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Modelling Food Price Volatility and Testing Heat Waves and/or Meteor Showers Effects: Evidence for Asia and Pacific

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Abstract

This paper assesses the volatility and cross country mean and volatility spillover effects of food prices within and across global and selected Asian and Pacific countries namely Australia, New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand. The principal method of analysis comprises the development of a set of component GARCH-type models of conditional variance. Volatility characteristics and spillover effects of food prices are examined across a full (1995-2010) and two subsamples (1995-2001 and 2002-2010) with daily food price indices. Main findings of the study are as follows: (1) like other asset prices, food price volatility can be modelled by CGARCH variant of GARCH-family models for world as well as country specific levels, (2) increased risk does not necessarily lead to increased returns for world and specified countries except few instances, (3) mixed evidence of cross country mean and volatility spillover effects are reported. No exact direction of spillover effects from exporter to importer or importer to exporter countries can be drawn rather mixed evidence of spillover from exporter to importer, exporter to exporter, importer to exporter and geographical proximity can be documented. The 'meteor shower' hypothesis that the conditional variance of the change in one market depends on the past information of other markets dominates 'heat wave' hypothesis that the conditional variance depends on the past information of that market while for shorter time period 'heat wave' effects dominate 'meteor shower' effects.

Keywords: food price, volatility, asymmetry, persistence, spillover effects, heat wave, meteor showers

1. Introduction

Commodity price fluctuation or volatility has attracted increasing attention in recent economic and financial literature and has been recognised as one of the more important economic phenomena (R.F. Engle, 1982). The importance of understanding commodity price movement is now well documented. For example, Pindyck(2004) pointed out that changes in commodity prices can influence the total cost of production as well as the opportunity cost of producing commodities currently rather than later. It has also been argued that price volatility reduces welfare and competition by increasing consumer search costs (Zheng, Kinnucan, & Thompson, 2008). In the same line, Apergis and Rezitis(2003b) noted down that price volatility leads both producers and consumers to uncertainty and risk and thus volatility of commodity prices has been studied to some extent.

Commodity prices in general are volatile and in particular agricultural commodity prices are renowned for their continuously volatile nature (Newbery, 1989) and also deserve much attention from policy makers. Kroner et al. (1999) reported that commodity prices are one of the most volatile of all international prices. It has been emphasized that continuous volatility causes concern for governments, traders, producers and consumers. Large fluctuations in prices can have a destabilizing effect on the real exchange rates of countries and a prolonged volatile environment makes it difficult to extract exact price signals from the market which leads to inefficient allocation of resources and also volatility can attract speculative activities (FAO, 2007).

Historic food prices show significant ups and down as can be seen in Figures 1 and 2. A large body of studies exist to document the causes and consequences of food price booms. The recent food price spike was explained from different angles such as supply shock (ESCAP, 2008; Hossain, 2007), demand shock (OECD, 2008), oil and metal price hike (Headey & Fan, 2008; Radetzki, 2006), chronic depreciation of US dollars against major currencies (Abott, Hurt, & Tyner, 2009; Headey & Fan, 2008) and increased demand for bio-fuel (Headey & Fan, 2008; Mitchell, 2008; Rosegrant, Zhu, Msangi, & Sulser, 2008). Along with these mainstream macroeconomic factors, the index based agricultural futures market attracted much attention for being one of the factors of the food price boom (Gilbert, 2010; Robles, Torero, & von Braun, 2009). Gilbert (2010) pin-pointed that the agricultural futures market is one of the major channels through which macroeconomic and monetary factors created the 2007-08 food price rises. Food commodity price futures are also gaining popularity like other financial funds. From 2005 to 2006, the average monthly volumes of futures for wheat and maize grew by more than 60 percent and those for rice by 40 percent(Robles et al., 2009). However, till date low attention has been paid for studying food price returns in the fashion of financial assets. Therefore, it is worthwhile to investigate the financial properties of food prices under the framework of generalized autoregressive conditional heteroscedasticity (GARCH) family models.

Volatility modelling is popular in financial economics. Financial variables such as stock price, interest rate and exchange rates are being modelled frequently by using financial econometrics models especially ARCH classes of models (Blair, 2001; Dewachter, 1996; Maneschiold, 2004; Wei, 2009). Recently energy prices have also been studied using the technique of Financial Econometrics, for example, Regnier(2007) has shown that the common view regarding energy price volatility is true. That is, testing a long span of data, he has shown that energy prices are more volatile than other commodity prices. Narayan and Narayan (2007) have documented mixed evidence concerning oil price shocks' volatility. However, only a few studies are available in the field commodity price volatility in general and food price volatility modelling in particular. Valadkhani and Mitchell (2002) studied Australia's export price volatility by using ARCH-GARCH models and provided evidence that Australia's export prices vary with world prices significantly. Apergis and Rezitis(2003a) examined volatility spillover effects from macroeconomic fundamentals to relative food price volatility in Greece by using GARCH models. They reported that the volatility of relative food prices shows a positive and significant impact on its own volatility in the case of Greece. In another paper (2003b) using similar GARCH models, they pointed out that agricultural input and retail food prices exert positive and significant effects on the volatility of agricultural output prices and also output prices have significant positive effects on its own volatility in Greece. Price volatility spillover effects in US catfish markets have been studied by Buguk et al. (2003). They used univariate EGARCH models to check volatility spillover and provided evidence of volatility spillovers in agricultural markets. Zheng et al. (2008) studied time varying volatility of US food consumer prices using Exponential GARCH models and news impact curves.

However, as stated before, food price volatility using daily food price indices in the fashion of financial assets is still an area in which little empirical attention has been paid. Since food prices are getting popular positions in the portfolio of fund managers of food futures and options, it appears worthwhile to devote effort to modelling food prices with extended GARCH models particularly Component GARCH (CGARCH) models in the context of world and some countries of Asia and Pacific as well. Hence, the objectives of this paper are to model and examine cross country mean and volatility spillover effects of food price returns using Component GARCH models expecting to add to the scarce literature of food price volatility study.

The next section of the paper provides an overview of food export and import scenarios of countries covered by the study; section 2 discusses the data used for our analysis; the methodology used to carry out the analysis along with empirical findings have been presented in section 3 and section 4 of the paper summarises the main results of the study and draws relevant conclusions.

1.1 Food Export Import Scenario

We selected 8 different countries of Asia and Pacific based on food import and export criteria. Australia, New Zealand, Thailand and India are major food exporters while South Korea, Singapore, Hong Kong and Taiwan are net food importers and there exists considerable economic integration among them. As of 2008-09, top four food export items of Australia include meat, grains, dairy products and wine. Korea, Taiwan, Singapore and Hong Kong ranked third, fifth, sixth and seventh export destination of Australia respectively for meat export. Major food exporter countries also possesses on the top list except India. New Zealand and Thailand ranked as eighteenth and twenty seventh. As cereal export destination of Australia except Hong Kong all other countries are among top twenty five countries. For dairy and poultry products also these countries are among the top export destinations of Australia. Meat, fish and dairy products are on the top of New Zealand food export items for 2009. For all these products Australia, Korea, Singapore, Taiwan, Hong Kong are among the major trade partners including Thailand and India among minor partners. Hong Kong, Singapore, Australia and Taiwan are among the major rice export partners of Thailand. Korea, Singapore, Hong Kong and Taiwan are among the top fish export partners of Thailand. India also has considerable trade relationship with these countries regarding export of food items such as dairy products, fruits, vegetables and cereals. Export import statistics of these countries support that there is strong trade relationship of agricultural products among these countries.

Furthermore, countries considered here are also member of some regional and trade associations. ASEAN-Australia-New Zealand free trade agreement (FTA) went into operation from 1 January 2010. An FTA between Australia and Thailand went into force in January 2005, FTA between Australia and Singapore has already been signed. A negotiation of Australia-India FTA is going on. Singapore-New Zealand and Thailand-New Zealand FTAs went into force in 2001 and 2005 respectively. An FTA between India and Thailand has been signed in 2004 (Park, 2009).

2. Data and Their Statistical Properties

The study uses 4000 daily observations of food producers' price indices for world aggregate and for Australia, New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand provided by DataStream Advance for the period 2 January 1995 to 30 April 2010. Returns of food prices for every variable are computed by using standard continuously computed logarithm technique as follows where P_t is the daily price of current time t:

$$R_t = \ln(\frac{P_t}{P_{t-1}}) \tag{1}$$

Table 1 displays summary statistics for each series. Large unconditional standard deviations of each series indicate high volatility of food prices, although the unconditional standard deviations for each return series show that net food importing countries returns are more volatile than those for net food exporting countries which asserts that net food importing countries are more affected by food price changes (von Braun, 2008). For the price series, only New Zealand data show negative skewness implying the distribution has a long left tail, whereas all other series have positive skewness implying long right tails. On the other hand, the world, Australia and Korean series show negative skewness meaning long left tails while other returns series show long right tails. The values of excess Kurtosis for all series are high (close to 3 or higher) except the price series of New Zealand, Korea and Singapore, implying that distributions are relatively peaked rather than normal. The Jarque-Bera tests reject the null hypothesis of normality at 1 and 5 percent levels of significance. In support of J-B test, we also plot theoretical Quantile-Quantile as shown in Figures 3 and 4. None of the plots exhibit good fit of the distribution of observations. The graphs show that both positive and negative large shocks create non-normal distribution of the series for both price and returns. Hence, the samples appropriately contain financial characteristics such as volatility clustering, long tails and leptokurtosis.

In addition to the above, unit root tests results are also presented in Table 1. In levels, all the food price series appear non-stationary, however, they appear stationary in first differences, implying all series are integrated of order 1, denoted I (1). This suggests using the returns for estimating the GARCH models for examining conditional volatility over the time period selected. Figures 1 and 2 show the plots of food prices and their returns. In the returns graphs, it is clearly visible that there is evidence of volatility clustering for the return series of world and for all individual countries. Figure 1 shows that since 2002 there was a sharp rises in food prices (Mitchell, 2008) of each country and therefore we divide total time period into two subsamples ranging from 1995 to 2001 and 2002 to 2010 for the purpose of estimation. By dividing into two subsamples we can distinguish whether there is any significant difference between high rise and non-high rise period of food prices.

Table 1. Statistical properties of data

Prices									
	WFP	AUSFP	NZFP	KORFP	SINFP	HKFP	TWNFP	INFP	THFP
Mean	1687.3	976.713	451.26	385.757	474.174	168.941	284.359	1078.30	550.57
Median	1447.5	895.335	483.450	333.6900	418.9700	116.6500	234.6900	899.3050	561.640
Maximum	3086.8	1905.49	744.57	871.13	1007.11	625.34	695.64	2989.23	1190.86
Minimum	939.8	477.210	206.460	124.310	117.190	33.390	116.250	254.140	176.560
Std. Dev.	542.4	363.048	129.657	180.137	218.316	132.946	135.559	630.132	171.329
Skewness	0.9645	0.63647	-0.24493	0.59562	0.52627	1.46040	0.86664	0.83363	0.37046
Kurtosis	2.9207	2.31378	1.86426	2.09315	1.98832	4.45968	2.67396	2.95978	3.35085
J-B	621.29	348.547	254.978	373.571	355.224	1776.97	518.426	463.562	112.012
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADFL (prob)	0.9075	0.5574	0.4467	0.5817	0.8510	0.9998	0.5963	0.9843	0.9667
ADFFD(prob)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Obs.	4000	4000	4000	4000	4000	4000	4000	4000	4000

Returns									
	WFP	AUSFP	NZFP	KORFP	SINFP	HKFP	TWNFP	INFP	THFP
Mean	0.00025	0.00015	-6.78E-0	0.000261	0.00012	0.00045	0.00021	0.00045	0.00017
Median	0.00063	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Maximum	0.06805	0.10508	0.21383	0.12514	0.15767	0.15568	0.15838	0.13291	0.16875
Minimum	-0.0568	-0.1138	-0.1967	-0.14811	-0.13523	-0.15054	-0.08981	-0.08622	-0.15808
Std. Dev.	0.00773	0.01230	0.01603	0.02322	0.01932	0.02093	0.02257	0.01565	0.01861
Skewness	-0.424	-0.045	0.078	-0.069	0.254	0.113	0.111	0.393	0.023
Kurtosis	10.860	11.0713	23.4145	7.71010	9.48634	9.26574	5.00237	8.14859	11.8719
J-B	10415.2	10856.4	69445.3	3699.7	7053.6	6550.1	676.3	4520.2	13115.6
Prob.	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ADFL (prob)	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Obs.	3999	3999	3999	3999	3999	3999	3999	3999	3999

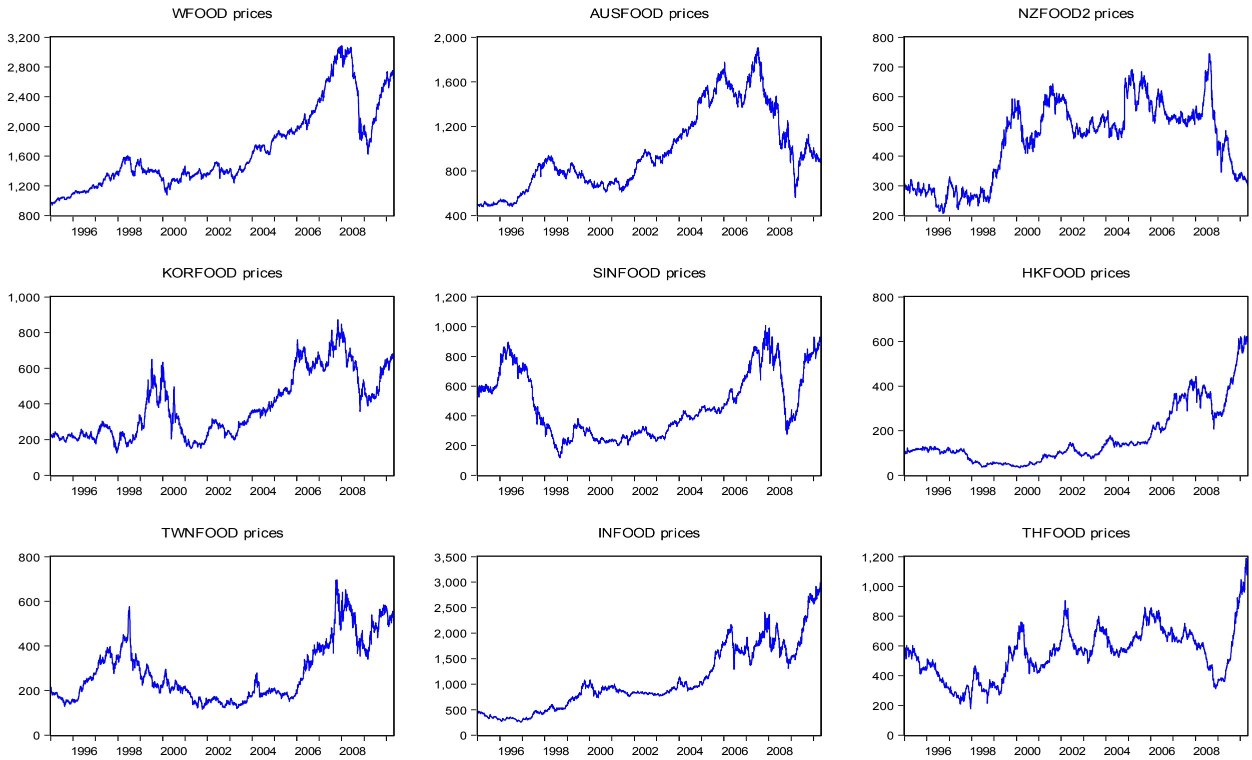

Figure 1. Daily food price indices 2 January 1995 to 30 April 2010

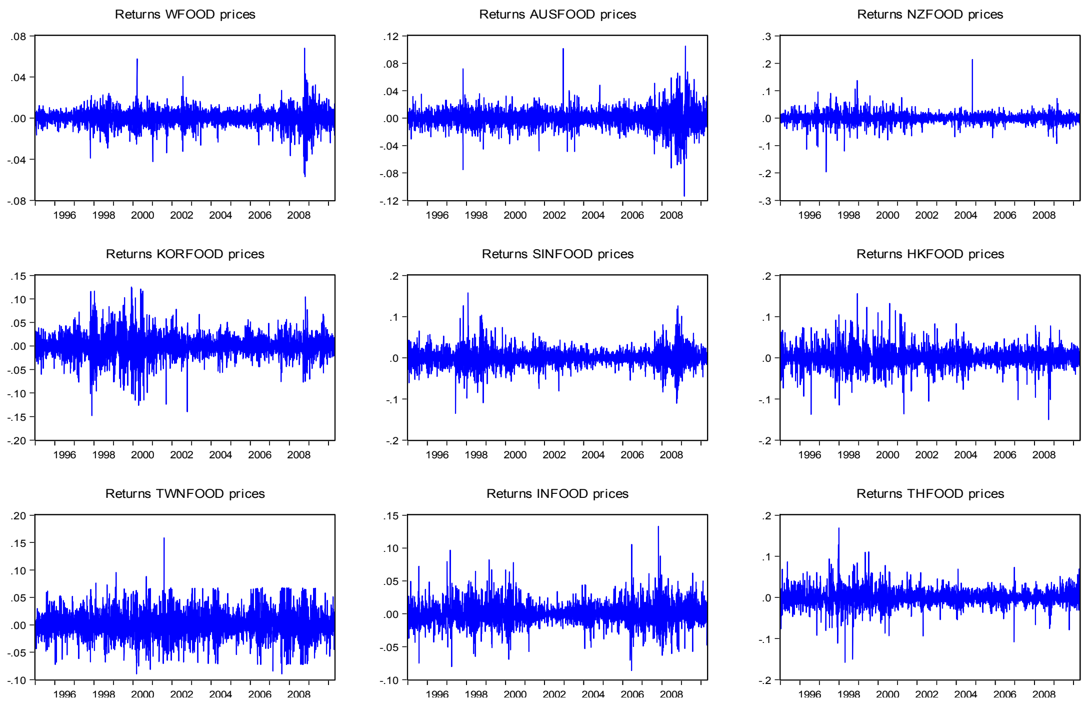

Figure 2. Daily food price returns 2 January 1995 to 30 April 2010

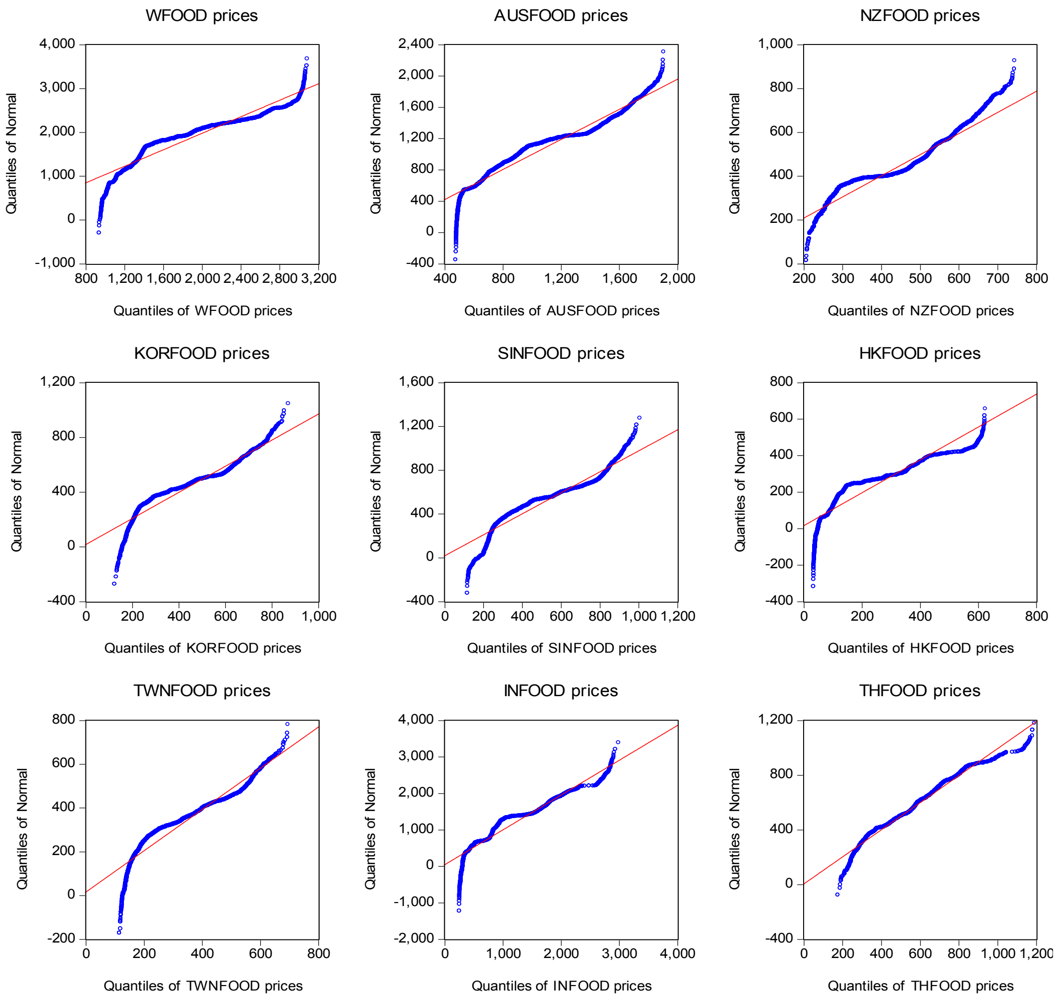

Figure 3. Theoretical quantile-quantile plot for food prices

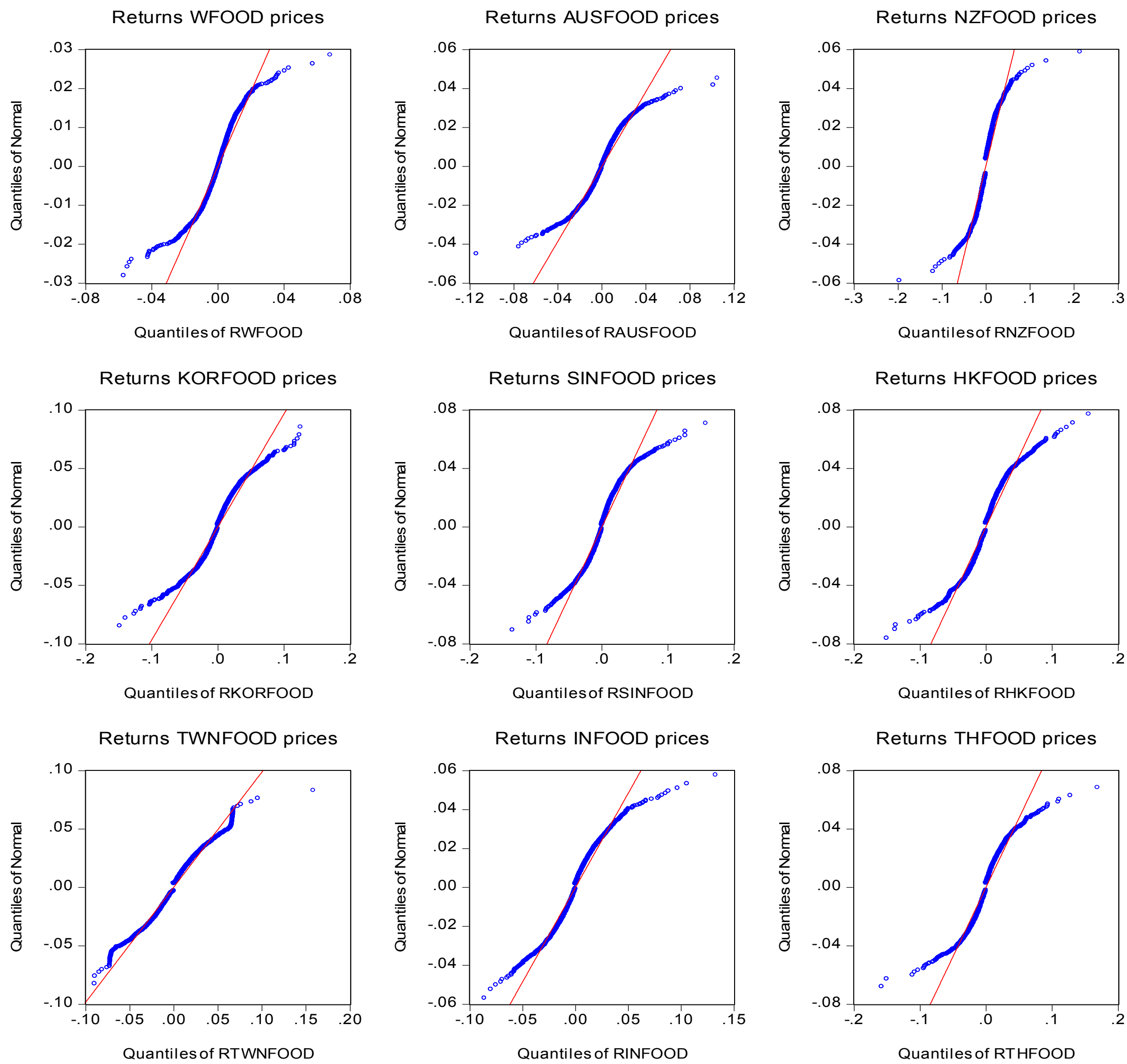

Figure 4. Theoretical quantile-quantile plot for food price returns

3. Methods and Empirical Results

3.1 Methods

3.1.1 CGARCH Models

For modelling financial characteristics of time series data, first scholarly efforts were put forward by Engle (1982). As an aid, he developed the Autoregressive Conditional Heteroskedasticity (ARCH) model which was later generalised by Bollerslev(1986) as GARCH models. Since then ARCH/GARCH models got momentum to grow in different dimensions not only for magnitudes but also on the directions to better capture the financial characteristics of assets (Robert F. Engle, 2001). One of these extended versions of GARCH family models is the Component GARCH (CGARCH) model developed by Ding et al. (1993). We use this variant of GARCH model in this study due to its superior performance in different aspects. According to Black and McMillan (2004), the CGARCH model decomposes conditional variances into a long-run time varying trend component and a short-run transitory component, which reverts to the trend following a shock. This model has superiority in terms of capturing both long and short-run properties of time series. Christoffersen et al. (2008) mention “The component model’s superior performance is partly due to its improved ability to model the smirk and the path of spot volatility, but its most distinctive feature is its ability to model the volatility term structure.”

In component GARCH (CGARCH) models, the constant conditional variance condition of GARCH (1, 1) model is replaced with a time varying component ‘q’ to capture long-run volatility. In general the ARMA (1, 1)-CGARCH (1, 1) model may be written in the following form:

Mean equation:

$$R_t = \beta_1 + \beta_2 R_{t-1} + \beta_3 e_{t-1} + \varepsilon_t \quad (2)$$
$$\varepsilon_t \sim iid(0, h_t)$$

Variance equations:

$$\begin{aligned} q_t &= \gamma_0 + \gamma_1(q_{t-1} - \gamma_0) + \gamma_2(e_{t-1}^2 - h_{t-1}) \\ h_t &= q_t + \gamma_3(e_{t-1}^2 - q_{t-1}) + \gamma_4(h_{t-1} - q_{t-1}) \end{aligned} \quad (3)$$

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 sum of parameters γ_3 and γ_4 measures the *transitory* shock persistence and γ_1 measures the long-run persistence derived from the shock to a permanent component given by γ_2.

We use CGARCH models to analyse data throughout the study. In the first stage, in order to estimate food price volatility of world and country specific data we use CGARCH-M (1, 1) models in asymmetric form to assess whether volatility in mean equations becomes a factor of risk or not and to see whether shocks to volatility are asymmetric or not. To this end, the ARMA (1, 1)-CGARCH (1, 1)-in mean models to be estimated may be written in the following general form:

Mean Equation:

$$R_{i,t} = \beta_1 + \beta_2 R_{i,t-1} + \beta_3 e_{t-1} + \beta_4 h_{i,t} + \varepsilon_{i,t} \quad (4)$$

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

Variance Equation:

$$\begin{aligned} q_{i,t} &= \gamma_0 + \gamma_1(q_{i,t-1} - \gamma_0) + \gamma_2(e_{i,t-1}^2 - h_{i,t-1}) \\ h_{i,t} &= q_t + \gamma_3(e_{i,t-1}^2 - q_{i,t-1}) + \gamma_4(e_{i,t-1}^2 - q_{i,t-1})d_{t-1} + \gamma_5(h_{i,t-1} - q_{i,t-1}) \end{aligned} \quad (5)$$

Where i refers to variables from 1 to 9 representing the world and 8 individual countries, β_2 and β_3 measure autoregressive and moving average coefficients, β_4 is the coefficient for volatility in the mean equation (measuring risk in mean return) and γ_4 provides a measure of asymmetry. The lag order of ARMA is set by Box-Jenkins (1976) methodology and hence the lag orders selected may differ across the series depending on the nature of data.

3.1.2 CGARCH Models for Mean and Volatility Spillover Effects

One of the objectives of this study is to examine whether past information regarding the mean return in one food market affects other markets' current mean return or not, and similarly past information of volatility in one market affects other markets' current volatility or not. The second portion reveals information regarding the 'heat waves' or 'meteor shower' effects of Engle et al. (1990). If the current volatility of one food market, for example Australian food market, is not influenced by past volatilities of other markets, for example New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand, we can say that volatility in Australian food market takes an independent path and this is termed as 'heat wave' effects. On the other hand, if current volatility of one market is influenced by any past volatility of other markets we say that volatility is interdependent or spills over from one market to another and this notion is termed 'meteor shower' effects. To evaluate 'heat wave' and 'meteor shower' effects following methods are followed.

In fact, as stated earlier, the models are estimated in two steps. For the first step, we model each food price return series through an ARMA-CGARCH-M model with equations 4 and 5. In the second step of estimation, in order to check mean and volatility spillover we compute standard deviation and conditional variance series from step 1 and incorporate them into appropriate mean and variance equations. More specifically, in line with the ideas of Engle et al. (1990), Baillie et al. (1993), Liu and Pan (1997), Lin and Tamvakis(2001), and Hammoudeh et al. (2003) we include conditional standard deviations derived for each variable from the first step into the mean equations of appropriate series to check mean spill over effects and insert conditional variances into the variance equations to assess volatility spillover effects form one food market to another. In particular, the following equations for checking mean spillover effects are estimated:

Mean Equation:

$$R_{i,t} = \beta_1 + \beta_2 R_{i,t-1} + \beta_3 e_{i,t-1} + \beta_4 \hat{h}_{j,t} + \varepsilon_{i,t} \tag{6}$$

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

Variance Equation:

$$\begin{aligned} q_{i,t} &= \gamma_0 + \gamma_1 (q_{i,t-1} - \gamma_0) + \gamma_2 (e_{i,t-1}^2 - h_{i,t-1}^2) \\ h_{i,t}^2 &= q_t + \gamma_3 (e_{i,t-1}^2 - q_{i,t-1}) + \gamma_4 (h_{i,t-1}^2 - q_{i,t-1}) \end{aligned} \tag{7}$$

wherei represents series 1 to 8 for 8 individual countries. In order to examine long-run volatility spillover effects we put estimated conditional variances in the permanent component of the variance equations and hence we estimate the following ARMA-CGARCH (1, 1) model:

Mean Equation:

$$R_{i,t} = \beta_1 + \beta_2 R_{i,t-1} + \beta_3 e_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

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

Variance Equation:

$$\begin{aligned} q_{i,t} &= \gamma_0 + \gamma_1 (q_{i,t-1} - \gamma_0) + \gamma_2 (e_{i,t-1}^2 - h_{i,t-1}^2) + \gamma_j \hat{h}_{j,t-1}^2 \\ h_{i,t}^2 &= q_{i,t} + \gamma_3 (e_{i,t-1}^2 - q_{i,t-1}) + \gamma_4 (h_{i,t}^2 - q_{i,t-1}) \end{aligned} \tag{9}$$

wherei represents number of return series of 8 countries, j stands for the number of computed conditional variance series for 7 countries except the one under estimation. Appropriate lag orders for ARMA were set by Box-Jenkins (1976) methods in each case and models are selected based on the lowest AIC, highest R squared and maximum log likelihood values. The parameters of each model are estimated via maximum likelihood methods. To avoid possible violations of normally distributed error term assumption, all models are estimated assuming generalised error distributions (GED).

Following Engle et al. (1990) and Baillie et al. (1993) we compute robust Wald tests from each ARMA-CGARCH model to examine mean and volatility spill over effects across different countries covered by the study.

3.2 Empirical Results

3.2.1 CGARCH Models of Food Price Volatility

Table 2 displays empirical results of CGARCH estimates for food price returns of world aggregate and other countries for the full sample period starting from 1995 to 2010. Asymmetric ARMA-CGARCH-in mean models for each series are estimated. Almost all parameters in the mean equations are statistically significant at least at 5% level of significance; GARCH in mean parameters are not statistically significant except for the New Zealand (β_3) and Korean series (β_4), implying risk does not necessarily lead to increased food price returns for many of the countries with the exceptions of New Zealand and Korea.

In Table 2, the variance equations show that almost all the parameters (γ_0, γ_1 and γ_2) under permanent components are statistically significant at 1% level of significance. That means that the initial effects of a shock to the permanent component measured by γ_1 are highly statistically significant in all cases. Long-run persistence parameters (γ_2) are close to unity in all cases, implying long-run persistence of shock. The half lives of shock to decay range from 53 days to 1322 days in all cases except New Zealand where the average decaying time for a random shock is around 9 days. It implies that the effects of shocks to volatility are highly persistent in all countries except New Zealand. Parameters measuring asymmetry (γ_4) are statistically significant for all the series except the Singapore return series, and the positive signs of coefficients in every case imply that positive shocks reduce volatility more than negative shocks. Only in the Singapore case, food price shocks show symmetric effects on volatility. The measures of short-run persistence parameters are significant in all cases with few exceptions. The sum of short-run persistence parameters (γ_3 and γ_5) are less than long-run persistence parameters in all cases, implying slower mean reversion in the long-run.

Table 2 also shows that GED parameters in all cases are less than 1 and statistically significant at the 1% level of significance, implying possible violation of normality assumptions. However, no other indication of serious misspecification of the models as specified is suggested by Ljung-Box Q statistics (both at level and squared) and ARCH (LM) tests with 10 lags.

Table 2. Asymmetric ARMA-CGARCH (1, 1)-M estimates for full sample period (1995-2010)

Parameters	RWFOOD AR(1)-CGARCH(1,1)-M	RAUSFOOD ARMA(2,1)-CGARCH(1,1)-M	RNZFOOD ARMA(2,2)-CGARCH(1,1)-M	RKORFOOD ARMA(1,1)-CGARCH(1,1)-M	RSINFOOD ARMA(1,1)-CGARCH(1,1)-M	RHKFOOD ARMA(1,1)-CGARCH(1,1)-M	RTWNFOOD ARMA(1,1)-CGARCH(1,1)-M	RINFOOD AR(1)-CGARCH(1,1)-M	RTHFOOD ARMA(2,2)-CGARCH(1,1)-M
β_1	0.0004	0.000306	-3.39E-06	-0.000215	0.000103	1.50E-05	-0.000261	-1.06E-05	2.37E-06
	(0.000140)[a]	(0.000195)	(1.93E-10)[a]	(0.000156)	(0.000267)	(1.93E-05)	(0.000496)	(0.000223)	(0.000146)
β_2	0.1210	0.9108	-1.81E-06	-0.279152	0.103598	-0.296881	0.712563	0.020015	0.726090
	(0.016270)[a]	(0.012593)[a]	(1.13E-08)[a]	(0.070179)[a]	(0.586492)	(0.001289)[a]	(0.115140)[a]	(0.013815)	(0.319522)[b]
β_3	2.9329	0.032734	0.000172	0.309243	-0.101459	0.297995	-0.731517	-0.070385	-0.647129
	(3.158709)	(0.009869)[a]	(5.67E-06)[a]	(0.069130)[a]	(0.586629)	(0.012227)[a]	(0.111493)[a]	(1.119215)	(0.109094)[a]
β_4		-0.947582		0.832407	-0.130736	-0.025130	0.939209		-0.725815
		(0.005436)[a]		(0.389605)[b]	(0.944110)	(0.485223)	(1.071056)		(0.319826)[b]
β_5		0.449158							0.646695
		(1.424413)							(0.108975)[a]
β_6									-0.010076
									(0.516007)
γ_0	0.000052	0.000113	0.018069	0.000615	0.000569	0.000460	0.000623	0.000962	0.000529
	(1.35E-05)[a]	(1.69E-05)[a]	(0.000596)[a]	(0.000219)[a]	(0.000553)	(7.61E-05)[a]	(0.000137)[a]	(0.003040)	(0.000216)[b]
γ_1	0.993080	0.993328	0.920279	0.990450	0.998059	0.994216	0.986992	0.999476	0.988324
	(0.002866)[a]	(0.002212)[a]	(0.000132)[a]	(0.004689)[a]	(0.002287)[a]	(0.007069)[a]	(0.005053)[a]	(0.001838)[a]	(0.006066)[a]
γ_2	0.050413	0.027109	-0.049617	0.0733937	0.040307	0.038030	0.0555664	0.031106	0.060941
	(0.010649)[a]	(0.004485)[a]	(0.000100)[a]	(0.013463)[a]	(0.009830)[a]	(0.014249)[a]	(0.005046)[a]	(0.008235)[a]	(0.018036)[a]
γ_3	9.62E-06	0.009489	0.167576	0.032286	0.104826	0.097507	0.059532	0.114966	0.102653
	(0.02433)	(0.026282)	(0.000144)[a]	(0.028457)	(0.029123)[a]	(0.031558)[a]	(0.007943)[a]	(0.029116)[a]	(0.039210)[a]
γ_4	0.091371	0.071431	0.005083	0.087685	-0.023629	0.064319	0.112666	0.086922	0.077961
	(0.026196)[a]	(0.035415)[b]	(0.000240)[a]	(0.040688)[b]	(0.032079)	(0.038793)[c]	(0.019259)[a]	(0.036983)[b]	(0.046429)[c]
γ_5	0.800633	-0.244412	0.511558	0.684564	0.762846	0.660190	0.524760	0.651681	0.598373
	(0.060632)[a]	(0.238757)	(0.000254)[a]	(0.100281)[a]	(0.061275)[a]	(0.065184)[a]	(0.102282)[a]	(0.060614)[a]	(0.097800)[a]
GED	1.538	1.296	0.132	1.176	1.120	0.949	1.100	1.012	0.816
	(0.044377)[a]	(0.024543)[a]	(0.000685)[a]	(0.031004)[a]	(0.026189)[a]	(0.022551)[a]	(0.032544)[a]	(0.025969)[a]	(0.021391)[a]
L-BQ(10)	13.542	21.992[a]	11.496	14.115[c]	20.293[a]	12.132	12.706	14.828[c]	24.549[a]
L-BQ^2(10)	4.1526	4.114	38.654[a]	3.772	2.576	2.381	8.661	9.797	3.747
ARCH-LM(10)	0.5862	0.4519	0.6427	0.6411	0.6738	0.4836	0.1938	0.023[b]	0.9094

Note: Values in parentheses including L-BQ are standard errors, [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively; Last row shows probabilities of ARCH-LM(10) tests

Table 3 reports Asymmetric ARMA-CGARCH-in mean model estimates for the sub-sample period ranging from 1995 to 2001. Coefficients of interests in the mean equations are GARCH in mean parameters, which are not all statistically significant at any level of significance except for Australia, New Zealand and Korea although for

Australia statistical significance is indicated only at 10% level.

Table 3 also reveals that for the variance equations the long-run persistence parameters for world and for all other countries are statistically significant at 1% level of significance. The average half-life of the effects of shocks on volatility is at least more than 21 days in every case, while only the New Zealand series shows very low persistence of the effect of shocks. The effect of shocks dies out rapidly (only three days) in New Zealand. Parameters measuring asymmetry are not statistically significant for Korea, Singapore and Hong Kong indicating that price shocks have symmetric effects on volatility for the 1995-2001 period data sets. In all other cases, there is evidence of positive asymmetric effects of shocks on price volatility meaning positive shocks reduce volatility more than negative shocks. The sums of the short-run persistence parameters are smaller than the long-run persistence parameters implying slower mean reversion in the long-run for all countrys as well as for world food prices.

In each equation the GED parameters are less than 2 and statistically significant at 1% level of significance, reinforcing the possible violation of normality assumptions. However, the results for the Ljung-Box Q statistics and the ARCH-LM test statistics do not suggest any other serious misspecification of the models.

Table 3. Asymmetric CGARCH (1, 1)-M estimates for sub-sample period (1995-2001)

Parameters	RWFOOD AR(1)-CGARCH(1,1)-M	RAUSFOOD ARMA(1,2)-CGARCH(1,1)-M	RNZFOOD ARMA(4,4)-CGARCH(1,1)-M	RKORFOOD AR(1)-CGARCH(1,1)-M	RSINFOOD ARMA(2,2)-CGARCH(1,1)-M	RHKFOOD ARMA(1,1)-CGARCH(1,1)-M	RTWNFOOD ARMA(1,1)-CGARCH(1,1)-M	RINFOOD ARMA(3,3)-CGARCH(1,1)-M	RTHFOOD AR(1)-CGARCH(1,1)-M
β_1	0.000230	0.000101	-2.90E-05	-0.000743	-0.000324	9.45E-05	-0.000439	-0.000566	-3.91E-05
	(0.000205)	(9.05E-06)[a]	(1.22E-08)[a]	(0.000197)[a]	(0.000547)	(0.000192)	(0.000850)	(0.000102)[a]	(9.12E-05)[a]
β_2	0.172637	-0.844670	-0.359957	0.074794	-1.037680	-0.582428	0.725021	0.444157	0.000187
	(0.024070)[a]	(0.065378)[a]	(2.82E-05)[a]	(0.021995)[a]	(0.154595)[a]	(0.131847)[a]	(0.128326)[a]	(0.011352)[a]	(0.003031)
β_3	5.570798	0.836347	0.581100	0.923485	-0.701380	0.581908	-0.726391	0.551049	0.113783
	(5.652416)	(0.068688)[a]	(0.000229)[a]	(0.089571)[a]	(0.122787)[a]	(0.131967)[a]	(0.128112)[a]	(0.005548)[a]	(0.087438)
β_4		-0.044835	0.433879		1.035440	-0.192516	1.154287	-0.243788	
		(0.023583)[c]	(0.000348)[a]		(0.154503)[a]	(0.371536)	(1.957191)	(0.114033)[b]	
β_5		3.908729	-0.433694		0.703599			-0.360958	
		(2.109195)[c]	(1.93E-06)[a]		(0.122226)[a]			(0.014051)[a]	
β_6			0.359928		0.532263			-0.582800	
			(2.80E-05)[a]		(1.424729)			(0.004153)[a]	
β_7			-0.581121					0.184092	
			(0.000229)[a]					(0.116612)	
β_8			-0.433866					2.604754	
			(0.000348)[a]					(0.406640)	
β_9			0.433717						
			(2.02E-06)[a]						
β_{10}			0.008615						
			(5.29E-06)[a]						
γ_0	4.87E-05	9.10E-05	0.008433	0.001475	0.000573	0.001313	0.001072	0.000444	0.016057
	(2.25E-05)[b]	(7.03E-06)[a]	(2.27E-06)[a]	(0.001655)	(0.000195)[a]	(0.000394)[a]	(0.000602)[c]	(0.000670)	(0.013186)
γ_1	0.994497	0.967077	0.791722	0.994431	0.991238	0.897906	0.999396	0.999055	0.999692
	(0.003993)[a]	(0.013725)[a]	(0.000452)[a]	(0.007161)[a]	(0.006160)[a]	(0.042694)[a]	(0.000562)[a]	(0.002654)[a]	(0.000305)[a]
γ_2	0.049005	0.026263	0.243943	0.081277	0.051512	0.273424	0.005159	0.018910	0.042864
	(0.014562)[a]	(0.010040)[a]	(0.000593)[b]	(0.021818)[a]	(0.009267)[a]	(0.055364)[a]	(0.004937)	(0.008004)[b]	(0.020114)[b]

γ_3	0.012697	-0.036911	0.223525	0.055701	0.1795571	-0.025898	0.027015	0.109384	0.182458
	(0.028821)	(0.024886)	(0.000831)[a]	(0.044779)	(0.066044)[a]	(0.049081)	(0.021443)	(0.043152)[b]	(0.033949)[a]
γ_4	0.114318	0.134583	0.006535	0.083143	-0.118048	0.086608	0.107364	0.122341	0.057822
	(0.037208)[a]	(0.004494)[a]	(0.000516)[a]	(0.061559)	(0.076449)	(0.085978)	(0.022150)[a]	(0.051537)[b]	(0.030499)[c]
γ_5	0.762908	-0.453021	0.115224	0.692270	0.328243	-0.682013	0.822171	0.631090	0.634993
	(0.073695)[a]	(0.229391)[b]	(0.001421)[a]	(0.124368)[a]	(0.245585)	(0.311485)[b]	(0.011038)[a]	(0.084229)[a]	(0.088326)[a]
GED	1.571	1.314	0.140270	1.125	0.988	0.6017	1.087	0.962	0.6113
	(0.068642)[a]	(0.057007)[a]	(0.001153)[a]	(0.045176)[a]	(0.033370)[a]	(0.023976)[a]	(0.047434)[a]	(0.036987)[a]	(0.021083)[a]
L-BQ(10)	19.738[b]	17.577[b]	7.3874[b]	13.482	18.177[a]	6.924	10.463	14.159[a]	17.944[b]
L-BQ^2(10)	10.009	11.019	4.0229	5.528	1.868	3.580	12.267	7.230	4.270
ARCH-LM(10)	0.8289	0.4301	0.7616	0.8365	0.8966	0.9295	1.942	2.103	0.6267

Note: Values in parentheses including L-BQ are standard errors, [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively; Last row shows probabilities of ARCH-LM(10) tests.

Results for the more recent period are given in Table 4, which presents Asymmetric ARMA-CGARCH-in mean model estimates for the sub-sample period of 2002 to 2010. GARCH in mean parameters are not statistically significant for any series at any level of significance with the exception of India only. In the Indian case, risk does matter in the returns to food prices. Other countries all fairly well exhibit stability in terms of news impacts. On the whole, these statistical results indicate that the scopes for making returns from failure of market efficiency are rather very weak in these countries.

In Table 4 it can also be seen that long-run persistence parameters for world and for all other countries are statistically significant at 1% level of significance. The average half life of decaying the effects of shock is at least more than 24 days in every case while high persistence is recorded for India of about 411 days and low persistence is recorded for Thailand at about 24 days. World average and all other countries lie in between these two extremes. Parameters measuring asymmetry are not statistically significant for Australia, New Zealand and Thailand implying price shocks have symmetric effects on volatility in these countries for the period 2002 to 2010. In all other cases, there is evidence of positive asymmetric effects of shocks on price volatility meaning positive shocks reduce volatility more than negative shocks with the exception of Singapore only, where negative shocks reduce volatility more than positive shocks. As the sums of the transitory persistence parameters are smaller than the permanent persistence parameters for each model, the evidence reveals slower mean reversion in the long-run for every case.

As for the other time periods studied, the GED parameters are less than 2 and statistically significant at 1% level of significance, suggesting possible violation of normality assumptions. However, as before, the Ljung-Box Q statistics and ARCH-LM statistics fail to indicate any other form of serious misspecification of the models, with the possible exception of the New Zealand model.

Table 4. Asymmetric CGARCH (1, 1)-M estimates for sub-sample period (2002-2010)

Parameters	RWFOOD	RAUSFOOD	RNZFOOD	RKORFOOD	RSINFOOD	RHKFOOD	RTWNFOOD	RINFOOD	RTHFOOD
	AR(1)-CGARCH(1,1)-M	ARMA(1,1)-CGARCH(1,1)-M	ARMA(2,2)-CGARCH(1,1)-M	CGARCH(1,1)-M	ARMA(1,1)-CGARCH(1,1)-M	ARMA(1,1)-CGARCH(1,1)-M	ARMA(1,1)-CGARCH(1,1)-M	ARMA(1,1)-CGARCH(1,1)-M	ARMA(1,2)-CGARCH(1,1)-M
β_1	0.000697	0.000508	-9.14E-05	-0.0000375	0.0005666	2.57E-05	-0.000281	-0.000100	-0.000292
	(0.000185)[a]	(0.000283)[c]	(0.000184)	(6.05E-05)[a]	(0.000325)[c]	(0.000634)	(0.000605)	(8.08E-05)	(0.000115)[b]
β_2	0.065317	0.009906	-0.348030	2.141939	-0.941691	-0.661936	0.738596	-0.250672	0.927405
	(0.003740)[a]	(0.003691)[a]	(0.032872)[a]	(1.108903)[c]	(0.048806)[a]	(0.142662)[a]	(0.125521)[a]	(0.089058)[a]	(0.021153)[a]
β_3	-00.859015	-0073462	-0.142193		0.952120	0.694556	-0.780557	0.203289	0.033189

	(3.697844)	(0.021876)^{a}	(0.014526)^{a}		(0.044066)^{a}	(0.135413)^{a}	(0.115548)^{a}	(0.096188)^{b}	(0.000475)^{a}
β_4		-1.794937	0.337788		0.273010	3.199925	1.366209	1.718216	-0.955304
		(1.929816)	(0.014526)^{a}		(1.425614)	(2.369710)	(1.269935)	(0.741466)^{b}	(0.022754)^{a}
β_5			0.137932						1.954405
			(0.035260)^{a}						(1.437844)
β_6			0.732232						
			(1.376876)						
γ_0	5.84E-05	0.000214	0.000151	0.000308	0.000362	0.000268	0.000673	0.000476	0.000245
	(1.89E-05)^{a}	(0.000138)	(1.90E-05)^{a}	(5.10E-05)^{a}	(0.000246)	(3.81E-05)^{a}	(0.000220)^{a}	(0.000611)	(5.33E-05)^{a}
γ_1	0.988679	0.997796	0.991485	0.977247	0.9918779	0.995039	0.986159	0.998314	0.971316
	(0.005988)^{a}	(0.002197)^{a}	(0.003901)^{a}	(0.011450)^{a}	(0.006963)^{a}	(0.006393)^{a}	(0.007208)^{a}	(0.002296)^{a}	(0.012804)^{a}
γ_2	0.077876	0.025143	0.011659	0.052500	0.096328	0.006228	0.069408	0.034839	0.093231
	(0.012946)^{a}	(0.007355)^{a}	(0.004604)^{b}	(0.025371)^{b}	(0.015449)^{a}	(0.005740)	(0.020505)^{a}	(0.011646)^{a}	(0.017630)^{a}
γ_3	-0.060919	0.104959	0215793	0.020186	0.141873	0.056985	0.100356	0.123551	-0.039203
	(0.030705)^{b}	(0.040097)^{a}	(0.042747)^{a}	(0.041509)	(0.056304)^{b}	(0.026112)^{b}	(0.043115)^{b}	(0.040365)^{a}	(0.052809)
γ_4	0108233	-0.063567	-0.047877	0.094287	-0.147434	0.101549	0.100356	0.093181	0.111056
	(0.046266)^{b}	(0.045703)	(0.065603)	(0.042484)^{b}	(0.068902)^{b}	(0.028238)^{a}	(0.062291)^{c}	(0.050856)^{c}	(0.073492)
γ_5	0.628563	0.669293	0.174531	0.771311	0.000951	0.768519	0.400726	0.623481	-0.032290
	(0.242354)^{a}	(0.150348)^{a}	(0.114523)	(0.095459)^{a}	(0.313480)	(0.025946)^{a}	(0.166780)^{b}	(0.082138)^{a}	(0.537805)
GED	1.544	1.214	1.009	1.260	1.325	1.226	1.155	1.111	1.066
	(0.065711)^{a}	(0.033372)^{a}	(0.035583)^{a}	(0.049337)^{a}	(0.058020)^{a}	(0.39823)^{a}	(0.047672)^{a}	(0.040876)^{a}	(0.037101)^{a}
L-BQ(10)	9.5108	11.365	3.8484	6.5330	14.824^{c}	18.677^{b}	13.759^{c}	7.5523	9.9607
L-BQ^2(10)	3.5729	2.4383	19.320^{a}	4.5800	8.7382	0.987	5.5469	3.9383	4.1087
ARCH-LM(10)	0.4479	0.6774	0.7941	0.0990	0.2205	0.3958	0.8737	0.3991	0.5980

Note: Values in parentheses including L-BQ are standard errors , ^{a}, ^{b} and ^{c} indicate significance at 1%, 5% and 10% level respectively; Last row shows probabilities of ARCH-LM(10) tests.

Major findings related to volatility modelling of food prices returns can be summed up as follows: (1) ARMA-CGARCH (1,1)-in mean models employed in the study to capture volatility characteristics of food price returns fits the data well for all countries and world context; (2) food price returns of each country as well as world integrated series show asymmetric and long-run persistent volatility for the full sample period with exception of Singapore and New Zealand where shocks have symmetric but persistent volatility in Singapore and transitory but asymmetric volatility in New Zealand food price returns; (3) for the subsample period 1995 to 2001, all food price return series show long-run persistent volatility while a mixed evidence of asymmetry is reported. Korea, Singapore and Hong Kong food price returns series show symmetric effects on volatility. All other countries' data demonstrate positive asymmetric effects on volatility; (4) similar to first subsample food price returns series of all countries and world for the period 2002 to 2010 show long-run persistency. Asymmetric effects are not found for Australia, New Zealand and Thailand while all other countries show positive asymmetric effects on food price returns volatility; (5) the sum of short-run persistence parameters in all series across all samples are smaller than long-run persistence parameters imply slower mean reversion in the long-run; (6) scant evidence of increased risks leading to increased returns has been found across all samples. The New Zealand and Korean series for the full sample, Australia, New Zealand and Korean series for subsample 1995-2001 and only Indian food price series for the last sample period 2002-2010 are found to be statistically significant for GARCH in mean equations.

Volatility characteristics of food prices can be modelled well by CGARCH-type models in the context of world and country specific level irrespective of the nature of food production and consumption. Though long-run persistency of shocks exists for all food markets the asymmetric natures differ across countries and time period. The hypothesis of risk does not increase returns cannot be rejected in all cases. Prior to 2001, few of the economies covered by the study show that risk leads to increased returns implying inefficiency in the market mechanism while in the period of sharp rises of food prices most of the markets show rapid adjustments of shocks within the market systems.

3.2.2 Mean and Volatility Spillover Effects across Countries

Table 5 exhibits robust Wald tests for mean spillover effects for the combined sample period of 1995 to 2010. The tests fail to find evidence of mean spillover effects for Korea, Hong Kong, Taiwan and Thailand food price return series. Mean returns of these countries are not systematically influenced even by their own lags. In the case of Australia, New Zealand, Singapore and India some evidence of cross country mean spillover is identified. Australian mean returns of food prices are influenced by New Zealand and India. New Zealand food prices are found to be influenced more significantly by other countries food price returns and mean spill over effects are detected from Australia, Korea and Singapore. Singapore food price returns in mean are found to be influenced by New Zealand and Korea and in both cases coefficients are statistically significant at 5% level of significance while Indian food price mean returns are found to be influenced by Singapore food price returns though the coefficient is statistically significant only at 10% level of significance.

Table 5. Robust Wald tests for mean spillover effects for the full sample period 1995-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
$h_{(t-1)}$AUS	2.048	10.235[a]	0.560	1.535	0.071	0.065	1.401	0.030
$h_{(t-1)}$NZ	3.525[c]	23.379[a]	0.015	5.332[b]	0.011	0.007	0.196	0.416
$h_{(t-1)}$KOR	0.816	25.10[a]	2.411	4.157[b]	0.003	0.440	0.095	0.015
$h_{(t-1)}$SIN	0.594	5.575[b]	1.031	0.313	0.002	0.032	2.843[c]	0.011
$h_{(t-1)}$HK	0.576	1.125	0.101	6.10E05	0.002	0.436	0.236	0.008
$h_{(t-1)}$TWN	0.153	0.062	0.131	0.460	9.15E-05	0.943	0.398	0.006
$h_{(t-1)}$IN	7.327[a]	0.313	0.273	1.217	2.93E-05	0.538	0.250	0.119
$h_{(t-1)}$TH	0.168	0.164	1.998	2.562	0.000	0.229	0.060	0.016
$\sum_j h_{j(t-1)}$	15.068[c]	46.351[a]	6.656	22.127[a]	0.134	2.606	4.213	0.592

Note: [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively.

Table 6 shows robust Wald tests for volatility spill over effects across countries for the period 1995 to 2010. Except for Taiwan, all variance series for food price returns are found to be interdependent because parameters measuring volatility spillover effects are found to be statistically significant in most cases. There are considerable volatility spillover effects from India and Thailand to Australian food price returns. In the case of New Zealand, strong volatility spillover effects are identified from all other countries except Taiwan. Korean food price returns take a relatively independent way of volatility though there is a little evidence of volatility spillover from Singapore food price returns. Volatility in Singapore food price returns are found to be influenced by Australia, Hong Kong and Thailand. Hong Kong food price returns are volatile due to its own shocks as well as shocks from its regional countries i.e. Korea, Singapore and Taiwan. There are statistically significant volatility spillover effects from Australia, Singapore, Hong Kong, Taiwan and Thailand food price returns to Indian food price returns. In the case of Thailand, volatility spillover effect is found to be statistically significant only from Korea. No other countries' food price returns affect volatility of Thai food returns to a measurable extent.

Table 6. Robust Wald tests for volatility spillover effects for the full sample period 1995-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
$h^2_{(t-1)}$AUS	-	111.399[a]	0.416	4.795[a]	0.859	0.167	4.814[b]	2.123
$h^2_{(t-1)}$NZ	0.004	-	0.187	1.306	0.298	0.160	0.011	0.744
$h^2_{(t-1)}$KOR	0.249	19.231[a]	-	0.449	6.572[b]	0.448	0.353	8.164[a]
$h^2_{(t-1)}$SIN	2.195	2.845[c]	3.545[c]	-	2.812[c]	0.329	5.281[b]	1.789
$h^2_{(t-1)}$HK	2.347	17.869[a]	1.95E-05	3.205[c]	-	0.691	3.870[b]	2.249
$h^2_{(t-1)}$TWN	2.282	1.330	0.503	0.087	5.429[b]	-	3.270[c]	0574
$h^2_{(t-1)}$IN	5.662[b]	9.035[a]	0.021	0.084	0.200	1.000	-	2.532
$h^2_{(t-1)}$TH	4.753[b]	12.391[a]	0.060	3.211[c]	1.053	1.316	4.218[b]	-
$\sum_j h^2_{j(t-1)}$	14.879[c]	166.401[a]	5.113	8.597	16.298[a]	3.485	23.922[a]	10.096

Note: [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively.

Table 7 displays robust Wald tests for mean spill over effects for the early subsample period of 1995 to 2001. None of the series shows any statistically significant evidence of mean spill over effects from one country's food price returns to another country with only one exception, the New Zealand food price return series. New Zealand mean returns series are influenced by all other countries' food price return's conditional standard deviation.

Table 7. Robust Wald tests for mean spillover effects for the sample period 1995-2001

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
$h_{(t-1)}$AUS	0.187	51044.27[a]	0.040	0.580	0.482	0.744	0.013	0.034
$h_{(t-1)}$NZ	0.006	7734.5[a]	0.204	0.472	0.442	1.106	0.151	0.294
$h_{(t-1)}$KOR	0.240	21276.26[a]	2.588	0.070	0.023	0.037	0.011	0.040
$h_{(t-1)}$SIN	0.001	483.752[a]	0.686	0.048	0.002	0.033	0.612	0.002
$h_{(t-1)}$HK	0.155	1216.483[a]	0.016	0.125	0.015	1.086	0.031	0.006
$h_{(t-1)}$TWN	0.226	236.021[a]	0.189	0.037	0.003	0.112	0.389	0.092
$h_{(t-1)}$IN	0.732	381.118[a]	0.046	0.495	0.005	0.041	0.169	0.009
$h_{(t-1)}$TH	0.922	87.913[a]	2.601	2.437	0.000	0.439	0.002	0.001
$\sum_j h_{j(t-1)}$	2.470	479489[a]	4.878	4.876	2.335	4.647	1.237	0.341

Note: [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively.

Table 8 shows Wald test statistics for volatility spillover for the period 1995 to 2001. Excepting Singapore all other countries food price returns show some evidence of volatility spillovers. Food price return volatility spillover is found to be statistically significant from New Zealand, Singapore, Hong Kong and Taiwan to Australia, from Australia, Korea, Singapore, Taiwan, India and Thailand to New Zealand. Food price return volatility from Australia to Korea, form Korea to Hong Kong and from Thailand to Taiwan is also found to be statistically significant though the level of significance is at only 10%. Indian food price return volatility is rather influenced by regional countries food prices e.g. Korea, Taiwan and Thailand. There is statistically significant food price return volatility spillover effects from New Zealand, Singapore, Taiwan and India to Thailand.

Table 8. Robust Wald tests for volatility spillover effects for the sample period 1995-2001

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
$h^2_{(t-1)}$AUS	-	69.755[a]	3.001[c]	2.458	0.182	0.088	0.259	0.178
$h^2_{(t-1)}$NZ	14.632[a]	-	0.002	0.182	1.503	0.129	0.252	3.345[c]
$h^2_{(t-1)}$KOR	1.629	13.596[a]	-	0.753	2.887[c]	0.096	5.242[b]	0.096
$h^2_{(t-1)}$SIN	3.286[c]	73.905[a]	0.039	-	0.338	1.740	0.018	6.764[a]
$h^2_{(t-1)}$HK	5.710[b]	1.316	0.136	0.946	-	0.669	0.472	0.120
$h^2_{(t-1)}$TWN	7.879[a]	41.308[a]	0.000	0.453	2.039	-	4.607[b]	2.702[c]
$h^2_{(t-1)}$IN	0.110	6.396[b]	0.120	0.406	0.028	0.755	-	4.143[b]
$h^2_{(t-1)}$TH	2.011	60.247[a]	0.062	0.550	0.000	2.850[c]	2.869[c]	-
$\sum_j h^2_{j(t-1)}$	59.758[a]	597.219[a]	4.046	4.952	6.921	3.962	8.645	14.883[c]

Note: a, b and c indicate significance at 1%, 5% and 10% level respectively.

Table 9 presents results of robust Wald tests for mean spillover for the recent period of 2002 to 2010. Very much different results are found for this latest subsample or for the period of sharp increase of food commodity prices. Except for New Zealand all countries show some evidence of mean spillover effects. Food price return mean spillover effect is found to be statistically significant from India to Australia, from Singapore to Korea, from Taiwan to Singapore, from Australia and Singapore to Hong Kong, from Korea to Taiwan, from Singapore to India and from India to Thailand.

Table 9. Robust Wald tests for mean spillover effects for the sample period 2002-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
$h_{(t-1)}$AUS	0.002	0.593	2.295	0.000	5.332[b]	0.196	0.279	0.005
$h_{(t-1)}$NZ	0.236	0.389	0.062	2.110	0.659	0.001	0.002	0.506
$h_{(t-1)}$KOR	0.254	0.630	2.940[c]	2.177	0.040	3.906[b]	0.221	1.565
$h_{(t-1)}$SIN	1.012	0.136	7.580[a]	0.099	10.618[a]	2.542	3.860[b]	1.058
$h_{(t-1)}$HK	1.837	1.038	0.654	1.528	3.384[c]	0.629	0.536	0.213
$h_{(t-1)}$TWN	0.190	1.956	1.880	2.922[c]	3.120[c]	1.164	0.710	0.045
$h_{(t-1)}$IN	5.653[b]	0.278	0.010	0.097	0.700	0.974	0.297	3.273[c]
$h_{(t-1)}$TH	0.950	1.408	0.062	0.307	3.708	0.220	0.080	0.034
$\sum_j h_{j(t-1)}$	12.186	5.755	15.355[c]	9.181	20.477[a]	8.250	6.989	7.065

Note: [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively.

Table 10 exhibits results of robust Wald test statistics for the volatility spillover effects of food price returns for the period 2002 to 2010. In this sharp volatile period, Singapore and Thailand food prices take independent ways to move. There is no evidence of return volatility spillover effects from other countries to these two countries. Australian food price return volatility is affected by Singapore, Taiwan and Indian food prices while New Zealand series does not show any statistically significant spillover effects from any other countries except from Hong Kong. Korean return series is found to be volatile by its own along with some volatility form its region, Singapore and Hong Kong. Strong volatility spill over effects for this period is identified for Hong Kong food price returns. There are statistically significant volatility spillover effects from New Zealand, Singapore, Taiwan and India to Hong Kong food price returns. Taiwan return series are found to be influenced by volatility of Korean food price returns. The tests find some evidences of volatility spillover effects from New Zealand and Hong Kong food market to Indian food market.

Table 10. Robust Wald tests for volatility spillover effects for the sample period 2002-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
$h^2_{(t-1)}$AUS	-	2.035	0.005	2.027	1.908	0.870	0.018	0.305
$h^2_{(t-1)}$NZ	0.390	-	0.154	0.043	15.898[a]	0.337	3.040[c]	0.645
$h^2_{(t-1)}$KOR	0.803	2.287	-	0.032	0.016	4.922[b]	0.035	0.2160
$h^2_{(t-1)}$SIN	5.040[b]	0.333	3.622[c]	-	8.249[a]	1.715	0.357	0.407
$h^2_{(t-1)}$HK	2.146	2.821[c]	2.818[c]	0.058	-	0.067	3.155[c]	1.209
$h^2_{(t-1)}$TWN	5.185[b]	0.020	0.842	0.564	77.507[a]	-	2.009	0.862
$h^2_{(t-1)}$IN	4.026[b]	1.140	0.018	0.005	57.727[a]	2.044	-	1.478
$h^2_{(t-1)}$TH	0.781	0.135	0.717	0.113	1.386	0.030	1.916	-
$\sum_j h^2_{j(t-1)}$	15.043[b]	8.894	7.742	2.811	754.193[a]	6.173	13.792[c]	5.246

Note: [a], [b] and [c] indicate significance at 1%, 5% and 10% level respectively.

Main findings of the mean and volatility spillover effects can be summarized as follows: There is no strong evidence of cross country mean spillover effects of food price returns across all samples. For the full sample period, mean spillover effects are found from India and New Zealand to Australia, from Australia, Korea and Singapore to New Zealand, from New Zealand and Korea to Singapore and from Singapore to India only. Mean spillover effects of food price returns from all countries to New Zealand are statistically significant while no evidence of spillover is found in the cases of the other countries. For the recent subsample 2002-2010, mean spillover effects from India to Australia; from Singapore to Korea, from Taiwan to Singapore; from Australia, Singapore and Taiwan to Hong Kong; from Korea to Taiwan; from Singapore to India and from India to Thailand are found to be statistically significant.

There are important differences between the first and second subsamples. During sharp rise of food price periods mean returns of food prices are not independent they are rather interdependent. In the first sample, all countries' data support the notion that food markets have strong-form efficiency (Baillie et al., 1993). That means the effects of news die out rapidly and do not make any opportunity for excess cross country mean returns, while in the second subsample there are some deviations from this inference. In the second subsample, there is some evidence of news not dying out rapidly in some cases with the exception of New Zealand only. For the first subsample period New Zealand food price returns show some evidence of failure of strong-form market efficiency, however, during the period of sharp rises in food prices New Zealand data do not support the failure of strong form efficiency.

Evidence of volatility spillover effects is stronger than mean spillover effects. For the full sample period, except Taiwan all other countries' food price returns show some sort of cross country volatility spillover effects. Volatility spillover effects of food price returns from India and Thailand to Australia; from Australia, Korea, Singapore, Hong Kong, India and Thailand to New Zealand; from Singapore to Korea; from New Zealand, Singapore and Taiwan to Hong Kong; from Australia, Singapore, Hong Kong, Taiwan and Thailand to India and Korea to Thailand are statistically significant. For the subsample period of 1995 to 2001, it is found that volatility spills over from New Zealand, Singapore, Hong Kong and Taiwan to Australia; from Australia, Korea, Singapore, Taiwan, India and Thailand to New Zealand; from Australia to Korea; from Korea to Hong Kong; from Thailand to Taiwan; from Korea, Taiwan and Thailand to India and from New Zealand, Singapore, Taiwan and India to Thailand. No volatility spillover effect is found in the case of Taiwan.

In the period 2002 to 2010, long-run volatility spillover effects are found to be statistically significant from Singapore, Taiwan and India to Australia; from Hong Kong to New Zealand, from Singapore and Hong Kong to Korea; from New Zealand, Singapore, Taiwan and India to Hong Kong; from Singapore to Taiwan; from New Zealand and Hong Kong to India. Although Volatility spillover effects are found in the case of New Zealand, Korea and India the evidence is weak because coefficients measuring volatility are significant only at 10 % level of significance.

Noticeable similarities and differences were observed between the two time periods. There are strong volatility spillover effects in Australia, New Zealand, India and Thai food market during 1995 to 2001 whereas strong evidences are found for Australia and Hong Kong market for the period 2002 to 2010. The New Zealand food market seems to be more stable during the 2002 to 2010 period. Its volatility originates from itself during this period.

Although there are significant trade relationships from net food exporter countries to net food importer countries covered by this study, no exact directions of mean or volatility spillover effects from exporter to importer or importer to exporter could be drawn. Instead, rather mixed evidence is found and geographical proximity also matters. Australia being a big net exporter of food products has no unique influence over food price return volatility of its importing countries. For the long horizon of time period it has been found that volatility spills over from Australia to New Zealand, Singapore and in India. Over the period of 1995-2001, there are statistically significant volatility spillover effects from Australia to New Zealand while during the period of 2002-2010 there is no evidence of volatility spillovers. That means even though Australia and New Zealand are neighbours with high trade relationship the food price volatility during recent food price hike in New Zealand is due to other reasons not Australian food price volatility. Indian food prices really seem to influence food prices in Australia. Thailand and some other importer countries also affect food price volatility of Australia. Out of the other three major exporters, India plays an important role to influence volatility of other countries' food prices. For the full sample and 1995-2001 periods it affects only exporters' prices while in the period of 2002-2010 it affects food prices of Thailand as well. New Zealand does not show any evidence of influencing food prices of other countries during 1995-2010 while for the period 1995-2010 it affects two other exporters namely Australia and Thailand. However, during the 2002-2010 period volatility spillover has been found from New Zealand to Hong Kong and India. Volatility spillover effects from Thailand is more important for full and first subsample while for the period 2002-2010 no mean or volatility spillover effects could not be recognised by the study.

Based on above discussion, mixed evidence of heat wave and meteor shower effects can be reported in this study for food markets. For the long time series meteor shower dominates heat wave effects while the reverse is true in short time series data. For the period 1995-2001, partial meteor shower effects are found to be statistically significant for Australia, New Zealand, India and Thailand; however, recent data supports some meteor shower effects for the Australian, Hong Kong and Taiwan food markets but other countries either show complete heat wave effects or weak meteor shower effects.

3.2.3 Diagnostic Validity of Models

All models estimated in CGARCH form for assessing mean and volatility spillover effects show no indication of serious misspecification. As presumed, all models show evidence of non-normality because GED parameters

(Tables 11 and 12) of all series for every subsample are less than 2 and statistically significant at 1% level of significance and, therefore, justification of estimating models by using generalised error distribution has been reinforced. As a measure of diagnostic check we compute Ljung-Box Q statistics at both level and squared form and also derived ARCH (LM) test statistics. The results are shown in Tables 11 and 12. Results for mean spillover effects are portrayed in Table 11for full sample, 1995-2001 and 2002-2010 periods respectively. Table 11, shows that there are no or little evidence of further autocorrelation in the series estimated because none or few of the statistics are significant at 5% level of significance. Similarly, the models for volatility spillover effects do not show any statistically significant further evidence of autocorrelation in them. Moreover, models capture volatility persistency and mean reversions which are properties of good volatility models (Robert F. Engle & Patton, 2001).

Table 11. Diagnostic test results for mean spillover models

1995-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
GED	1.242	0.240646	1.187357	1.27952	0.902352	1.096323	1.032405	0.853242
	(0.025657)[a]	(0.002240)[a]	(0.033013)[a]	(0.026434)[a]	(0.022168)[a]	(0.033366)[a]	(0.025549)[a]	(0.021189)[a]
L-BQ(10)	16.999[b]	10.826	12.495[c]	16.418[c]	12.695	13.168	10.494	24.352[a]
L-BQ^2(10)	4.4515	22.488[a]	4.2894	2.5196	2.3665	8.1679	8.8692	3.5431
ARCH-LM(10)	0.4113	0.5470	0.4917	0.8464	0.4804	0.2557	0.0371[b]	0.9585

1995-2001

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
GED	1.327479	0.239997	1.120643	0.960746	0.6545811	1.067734	0.929042	0.656796
	(0.057172)[a]	(0.005465)[a]	(0.048069)[a]	(0.033895)[a]	(0.023459)[a]	(0.047652)[a]	(0.035645)[a]	(0.025159)[a]
L-BQ(10)	23.657[a]	8.1726	12.333	18.256[c]	6.5536	12.610[c]	17.133[c]	17.704[c]
L-BQ^2(10)	8.3050	6.4606	5.2592	1.5547	3.1602	8.4095	7.2449	2.7198
ARCH-LM(10)	0.3390	0.2626	0.6769	0.8165	0.7194	0.1526	0.0357[b]	0.9451

2002-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
GED	1.175847	1.141178	1.253234	1.333386	1.206024	1.159763	1.105883	1.071857
	(0.032278)[a]	(0.029658)[a]	(0.048544)[a]	(0.058072)[a]	(0.040263)[a]	(0.049552)[a]	(0.039772)[a]	(0.038404)[a]
L-BQ(10)	10.338	9.8309[c]	6.1328	16.707[c]	13.447[b]	14.085[c]	7.3587	8.8827
L-BQ^2(10)	2.1873	3.3912	5.5197	8.3852	2.5944	5.8172	3.5789	3.1681
ARCH-LM(10)	0.6946	0.9036	0.0875[c]	0.1318	0.3630	0.6097	0.6886	0.6254

Table 12. Diagnostic test results for volatility spillover models

1995-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
GED	1.250227	0.221638	1.177589	1.108661	0.903723	1.076904	1.034904	0.943824
	(0.029670)[a]	(0.001584)[a]	(0.032781)[a]	(0.026815)[a]	(0.022724)[a]	(0.032611)[a]	(0.026989)[a]	(0.021543)[a]
L-BQ(10)	22.902[b]	10.045	12.638	19.017[b]	13.103	11.011	10.625[c]	22.550[a]
L-BQ^2(10)	3.5585	20.283[a]	4.1018	1.9872	4.2836	7.9565	6.9892	3.1908
ARCH-LM(10)	0.5220	0.5382	0.6611	0.7236	0.5976	0.2702	0.0606[c]	0.8516

1995-2001

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
GED	1.352684	0.131766	1.138988	0.959347	0.773351	1.080798	0.972215	1.271989
	(0.060391)[a]	(0.001466)[a]	(0.053619)[a]	(0.035571)[a]	(0.028159)[a]	(0.049186)[a]	(0.039004)[a]	(0.033293)[a]
L-BQ(10)	12.118[b]	8.1319	13.806	17.934[b]	8.8126	8.9371	13.968	20.683[b]
L-BQ^2(10)	8.3466[c]	5.9479	5.4568	1.3798	4.0693	7.4027	4.7589	7.1917
ARCH-LM(10)	0.5288	0.8079	0.7795	0.9626	0.7107	0.2290	0.2269	0.3910

2002-2010

	AUS	NZ	KOR	SIN	HK	TWN	IN	TH
GED	1.241684	1.080069	1.262160	1.329859	1.279597	1.160903	1.113387	1.077635
	(0.043821)[a]	(0.035542)[a]	(0.050405)[a]	(0.057587)[a]	(0.047463)[a]	(0.050089)[a]	(0.040620)[a]	(0.039082)[a]
L-BQ(10)	11.139	5.5443	2.7190	13.583[c]	9.7994	14.335[c]	9.2152	9.9545
L-BQ^2(10)	3.4204	18.414[c]	4.7724	7.7064	4.3315	5.3133	5.0666	3.4548
ARCH-LM(10)	0.7852	0.7946	0.1138	0.3884	0.2759	0.9376	0.4742	0.5686

4. Conclusions

The objectives of this study were to model food price returns in the context of world and selected Asia and Pacific countries including Australia, New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand in the fashion of financial asset modelling, and examining cross country mean and volatility spillover effects by using Component GARCH models with daily food producer price indices ranging from 1995 to 2010. Volatility characteristics and mean and volatility spillover effects are tested across the full sample (1995-2010) and two subsamples (1995-2001 and 2002-2010). Main findings of the study are as follows. Food price returns can be modelled well with Component GARCH models irrespective of the food export-import status of the country. Food price returns are found to be long-run persistent following a random shock across different time periods for all countries and world aggregates, implying durable effects of shocks to volatility with the exception of New Zealand only. New Zealand data support long-run persistency only for the recent subsample. However, asymmetry differs for countries across different subsamples and the full sample. World aggregate food price returns show asymmetric effects to volatility. Australia, New Zealand and Thailand food prices show asymmetric effects of shocks to volatility for the full and the early subsample, while they show symmetric effects for the recent subsample. Korea and Hong Kong food prices respond asymmetrically for the full sample period and the more recent subsample while they show symmetric effects to the early subsample. For Taiwan and India the data exhibit asymmetric effects across all samples. In the Singapore case, symmetric effects are found for the early subsample while for recent subsample it is asymmetric. It is evident from the analysis that net food importer countries' food prices have symmetric effects of shocks to volatility in the remote past while they have asymmetric effects in the recent past. And the results are completely opposite for food exporter countries. It implies that negative shocks in the recent past which increase food prices in the food importer countries are not fully compensated by positive shocks which reduce prices. However, in food exporter countries recent data support that food price hikes due to negative shocks are fully compensated by food price drops induced by positive shocks. It is significant in the sense that food importer countries are food price takers while exporter countries have some control over the food prices. However, in the Taiwan and Indian cases, there is evidence that rises of food prices because of negative shocks are not cancelled out by price reductions due to positive price shocks. There is no strong evidence of increased returns due to increased risk followed by a shock except in few instances. In regards to the mean and volatility spillover effects, this study reports mixed evidence of cross country spillover effects. Scant evidence of mean spillover effects is found for different countries across different subsamples. Over the full sample period, some cross country mean spillover effects are found for Australia, New Zealand and Singapore. For the first sample period mean spillover effects from other countries are found for New Zealand only. Over the recent subsample, some sort of mean spillover is found for all countries except New Zealand. It implies that food markets are more interdependent than before and shocks create some room for excess returns. The 'meteor shower' hypothesis that the conditional variance of the change in one market depends on the past information of other markets dominates 'heat wave' hypothesis that the conditional variance depends on the past information of that market, while for shorter time period 'heat wave' effects dominate 'meteor shower' effects. Partial meteor shower effects are found to be statistically significant for Australia, New Zealand, India and Thailand over the early subsample; however, recent data supports some meteor shower effects for the Australian, Hong Kong and Taiwan food markets. No exact directions for mean and volatility spillover effects from exporter to importer or importers to exporters can be identified based on the empirical findings of the study. However, it can be concluded that regime shifts and geographical proximity matter for cross country mean and volatility spillover effects. The empirical results of this study will be useful for food policymakers of concerned countries in terms of considering financial characteristics of food prices along with its primary product features, and also should inform policy responses of countries to prepare appropriate measures to respond to cross country spillover effects. The time periods involved, short or long-run, are relevant, as are geographical proximities, in preparing policy options. The findings in this study also provide some empirical insights for food futures and options traders. Although the results of this study are econometrically robust, it leaves room for future research to extend the work within the framework of *multivariate* GARCH models. The study can also be extended in terms of using data for different food commodity prices to identify volatility characteristics at specific commodity level.

References

Abott, P. C., Hurt, C., & Tyner, W. E. (2009). What's driving food prices? Farm foundation issue report.

Apergis, N., & Rezitis, A. (2003a). Agricultural price volatility spillover effects: the case of Greece. *European Review of Agricultural Economics, 30*(3), 389-406. http://dx.doi.org/10.1093/erae/30.3.389

Apergis, N., & Rezitis, A. (2003b). Food price volatility and macroeconomic factor volatility: 'heat waves' or 'meteor showers'? *Applied Economics Letters, 10*(3), 155-160. http://dx.doi.org/10.1080/1350485022000044011

Baillie, R. T., Bollerslev, T., & Redfearn, M. R. (1993). Bear squeezes, volatility spillovers and speculative attacks in the hyperinflation 1920s foreign exchange. *Journal of International Money and Finance, 12*(5), 511-521. http://dx.doi.org/10.1016/0261-5606(93)90037-C

Black, A. J., & Mcmillan, D. G. (2004). Long run trends and volatility spillovers in daily exchange rates. *Applied Financial Economics, 14*(12), 895-907. http://dx.doi.org/10.1080/0960310042000203037

Blair, B. J., Poon, Ser-Huang, & Taylor, S. J. (2001). Modelling S&P 100 volatility:the information content of stock returns. *Journal of banking and finance, 25*, 1665-1679. http://dx.doi.org/10.1016/S0378-4266(00)00157-6

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics, 31*, 327-327. http://dx.doi.org/10.1016/0304-4076(86)90063-1

Box, G. E. P., & Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control.* San Fransisco, CA: Holden-Day.

Buguk, C., Hudson, D., & Hanson, T. (2003). Price volatility spillover in agricultural markets: An examination of U.S. catfish markets. *Journal of Agricultural and Resource Economics, 28*(1), 86-99.

Christoffersen, P., Jacobs, K., Ornthanalai, C., & Wang, Y. (2008). Option valuation with long-run and short-run volatility components. *Journal of Financial Economics, 90*(3), 272-297. http://dx.doi.org/10.1016/j.jfineco.2007.12.003

Dewachter, H. (1996). Modeling interest rate volatility: regime switches and level links. *Weltwirtschaftliches Archiv, 132*(2), 236-258. http://dx.doi.org/10.1007/BF02707806

Ding, Z., Granger, C. W. J., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance, 1*(1), 83-106. http://dx.doi.org/10.1016/0927-5398(93)90006-D

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987-1007. http://dx.doi.org/10.2307/1912773

Engle, R. F. (2001). GARCH 101: the use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives, 15*(4), 157-168. http://dx.doi.org/10.1257/jep.15.4.157

Engle, R. F., Ito, T., & Lin, W.-L. (1990). Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica, 58*(3), 525-542. http://dx.doi.org/10.2307/2938189

Engle, R. F., & Patton, A. J. (2001). What good is a volatility model? NYU Working Paper, S-DRP-01-03.

ESCAP. (2008). Economic and Social Survey of Asia and Pacific: UN publications.

FAO. (2007, November). FAO Outlook.

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

Hammoudeh, S., Li, H., & Jeon, B. (2003). Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating Oil in different locations. *North American Journal of Economics and Finance, 14*(1), 89-114. http://dx.doi.org/10.1016/S1062-9408(02)00112-2

Headey, D., & Fan, S. (2008). Anatomy of a crisis: the causes and consequences of surging food prices. *Agricultural Economics, 39*, 375-391. http://dx.doi.org/10.1111/j.1574-0862.2008.00345.x

Hossain, M. (2007, April-June). Rice facts, a balancing act. *Rice Today.*

Lin, S. X., & Tamvakis, M. N. (2001). Spillover effects in energy futures markets. *Energy Economics, 23*(1), 43-56. http://dx.doi.org/10.1016/S0140-9883(00)00051-7

Liu, Y. A., & Pan, M.-S. (1997). Mean and volatility spillover effects in the U.S. and Pacific-basin stock markets. *Multinational Finance Journal, 1*(1), 47-62.

Maneschiold, P.-O. (2004). Modelling exchange rate volatility: evidence from Sweden. *Economia Internazionale/International Economics, 57*(2), 145-172.

Mitchell, D. (2008). A note on rising food prices.

Narayan, P. K., & Narayan, S. (2007). Modelling oil price volatility. *Energy Policy, 35*(12), 6549-6553. http://dx.doi.org/10.1016/j.enpol.2007.07.020

Newbery, D. M. (1989). The theory of food price stabilisation. *Economic Journal, 99*(398), 1065-1082. http://dx.doi.org/10.2307/2234088

OECD. (2008). Rising food prices: causes and consequenses.

Park, I. (2009). Regional trade agreements in East Asia: will they be sustainable? *Asian Economic Journal, 23*(2), 169-194. http://dx.doi.org/10.1111/j.1467-8381.2009.02008.x

Pindyck, R. S. (2004). Volatility in natural gas and oil markets. *Journal of Energy and Development, 30*(1), 1-19.

Radetzki, M. (2006). The anatomy of three commodity booms. *Resources Policy, 31*(1), 56-64. http://dx.doi.org/10.1016/j.resourpol.2006.06.003

Regnier, E. (2007). Oil and energy price volatility. *Energy Economics, 29*(3), 405-427. http://dx.doi.org/10.1016/j.eneco.2005.11.003

Robles, M., Torero, M., & von Braun. (2009). When speculation matters. *International Food Policy Institute Issue Brief, 57*.

Rosegrant, M. W., Zhu, T., Msangi, S., & Sulser, T. (2008). Global Scenarios for Biofuels: Impacts and Implications. *Review of Agricultural Economics, 30*(3), 495-505. http://dx.doi.org/10.1111/j.1467-9353.2008.00424.x

Valadkhani, A., & Mitchell, W. F. (2002). Assessing the impact of changes in petroleum prices on inflation and household expenditures in Australia. *Australian Economic Review, 35*(2), 122-132. http://dx.doi.org/10.1111/1467-8462.00230

Von Braun, J. (2008). Rising food prices: what should be done? *Euro Choices, 7*(2), 30-35. http://dx.doi.org/10.1111/j.1746-692X.2008.00099.x

Wei, C. (2009). Using the component GARCH modelling and forecsting method to determine the effect of unexpected exchange rate mean and volatility spillover on stock markets. *International Research Journal of Finance and Economics,* (23), 62-74.

Zheng, Y., Kinnucan, H. W., & Thompson, H. (2008). News and volatility of food prices. *Applied Economics, 40*(13-15), 1629-1635. http://dx.doi.org/10.1080/00036840600892910