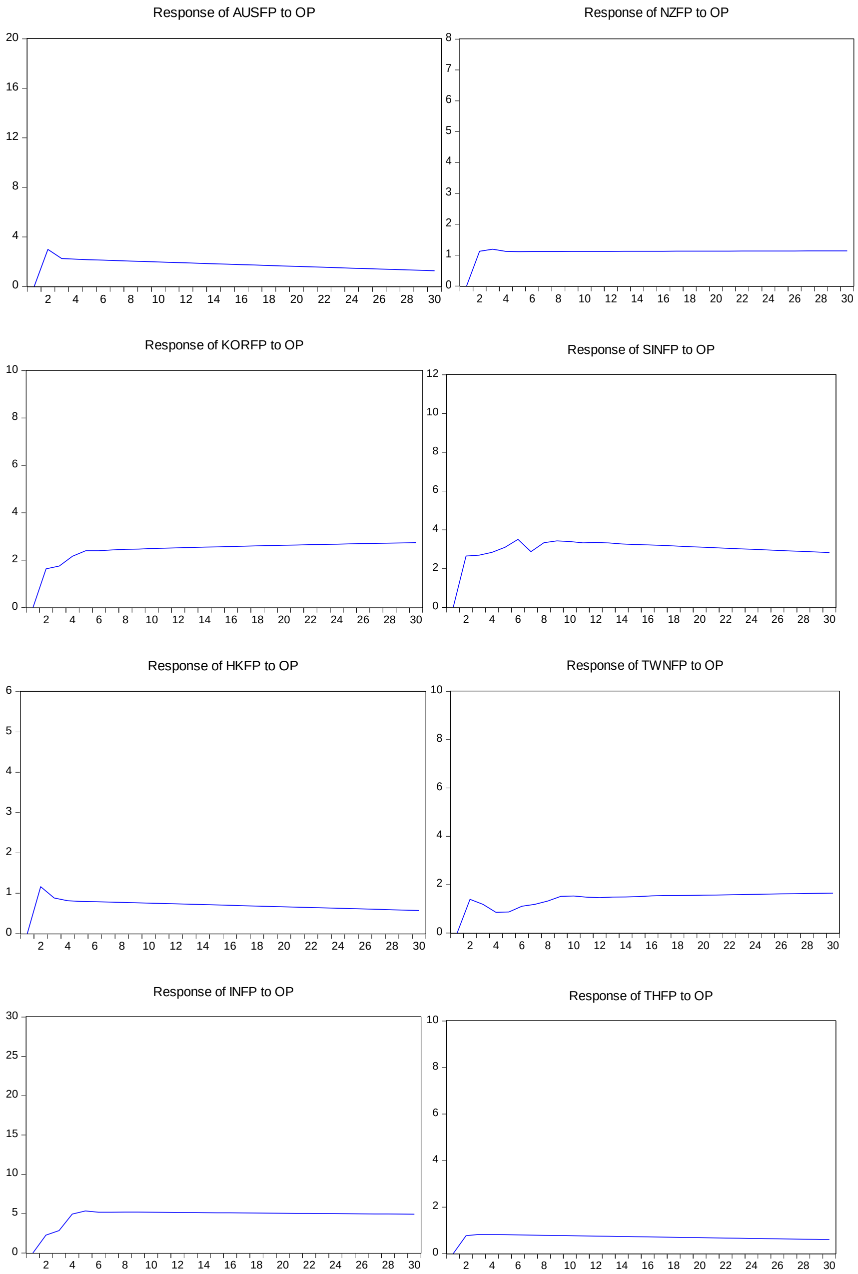


Figure 4 exhibits impulse response functions of food prices to the World oil price shock over the period 2002-2010. Similar to the above two periods, food prices positively respond to the oil prices. In Australia food prices increase immediately with the oil price shock at about 4 percent and then die out gradually with more than 30 days. Although the magnitude for New Zealand food market is about 1.5 percent the effects of shocks persists over time and die out even after a longer period. The Korean and Singapore markets show similar patterns with the oil price shocks. Responding immediately with the shock food prices rise about 2 percent and then they take another jump at period 4 which lift prices up to about 4 percent. The effects remain persistent over the 30 days and then die out slowly. For the Hong Kong food market the oil prices contribute to 1 percent increase in the price at day 1 while the effects of shocks disappear gradually after 30 days. Taiwan food market also reacts positively at about 2 percent at the beginning and then cool down a bit at day 5 and then takes another pick up which remains stable for a long time. A similar pattern can be observed in the Indian food market though the magnitude is about 5 percent. Thai food prices shows relatively lower positive responses to the oil price shocks than all other markets. The magnitude of increase of the food price is less than 1 percent.

Figure 4 Impulse response functions of food prices to a Cholesky one standard deviation to oil price shock over the period 2002-2010



In summary, impulse response analysis supports Granger causality results. Significant positive contribution of oil prices to the sources of food price changes can be observed across different time periods. Consistent with the variance decomposition analysis impulse response functions also reaffirms that food market and oil market are more interdependent in the recent period than the past. The magnitude of the responses due to food price shocks are higher in the recent period than the early subsample and also effects of shocks are persistent than previous period.

4. 2 Volatility spillover effects from oil to food price returns

Table 7 presents estimation output of different GARCH models for spillover effects over the full sample period 1995-2010. In each returns series, CGARCH models provide better fits to the data than the other models either in symmetric or asymmetric form. For Australia, Singapore, Hong Kong and India the symmetric CGARCH fits better while for the other four countries the asymmetric CGARCH model better captures the volatility characteristics of food price returns. For symmetric CGARCH models γ_5 is the measure for volatility spillover effects and for asymmetric models γ_6 measures it. Both γ_5 and γ_6 measure transitory or short run volatility spillover effects. Spillover parameters were initially incorporated in permanent components, but none of the relevant parameters were found statistically significant and hence variance spillover effects are restricted to the transitory components. Almost all parameters including constants, ARCH, GARCH and leverage effects (where applicable) are significant mostly at 1% or 5% level of significance in each model. In all cases oil price posits positive volatility spillover effects to food price returns. For 1% increase of oil price returns Taiwan (0.396), Australia (0.283), Korea (0.269), Thailand (0.126) and Hong Kong (0.117) food prices show more volatility spillover effects while India (0.0520), Singapore (0.084) and New Zealand (0.114) food prices show relatively low volatility spillover effects during the period 1995-2010. Diagnostic test statistics (LB-Q and ARCH-LM) do not indicate model specification errors. No or little evidence of further autocorrelation can be observed. GED parameters are all less than 2 and significant at 1% level of significance implying the justification of using the generalized error distribution instead of normal.

Table 7 Estimated volatility model over the period 1995-2010

Parameters	RAUSFP CGARCH	RNZFP CGARCH	RKORFP CGARCH	RSINFP CGARCH	RHKFP CGARCH	RTWNFP CGARCH	RINFP CGARCH	RTHFP CGARCH
γ_0	8.98E-05[a] (1.25E-05)	0.000215[a] (5.15E-05)	0.000470[a] (0.000148)	0.00038[c] (0.000181)	0.000347[a] (6.64E-05)	0.000437[a] (9.26E-05)	0.001781[a] (0.004161)	0.000806[c] (0.000493)

γ_1	0.992829[a]	0.996477[a]	0.985141[a]	0.997307[a]	0.988714[a]	0.979262[a]	0.999623[a]	0.9888396[a]
	(0.002207)	(0.001615)	(0.005568)	(0.001854)	(0.004794)	(0.008189)	(0.000925)	(0.007307)
γ_2	0.019456[a]	0.008753[a]	0.083153[a]	0.028348[a]	0.023865[a]	0.055999[a]	0.041820[a]	0.079598[a]
	(0.002132)	(0.003127)	(0.013621)	(0.007645)	(0.008436)	(0.014502)	(0.007909)	(0.025150)
γ_3	0.046410[a]	0.082820[a]	0.011048	0.101908[a]	0.138537[a]	0.055765	0.152485[a]	0.128490[a]
	(0.015616)	(0.024807)	(0.029456)	(0.020779)	(0.024214)	(0.036180)	(0.026619)	(0.048503)
γ_4	-0.517645[b]	0.064307	0.120711[b]	0.741272[a]	0.638104[a]	0.130157[b]	0.606702[a]	0.100317[c]
	(0.213108)	(0.044050)	(0.047567)	(0.060482)	(0.062497)	(0.054766)	(0.069626)	(0.059209)
γ_5	0.283881[a]	0.584940[a]	0.562814[a]	0.084336[c]	0.117693[b]	0.447855[a]	0.052099[a]	0.556703[a]
	(0.094862)	(0.084910)	(0.153289)	(0.045546)	(0.058793)	(0.139472)	(0.019524)	(0.107299)
γ_6		0.114976[b]	0.269618[b]			0.396927[b]		0.126942[a]
		(0.053218)	(0.137220)			(0.163514)		(0.054599)
GED	1.238	0.753820	1.169156	1.108865	0.978270	1.108342	1.044324	0.751777
	(0.030443)	(0.021156)	(0.031192)	(0.025874)	(0.058793)	(0.032255)	(0.025333)	(0.022570)
LB(Q)	12.401[c]	5.8325	26.604[b]	20.894[c]	15.664	13.684	25.537[b]	32.029[a]
$LB(Q)^2$	3.2918	5.8537	4.7433	3.3551	3.6708	9.6166	11.148	3.9813
ARCH-LM	-0.005490	-0.003932	0.004520	0.009855	-0.015268	-0.010877	-0.019594	-0.002489
	(0.015880)	(0.015865)	(0.015863)	(0.015864)	(0.015850)	(0.015881)	(0.015908)	(0.015685)

Notes: The values are coefficients of variance equation and values in parentheses are standard errors and **a, b, c** indicates 1%, 5% and 10% significance level respectively

Table 8 reports variance coefficients of estimated GARCH models over the period 1995-2001. GARCH, TGARCH and CGARCH models are found to be good fit for food price returns over this sample period. In the case of Australia, Korea and India GARCH models fit well while for New Zealand and Taiwan the TGARCH better captures volatility. For the remaining countries (Singapore, Hong Kong and Thailand), CGARCH models outperform other models, and except Hong Kong, the asymmetric CGARCH model outperforms the symmetric version. For the GARCH set of models γ_3 measures volatility spillover effects; for TGARCH models γ_4 and symmetric CGARCH models γ_5 while for asymmetric CGARCH γ_6 measure volatility spillover effects. Almost all parameters are significant at 99% and 95% confidence levels. Parameters measuring volatility spillover effects are all significant except RSINFP and RINF. Significant parameters are all positive showing positive spillover from oil price to price returns. Over this sample period, a 1% increase in volatility of oil price poses a rise of volatility 0.668% for Hong Kong, 0.593% for Thailand, 0.196% for New Zealand, 0.195 for Taiwan and 0.170% for Korea while Australian food price returns show lowest volatility spillover effects, 0.069%. Similar to the full sample period, there is no or little evidence of misspecification of models along with the support of using GED distribution.

Table 8 Estimated volatility model over the period 1995-2001

Parameters	RAUSFP GARCH	RNZFP TGARCH	RKORFP GARCH	RSINFP CGARCH	RHKFP CGARCH	RTWNFP TGARCH	RINFP GARCH	RTHFP CGARCH
γ_0	1.35E-05[b]	8.88E-05[a]	1.27E-05[b]	0.000500[b]	0.000141[a]	2.14E-05[b]	2.84E-05[a]	0.002814
	(5.43E-06)	(2.12E-05)	(5.17E-06)	(0.000231)	(5.15E-05)	(8.64E-05)	(8.84E-06)	(0.005877)
γ_1	0.079151[a]	0.231205[a]	0.134575[a]	0.987637[a]	0.962035[a]	0.038539[c]	0.192313[a]	0.994564[a]
	(0.019023)	(0.068615)	(0.024983)	(0.007798)	(0.016435)	(0.021482)	(0.041093)	(0.011097)
γ_2	0.695122[a]	-0.175145[b]	0.832832[a]	0.057567[a]	0.031584[c]	0.097023[a]	0.729171[a]	0.129747[b]
	(0.039484)	(0.069402)	(0.025198)	(0.017971)	(0.016275)	(0.046177)	(0.049582)	(0.052613)
γ_3	0.069573[b]	0.474884[a]	0.170713[b]	0.197526[a]	0.097657[a]	0.826096[a]	-0.011553	0.102879
	(0.034082)	(0.099460)	(0.072275)	(0.071598)	(0.029170)	(0.046177)	(0.040790)	(0.079991)
γ_4		0.196520[c]		-0.143172[c]	0.617553[a]	0.195812[b]		0.230425[a]
		(0.121795)		(0.086870)	(0.115736)	(0.089532)		(0.088942)

γ_5				0.172110	0.668274^{b}			0.534509^{a}
				(0.264376)	(0.302537)			(0.115162)
γ_6				0.204388				0.593351^{b}
				(0.528765)				(0.287011)
GED	1.311894	0.823698	1.124373	0.967125	0.926462	1.146655	0.883660	0.645190
	(0.057462)	(0.027520)	(0.047425)	(0.033366)	(0.031478)	(0.048857)	(0.034408)	(0.026958)
LB(Q)	20.475^{b}	4.6586	13.205	19.146^{c}	10.096	13.290	32.382^{a}	24.713^{a}
LB(Q)^2	8.9510	2.2599	7.5181	2.1667	5.4189	14.652	9.9043	4.0983
ARCHLM	0.013983	-0.011050	0.006662	8.32E-06	-0.035387	-0.020561	-0.040192	-0.005806
	(0.023584)	(0.023576)	(0.023566)	(0.023585)	(0.023552)	(0.023584)	(0.023549)	(0.023007)

Notes: The values are coefficients of variance equation and values in parentheses are standard errors and **a**, **b**, **c** indicates 1%, 5% and 10% significance level respectively

Table 9 displays variance coefficients of estimated GARCH models for the latest sample period. Like for the full sample period, in this case also CGARCH models dominate other models in terms of capturing volatility characteristics of food price volatility returns. GARCH model fits the data extremely well for RKORFP series whereas TGARCH better captures this effect for RNZFP and RSINFP. For rest of the series the CGARCH models perform best. Among CAGRCH models asymmetric versions are best fitting for RHKFP and RTHFP, while in all other cases symmetric CGARCH models were found to be the best performers according to the information criteria. Almost all parameters have the right signs and are statistically significant for each model. For GARCH model γ_3 and for TGARCH model γ_4 is the measure for volatility spillover effects. For CGARCH models γ_3 measures permanent volatility effects and γ_5 (for symmetric) and γ_6 (for asymmetric) measure transitory volatility spillover effects from oil price returns. Parameters measuring volatility spillover effects are all found to be positive and statistically significant. There is evidence of permanent volatility spillover effects from oil to food price returns for the Australia and Taiwan market. Hong Kong (0.262%) and Thai (0.229%) food price returns show highest volatility spillover effects for 1% volatility in oil price while all other food prices show positive volatility spillover effects ranges from 0.02 to 0.03% and Australia shows the lowest volatility among all countries. As in the case of the other two sample periods, there is no evidence of remaining serial correlation along with the justification of using GED distribution for estimation purpose.

Table 9 Estimated volatility model over the period 2002-2010

Parameters	RAUSFP CGARCH	RNZFP TGARCH	RKORFP GARCH	RSINFP TGARCH	RHKFP CGARCH	RTWNFP CGARCH	RINFP CGARCH	RTHFP CGARCH
γ_0	1.11EE-05	1.40E-05^{a}	1.61E-05^{a}	2.14E-06^{c}	0.000170^{a}	0.000525^{b}	0.001079	0.000189^{a}
	(3.71E-05)	(3.88E-05)	(5.01E-06)	(1.33E-06)	(3.72E-05)	(0.000213)	(0.003889)	(5.12E-05)
γ_1	0.993857^{a}	0.054158^{a}	0.104652^{a}	0.078318^{a}	0.984032^{a}	0.969810^{a}	0.999319^{a}	0.978575^{a}
	(0.002596)	(0.014005)	(0.019544)	(0.018986)	(0.006620)	(0.017245)	(0.002579)	(0.008372)
γ_2	0.019310^{a}	0.062366^{b}	0.820282^{a}	0.040101^{c}	0.025408^{a}	0.127845^{a}	0.040636^{a}	0.068656^{a}
	(0.006368)	(0.030687)	(0.02761)	(0.023290)	(0.009705)	(0.033711)	(0.011160)	(0.016086)
γ_3	0.005761^{a}	0.778462^{a}	0.036936^{b}	0.875953^{a}	0.030365	0.039886^{c}	0.163056^{a}	-0.015831
	(0.002087)	(0.041646)	(0.016797)	(0.018428)	(0.031555)	(0.021055)	(0.037629)	(0.047327)
γ_4	0.067664^{a}	0.030908^{b}		0.029831^{c}	0.15750^{a}	0.141829^{a}	0.612686^{a}	0.150626^{b}

	(0.025930)	(0.013334)		(0.015464)	(0.055156)	(0.053675)	(0.090643)	(0.076978)
γ_5	0.681023^{a}				0.565659^{a}	0.120579	0.030574^{c}	0.101348
	(0.158245)				(0.104908)	(0.252150)	(0.016317)	(0.348666)
γ_6					0.268427^{a}			0.229151^{b}
					(0.083385)			(0.107225)
GED	1.223210	1.057477	1.244413	1.326057	1.255012	1.126272	1.097570	1.060483
	(0.041661)	(0.035489)	(0.046454)	(0.058790)	(0.047718)	(0.046230)	(0.039972)	(0.036751)
LB(Q)	13.047	5.3655	8.7654	16.518	18.256^{b}	15.890	15.274	21.071^{c}
$LB(Q)^2$	3.2459	13.625	4.6349	9.4149	3.6939	8.0117	4.0215	3.1687
ARCHLM	-0.004360	0.009164	-0.004702	0.008917	0.011208	-0.004223	0.010913	-0.001522
	(0.021598)	(0.021586)	(0.021349)	(0.021430)	(0.021580)	(0.021571)	(0.021742)	(0.021694)
					(0.023552)			

Notes: The values are coefficients of variance equation and values in parentheses are standard errors and **a, b, c** indicates 1%, 5% and 10% significance level respectively

To sum up, based on the above analysis it can be inferred that the oil and food markets are interdependent in terms of volatility spillover effects. There is a significant positive volatility spillover effect from oil price returns to food price returns irrespective of the market status, whether it is net food exporter or net food importer, and across different time periods. For long horizon periods the magnitudes of volatility spillover effects are higher than for shorter time periods and the most recent data shows even lower magnitudes. The Australian market shows high volatility spillover effects for the full sample period while for remote past and recent past sample periods the volatility spillover effects are lower, athough a permanent volatility spillover has been observed with low magnitude for the recent subsample. Korean and Taiwan food markets follow the pattern of Australia. The New Zealand market shows relatively lower volatility effects for the longer sample while a bit higher volatility effects can be seen for remote past period and very low significant effects are observed for recent subsample. Hong Kong and Thai markets are similar to the New Zealand market. However, Singapore and Indian markets show similar patterns in terms of volatility spillover from the oil market. For the full sample period they both show low magnitudes of spillover effects, for the 1995-2001 period no spillovers and for the recent subsample again low magnitude can be observed. Interestingly, it can be noted that in recent periods all food markets are more efficient or competitive than for earlier periods because the magnitudes of volatility spillover is lower during this period. Since with few exceptions no evidence of permanent volatility spillover effects can be found it can be documented that volatility spillover from oil price to food price is short run consistent with mean spillover effects.

4.3 Robustness analysis

In order to gauge the robustness of the previous results regarding mean and volatility spillover effects, we also estimated multivariate GARCH models in bivarate BEEK formulation. The results are shown in Table 10-11. Table 10 reports the results for mean return spillover effects across the three time periods considered. The upper panel of the Table shows the coefficients for the *entire* period 1995-2010. The element a_{12} measures the mean spillover effect from oil price returns to food price returns and a_{21} measures mean return spillover from food prices to oil prices for every model. It can be seen that all of the mean spillover parameters from oil price to food price are statistically significant at 1% level except for the Indian food price parameter which is significant at 5% level . On the other hand, it can also be noticed that none of the parameters measuring mean spillover from food market to oil market are statistically significant, except for Korean. These results imply that there is a unidirectional mean spillover effect from oil price to food prices and not vice versa.

The middle panel of the Table displays the conditional mean coefficient matrix over the *early* subsample period 1995-2001. Here it can also be viewed that there is strong evidence of unidirectional mean spillover effects from oil market to food markets except for Korea and India. No single evidence of mean spillover from food market to oil market can be documented over this subsample.

The lower panel of the Table 10 reports results for the *latest* subsample period 2002-2010. The spillover results are very much consistent with the previous two cases. All the elements measuring mean spillover from oil price to food prices are statistically significant at least at 95 percent level of confidence and there is no significant evidence of mean spillover from food markets to oil market.

The significant parameters in all cases with negligible exceptions show that a 1% increase in oil price returns enhances food price mean returns more than 0.10 percent across time periods and the transmission rate is higher for net food exporter countries. Over the full sample period the Hong Kong market receives the highest mean spillover (0.238) from a 1% increase of oil prices followed by Taiwan (0.195), Singapore (0.172) and Korea (0.153). Over the early subsample Taiwan food price returns receive higher mean spillover form oil prices followed by Hong Kong. During the recent period again Hong Kong market receives higher mean spillovers from oil prices followed by Singapore, Taiwan and Korea. In this period the magnitudes of spillover effects are greater than 0.19 meaning more interdependence between food and oil market.

These results once again affirm the findings of the VAR approach where it was also documented that there is unidirectional mean spillover effects from oil prices to food prices and not vice versa.

Table 10 Estimated return coefficients for MGARCH conditional mean equations

	AFP(*i*=1)	OP(i=2)	NFP(*i*=1)	OP(i=2)	KFP(*i*=1)	OP(i=2)	SFP(*i*=1)	OP(i=2)	HFP(*i*=1)	OP(i=2)	TFP(*i*=1)	OP(i=2)	IFP(*i*=1)	OP(i=2)	TFP(*i*=1)	OP(i=2)
1995-2010																
ρ	0.0002[c] (0.0001)	0.0006[a] (0.000)	-3.97E-05 (0.000)	0.0005[a] (0.000)	0.0002 (0.000)	0.0005 (0.000)	0.0005[c] (0.000)	0.0005[a] (0.000)	0.0007[b] (0.0003)	0.0006[a] (0.000)	0.0002 (0.000)	0.0005[a] (0.000)	0.0001[b] (0.000)	0.0005[a] (0.000)	0.0001 (0.000)	0.0005[a] (0.000)
a_{i1}	-0.035[c] (0.019)	-0.014 (0.015)	0.0247 (0.022)	0.008 (0.008)	0.048[b] (0.019)	0.015[a] (0.007)	0.012 (0.018)	-0.009 (0.008)	0.028 (0.020)	-0.008 (0.006)	0.003 (0.018)	-0.011 (0.000)	0.058[a] (0.019)	0.014 (0.010)	-0.0009 (0.0218)	0.008 (0.008)
a_{i2}	0.114[a] (0.019)	0.141[a] (0.017)	0.128[a] (0.023)	0.142[a] (0.017)	0.153[a] (0.027)	0.137[a] (0.017)	0.172[a] (0.023)	0.136[a] (0.018)	0.238[a] (0.029)	0.144[a] (0.018)	0.195[a] (0.028)	0.142[a] (0.017)	0.033[b] (0.016)	0.145 (0.017)	0.102[a] (0.020)	0.144[a] (0.017)
1995-2001																
ρ	0.0001 (0.000)	0.0005[b] (0.000)	0.0004 (0.000)	0.0004[b] (0.000)	-0.0003 (0.000)	0.0005[b] (0.000)	-0.0002 (0.000)	0.0004[b] (0.000)	7.30E-05 (0.000)	0.0005[a] (0.000)	3.66E-05 (0.000)	0.0005[a] (0.000)	0.0003 (0.000)	0.0004[b] (0.000)	-0.0002 (0.000)	0.0005[a] (0.000)
a_{i1}	-0.007 (0.027)	-0.017 (0.023)	0.061[b] (0.029)	0.007 (0.010)	0.111[a] (0.027)	0.012 (0.008)	0.021 (0.028)	-0.014 (0.009)	-0.008 (0.030)	-0.002 (0.007)	0.024 (0.026)	-0.011 (0.010)	0.116[a] (0.028)	0.005 (0.014)	0.021 (0.029)	0.007 (0.009)
a_{i2}	0.111[a] (0.024)	0.155[a] (0.027)	0.120[b] (0.051)	0.167[a] (0.026)	0.033 (0.059)	0.154[a] (0.026)	0.092[b] (0.044)	0.164[a] (0.002)	0.181[a] (0.055)	0.166[a] (0.026)	0.196[a] (0.052)	0.159[a] (0.026)	0.010 (0.032)	0.165[a] (0.026)	0.076[c] (0.044)	0.158[a] (0.026)
2002-2010																
ρ	0.0004[b] (0.000)	0.0008[a] (0.000)	-0.0002 (0.000)	0.0008[a] (0.000)	0.0004 (0.000)	0.0007[a] (0.000)	0.0008[a] (0.000)	0.0006[a] (0.000)	0.0009[b] (0.000)	0.0008[a] (0.000)	0.0005 (0.000)	0.0007[a] (0.000)	0.0005[b] (0.000)	0.0008[a] (0.000)	0.0001 (0.000)	0.0007[a] (0.000)
a_{i1}	-0.064[b] (0.025)	-0.013 (0.021)	-0.013 (0.029)	0.018 (0.017)	-0.015 (0.027)	0.012 (0.015)	0.006 (0.023)	-0.004 (0.018)	0.062[b] (0.026)	-0.022 (0.013)	-0.014 (0.025)	-0.012 (0.011)	0.031 (0.025)	0.018 (0.016)	-0.019 (0.023)	-0.002 (0.015)
a_{i2}	0.114[a] (0.027)	0.129[a] (0.023)	0.122[a] (0.021)	0118[a] (0.023)	0.193[a] (0.030)	0.127[a] (0.023)	0.196[a] (0.028)	0.110[a] (0.025)	0.253[a] (0.040)	0.124[a] (0.025)	0.195[a] (0.035)	0.126[a] (0.024)	0.040[b] (0.019)	0.124[a] (0.023)	0.107[a] (0.021)	0.132[a] (0.023)

Notes: The values are coefficients of conditional mean equation and values in parentheses are standard errors and **a, b, c** indicates 1%, 5% and 10% significance level respectively

Table 11 displays coefficients measuring volatility spillover effects from World oil to food prices across the three sample periods. The complete variance covariance matrices are not reported in order to preserve space but can be supplied upon request. All parameters measuring volatility spillover effects from oil prices to food prices for all countries' food price returns are statistically significant at 1% level of significance for all three periods though the magnitudes differ across time. As for the previous analysis the latest data exhibits higher volatility spillover than the early and whole sample periods, impliying that food and oil markets are more interdependent in recent time periods than in the past. For Australia the volatility spillovers from oil prices are in the range of 0.03 to 0.04 percent due to 1 percent volatility in oil market across all three time periods. In the case of New Zealand the effects varies between 0.07 to 0.11 percent and for Korea the effects are in between 0.03 to 0.08 percent. In Singapore the effects range from 0.03 to 0.08 percent while for Hong Kong it is in between 0.04 to 0.06 percent. For Taiwan the magnitudes lies between 0.03 to 0.09 percent while for India it is just in the range of 0.009 to 0.05. The Thai market shows the lowest effect for the early period (0.06) and highest effects for the recent period (0.07). In terms of volatility spillover effects from oil to food market, no clear distinction can be made between net food exporter and net food importer countries. New Zealand is found to have high volatility responsives to oil prices while Australia is found to be the lowest respondent.

Table 11 Estimated variance coefficients indicating volatility spillover effects in BEEK-type bivariate GARCH model

	AFP	NFP	KFP	SFP	HFP	TFP	IFP	TFP
1995-2010								
OP	0.035[a] (0.004)	0.077[a] (0.012)	0.061[a] (0.006)	0.055[a] (0.005)	0.063[a] (0.007)	0.053[a] (0.005)	0.046[a] (0.004)	0.060[a] (0.008)
1995-2001								
OP	0.041[a] (0.008)	0.074[a] (0.015)	0.036[a] (0.005)	0.036[a] (0.006)	0.046[a] (0.008)	0.032[a] (0.005)	0.047[a] (0.009)	0.056[a] (0.009)
2002-2010								
OP	0.040[a] (0.005)	0.114[a] (0.028)	0.085[a] (0.014)	0.0067[a] (0.008)	0.064[a] (0.007)	0.091[a] (0.014)	0.056[a] (0.007)	0.074[a] (0.011)

Notes: The values are volatility spillover coefficients of variance equations and values in parentheses are standard errors and **a, b, c** indicates 1%, 5% and 10% significance level respectively

The mean and volatility spillover effects analyzed in this section within the bivariate BEEK-type GARCH models are consistent with the analysis of section 4.1 and 4.2 within the framework of VAR and univarite GARCH models with few exceptions. Although in univariate analysis we found that the magnitudes of measuring volatility spillover effects from oil to food prices for the recent subsample is lower than earlier subsample, we prefer to accept multivariate results over univarite one where we found that spillover effects are higher in recent period consistent with mean spillover effects. The reason could be more interdependencies between agricultural sector and energy sectors in the recent period.

5. Conclusions

This study attempted to examine the mean and volatility spillover effects of World oil prices on food prices in the context of Australia, New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand over the period 1995-2010. The major conclusions we draw are as follows. There are significant positive mean and volatility spillover effects from World oil prices to food prices of the selected Asia Pacific countries and not vice versa, though the magnitudes of effects differ from country to country for different time horizons. Higher mean and volatility spillover effects are revealed for the recent past than the remote past implying that the oil and food markets are more interdependent in recent time than in the past. Particularly after 2001, food prices are found to be more affected by World oil prices and the effects of shocks also persist for a longer period while before 2001 the effects are short-lived. Little evidence of *long run* positive relationships in terms of both mean and volatility spillover effects between World oil prices and food prices selected Asia Pacific countries can be documented which is consistent with Zhang *et al.*(2010). However, there is substantial evidence of *short run* relationships between them though Australian and Taiwan food prices exhibit permanent volatility spillover from oil to food price during recent time period. Similar with mean spillover effects it was found that low evidence of permanent volatility spillover effects can be reported in most of the cases as the volatility spillover effects are transitory. The recent time period shows higher volatility spillovers than early period. In terms of mean spillover effects net food importer countries' food prices show higher effects than net food exporter countries, however, no distinction can be made between exporters and importers in terms of volatility spillover effects. The results of this study are robust because consistent results are found through cross check by both univariate and multivariate time series analysis. Empirical findings of this study suggest that the world crude oil prices should be considered for the purpose of policy analysis and forecasting of food prices.

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