PRICE TRANSMISSIONS BETWEEN FOOD AND OIL

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ABSTRACT

PRICE TRANSMISSIONS BETWEEN FOOD AND OIL

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The upward movement in oil and food prices in the 2000s has triggered interest in the information transmission mechanism between the two markets. This research investigates the volatility spillover between oil, food, and agricultural raw material price indexes for the period January 1980 to April 2008. The results of the Cheung-Ng procedure show that variation in oil prices does not Granger cause the variance in food and agricultural raw material prices. However, there is bi-directional spillover between agricultural raw material and oil markets. Besides, it examines volatility spillover between maize, wheat, soybean, rice, and oil spot prices for the period January-1998 to February-2009. The results show that volatility spillover in oil returns leads fluctuations in maize, soybean, wheat, and rice returns in 3 months. In addition, there are bi-directional spillovers between oil and soybean returns, rice and wheat returns.

This topic is essential for countries whose populations grow rapidly because forecasting of commodity prices plays an important role in instituting the economic policy. Also, understanding the dynamics of the economy leads to better economic policies. Thus, results are important for investors and policy makers interested in price shocks and transmission.

Keywords: Oil prices, Food prices, Volatility Spillover

ÖZ

GIDA VE PETROL FİYATLARİ ARASINDAKİ ETKİLESİM

Kaltalıoğlu, Müge

Yüksek Lisans, İşletme Bölümü

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2000'li yıllarda gözlemlenen gıda ve petrol fiyatlarındaki artış, iki piyasa arasındaki bilgi aktarım mekanizmasına olan ilgiyi artırdı. Bu çalışma Ocak 1980 tarihinden Nisan 2008 tarihine kadar, petrol, gıda ve tarımsal ham made fiyat endeksleri arasındaki oynaklık yayılma etkisini incelemektedir. Cheung-Ng prosedürü petrol fiyatlarındaki varyasyonun, gıda ve tarımsal ham madde fiyatlarına Granger olarak neden olamayacağını göstermektedir. Fakat tarımsal hammadde ve petrol piyasaları arasında çift yönlü yayılma etkisi bulunmuştur. Ayrıca, Ocak 1998 ve Şubat 2009 tarihleri arasında mısır, buğday, soya fasulyesi, pirinç ve petrol piyasaları arasındaki oynaklık yayılma etkisini incelenmektedir. Petrol piyasalarındaki volatilite yayılımı, 3 ay içerisinde mısır, buğday, soya fasulyesi ve pirinç piyasalarında da dalgalanmalara neden olmaktadır. Bununla birlikte petrol ve soya fasulyesi piyasaları arasında ve pirinç ve buğday piyasaları arasında çift yönlü volatilite yayılımı bulunmuştur.

Bu konu, nüfusu hızla büyüyen ülkeler için çok önemlidir. Çünkü ticari malların fiyatının, gelecek yıllara ait tahmini ekonomi politikasında önemli bir rol oynar. Ayrıca, daha iyi ekonomi politikaları kurmak için ekonominin dinamiklerini anlamak gerekir. Bu nedenle bulgular fiyat şokları ve transmisyonları ile ilgilenen yatırımcılar ve politika oluşturanlar için önemlidir.

Anahtar Kelimeler: Gıda Fiyatları, Petrol Fiyatları, Oynaklık Yayılma Etkisi

To My Parents and To My Sister

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CHAPTER 1

INTRODUCTION

The upward trends in world food prices and oil prices in 2000s have triggered an increased interest on the information transmission dynamics between the two markets. As the food prices are dragged up cost of food commodities per household is increasing and consumers have concerns about their wealth (Wright & Bobenrieth, 2009). OECD and Food and Agriculture Organization of the United Nations (2009) mentioned that between 2007 and 2008, many commodity prices were increased tremendously. FAO (2010) emphasized increasing international wheat prices as well as increasing domestic wheat prices in Kyrgyzstan, Tajikistan, Mongolia, and Afghanistan. It is estimated in the proceedings of OECD Agriculture Ministerial Meeting (2010) that prices will be at least as high as 2007-2008 in the next ten years and average crop prices are expected to increase between 10% and 20%. Moreover, food and agricultural materials go behind energy prices (Agricultural trade policy analysis, 2008). A large price increase in all agricultural commodities is observed. Between February 2007 and February 2008, wheat prices increased by 113% and by 93% in the US and the EU, respectively. Soybean prices increased by 83%, whereas the increase in price of Thai rice was 52%, in the U.S. maize price increase was 24% over the February 2007-February 2008 period. So, there is an evident increase in the prices over time. Other commodities like metals have experienced the largest increase followed by energy prices. USDA stated in the report that wheat supplies in India has decreased and thus dragged up the wheat prices (Vocke, Allen, & Liefert, 2009). Also the wheat prices in China which is more than the global average is highlighted (Vocke, Allen, & Liefert, 2009). As commodity markets are increasingly viewed as alternative investment areas, existence and direction of spillovers must be carefully evaluated by investors. The existence and nature of the link between alternative investments will determine the extent to which investors will be involved in each market for risk management purposes.

Figure 1.1Food spot market (FPI), Oil spot market (OPI) and Agricultural raw material spot market (ARMI)

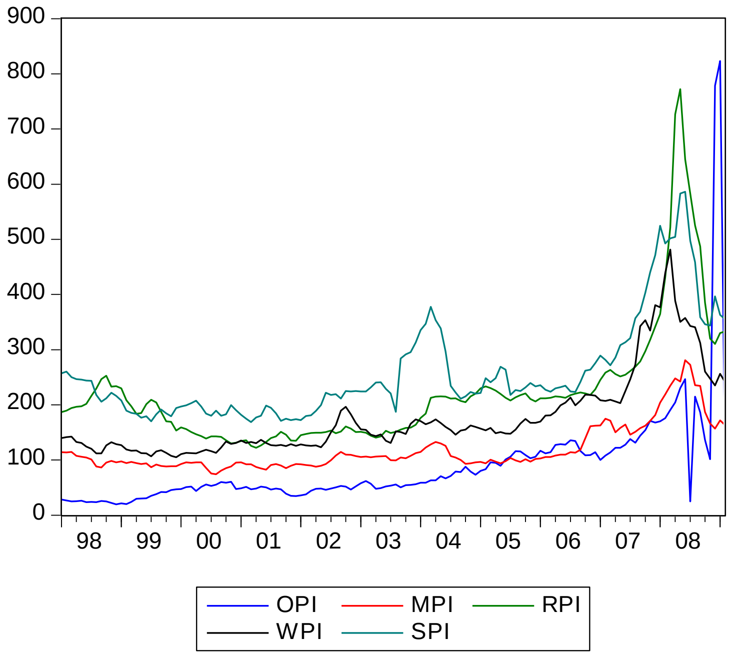

Figure 1.2 Oil spot market (OPI), Maize spot market (MPI), Rice spot market (RPI), Wheat spot market (WPI) and Soybean spot market (SPI)

One conjecture about the recent rise in food prices is that rising energy prices drive the food prices up (Timmer, 2008), since energy is an important input in agricultural activities. The link between food and energy markets, however, may be rather complex (Abbott et al. 2008). There might be feedback mechanisms that result in food prices leading the energy prices. One such mechanism may exist due to the use of some food items in energy generation. Increased demand for energy may have been driving the oil prices as well as food prices.

The USDA's Chief Economist asserts that much of the increase in farm prices of maize and soybeans is due to the biofuels production (Glauber, 2008). Allen (2010) mentioned in her article in The Guardian that food prices will increase due to biofuel production and rising demand of emerging markets. Wald (2006) points out in his article in The New York Times that as the fuel prices increase, ethanol prices will soar. As a result, prices of corn, which is a feedstock for ethanol production, are rising. With the increase in the oil prices, corn prices rise overtly and ethanol becomes more valuable with this increase (Martin, 2008). There is a large literature on food and energy demands, productions and prices. Also, Chakravorty, Hubert, & Nostbakken (2009) draw attention to the fact that the increase in biofuel production may have an influence on food prices. The biofuels dragging up the crop prices is critized by various studies (Abott et al 2008, Borger 2008, Mitchell 2008, Tyner and Taheripour, 2008 and Tokgoz et al. 2007).

In Agricultural Trade Policy Analysis (2008) it is stated that from 2005 to 2007 biodiesel production increased by 5.5 million tones. So the commodities are used to produce biodiesel rather than food uses. Between 2004 and 2007 a dramatic price increase is observed in food prices for commodities such as corn, wheat and vegetable oil when ethanol and biodiesel is started to produce for energy use in transportation in the world (The Economist 2007). Additionally, Collins (2008) put forth that 60 % of the increase in maize prices from 2006 to 2008 may be caused from the increase in maize used in ethanol.

> Recently, Braun (2007) stated that "the IMPACT model has incorporated 2005/06 developments in supply and demand, and has generated two future scenarios based on these developments. Under the planned biofuel expansion scenario, international prices increase by 26 percent for maize and by 18 percent for oilseeds. Under the more drastic biofuel expansion scenario, maize prices rise by 72 percent and oilseeds by 44 percent".

One can conjecture that the increased demand for bio- energy results in an increase in food prices and there might be a switch to alternatives like the good old oil. If this conjecture holds, then one expects to see world food prices leading the oil prices. However, the increase in food prices is not limited to food items that are also used in bio-fuel production. Braun

(2007) also mentions that biofuel production has not the sole responsibility of increasing food prices. There are other major issue like drought, diversion of food for fuel and higher income growth.

Wright & Bobenrieth (2009) argue that instability of food commodity prices in 2007 and 2008 has created concerns about the volatile prices and also about the governmental policies on price stabilization.

An article in New York Times mentioned that Joachim von Braun, the director of the International Food Policy Research Institute said that volatility of food prices will be influenced by the volatility of energy prices (Wald, 2006).

> It is also highlighted that The FAO Secretariat noted that "some studies suggest that speculation in food markets played a certain role in the increasing level and volatility of world food prices in 2007-2008 and calls upon the World Bank, the IMF, UNCTAD, FAO and other relevant intergovernmental organizations" in order to work collectively in the analysis of the price movements (Wald, 2006).

On the other hand, Wright and Bobenrieth (2009) noted that the soaring prices are usual considering the historical data since it is faced with the increasing prices during depleting stocks. It is also explained that emerging biofuel demand and low levels of harvests are responsible from the increasing prices. In addition restrictions on the exports make it impossible to stabilize the global agriculture market.

An earlier study by Hochman et al. (2008) took a different approach which states the possible impact of food prices on ethanol prices. The reason given is the fact once food prices increase, biofuel production will become less profitable. On the contrary, Hochman et al. (2008) mention that in case of a contemporaneous decrease in food prices and increase in energy prices, biofuel production will be more lucrative.

Volatility in agricultural commodity prices in 2007-2008 caused a dilemma which is producing for human consumption or producing for other uses (Monbiot, 2004).

> "FAO identified a number of possible causes contributing to the price rise: low levels of world cereal stocks; crop failures in major exporting countries; rapidly growing demand for agricultural commodities for biofuels; and rising oil prices." And also it is stated that "government export restrictions, a weakening US Dollar and a growing appetite by speculators and index funds for wider commodity portfolio investment on the back of enormous global excess liquidity. What made the 2007/08 price spike exceptional was the concurrence of so many factors culminating in an unprecedented price rally and the fuelling of volatility." (Food and Agriculture Organization of the United Nations, 2009).

In addition there are other contributors to the increasing prices such as "macro-economic factors, exchange rates, volatile oil prices" (Food and Agriculture Organization of the United Nations, 2009).

Food consumption item prices are also showing an upward trend. However, to the extent of our knowledge, there are no studies that examine the dynamic link between world oil and food consumption item prices. This thesis is probably the first to examine the volatility spillover between world oil, food, and agricultural raw material prices and volatility spillover between oil, maize, rice, wheat, and soybean markets. Besides, it searches which volatility transmission in one market influences volatility spillover in the other. We find that the burden of price hikes in food and agricultural raw materials cannot be attributed to oil price increases. The lack of cointegration is also confirmed via generalized impulse response analysis. Furthermore, there is no volatility spillover from oil to food price index. On the other hand, a change in petroleum prices has an influence on the other spot market prices. That is, there is volatility spillover from oil prices to wheat, rice, soybean and maize returns in 3 months. Another important finding is the significant impact from wheat prices to other price indexes. Furthermore, there is a contemporaneous link between oil and soybeans returns, rice and wheat returns. The results of this study have important implications for both policy makers and global investors who need to follow the price shocks and transmission mechanisms between alternative investment areas closely. Investors and hedgers interested in hedging or risk management utilize futures markets and options markets in order to transfer their risks. So, proper functioning of those markets attracts the attention. Therefore, research results will be beneficial in forecasting prices, establishing strategies.

The remaining of the thesis evolves as follows. Next section discusses the relevant literature. Third section introduces methodology and fourth section presents data characteristics. Fifth and sixth sections discuss relevant tests and empirical findings and the last section concludes.

This thesis examines weather oil price changes affects the food prices or vice versa. This thesis is probably the first to examine the temporal relationship between oil, food, and agricultural raw material price indexes and volatility spillover between certain commodities and oil prices._This study also examines long-term and short-term dynamics between oil prices, food prices, and agricultural raw material prices. It also analyses volatility spillover effects across oil, maize, rice wheat, soybean markets. Besides, it searches which volatility transmission in one market influences volatility spillover in the other. We find that the burden of price hikes in food and agricultural raw materials cannot be attributed to oil price increases. The lack of cointegration is also confirmed via generalized impulse response analysis. Furthermore, there is no volatility spillover from oil to food price index. On the other hand, a change in petroleum prices has an influence on the other spot market prices. That is, there is volatility spillover from oil prices to wheat, rice, soybean and maize returns in 3 months. Another important finding is the significant impact from wheat prices to other price indexes. Furthermore, there is a contemporaneous link between oil and soybeans returns, rice and wheat returns. The results of this study have important implications for both policy makers and global investors who need to follow the price shocks and transmission mechanisms closely.

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CHAPTER 2

LITERATURE

There is a large literature on information transmission between various commodity markets. For the sake of brevity, we concentrate on the studies related to the food prices and oil prices. Coyle et al. (1998) examines the structural changes in the food market and argues that the changes in the food market can also be associated to the process where food is an input to the system. Biodiesel production is one of them. They emphasize the relation between the increased demands and food prices. Since commodities can be used in the production of biodiesel, demand in those commodities are increased as a results of increased energy use. This is reflected in increased prices of those commodities over time. They find that increased demand for maize used in ethanol production and the increased demand for rapeseed used in biodiesel production are responsible for rising prices (Soaring Food Prices: Facts, Perspectives, Impacts and Actions Required 2008). Furthermore, Zhang et.al. states that "the Council of Economic Advisors estimate that retail food prices increased only around 3 % in 2007 due to ethanol production" (Zhang, Lohr, Escalante, & Wetzstein, 2010). They also highlight that "Competitive markets will efficiently respond to price signals". Crop yields and changes in the land allocations have an influence on temporary price volatilities. However with the increasing ethanol production those prices hikes and changes in land allocations are inevitable. Sugar which is an important input in ethanol production has an influence on increasing agricultural commodity prices (Zhang, Lohr, Escalante, & Wetzstein, 2010). In fact, biofuel production affects sugar prices which in turn affect agricultural commodity prices (Zhang, Lohr, Escalante, & Wetzstein, 2010). They also found out that sugar prices have significant effect on corn prices. Moreover, soybean, wheat, sugar, and rice are not affected from the volatility in corn prices. In contrast aforementioned staples have an effect on corn prices. Mitchell (2008) also emphasized that production of US and EU biofuel has a significant impact on food prices. Also the USDA's chief Economist asserts that much of the increase in farm prices of maize and soybeans is due to the bio-fuel production (Glauber, 2008). Muhammad and Kebede (2009) highlight that emerging ethanol market created a link between oil prices and corn prices. They stated that “agricultural sector is now importing instability form the oil sector.”

Many studies shows that changes in fuel prices have an influence on food prices (Arndt et al., 2008; Rosegrant et al., 2008; Tyner and Taheripour, 2008; Yang et al., 2008). Tyner and Taheriour (2008) emphasized that rise in oil prices have an influence on the increasing corn prices. Rosegrant et al. (2008) states that allocation of land for food crops resulted in a volatility spillover between food and oil prices. In this study it is estimated that increased demand in biofuel causes 39% of the increase in corn prices and 30% of increase in grain prices. Gilbert (2010) indicates that all agricultural markets are affected by the change in oil prices. He also mentioned two different ways of influence of oil prices on food prices. Oil prices have an influence on food prices either by increasing cost of food production or by using food an input for biofuel production. Gilbert (2010) also emphasized cost of food production has increased because of the transportation cost and the fertilizer cost. Minot (2010) emphasized that increase in oil prices resulted in increase in the cost of fertilizers as well as cost of sea freight and the cost of overland transportation which caused an increase in the retail costs. It is mentioned that half of the transportation cost is made up of the cost of fuel which is the half of the cost of the imported food.

Baffes (2007) found the effect of oil price on agricultural commodity prices as 17%. According to Mitchell (2008) production cost of agricultural commodities are affected by both energy costs and transport costs and the effect is between 15-20%. Braun et al. (2008) indicates that increased transportation costs are attributed to the increased energy prices which also have an influence on the increased fertilizer prices, pesticide prices. Thus, agricultural production costs have increased. With the increasing energy prices, the transportation cost also increases owing to the fuel usage. Since the food commodities are transferred from manufacturing areas to consuming areas, transportation cost directly affects the price of the commodities. Thus, the commodity prices increase with the increasing energy prices. As a result, increasing energy prices not only affects the fuel and oil prices but also influences the food prices. Since the energy and food have a strong influence on humans’ wealth, with the raising prices and decreasing purchasing power of citizens’, there becomes a motive to find alternatives for fuel which is biofuel and ethanol. So, the tendency in energy prices is a motive to produce biofuels. This creates a tendency for the production of biofuels which simultaneously creates a new demand for food commodities.

IFPRI (2008) mentioned the possible effect of commodity speculation on the increasing agricultural prices. Cooke and Robles (2009) highlight impact of the futures market developments on food price spikes between 2006 and 2008.

Presence of a link between agricultural prices and energy prices is mentioned in the proceedings of OECD Agriculture Ministerial Meeting (2010) and it is stated that the biofuel industry strengthens the link between agricultural market and the crude oil market. In addition it is emphasized that biofuel production is increasing which affects the wheat, maize, oilseed, and sugar prices. Saghaian (2010) investigated the link between corn, soybean, wheat, ethanol and crude oil prices. In this study, correlations are found between soybean and wheat (83%), corn and soybean (88%), and corn and wheat (90%). Results also showed wheat market is influenced by the corn and soybean markets. Moreover, it is stated that "innovations in corn and soybeans price series affect residuals in each other, but they are not connected by directed paths." Bidirectional relation is also found between ethanol prices and corn prices, corn and wheat prices. Saghaian (2010) also emphasized that soybean and wheat prices Granger cause ethanol prices while the vice versa does not hold. In addition corn and wheat prices have an influence on soybean prices and "crude oil prices Granger cause corn, soybeans, and wheat prices" Baffes (2007) examines the price transmission between crude oil prices and 35 other commodity prices between 1960 and 2005. According to his results, 10% increase in the price of crude oil results in 1.6% increase in non-energy commodity price indexes. He also states that there is information transmission from crude oil to agricultural commodities. He mentions that as long as the crude oil prices continue to remain high for a certain amount of time the price booms will be higher than the booms experienced before, especially for food commodities, fertilizers and precious metals.

There are a group of studies that focus on transmission between various food-related markets. Rezitis (2003) underlines that both farm and retail prices in Greece have significant effects on each other. Volatility spillover effects are also present between producer and consumer prices. Retail and farm prices arrange themselves according to one another. In another study that deals solely with food prices, Christian and Rashad (2008) examine the increased food prices between 1950 and 2005 and report a decrease in farm value of retail prices. Vavra and Goodwin (2005) examine the relation between retail prices and consumer prices of food and discover presence of asymmetric affects of price changes in U.S. They find that with decreasing retail prices, consumer prices tumble as well. Furthermore, the links between retail and farm prices is not contemporaneous but with a time lag. The reaction of the other market is influenced by the size and the speed of the transmission. In an earlier study, Minten and Kyle (2000) emphasize that the increase in the wholesale prices is significantly transmitted to the retail prices within the same week of the price change in wholesale level. Aksoy and Isik-Dikmelik (2008) document that a change in the commodity prices is more significant in countries in which people consume more staples rather than various kinds of foods to extend that consumption of staple food crops affects the household income. Because both the producers (net food sellers) and consumers (net food buyers) in rural areas are affected from the changing prices of crops that are produced or consumed in that area considering the variety of food in urban areas. So, the main staples used in rural are mostly the ones that are produced there. Generally, those aforementioned crops consist of wheat, rice, and maize, proportion of which is of great importance in overall food consumption. Consequently, it is inferential that the increase in the staple food crop prices has a significant influence on the household welfare. So, price change in that commodity will have a greater effect. Since volatility in prices has an influence in the market uncertainty and market risk, it has an effect on both consumers and producers. Thus, accurate forecasting becomes more difficult that accordingly affects the welfare of consumers and producers (Apergis & Rezitis, 2003).

Apergis and Rezitis (2003) used GARCH model to examine the link between agricultural input prices, agricultural output prices, and retail food prices. Z.Zhnag et al. (2010) used vector error correction model, Granger causality test, and variance decomposition in order to investigate the long-run and shot-run relationship between fuels which are ethanol, gasoline, and oil and agricultural commodities which are corn, rice, soybean, sugar, and wheat. Rezitis (2003) used GARCH model to examine the relation between lamb, beef, pork and poultry producer and consumer prices. Saghaian (2010) utilized cointegration test, vector error correction model, and Granger causality test to examine the link between corn prices, soybean prices, wheat prices, crude oil prices and ethanol prices. Kargbo (2000) utilized cointegration test, vector error correction model to examine the relation between food prices, indices of domestic food production, income, money supply, real exchange rates and African governments’ trade policies. Minot (2010) used vector error correction model to examine the link between maize, rice, and wheat prices of the world and nine sub-Saharan African countries.

Since there are limited number of studies that addresses the relationship between world consumption food items, agricultural raw materials, and oil prices, we next consider studies on volatility spillover in various markets. In the literature, the return and volatility spillover effects are examined by a variety of methods. Worthington et al. (2005) apply MGARCH method to analyze transmission prices and price volatility in Australian electricity spot markets. Fan et al. (2008) look for the spillover effect between two markets, WTI (West Texas Intermediate crude oil) and Brent crude oil spot markets. GED-GARCH method is used to estimate the conditional heteroscedasticity. The results point out two-way Granger causality. Hence, both markets have an effect on each other.

Spillover effects in energy futures markets have been the subject of many studies as well. Lin and Tamvakis (2001), for example, examine the information transmission between two oil markets (NYMEX and IPE). They find that closing prices in NYMEX lead prices in IPE the next morning. However, there is bidirectional spillover when both exchanges are trading simultaneously. Baffes (2007) examines the price transmission between crude oil prices and 35 other commodity prices between 1960 and 2005. He states that there is information transmission from crude oil to agricultural commodities. He mentions that as long as the crude oil prices continue to remain high for a certain amount of time the price booms will be higher than the booms experienced before, especially for food commodities, fertilizers and precious metals. Ewing and Thompson (2007) argue that a possible explanation for the increase in consumer prices is the increase in crude oil prices. But they also point out that with the increase in the industrial production; there is an avowed rise in oil prices.

As Askari and Krichene (2008) state even if the oil prices rise tremendously, change in the demand for commodities or for oil will be relatively small if the elasticity is low. That is, increasing oil price will not have a significant influence on demand for food commodities.

Moreover, Rezitis (2008) highlights that it is difficult to forecast prices in case of increased price volatility which could be detrimental for marker participants' prosperity. Countries with high population growth rates and that rely heavily on food imports and international organizations that supply aid to poor countries to prevent starvation must be able to forecast food prices correctly to adjust their budgets and long run plans accordingly. Hence, they are interested in whether there is a strong link between oil and food prices, and if there is what the nature of this link is. As a result of price volatility not only consumers but also producers and investors lose large sums of money. And it can be stated that price volatility can be welfare decreasing. As commodity markets are increasingly viewed as alternative investment areas, understanding the information transmission between the alternative markets has become important for investors as well. The existence and nature of the relationship between alternative markets will determine the extent investors will be involved in each market for portfolio creation and hedging purposes. Although from an investor's point of view the two global markets may be directly related, from a production point of view prices of the agricultural raw materials may be playing an intermediary role in transmitting shocks in one market to the other one. In addition governments can benefit from the results for government food market interventions. Narrowing the difference between consumer and producer prices and stabilizing them are some of the goals of many governments' food policies (Timmer 1989; Islam and Thomas, 1996). Since the aim of the food policy is reducing poverty and hunger and the variables affecting the food prices are important in decision-making, this thesis would be useful to assess whether energy prices have an influence on food prices.

As world food markets are open to investors and speculators, just like the oil markets, the prices in both commodity markets may be governed by similar dynamics. Food, oil and energy prices have been studied extensively in the literature. There are many studies modeling spillovers between different food commodities, and also various papers concerning different crude oil prices. However, to the extent of our knowledge there aren't any studies that explicitly examine the temporal link between world food, agricultural raw material, and oil prices and between rice, maize, wheat, soybean and oil prices. Next section introduces methodology.

CHAPTER 3

METHODOLOGY

3.1 Cointegration Test

Johansen's cointegration test (1991) is used to determine the absence or presence of cointegrating relationship among variables. Although there are many other tests like Engle and Granger (1987), Engle and Yoo (1987) 3-step method, Johansen's cointegration test (1991) has superiority of considering all variables as endogenous and its capability of testing more than one cointegrating relationship.

x_t and y_t are said to be cointegrated if there exists a parameter α such that

$$u_t = y_t - \alpha x_t \tag{1}$$

Linear combination of I (1) variables will be I (0) provided that the variables are cointegrated. Assuming x_t and y_t are integrated processes, if there is a linear combination which is integrated of a lower order, both variables are cointegrated. To be clearer, if the variables of a dynamic linear model are cointegrated, disturbances will be stationary. It is worth noting that, only linear combinations or linear transformation of a number cointegrating vectors will be stationary.

Johansen cointegration test starts with constructing a vector autoregressive (VAR) model with *k* lags under the consideration that variables are I (1):

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_k y_{t-k} + u_t \tag{2}$$

Then we should turn it into a vector error correction model (VECM):

$$\Delta y_t = \pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t \tag{3}$$

Where $\pi = \left(\sum_{.=1}^{k} \beta_i\right) - I_g$, (4)

$$\Gamma_i = \left(\sum_{j=1}^{i} \beta_j\right) - I_g \tag{5}$$

And g is the number of variables in VAR model, Γ is the coefficient matrix and π is the long-run coefficient matrix. It is worth mentioning that the rank of a matrix (π) is equal to the number of its characteristic roots (eigenvalue) that are different from zero. And cointegration can be tested by examining the rank of a π matrix via its eigenvalues. That is if π=0, all variables are non-stationary and there are no cointegrating vectors and for π=1, there is one cointegrating vector. If π>1, there is more than 1 cointegrating vectors.

Another important aspect is that Johansen model is sensitive to the lag length selection. Akaike, Schwarz and Hannan-Quinn information criterions are used to determine the optimum lag length of 2. There are two test statistics for cointegration:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln{(1 - \hat{\lambda}_i)} \tag{6}$$

$$\lambda_{max}(r, r+1) = -T ln(1 - \hat{\lambda}_{r+1}) \tag{7}$$

Where r is the number of cointegrating vectors, g is the number of variables under consideration, $\hat{\lambda}_i$ is the estimated eigen value ($\hat{\lambda}_i$,i=1,…,g)

λ_{trace} has a null hypothesis of number of cointegrating vectors being less than or equal to r while alternative hypothesis is that there are more than r cointegrating vectors. Additionally, λ_{max} has a null of r cointegrating vectors against r+1 cointegrating vectors. For both tests if the test statistics is more than the critical value, we reject the null hypothesis. Testing is conducted as a sequence and under the null, r=0, 1,..g-1. When r=0, failing to reject H_0 will complete the test. But if this is not the case meaning when H_0: r = 0 is not rejected, the test continues until the null is no longer rejected.

All in all according to the Johansen's cointegration test (1991), only linear combinations or linear transformation of a number cointegrating vectors will be stationary. Generally cointegration is expected in spot and futures market, ratio of relative prices and an exchange rate, equity prices and dividends. Absence of a cointegrating relationship spots nonexistence of long-run relationship.

3.2 Vector Autoregressive Model

For forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables, vector autoregressive (VAR) model is used. It is a combination of simultaneous equation models and univariate time series models. There is more than one dependent variable in VAR models. Also, all endogenous variables are treated as a function of lagged values of all the endogenous variables in the system. That is to say, current values depend on previous values of all variables and error terms.

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \cdots . + \beta_{1k}y_{1t-k} + \alpha_{11}y_{2t-1} + \cdots + \alpha_{1k}y_{2t-k} + u_{1t} \tag{8}$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \cdots + \beta_{2k}y_{2t-k} + \alpha_{21}y_{1t-1} + \cdots + \alpha_{2k}y_{1t-k} + u_{2t} \tag{9}$$

u_{it}; White noise

$E(u_{it}) = 0, (i = 1,2)$

$E(u_{1t}u_{2t}) = 0$

In the standard form, VAR (1) model is written as follows:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \alpha_{11}y_{2t-1} + \gamma_{11}y_{3t-1} + u_{1t} \tag{10}$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \alpha_{21}y_{3t-1} + \gamma_{21}y_{1t-1} + u_{2t} \tag{11}$$

$$y_{3t} = \beta_{30} + \beta_{31}y_{3t-1} + \alpha_{31}y_{1t-1} + \gamma_{31}y_{2t-1} + u_{3t} \tag{12}$$

Or

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} & \gamma_{11} \\ \gamma_{21} & \beta_{21} & \alpha_{21} \\ \alpha_{31} & \gamma_{31} & \beta_{31} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix} \tag{13}$$

All the variables in a VAR model are treated as endogenous and there is no need to impose restrictions. Since there is no feedback from left-hand side variables to right hand side variables, Ordinary least Square (OLS) method can be used for each equation if there is no contemporaneous terms on the right hand side of the equations. To use VAR model, all of the components should be stationary.

To define the appropriate lag length in VAR model, an information criterion is used. It contains two factors which are residual sum of squares (RSS) and a penalty term for loss of degrees of freedom for adding extra parameters. To put it another way, an extra term will decrease RSS while increasing penalty term. Choosing the number of parameters minimizing information criterion is the purpose. Akaike's (1974) information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and Hannan-Quinn criterion (HQIC) are ones used for VAR models.

These are expressed as;

$$AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \tag{14}$$

$$SBIC = \ln(\hat{\sigma}^2) + \frac{k}{T} lnT \tag{15}$$

$$HQIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \ln{(lnT)}) \tag{16}$$

Where$\hat{\sigma}^2$; residual variance

K=p+q+1; total number of parameters estimated

T; sample size

The most stiff information criterion is the SBIC which followed by HQIC and AIC respectively.

However VAR models requires multivariate version of the information criterions mentioned above since number of lags should be same for each equation in a VAR model. So, multivariate versions are expressed as;

$$MAIC = \log\ |\hat{\sum}| + 2k'/T \tag{17}$$

$$MAIC = \log\left|\hat{\Sigma}\right| + \left(\frac{k'}{T}\right)\log\,(T) \tag{18}$$

$$MAIC = \log\left|\hat{\Sigma}\right| + \left(\frac{k'}{T}\right)\log\,(\log\,(T)) \tag{19}$$

$\hat{\sum}$; Variance-covariance matrix of residuals

T; number of observations

k'; Total number of regressors in all equations.

$k' = p^2k + p$

P; p equations in the VAR system with k lags of the p variables

3.3 Generalized Impulse Response

Generalized impulse responses are used to assess how a shock to a variable influences another endogenous variable and how long the effects will last. Koop et al. (1996) and Pesaran and Shin (1998) developed the generalized impulse response analysis which are not sensitive to the ordering of variables; hence, not subject to the Lutkepohl's orthogonality critique.

A shock to a variable both has a significant influence on itself and affects other endogenous variable in the model. When a unit shock is applied to a variable, the response of the dependent variable in the VAR can be examined by means of generalized impulse response analysis. That is, impulse response takes into account one shock to one of the disturbances on current and expected values of endogenous variables. For instance, considering equations 17-19 defined in the preceding section, it is obvious that a change in u_{1t} will immediately change the value of y_{1t}. But it will also change the future values of y_{1t}, y_{2t}, and y_{3t} as lagged y_{1t} appears in all three equations. For stationary VARs, impulse responses should die out in time to extend that unit shock is applied to each variable from each equation and responses are evaluated. If the system is stable, the shock will die out.

3.4 CN Procedure

The CN procedure takes the squared standardized residuals $\varepsilon_{it}^2 = (z_{it} - \hat{\mu}_{it})^2/\hat{h}_{it}^2$ from the univariate models and examines the cross-correlations, where z_{it} are the stationary variables and $\hat{h}_{it}$ are the time varying variances. Then the sample residual cross-correlation functions between the two standardized residuals $(\hat{\rho}_{u_1u_2}(k))$ are derived. The sample residual cross-correlation functions between the squares of the two standardized residuals $\hat{\rho}_{v_1v_2}(k)$ are derived and the test statistic $\sqrt{T}\hat{\rho}_{v_1v_2}(k)$ is computed where T is the sample size v_i are the squared standardized error terms estimated via$\hat{\varepsilon}_{it}^2$. The test statistic asymptotically follows the normal distribution. The CN procedure enables us to see the time lag through which the volatility spillover occurs.

3.5 ARCH / GARCH

In general, models can be linear in mean and linear in variance, linear in mean but non-linear in variance, non-linear in mean but linear in variance. Model can also be nonlinear in both mean and variance. ARCH and GARCH models are non-linear models which are useful for modeling and forecasting financial data.

Campbell,Lo and MacKinlay(1997) defined non-linear models as follows:

$$y_t = f(u_t, u_{t-1}, u_{t-2}, \ldots) \tag{20}$$

$$y_t = g(u_t, u_{t-1}, u_{t-2}, \ldots) + u_t\sigma^2(u_{t-1}, u_{t-2}, \ldots) \tag{21}$$

u_t ;iid term

f; non-linear function

g; function of past error terms

σ^2 ; variance term

Campbell, Lo and MacKinlay(1997) used g function for non-linear in mean models and σ^2 function for non-linear in variance models.

To detect nonlinear pattern in the data and to find the appropriate model for the data, there are tests that can be conducted. Those tests are portmanteau and specific tests. Portmanteau tests can detect the non-linearity in the data however they lack identifying the type of the non-linearity. On the other hand, specific tests can identify specific types of non-linear structure. But they are not capable of finding other types of non-linearity.

3.5.1.1 The ARCH (Autoregressive Conditional Heteroscedastic) Model

The ARCH model is used to model and forecast conditional variances. In the model specifications, the variance of the dependant variable depends upon the past values of endogenous variables and exogenous variables. The model is proposed by Engle (1982)

Consider a structural model like

$$y = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + u \ \left(u_t \sim N(0, \sigma_t^2)\right) \tag{22}$$

In classical linear regression models (CLRM), the assumption is the homoscedasticity of the variance of errors. That is, the variance of errors is homoscedastic in case of constancy. If the variance of errors is not constant, then this is known as heteroscedasticity. Making the right assumption is important. If the assumption is the presence of homoscedastic errors in case of a heteroscedasticity, standard error estimates would be wrong. Considering the fact that standard errors are the parameters which give an indication of the regression parameters accuracy, an incorrect assumption would affect the robustness of the model. It would be appropriate to state that in the estimation values for the coefficients, standard errors are measure of degree of uncertainty. Thus, if the standard errors are wrong, then calculated precision of the estimates would be wrong and this would affect the robustness of the test.

In financial markets, volatility clustering or volatility pooling is a point at issue. According to the features large returns are expected to follow large returns while small returns are expected to follow small returns. That is, the current volatility of the returns is the sign of the immediate previous periods.

In case of either false homoscedasticity assumption or volatility clustering, ARCH class of model can be used. In addition, model responds to time-varying shocks. Actually those are the reasons why ARCH-type models are useful.

Under ARCH model, autocorrelation in volatility is

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad \text{(ARCH(1))} \tag{23}$$

In general ARCH (q) models, error variance depends on q lags of squared errors. The model is written as

$$y = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + u_t \quad \left(u_t \sim N(0, \sigma_t^2)\right) \tag{24}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 \tag{25}$$

where

σ_t^2 ; Conditional variance of the error term at time t

“ARCH (q) is stationary if the sum of the parameters of the autoregressive part is smaller than 1”

ARCH restrictions are;

$$\alpha_0 \geq 0\ ;\ \alpha_i \geq 0 \tag{26}$$

$$1 > \sum_{i=1}^{q} \alpha_i \geq 0 \tag{27}$$

3.5.1.2 Testing For ARCH Affects

To test the ARCH effects, the linear regression should be run and the residuals should be saved. Then the residuals should be squared and regressed them on q own lags to test for ARCH (q). Afterwards regression should be conducted.

$$y = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + u_t \tag{28}$$

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \gamma_2 \hat{u}_{t-2}^2 + \cdots + \gamma_q \hat{u}_{t-q}^2 + v_t \tag{29}$$

$v_t\ ;\ error\ term$

Obtain R^2 and then calculate TR^2

H_0: $\gamma_1 = 0$ and $\gamma_2 = 0$ and $\gamma_3 = 0$ …… $\gamma_q = 0$

H_1: $\gamma_1 \neq 0$ or $\gamma_2 \neq 0$ and $\gamma_3 \neq 0$ ….. $\gamma_q \neq 0$

If the test statistics (TR^2) is larger than the critical value in Chi-square distribution (χ^2), then reject the null hypothesis. This indicates the presence of ARCH effect.

3.5.2.1 The GARCH (Generalized Autoregressive Conditional Heteroscedastic) Model

Generalized ARCH model, the generalized autoregressive conditional heteroscedastic (GARCH), was developed by Bollerslev (1986). The GARCH process allow current conditional variance to be dependent upon lagged conditional variance and lagged squared of errors. Conditional variance equation is

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (30)$$

α_0 ; constant term

u_{t-1}^2 ; ARCH term (Information about volatility during the previous period, from mean equation)

σ_{t-1}^2 ; GARCH term (last period's forecast variance)

σ_t^2; conditional variance (one-period-ahead forecast variance based on past information)

This model is known as conditional variance model, GARCH (1, 1). This model allows one-period-ahead estimation of the conditional variance with the past information.

It is possible to design the GARCH model as an ARMA model for the conditional variance.

Consider conditional variance as;

$$\varepsilon_t = u_t^2 - \sigma_t^2 \qquad (31)$$

Substituting equation 31 in equation 30 and rearranging;

u_t^2=α_0+$\alpha_1 u_{t-1}^2 + \beta u_{t-1}^2 - \beta \varepsilon_{t-1} + \varepsilon_t$ (3) (32)

So that

$$u_t^2 = \alpha_0 + (\alpha_1 + \beta) u_{t-1}^2 - \beta \varepsilon_{t-1} + \varepsilon_t \qquad (33)$$

This is an ARMA (1, 1) model.

To obtain a GARCH (p,q) model; it would be sufficient to extend the GARCH (1,1) model. In GARCH (p,q) model current conditional variance depends upon p lags of the conditional variance and q lags of the squared error. That is

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2 \tag{34}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_1 \sigma_{t-j}^2 \tag{35}$$

To detect GARCH type nonlinearity, Q^2 test is used.

GARCH is more parsimonious than ARCH model because it avoids over fitting. It is less likely to breech non-negativity constraints.

3.5.2.2 Estimation of ARCH/GARCH Models

In the estimation of ARCH/GARCH models, maximum likelihood technique, which is based on finding the most likely values of the parameters, is used. This technique works by specifying a log-likelihood function and maximizing the values of the parameters. Maximum likelihood method can be utilized in both linear and non-linear models. Considering mean and variance equations, log-likelihood function should be formed to maximize the values of the parameters. Then, parameter values and their standard errors should be obtained.

$$y_t = \mu + \phi y_{t-1} + u_t, u_t \sim N(0, \sigma_t^2) \tag{36}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{37}$$

$$L = -\frac{T}{2} log(2\pi) - \frac{1}{2} \sum_{t=!}^{T} log(\sigma_t^2) - \frac{1}{2} \sum_{t=1}^{T} (y_t - \mu - \phi y_{t-1})^2 / \sigma_t^2 \tag{38}$$

3.5.3 EGARCH

The EGARCH model can be employed to explain the leverage effect. It is simply an extension of the GARCH model and it was developed by Nelson (1991). Conditional variance equation is;

$$\log(\sigma_t^2) = \omega + \beta * \log(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{39}$$

EGARCH model is more parsimonious than a GARCH model. The model allows asymmetries for instance if the relation between volatility and returns is negative, γ will be negative. There is also no need to set non-negativity constraints to the parameters owing to the logged conditional variance.

In addition, if the sum of the GARCH and ARCH coefficients ($\alpha + \beta$) are very close to 1, then volatility shocks are quite persistent.

3.6 Residual Tests

3.6.1 Correlogram of residuals

Correlogram provides autocorrelations, partial autocorrelations and Ljung-Box Q statistics for the given number of lags. If the model is correctly specified, there should be no serial correlation left in the residuals. That is, the residuals should be nearly white noise. If the test results are significant, the model should be re-specified.

3.6.2 Correlogram of Squared Residuals

This test provides the Ljung-BoxQ-statistics, autocorrelations and partial autocorrelations of the squared residuals for the specified number of lags.
Correlograms of squared residuals are used for detection of GARCH type nonlinearity. It tests remaining arch effect in the variance equations as well as checking specifications of the variance equations. If the equation is correctly specified Q statistics will be not significant. Also autocorrelations and partial autocorrelations should be zero at all lags.

3.6.3 ARCH LM Test

ARCH model is used in the presence of heteroscedasticity which is controlled by ARCH LM and LM serial correlation tests. To test autoregressive conditional heteroscedasticity (ARCH) in the residuals ARCH LM (Lagrange multiplier) is utilized. Null hypothesis in ARCH LM test is no ARCH up to order q in the residuals.
Regression equation is;

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2\right) + u_t \tag{40}$$

e is the residual and q is order of the regression.

In the presence of ARCH effects, loss of efficiency is a foregoing fact.

CHAPTER 4

DATA CHARACTERISTICS

Agricultural raw material spot prices (ARMI), food spot prices (FPI) and oil spot prices (OPI), maize spot prices (MPI), wheat spot prices (WPI), soybean spot prices (SPI), rice spot prices (RPI) and oil spot prices (OPI) are the variables taken into consideration in this thesis. The monthly ARMI, FPI,OPI data covers the period January-1980 to April-2008 while MPI, WPI, SPI, RPI and OPI data covers the period January-1998 to February-2009. So, period of OPI is chosen in line with other data in the group. We formed two groups, one of which contains ARMI, FPI, and OPI. Other consists of MPI, WPI, SPI, RPI and OPI. All variables are transformed into their natural logarithms for cointegration analysis and then their first differences are taken to represent returns for further analysis:

DLARMI:	differenced natural log of agricultural raw material spot prices
DLFPI:	differenced natural log of food spot prices
DLOPI:	differenced natural log of oil spot prices
DLMPI:	differenced natural log of maize spot prices
DLWPI:	differenced natural log of wheat spot prices
DLSPI:	differenced natural log of soybean spot prices
DLRPI:	differenced natural log of rice spot prices
DLOPI:	differenced natural log of oil spot prices

ARMI measures the price changes for timber, cotton, wool, rubber and hides price indices. FPI measures the price changes for fruits, vegetables, meat, poultry, fish, grocery food and non-alcoholic beverages. We have chosen the FPI to understand whether shocks in world oil prices are transferred to food consumption items. ARMI is chosen to control any confounding effect the agricultural raw material prices may have on the relationship between food and oil prices. OPI measures the price changes for crude oil. The three price indexes are sourced from International Monetary Fund (IMF). MPI measures the price changes for maize. WPI measures the price changes for wheat, so does SPI for soybean, and RPI for rice. OPI measures the price changes for crude oil. Oil price indexes are sourced from International Monetary Fund (IMF). Maize, wheat, soybean, rice price indexes sourced from Food and Agricultural Organization of the United Nations (FAO).

Line graphs of ARMI, OPI, and FPI spot market prices presented in Figure 1.1 indicate non-stationary trend in the data. Also it can be stated that there is high volatility in oil spot market by going through the graphic.

It is worth mentioning that descriptive statistics given in Table 4.1 shore up the information obtained from the plot. That is, standard deviation of OPI is far more than FPI and ARMI. In addition, OPI has the highest coefficient of variation while FPI has the lowest of all. That is to say, the most volatile variable is the oil prices followed by agricultural raw material prices and food prices respectively. According to Table 4.1, kurtosis exceeds 3 pointing out the presence of fat tails which can also be seen in OPI and FPI. Additionally, negative skewness is the harbinger of extreme left tail. Besides, Jarque-Bera test statistics are significant implying a deviation from normality. The three price indexes seem to have similar characteristics with most financial series.

To understand the dynamics underlying the changes in price indexes, variables are exposed to various tests. In employing those tests, stationarity is of great importance for robust regression results. The next section discusses the stationarity properties of the series in concern. Then we precede with the cointegration analyses.

Table 4.1 Descriptive Test Statistics

	ARMI	OPI	FPI
Mean	93.15299	52.89554	101.7999
Median	97.28017	46.18479	100.3424
Maximum	132.3509	204.3880	172.5399
Minimum	56.92235	18.51047	75.39381
Std. Dev.	18.14362	30.91256	14.49051
Skewness	-0.416911	2.104470	1.261623
Kurtosis	2.275578	7.933221	7.063554
Jarque-Bera	17.28401	595.7344	324.1227
Probability	0.000177	0.000000	0.000000

Table 4.1 (continued)

Sum	31672.02	17984.48	34611.95
Sum Sq. Dev.	111595.8	323943.8	71181.45
Observations	340	340	340

Unit Root Tests

In order to have robust estimation results, identification of the stationarity of the data has an utmost importance. Stationarity properties of the variables are determined by various unit root tests. Since some unit root tests can give contradictory results, a variety of tests are conducted to check reliability. To continue with the cointegration and VEC analyses based on Johansen (1991, 1995) and Johansen and Juselius (1990) procedure, all series must be integrated of the same order.

For the robustness of the investigation, six different unit root tests are conducted as mentioned before. Aforementioned tests are augmented Dickey-Fuller (1979) (ADF), Elliot-Rothenberg-Stock (1996) Dickey-Fuller GLS detrended (DF-GLS), Phillips-Perron (1988) (PP), Kwaitkowski-Phillips-Schmidt-Shin (1992) (KPSS), Point Optimal (ERS-PO), and Ng and Perron's (2001) MZ_{α} (NP). The null hypothesis of the all unit root tests, apart from KPSS, is that the series in concern has a unit root against an alternative of stationarity. On the other hand stationarity of the variable is the null of KPSS.

The result of the unit root tests are presented in Table 4.2 for levels and first differences, respectively. According to Table 4.2, it can be concluded that all the variables are integrated of order 1, even though there are slight differences between the results of different tests.

Table 4.2 Unit root test results[a]

Levels

		ADF	DF-GLS	PP	KPSS	ERS-PO	NG(Mza)
Intercept							
	LOPI	-0.867	-1.06	-0.265	0.678[b]	6.75[a]	-3.72
		(1)	(1)	(8)	(15)	(1)	(1)
	LARMI	-1.49	-0.961	-1.32	1.33[a]	8.66[a]	-2.79
		(1)	(1)	(3)	(15)	(1)	(1)
	LFPI	-0.818	-0.992	0.436	0.374[c]	7.15[a]	-3.40
		(1)	(1)	(0)	(15)	(1)	(1)

Table 4.2 (continued)
Trend & d intercept

LOPI	-1.51 (1)	-1.08 (1)	-0.879 (10)	0.463[a] (15)	20.9[a] (1)	-4.07 (1)
LARMI	-2.37 (1)	-2.21 (1)	-2.28 (4)	0.348[a] (15)	9.38[a] (1)	-9.86 (1)
FPI	-0.263 (1)	-0.768 (1)	0.269 (5)	0.214[b] (14)	20.8[a] (1)	-3.33 (1)

First differences

	ADF	**DF-GLS**	**PP**	**KPSS**	**ERS-PO**	**NG(MZa)**
Intercept						
LOPI	-14.0[a] (0)	-13.6[a] (0)	-13.5[a] (12)	0.437[c] (8)	0.185 (0)	-158[a] (0)
LARMI	-15.0[a] (0)	-2.66[a] (4)	-15.0[a] (0)	0.065 (3)	0.506 (0)	-9.80[b] (4)
LFPI	-13.5[a] (0)	-11.0[a] (0)	-13.4[a] (7)	0.553[b] (1)	0.231 (1)	-162[a] (0)
Trend & intercept						
LOPI	-14.1[a] (0)	-14.1[a] (0)	-13.6[a] (14)	0.034 (11)	0.586 (0)	-162[a] (0)
LARMI	-15.0[a] (0)	-4.63[a] (4)	-15.0[a] (0)	0.069 (3)	0.793 (0)	-20.9[a] (4)
LFPI	-13.7[a] (0)	-12.3[a] (0)	-13.4[a] (10)	0.138[c] (2)	0.692 (0)	-161[a] (0)

[a]Superscripts a, b, and c represent significance at the 1, 5, and 10% respectively.

Subjecting variables into aforementioned unit root tests is the first step of analyzing long-run relationship between variables in consideration. Once the common order of integration is identified, the next step is to conduct Johansen and Juselius' (1990) and Johansen (1991, 1995) multivariate cointegration procedure. And in the next section provides details of the procedure.

CHAPTER 5

COINTEGRATION TESTS

Since their introduction, cointegration tests have a wide usage in econometrics. In this section it is Johansen's cointegration test (1991) which is used to determine the absence or presence of cointegrating relationship among variables. Although there are many other tests like Engle and Granger (1987), Engle and Yoo (1987) 3-step method, Johansen's cointegration test (1991) has superiority of considering all variables as endogenous and its capability of testing more than one cointegrating relationship.

As mentioned in the methodology section, if the variables of a dynamic linear model are cointegrated, disturbances will be stationary. It is worth noting that, only linear combinations or linear transformation of a number cointegrating vectors will be stationary. So, it is necessary to determine the stationarity of the disturbances and in the previous section verified it is by unit root tests.

Johansen's cointegration test (1991) show that only linear combinations or linear transformation of a number cointegrating vectors will be stationary. In addition in the absence of a cointegrating relationship it is impossible to mention a long-run relationship between variables.

The results of the cointegration tests are reported in Table 5.1. Both trace statistics and maximum eigenvalue statistics state that null hypothesis is not rejected meaning that there is no cointegrating vector between series. To put it another way, there is no cointegration and no long-term equilibrium between spot prices.

Table 5.1 Cointegration test results

λ_{trace}				λ_{max}			
H_0	H_1	statistics	5 %	H_0	H_1	statistics	5 %
r=0	r≥1	19.01994	29.79707	r=0	r=1	13.07418	21.13162
r≤1	r≥2	5.945755	15.49471	r≤1	r=2	5.563225	14.26460
r≤2	r≥3	0.382530	3.841466	r≤2	r=3	0.382530	3.841466

As presented in Table 5.1 there are no cointegrating vectors. On account of the absence of cointegration, we can continue with a VAR model in first differences (returns). We develop a VAR model with the first differenced natural log of spot prices of food and oil commodities in addition to agricultural raw material prices. The lag length selection criteria unanimously chose 1. In the standard form, VAR (1) model is written as follows:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \alpha_{11}y_{2t-1} + \gamma_{11}y_{3t-1} + u_{1t} \tag{41}$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \alpha_{21}y_{3t-1} + \gamma_{21}y_{1t-1} + u_{2t} \tag{42}$$

$$y_{3t} = \beta_{30} + \beta_{31}y_{3t-1} + \alpha_{31}y_{1t-1} + \gamma_{31}y_{2t-1} + u_{3t} \tag{43}$$

or

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} & \gamma_{11} \\ \gamma_{21} & \beta_{21} & \alpha_{21} \\ \alpha_{31} & \gamma_{31} & \beta_{31} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix} \tag{44}$$

In our model VAR system is as follows:

$$\begin{pmatrix} DLFPI \\ DLARMI \\ DLOPI \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0.2881 & 0.0006 & -0.0029 \\ 2.2273 & 0.2102 & -0.01736 \\ 0.0422 & 0.0002 & 0.2640 \end{pmatrix} \begin{pmatrix} DLFPI_{t-1} \\ DLARMI_{t-1} \\ DLOPI_{t-1} \end{pmatrix} + \begin{pmatrix} 0.0007 \\ 0.1053 \\ 0.0025 \end{pmatrix} \tag{45}$$

According to Akaike, Schwarz, and Hannan-Quinn information criteria the optimum lag is found to be 1 for the VAR in returns. The necessary and sufficient condition for stability is that all characteristic roots lie outside the unit circle. Then π is of full rank and all variables are stationary and the system satisfies the stability condition. Additionally, there is not enough evidence to reject the null of no autocorrelation and null of no serial correlation in residuals. Furthermore, homoscedasticity is not rejected according to residual heteroscedasticity tests. The Ramsey RESET test for misspecification, and CUSUM and CUSUM of squares plots do not indicate any violations of regression assumptions. We checked the main regression assumptions and could not detect any severe violations of the common assumptions.

Having identified a stable VAR system that satisfies the common assumptions, the next step is to consider how innovations in one market influence others. The generalized impulse response analysis enables us to see whether one standard deviation shocks to each variable have temporary or permanent effects on other variables.

Generalized Impulse Responses

The cointegration tests have revealed the absence of long-term relationship between the returns of food, agricultural raw material and oil markets. In order to assess how a shock to a variable influences another endogenous variable and how long the effects will last, we use generalized impulse responses.

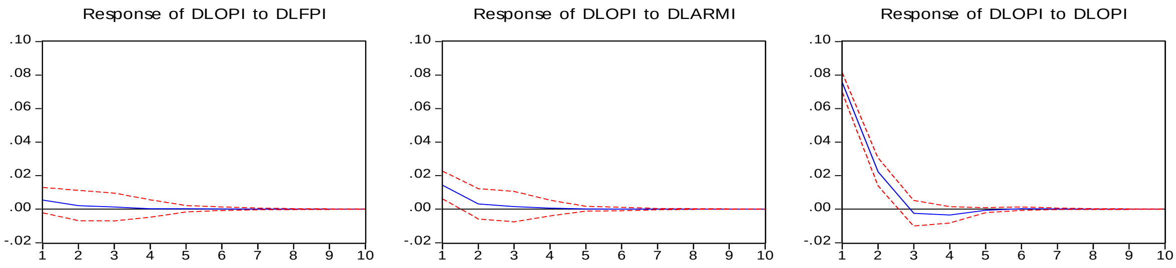

Figure 5.1Generalized impulse responses of DLOPI to innovations

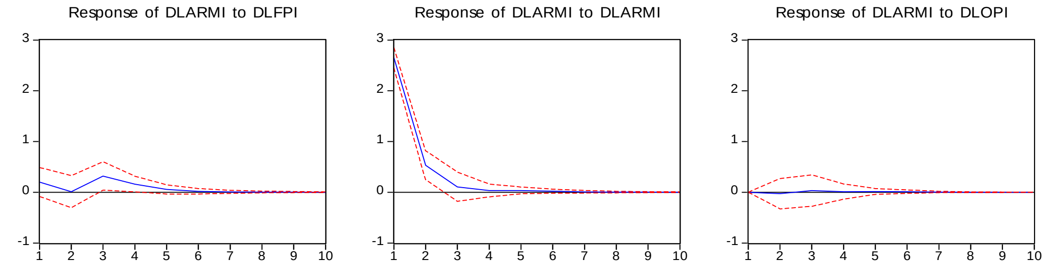

Figure 5.2 Generalize impulse responses of DLARMI to innovations

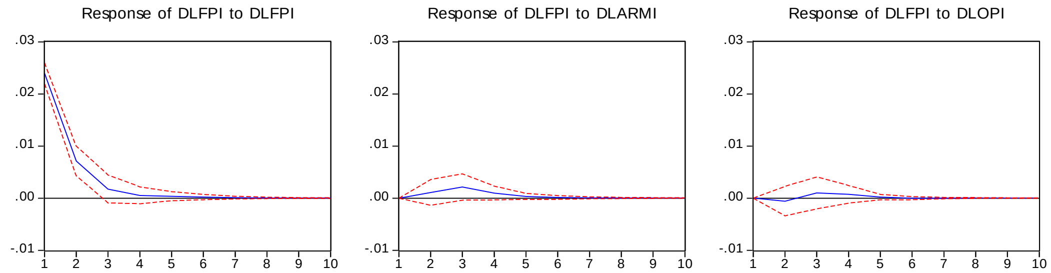

Figure 5.3 Generalized impulse responses of DLFPI to innovations

Generalized impulse response functions are given in Figure 5.1-5.3. Horizontal axes indicate the number of days after shock and vertical axes represent the standardized responses to shocks to each variable. Of all the response estimation methods, Monte Carlo is chosen to provide the confidence bands. The returns in spot food and agricultural raw material markets do not seem to respond at all to a shock in the oil returns. Graphs above indicate that all of the self shocks create positive initial impacts; however, responses die out within three days. Although a positive initial impact of a shock in agricultural raw material returns on oil returns is observed, the magnitude is very low and the effect dies off fast.

Volatility Spillover

The lack of Granger causality in mean does not exclude the information transmission between the markets in terms of volatility. The extent of fluctuations in one market may lead fluctuations in the other. In order to assess this we consider the Granger causality in mean and variance approach developed by Cheung and Ng (1996) (CN hereafter). According to this procedure we first examine the mean equations of the three series. The series in concern must be stationary, therefore the first differences of natural logs are considered. For the food and oil returns Akaike information criteria selects a mean equation with constant only; whereas, for the agricultural raw material returns ARMA (2, 2) are selected. We find that there are ARCH effects that need to be modeled explicitly. Hence, we construct the univariate GARCH models. For agricultural raw material and food returns GARCH (1, 1), for oil returns EGARCH (1, 1) model were appropriate. Table 5.2 summarizes the CN Granger causality in variance tests.

Table 5.2 indicates that volatility spillover in food returns leads fluctuations in agricultural raw material returns at lag 5 at the 5% significance level. There is also weak evidence of Granger causality in variance from raw materials to food returns at lags 1 and 5. The results also show that at 5% significance there is a contemporaneous link between oil and agricultural raw material returns. At the 5% significance level oil volatility leads agricultural raw material volatility at lag 8. The CN procedure provides some evidence of a volatility spillover from oil to food returns at lag 1. However, the result is weak since the test statistic is very close to the 10% critical value of 1.28.

Although the CN procedure seems to have uncovered links between the volatilities of the three indexes, the evidence is not too strong and the fact that the test results indicate spillover occurring in 5 to 8 months casts doubts on the evidence as well. The only link that can be easily interpreted is the contemporaneous adjustment of the agricultural raw material and oil returns since they are closely linked to the production processes. Overall we can easily conclude that the neutrality between agricultural raw material, food and oil returns is confirmed by the volatility spillover tests.

Table 5.2 Granger causality in variance test statistics[a]

$\sqrt{T}\hat{\rho}_{v_1 v_2}(k)$

	DLARMI and DLFPI		DLARMI and DLOPI		DLOPI and DLFPI	
i	lag	lead	lag	lead	lag	lead
0	0.73981	0.73981	1.806384[b]	1.80638[b]	0.07917	0.07917
1	-0.7123	-1.2942[c]	-0.1395	-0.7527	-0.0644	-1.3404[c]
2	0.58194	-0.6444	-0.8059	-0.3047	-0.6684	-0.2338
3	-0.6444	1.07759	-1.0152	0.63701	-0.1123	-1.0863
4	-0.2607	0.27353	0.70677	0.3286	0.37008	0.3977
5	1.672374[b]	1.36397[c]	-0.8004	0.16338	0.80829	-0.4548
6	-1.1786	0.27353	-1.2575	0.74715	-0.8433	-0.8396
7	0.87382	-0.8573	-0.4681	0.64802	0.69229	-0.5468
8	-1.1051	0.23681	1.92938[b]	0.2056	0.55604	-0.0939
9	-0.0991	-0.2056	-0.8702	0.05874	-0.3903	0.67756
10	-0.6554	0.22396	-0.9509	-0.279	-0.3406	0.32221
11	-0.4443	-0.7765	-0.8812	-0.8885	-0.5671	-0.4861
12	-0.6756	0.14135	0.1799	1.04271	-0.0442	-1.1158

[a] Superscripts a, b, and c denote significance at 1, 5, and 10% respectively.

The second variable Granger causes the first variable in variance if the test statistic is significant for some lags; vice versa if the test statistic is significant for some leads.

CHAPTER 6

VOLATILITY TRANSMISSION

Line graphs of WPI, RPI, OPI, MPI, and SPI spot market prices presented in Figure 1.2 which indicates non-stationary trend in the data. Also it can be stated that there is high volatility in all spot markets by going through the graphic.

It is worth mentioning that descriptive statistics given in Table 6.1 shore up the information obtained from the plot. That is, standard deviations of all price series are different from each other. In addition, RPI has the highest coefficient of variation while MPI has the lowest of all. That is to say, the most volatile variable is the rice prices followed by oil prices, soybean prices, wheat prices and maize prices respectively. According to Table 6.1, kurtosis exceeds 3 pointing out the presence of fat tails which can be seen in all series. Additionally, negative skewness is the harbinger of extreme left tail. But there is none of all. Besides, Jarque-Bera test statistics are significant implying a deviation from normality.

To understand the dynamics of the model, variables are exposed to various tests. In employing those tests, stationarity is of great importance for robust regression results. The next section discusses the stationarity properties of the series in concern. Then we discuss non-linearity, autoregressive conditional heteroscedastic model and generalized autoregressive conditional heteroscedastic model.

Table 6.1 Descriptive Statistics

	OPI	MPI	RPI	WPI	SPI
Mean	87.66490	118.3196	220.8755	175.7236	257.3808
Median	56.52101	102.9000	206.5000	151.4750	225.1300
Maximum	823.0484	280.9500	772.0000	481.5000	586.2100

Table 6.1 (continued)

Minimum	19.51456	73.91000	122.2500	105.0000	168.7200
Std. Dev.	100.4204	41.89051	109.9918	74.71999	90.15589
Skewness	5.482027	1.965633	2.817965	1.904797	1.744301
Kurtosis	38.92725	6.487450	12.14846	6.333832	5.712818
Jarque-Bera	7877.960	154.1959	644.6411	143.0866	109.0410
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	11747.10	15854.83	29597.32	23546.96	34489.03
Sum Sq. Dev.	1341207.	233390.4	1609060.	742549.1	1081035.
Observations	134	134	134	134	134

Unit Root Tests

In order to have robust estimation results, identification of the stationarity of the data has an utmost importance. Stationarity properties of the variables are determined by various unit root tests. Since some unit root tests can give contradictory results, a variety of tests are conducted to check reliability. To continue with the cointegration and VEC analyses based on Johansen (1991, 1995) and Johansen and Juselius (1990) procedure, all series must be integrated of the same order.

The result of the unit root tests are presented in Table 6.2 for levels and first differences, respectively. According to Table 6.2, we can safely conclude that all the variables are integrated of order 1, even though there are slight differences between the results of different tests.

Table 6.2 Unit root test results

Levels		***ADF***	***DF-GLS***	***PP***	***KPSS***	***ERS-PO***	***NG(Mza)***
Intercept							
	LOPI	0.011(6)	1.665^{c}(6)	-3.325^{b} (8)	1.348^{a}(9)	66.88^{a}(6)	-0.134(6)
	LMPI	-1.33(1)	-1.37(1)	-1.25(5)	0.925^{a}(9)	5.78^{a}(1)	-4.35(1)
	LRPI	-1.66(1)	-1.61^{c}(1)	-1.22(5)	0.80(9)	4.31^{a}(1)	-6.55^{c}(1)

Table 6.2 (continued)

	LSPI	-1.17(0)	-1.22(0)	-1.35(2)	0.88(9)	6.99^{a}(0)	-3.44(0)
	LWPI	-1.16^{a}(1)	-0.97(1)	-1.032(3)	1.12^{a}(9)	9.58^{a}(1)	-2.51(1)
Trend & intercept							
	LOPI	-2.14(6)	-1.51(6)	9.21^{a}(8)	0.112(8)	17.70^{a}(6)	-3.41(6)
	LMPI	-2.82(1)	-1.92(1)	-2.69(5)	0.23^{a}(9)	14.49^{a}(1)	-7.35(1)
	LRPI	-2.66(1)	-2.30(1)	-2.10(5)	0.26^{a}(9)	9.16^{a}(1)	-10.85(1)
	LSPI	-2.58(0)	-1.69(0)	-2.75(2)	0.154^{b}(9)	19.58^{a}(0)	-5.39(0)
	LWPI	-2.98(1)	-2.14(1)	-2.74(3)	0.191^{b}(9)	11.39^{a}(1)	-9.018(1)
First differences							
		ADF	***DF-GLS***	***PP***	***KPSS***	***ERS-PO***	***NG(MZa)***
Intercept							
	LOPI	-7.57(5)	-0.457(6)	-20.21^{a} (7)	0.082(7)	89.55^{a}(5)	17.37^{a}(6)
	LMPI	-8.71^{a}(0)	-8.62^{a}(0)	-8.79^{a}(4)	0.115(5)	0.435(0)	-60.95^{a}(0)
	LRPI	-6.039(0)	-6.01^{a}(0)	-5.89^{a}(6)	0.103(5)	0.545(0)	-45.51^{a}(0)
	LSPI	-10.13^{a}(0)	-10.11(0)	-10.13(0)	0.124(1)	0.38(0)	-72.01^{a}(0)
	LWPI	-8.85^{a}(0)	-8.89^{a}(0)	-8.85^{a}(3)	0.088(3)	0.459(0)	-62.51^{a}(0)
Trend & intercept							
	LOPI	-7.57^{a}(5)	1.09(6)	-19.97^{a} (7)	0.06(7)	188.74^{a}(5)	9.53(6)
	LMPI	-8.71^{a}(0)	-8.70^{a}(0)	-8.795^{a} (5)	0.045(4)	1.56(0)	-62.19^{a}(0)
	Table 6.2(continued)						
	LRPI	-6.047^{a} (0)	-6.04^{a}(0)	-5.88^{a}(6)	0.043(5)	2.01(0)	-45.51^{a}(0)
	LSPI	-10.15^{a} (0)	-10.11^{a} (0)	-10.14^{a} (1)	0.054 (1)	1.41 (0)	-66.05^{a} (0)
	LWPI	-8.83^{a} (0)	-8.77^{a} (0)	-8.83^{a} (3)	0.059 (3)	1.55 (0)	-62.06^{a} (0)

Superscripts a, b, and c represent significance at the 1, 5, and 10% respectively.

Subjecting variables into aforementioned unit root tests is the first step of analyzing long-run relationship between variables in consideration. The second step is to analyze non-linearity; conducting autoregressive conditional heteroscedastic model and generalized autoregressive conditional heteroscedastic model and next section provides details of the procedure.

Autoregressive Conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

ARCH model is used in the presence of heteroscedasticity which is controlled by ARCH lm and lm serial correlation tests.

ARCH lm test is conducted on the residuals of the ARMA to test ARCH effects. According to the conducted test, null hypothesis of constant variance is failed to reject. Then residuals do not exhibit nonlinear dynamics. To put it another way, conditional heteroscedasticity is no longer present in the data. So it can be concluded that there is no evidence of ARCH effect. Also, Lm serial correlation test is conducted to test heteroscedasticity. Dlmpi, dlrpi, dlopi and dlwpi are heteroscedastic and there is serial correlation in series.

Afterwards univariate GARCH models are constructed. Firstly, of all the models, models having lowest value of Akaike, Schwarz, and Hannan-Quinn criterion are chosen for both and EGARCH and GARCH models as seen in the Table 6.3 and Table 6.4 respectively. Secondly, from previously chosen EGARCH and GARCH models, leverage effect is investigated.

Coefficient of γ (RESID(-1)/@SQRT(GARCH(-1))) is taken into consideration. If the value is less than 0.05, then it is significant at 5 % and leverage effect is present for the model. This indicates the presence of asymmetric effect and the leverage effect is exponential. In case of insignificant coefficient, GARCH model is evaluated for the procedure. In GARCH model, coefficient of β (GARCH(-1)) is taken into consideration. Chosen models are as follows: For oil returns EGARCH (0, 0), for rice returns EGARCH (0, 0), for soybean returns EGARCH (2, 0) for wheat returns GARCH (2, 2), for maize returns GARCH (2, 0) models were appropriate.

Table 6.3 EGARCH

ARMA(p,q)

DLSPI		α_0	Prop.	α	Prob.	β	Prob.	γ	Prob.	AIC
p	q									
2,000	2,000	-3,139	0,003	0,602	0,009	0,514	0,005	-0,348	0,0131*	-2,550
2,000	1,000	-3,155	0,002	0,605	0,009	0,511	0,003	-0,352	0,0119*	-2,564
2,000	0,000	-2,972	0,018	0,524	0,068	0,523	0,014	-0,323	0,051	-2,512
1,000	0,000	-2,987	0,016	0,525	0,059	0,524	0,014	-0,302	0,060	-2,525
1,000	2,000	-2,592	0,008	0,569	0,044	0,599	0,000	-0,301	0,0807**	-2,5099*
0,000	2,000	-2,786	0,012	0,538	0,062	0,560	0,003	-0,301	0,069	-2,526
0,000	1,000	-2,859	0,010	0,523	0,056	0,547	0,004	-0,292	0,067	-2,539
0,000	0,000	-3,322	0,010	0,486	0,040	0,457	0,046	-0,289	0,0493*	-2,529
DLWPI										
2,000	2,000	-0,825	0,072	0,265	0,089	0,894	0,000	0,108	0,164	-2,881
2,000	1,000	0,038	0,027	-0,022	0,000	1,002	0,000	0,051	0,241	-2,848
2,000	0,000	0,078	0,009	-0,119	0,167	0,997	0,000	0,127	0,0002*	-2,899
1,000	0,000	-0,519	0,228	0,261	0,087	0,944	0,000	0,078	0,228	-2,831
1,000	2,000	-0,376	0,323	0,208	0,104	0,962	0,000	0,078	0,148	-2,8246*
0,000	2,000	-0,635	0,117	0,283	0,032	0,926	0,000	0,053	0,375	-2,825
0,000	1,000	-0,663	0,109	0,281	0,038	0,921	0,000	0,055	0,350	-2,837
0,000	0,000	-1,136	0,076	0,496	0,015	0,869	0,000	0,029	0,735	-2,837
DLOPI										
2,000	2,000	-0,656	0,001	0,808	0,000	0,965	0,000	0,432	0,0002*	-0,860
2,000	1,000	-0,546	0,001	0,858	0,000	0,996	0,000	0,410	0,0041*	-0,893
2,000	0,000	-0,767	0,001	1,150	0,000	0,954	0,000	0,594	0,0001*	-0,622
1,000	0,000	-0,707	0,002	1,148	0,000	0,969	0,000	0,743	0,0003*	-0,559
1,000	2,000	-0,550	0,002	0,855	0,000	1,000	0,000	0,393	0,0027*	-0,913
0,000	2,000	-0,739	0,000	1,054	0,000	0,952	0,000	0,495	0,0015*	-0,779
0,000	1,000	-1,010	0,000	0,726	0,000	0,818	0,000	0,487	0,0003*	-0,345
0,000	0,000	-5,182	0,000	0,035	0,680	-0,862	0,000	-0,246	0,0009*	0,1579*
DLMPI										
2,000	2,000	-2,246	0,007	0,447	0,082	0,671	0,000	-0,177	0,218	-2,828
2,000	1,000	-2,126	0,027	0,396	0,143	0,684	0,000	-0,107	0,465	-2,833
2,000	0,000	-0,024	0,865	-0,040	0,684	0,989	0,000	0,133	0,0047*	-2,914
1,000	0,000	-1,663	0,287	0,256	0,246	0,743	0,003	-0,045	0,706	-2,81596*
1,000	2,000	-0,060	0,807	-0,144	0,103	0,972	0,000	0,149	0,022*	-3,000
0,000	2,000	0,132	0,021	-0,106	0,122	1,006	0,000	0,030	0,314	-2,980
0,000	1,000	0,135	0,000	-0,073	0,000	0,027	0,000	1,010	0*	-2,973
0,000	0,000	0,090	0,000	-0,121	0,000	0,997	0,000	0,013	0*	-2,937

Table 6.3 (continued)

DLRPI

2,000	2,000	-0,435	0,125	0,274	0,051	0,964	0,000	0,227	0,0002*	-3,385
2,000	1,000	-0,506	0,055	0,317	0,012	0,956	0,000	0,242	0,0018*	-3,371
2,000	0,000	-0,503	0,035	0,301	0,009	0,954	0,000	0,246	0,0007*	-3,381
1,000	0,000	-0,493	0,057	0,293	0,015	0,955	0,000	0,254	0,0023*	-3,388
1,000	2,000	-0,523	0,028	0,307	0,007	0,951	0,000	0,255	0,0007*	-3,379
0,000	2,000	-0,555	0,015	0,317	0,004	0,947	0,000	0,260	0,0006*	-3,411
0,000	1,000	-0,563	0,015	0,338	0,003	0,949	0,000	0,232	0,0001*	-3,415
0,000	0,000	-0,719	0,031	0,447	0,009	0,937	0,000	0,179	0,0082*	-3,238102*

Table 6.4 GARCH

ARMA(p,q)
DLMPI

p	q	α_0	Prop.	α	Prob.	β	Prob.	AIC
2	2	0,000583	0,2698	0,140583	0,2064	0,703004	0,0029	-2,83201
2	1	0,000447	0,3717	0,104801	0,2267	0,774226	0,0003	-2,84776
2	0	0,000591	0,2857	0,131991	0,2113	0,709337	0,0025	-2,81432*
1	0	0,00038	0,4244	0,091188	0,2419	0,804295	0,0001	-2,84080
1	2	0,000643	0,2585	0,14046	0,1931	0,683936	0,0057	-2,85432
0	2	0,00067	0,2565	0,131424	0,2348	0,685577	0,0063	-2,83640
0	1	0,000454	0,2886	0,111161	0,1561	0,766504	0,0001	-2,85510
0	0	0,000682	0,1581	0,144877	0,1514	0,673524	0,0017	-2,80855
DLWPI								
2	2	0,000328	0,1483	0,277443	0,0205	0,654022	0,0000	-2,82457*
2	1	0,000329	0,152	0,272869	0,0114	0,660129	0,0000	-2,84546
2	0	0,000342	0,1498	0,313277	0,0115	0,625078	0,0000	-2,84604
1	0	0,000345	0,1513	0,302775	0,0114	0,637647	0,0000	-2,85658
1	2	0,00033	0,1614	0,294176	0,0143	0,646331	0,0000	-2,84780
0	2	0,000378	0,1252	0,295598	0,0126	0,630772	0,0000	-2,86200
0	1	0,000378	0,133	0,299054	0,0124	0,633335	0,0000	-2,86701
0	0	0,000377	0,1243	0,298131	0,0107	0,629369	0,0000	-2,87437

Table 6.5 Chosen Models and Relevant Coefficients

	α_0	Prop.	α	Prob.	β	Prob.	γ	Prob.	Arch lm
DLMPI GARCH 2,0	0,0006	0,2857	0,1320	0,2113	0,7093	0,0025			0,5659
DLSPI EGARCH 1,2	-2,5922	0,0077	0,56925	0,0443	0,59931	0,0003	-0,3009	0,0807**	0,7897
DLRPI EGACRH 0,0	-0,7194	0,0313	0,4465	0,0086	0,9373	0	0,1792	0,0082*	0,9734
DLWPI GARCH 2,2	0,0003	0,1483	0,2774	0,0205	0,6540	0,0000	-2,8246*	0,0003	0,5048
DLOPI EGARCH 0,0	-5,181	0	0,0345	0,6799	-0,8624	0	-0,2460	0,0009	0,4069

Correlogram provides autocorrelations, partial autocorrelations and Ljung-Box Q statistics for the given number of lags. If the model is correctly specified, there should be no serial correlation left in the residuals. That is, the residuals should be nearly white noise. If the test results are significant, the model should be re-specified. Correlograms of squared residuals are used for detection of GARCH type nonlinearity. It tests remaining arch effect in the variance equations as well as checking specifications of the variance equations. If the equation is correctly specified Q statistics will be not significant. Also autocorrelations and partial autocorrelations should be zero at all lags.

According to the analysis conducted chosen GARCH and ARCH models are correctly specified and test statistics are not significant. Thus, there are no serial correlations left in residuals in the specified models.

Table 6.6 Correlogram of Residuals and Squared Residuals

	Number of lags	Q	Q2
DLMPI	5	0,127	0,783
	10	0,119	0,958
	15	0,284	0,989
	20	0,115	0,991
DLRPI	5	0	0,567
	10	0,003	0,792
	15	0,026	0,704
	20	0,051	0,576
DLWPI	5	0,118	0,005
	10	0,288	0,144
	15	0,359	0,156
	20	0,666	0,175
DLOPI	5	0,002	0,467
	10	0,001	0,841
	15	0,012	0,984
	20	0,057	0,999
DLSPI	5	0,863	0,487
	10	0,893	0,927
	15	0,694	0,961
	20	0,526	0,994

For the aforementioned EGARCH and GARCH models, serial correlation in series is removed. Since serial correlation and heteroscedasticity is removed from the model, volatility spillover can be examined by means of Granger Causality in mean and variance approach developed by Cheung and Ng (1996) (CN hereafter) Table 6.7 summarizes CN Granger causality in variance tests.

Table 6.7 Granger Causality in Variance Test Statistics

$\sqrt{T}\hat{\rho}_{v_1 v_2}(k)$

	DLMPI and DLWPI		DLOPI and DLSPI		DLOPI and DLRPI		DLOPI and DLWPI		DLMPI and DLOPI	
i	lag	lead	lag	lead	lag	lead	lag	lead	lag	lead
0	0,708	0,708	4,127[a]	4,127[a]	-0,375	-0,375	-0,680	-0,680	-0,007	-0,007
1	0,448	0,208	-0,242	-0,162	0,343	-0,352	-0,333	-0,583	1,415[c]	4,559[a]
2	0,711	1,787[b]	3,546[a]	2,377[a]	-0,619	-0,258	-0,405	0,540	-0,063	-0,003
3	-1,051	-0,287	-0,477	-0,692	2,249[b]	2,632[a]	2,618[a]	2,255[b]	4,757[a]	0,082
4	0,009	0,540	0,256	-0,453	1,206	0,992	-0,130	-0,600	-0,430	0,309
5	-1,423[c]	-0,662	0,810	1,495[c]	2,297[b]	-0,669	1,460[c]	-0,415	-0,451	0,256
6	1,190	-1,327[c]	1,845[b]	0,731	-0,187	-0,450	-0,636	0,005	0,268	1,315[c]
7	-1,087	-0,460	0,354	-0,604	0,441	-0,668	1,026	-0,015	0,060	-0,110
8	0,666	0,902	0,402	0,010	0,374	-0,006	-0,518	0,033	-0,025	0,195
9	0,758	1,212	1,429[c]	-0,006	0,983	0,036	-0,389	-0,007	0,005	-0,576
10	0,442	0,498	-0,246	-0,047	0,012	-0,013	4,718[a]	-0,027	0,003	-0,323
11	2,681[a]	2,180[b]	2,220[b]	-0,048	-0,273	0,046	1,042	0,008	0,005	-0,101
12	0,635	0,425	-0,108	-0,046	-0,203	-0,009	0,502	-0,013	-0,025	1,581[c]

$\sqrt{T}\hat{\rho}_{v_1 v_2}(k)$

	DLRPI and DLWPI		DLSPI and DLWPI		DLRPI and DLSPI		DLMPI and DLRPI		DLMPI and DLSPI	
i	lag	lead	lag	lead	lag	lead	lag	lead	lag	lead
0	-0,066	-0,066	0,405	0,405	-0,929	-0,929	-0,116	-0,116	1,079	1,079
1	0,576	-1,006	2,232[b]	0,822	-0,530	0,992	0,096	-0,047	3,769[a]	1,091
2	-0,328	-0,018	0,650	1,768[b]	-1,044	-0,322	-0,752	0,156	-1,074	0,066
3	-1,161	0,126	1,497[c]	0,201	1,056	3,037[a]	-0,098	1,256	1,988[b]	0,103
4	1,784[b]	-1,612[b]	-0,080	-0,786	1,753[b]	-1,114	2,875[a]	1,018	-0,787	0,077
5	1,798[b]	0,522	0,943	-0,578	0,322	0,797	-1,086	-0,548	1,324[c]	-0,856
6	1,559[c]	0,413	-1,747[b]	-0,830	2,615[a]	-0,052	2,089[b]	0,470	-0,619	0,716
7	2,417[a]	-0,445	0,155	-1,301[c]	-0,344	-0,341	-0,111	-1,103	-0,325	0,371
8	0,944	1,251	1,417[c]	-0,158	-0,782	0,043	0,735	0,200	0,093	-1,107
9	0,188	-0,001	-0,276	0,698	-0,964	-0,415	-0,063	1,031	-0,126	-0,298
10	-0,279	-0,288	1,681[b]	-1,099	-0,144	-0,001	-1,512[c]	0,024	2,518[a]	1,155
11	-0,925	-0,852	1,482[c]	0,180	-1,322[c]	0,858	-0,346	-0,255	1,194	-0,089
12	-0,285	0,056	1,987[b]	1,280[c]	-0,481	-0,694	0,702	0,062	0,062	3,216[a]

[a] Superscripts a, b, and c denote significance at 1, 5, and 10% respectively

There is evidence of granger causality in variance from maize to wheat returns at lags 2,6 and 11. However the result at 6th lag is weak since the test statistic is very close to the 10 % critical value of 1.28. Volatility spillover in wheat returns leads fluctuations in maize returns at lag 5 at the 5% significance level and at lag 11 at the 1 % significance level. The results show that at 1% significance level there is a contemporaneous link between oil and soybean returns. The CN procedure provides some evidence of volatility spillover from soybean to oil returns at lag 5 yet the result is weak. Volatility spillover in soybeans leads fluctuations in oil returns at lags 6, 11 at 5 % significance level and at lag 9 at 10 % significance level. At the 5% significance level rice volatility leads oil volatility at lags 3 and 5. There is strong evidence Granger causality in variance from oil returns to rice returns at lag 3. At 1% significance level wheat volatility leads oil volatility at lags 3 and 10; and at 10% significance level at lag 5. The results show that there is evidence of Granger causality in variance from oil to wheat returns at lag 3. Volatility spillover in oil returns leads fluctuations in maize returns at lag 1 at 10 % significance level and at lag 3 at 1% significance level. The results indicate evidence of volatility spillover from maize to oil returns at lags 1,6 and 12. But the results are weak at lags 6 and 12. Volatility spillover in wheat returns lead fluctuations in rice returns at lags 4, 5, 6 and 7. The result is weak at lag 6. In addition there is a weak evidence of Granger causality in variance from rice returns to wheat returns. Moreover, volatility spillover in wheat returns leads fluctuations in soybean returns. Also, soybean volatility leads wheat volatility at lags 2, 7 and 12. There is also an evidence of volatility spillover from soybean returns to rice returns at lags 4, 6 and 11. The spillover is strong at lag 6 and weak at lag 11. Volatility spillover in rice returns leads fluctuations in maize returns at lags 4, 6 and 10. However, the result at lag 10 is weak since the test statistics is very close to 10 % critical value. The procedure provides some evidence of volatility spillover from soybean to maize at lags 1, 3, 5, and 10 yet the result is weak at lag 5. Last of all, there is a strong evidence of a volatility spillover from maize to soybean at 1% significance level at lag 12.

CN procedure seems to have uncovered links between the volatilities of the three indexes. Volatility spillover occurs from oil returns to other variables in 1 to 3 months. Volatility spillover from maize returns to wheat, oil and soybean returns occurs in 1 to 12 months. Volatility spillover from wheat returns occurs in 1 to 12 months. For soybean returns, spillover occurs up to 12 months. For rice returns, spillover occurs in 3 to 5 months to oil, wheat, and soybean while volatility spillover from rice to maize occurs in 4 to 10 months.

Contemporaneous adjustments of oil and soybean returns, rice and wheat returns can be easily seen from the Table 6.7.

CHAPTER 7

CONCLUSION

Agricultural raw material and food prices must be closely followed by countries that experience a rapid population growth. As these markets become subject to international speculative moves, the ability to correctly forecast the prices becomes even more important to design policies that work. The success of the economic policies depends on understanding the dynamics that govern these prices in the global arena. The dynamics of the commodity prices make them attractive for investors and speculators. If commodity markets are seen as alternative investment areas, then it is natural to expect that food prices are influenced by the same factors with prices of financial assets and other alternative investment areas. Therefore, the responsiveness of financial returns to oil price shocks are of great interest to investors.

The recent concern of both governments and investors is on the impact of oil shocks on global food prices. We find that there is no long run link between oil, food and agricultural raw material prices. The increases in food and agricultural raw material prices cannot be attributed to the positive shocks in oil prices. Furthermore, there is no volatility spillover from the oil returns to the food returns. Overall our results indicate that there is no information transmission between the means and/or variances of the three indexes, that are agricultural raw materials, food, and oil returns, except for the contemporaneous link between oil and agricultural raw materials. Since there is no relationship between the three market returns studied, investors can consider them in their portfolio formation and hedging activities. Furthermore, policy makers cannot use developments in the world oil market to improve their forecasts of the food and agricultural raw material prices and volatilities.

However, there is information transmission between the means and/or variance of the maize, oil, rice, soybean, and wheat indexes. A change in petroleum prices has an influence on the other spot market prices. This spillover is observed within 3 lags. That is, there is volatility spillover from oil prices to wheat, rice, soybean and maize returns. Another important finding is the significant impact from wheat prices to other price indexes. Moreover, there is a contemporaneous link between oil and soybeans returns, rice and wheat returns. As a result, investors should consider these relations in their portfolio formation and hedging activities.

Further research examining the information transmission mechanisms between biodiesel and ethanol and individual prices of different food items or different agricultural indexes (i.e. wheat, corn, soybean etc.) may prove to be fruitful.

REFERENCES

Abbott, P.C., Hurt, C., and Tyner, W.E. (2008). What's Driving Food Prices*? Farm Foundation Issue Reports.* http://purl.umn.edu/37951.

Agricultural Trade Policy Analysis (2008). *High Prices on Agricultural Commodity Markets: Situation and Prospects: a Review of Causes of High Prices and Outlook for World Agricultural Markets.* Review, European Commission, Directorate-General for Agriculture and Rural Development, Brussels.

Allen, K. (2010, June 15). Food prices to rise by up to 40% over next decade, UN report warns. *The Guardian* .

Akaike, H. (1974). ``A new look at the statistical model identification"**.** *IEEE Transactions on Automatic Control*, AC-19(6), 716-723.

Aksoy, M. A., Isik-Dikmelik (Chakravorty, Magne, & Moreaux, A Dynamic Model of Food and Clean Energy, 2008), A. (2008, June). Are Low Food Prices Pro-poor? Net Food Buyers and Sellers in Low-Income Countries. The World Bank (Policy Research Working Paper 4642).

Apergis, N., & Rezitis, A. (2003). Agricultural price volatility spillover effects: the case of Greece. *European Review of Agricultural Economics , 30* (3), 389-406.

Arndt, C., Benfica, R., Maximiano, N., Nucifora, A., Thurlow, J. (2008). Higher fuel and food prices: impacts and responses for Mozambique. *Agricultural Economics, 39*, 497-511.

Askari, H., Krichene, N. (2008). Oil price dynamics. *Energy Dynamics, 30,* 2134-2153.

Baffes, J. (2007). Oil spills on other commodities. *Resources Policy, 32,* 126-134.

Bénabou, R. and Gertner, R.(1993). Search with learning from prices: does increased inflationary uncertainty lead to higher markups? *Review of Economic Studies, 60,* 69-93.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics, 31,* 307-27.

Borger, J. US Attacked at Food Summit Over Biofuels. (2008, June, 4) *The Guardian.*

Braun, J. V. (2007). The world food situation: new driving forces and required actions. *International Food Policy Research Institute,* Washington, D.C.

Campbell, J.Y., Lo, A.W. and MacKinlay, A.C. (1997). *The Econometrics of Financial Markets,* Princeton University Press, Princeton, New Jersey.

Chakravorty, U., Magne, B., & Moreaux, M. (2008). A dynamic model of food and clean energy. *Journal of Economic Dynamics and Control*, *32 (4),* 1181-1203.

Chakravorty, U., M.-H. Hubert and L. Nostbakken (2009). Fuel versus Food. *Annual Review of Resource Economics*, *1,* 645-663.

Cheung, Y., Ng, L.K. (1996). A causality-in-variance test and its application to financial market prices. *Journal of Econometrics, 72*, 33–48.

Christian, T., Rashad, I. (2008, October 29). Trends in U.S. Food Prices, 1950- 2007. *Economics and Human Biology* .

Collins, K. (2008). The role of biofuels and other factors in increasing farm and food prices: a review of recent development with a focus on feed grain markets and market prospects. Kraft Foods Global.

Cooke, B., & Robles, M. (2009). Recent food price movements: A time series analysis. *IFPRI Discussion Paper* .

Coyle, W., Gehlhar, M., Hertel, T., Wnag, Z., and Yu, W. (1998). Understanding the determinants of structural change in world food markets. *AAEA.* Utah.

Dickey, D.A., Fuller, W.A. (1979). Distribution of estimators for time series regressions with a unit root. *Journal of American Statistical Association, 74,* 427-31.

Elliott G, Rothenberg TJ, Stock JH. 1996. Efficient tests for an autoregressive unit root. *Econometrica, Economic Society.64 (4),* 813-36.

Engle, R.F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom Inflation. *Econometrica*, *50(4),* 987-1007.

Engle, R.F., Granger, C.W.J (1987). Co-integration and error correction: representation, estimation and testing. *Econometrica 55*, 251-76.

Engle, R.F., Yoo, B.S. (1987). Forecasting and Testing in Cointegrated Systems. *Journal of Econometrics*, 35,143-59.

Ewing, B. T., Thompson, M. A. (2007). Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices. *Energy Policy*, 35, 5535-5540.

Fan, Y., Zhanh, Y.-J., Tsai, H.-T., and Wei, Y.-M. (2008). Estimating 'value at risk' of crude oil price and its spillover effect using the ged-garch approach. *Energy Economics , 30,* 3156-3171.

FAO (Food and Agriculture Organization of the United States). (2008). Soaring food prices: Facts, perspectives, impacts and actions required. *High-Level Conference on World Food Security: The Challenges of Climate Change and Bioenergy*. Rome.

FAO (Food and Agriculture Organization of the United Nations). 2009. *Food outlook June 2009.* http://www.fao.org/docrep/011/ai482e/ai482e00.HTM

FAO(Food and Agricultural Organization of the United Nations). 2010. *Global food price monitor October*. FAO.

Gilbert, C. L. (2010). How to understand high food prices. *Journal of Agricultural Economics , 61* (2), 398-425.

Glauber, J. (2008). *In testimony before the Joint Economic Committee of Congress on May 1, 2008.*

Hochman G, S. Sexton, D. Zilberman. 2008. The economics of trade, biofuel and the environment. *University of California, Berkeley, Working Paper.*

Islam, N., & Thomas, S. (1996). *Food grain price stabilization in developing countries. Issues and experiences in Asia.* Washington, D.C.: International Food Policy Research Institute.

IFPRI. (2008). High Food Prices: The what, who, and how of proposed policy actions. *Policy Brief.* Washington, DC.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and control, 12,* 231-254

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica, 59,* 1551–1580.

Johansen, S. (1995) *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models.* Oxford: Oxford University Press.

Johansen, S., Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration-with applications to the demand for money. *Oxford Bulletin of Economics and Statistics, 52*, 169-210.

Kargbo, J. (2000). Impacts of monetary and macroeconomics factors on food prices in eastern and southern Africa. *Applied Economics* , 1373-1389.

Koop, G., Pesaran, M.H., and Potter, S.M., (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74*, 119-147.

Kwaitkowski, D., Phillips, P.C.B., Schmidt, P. and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of, 54*, 159-178.

Lin, S. X., Tamvakis, M. N. (2001). Spillover effects in energy futures markets. *Energy Economics* , *23*, 43-56.

Martin, A. (2008, March). Fuel choice, food prices and finger-pointing. *New York Times*, B1-B6.

Minot, N. (2010). Food price transmission and welfare impact in sub-saharan Africa. *IFPRI*

Minten, B., Kyle, S. (2000). Retail margins, price transmission and price asymmetry in urban food markets: The case of Kinshasa. *Journal of African Economies, 9 (1),* 1-23.

Muhammad, A., & Kebede, E. (2009). The emergence of an agro-energy sector: Is agriculture importing instability from the oil sector? (A. a. Association, Ed.) *Choice* .

Monbiot, G., 2004. Feeding cars, not people. Monbiot.com, November 23, 2004, http://www.monbiot.com/archieves/2004/11/23/feeding-cars-not-people/, last accessed April 2009.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59(2),* 347-70

OECD. (2010). Markets, prices and food security: what will the future bring? *OECD Agriculture Ministerial Meeting.* Paris: OECD.

OECD, Food and Agriculture Organization of the United Nations. (2009). *OECD-FAO agricultural outlook 2009-2018.* OECD Publishing.

Pesaran, M. H., Shin, Y., (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters, 58,* 17-29.

Phillips PC, Perron P. 1988.Testing for a unit root in time series regression. *Biometrika., 75,* 335-46.

Rosegrant, M. W., Zhu, T., Msangi, S., & Sulser, T. (2008). Global scenarios for biofuels: Impacts and implications. *Revire of Agricultural Economics , 30,* 495-505.

Rezitis, A. (2003). Mean and volatility spillover effects in Greek producer-consumer meat prices. *Applied Economics letters, 10 (6),* 381-384.

Food prices: Cheap no more. (2007, December, 6). *Economist.* http://www.economist.com/printedition/displayStory.cfm?Story_ID=10250420

Saghaian, S. H. (2010, August). The impact of the oil sector on commodity prices: Correlation or causation? *Journal of Agricultural and Applied Economics* , 477-485.

Schwartz, G. (1978). `Estimating the dimension of a model. *Annals of Statistics*, *6*,461-464.

Timmer, P.C. (1989).Food price policy, the rationale for government intervention. *Food Policy, 14(1),* 17-27

Timmer, P.C. (2008). The Causes of High Food Prices. Asian Development Bank *Economics Working Paper Series, 12.*

Tokgoz, S., Elobeid, A., Fabiosa, J., Hayes, D., Babcock, B. A., Yu, T., et al. (2007). *Emerging biofuels: Outlook of effects on U.S. grain, oilseed, and livestock markets.* Iowa State University. Ames, Iowa: Center for Agricultural and Rural Development.

Tyner, W. E., & Taheripour, F. (2008). Policy options for integrated energy and agricultural markets. *Transition to a Bio-Economy: Integration of Agricultural and Energy System.* Atlanta, GA.

Vavra, P., B. K. Goodwin. (2005). Analysis of price transmission along the food chain. OECD *Food, Agriculture and Fisheries Working Papers, 3*, OECD Publishing.

Vocke, G., Allen, E., & Liefert, O. (2009). *Wheat outlook.* USDA (United Stated Department of Agriculture) Economis Research Service.

Wald, M. L. (2006, January 16). Corn farmers smile as ethanol prices rise, but experts on food supplies worry. *The New York Times* .

Worthington, A., Kay-Spratley, A., Higgs, H. (2005). Transmission of prices and price volatility in Australian electricity spot markets a multivariate garch analysis. *Energy Economics, 27,* 337-350.

Wright, B. D., & Bobenrieth, E. (2009). *The food price crisis of 2007/2008: Evidence and implications.* FAO. FAO.

Yang, J., Wiu, H.Q., Huang, J., Rozelle, S., 2008. Fighting global price rises in the developing world: The response of China and its effect on domestic and world markets. *Agricultural Economics, 39*, 453-464.

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2010). Food versus fuel: What do prices tell us? *Energy Policy , 38*, 445-451.