THE EFFECTS OF EXCHANGE RATES, OIL PRICES, GLOBAL RISK PERCEPTIONS AND GLOBAL WARMING ON FOOD PRICES

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ABSTRACT

THE EFFECTS OF EXCHANGE RATES, OIL PRICES, GLOBAL RISK PERCEPTIONS AND GLOBAL WARMING ON FOOD PRICES

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This thesis examines the relationship between food prices, oil prices, carbon emission prices, exchange rates and global risk perception. To obtain the effects of these variables on the food prices, Toda and Yamamoto procedure is employed for 5-day week daily time series covering the period February 27, 2008 and March 21, 2011. The empirical results indicate that only volatility index Granger causes food prices. Furthermore, according to results of generalized impulse response plots food prices respond to all variables in the short run.

Keywords: Food prices, oil prices, global risk perception, exchange rates, global warming

ÖZ

DÖVİZ KURLARI, PETROL FİYATLARI, KÜRESEL RİSK ALGISI VE KÜRESEL ISINMANIN GIDA FİYATLARI ÜZERİNDEKİ ETKİSİ

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Bu çalışma gıda fiyatları, döviz kuru, petrol fiyatları, küresel ısınma ve küresel risk algısı arasındaki ilişkiyi incelemektedir. Bu ilişkinin incelenmesinde, 27 Şubat 2008 ile 21 Mart 2011 arasındaki günlük veriler kullanılarak Toda ve Yamamoto prosedüründen faydalanılmıştır. Ampirik bulgular yalnızca küresel risk algısı ölçütü olan oynaklık katsayısının gıda fiyatları üzerinde etkili olduğunu göstermektedir. Ayrıca, genelleştirilmiş tepki fonksiyonu sonuçlarına göre bütün değişkenlerin uzun dönemde gıda fiyatları üzerinde etkisi bulunmaktadır.

Anahtar Kelimeler: Gıda fiyatları, petrol fiyatları, döviz kuru, küresel risk algısı, küresel ısınma

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FAO	Food and Agriculture Organization
IMF	International Monetary Fund
OECD	Organization for Economic Co-operation and Development
USDA	U.S Department of Agriculture

CHAPTER 1

INTRODUCTION

Prices of food commodities traded internationally began to have an upward trend after 2006 and increased sharply in the middle of the year 2008. FAO (2011) pointed out that before this historically highest level, they had been relatively stable since 1970s. Price rises in 2008 reached over and above 100 percent for some of the commodities. IMF values show that prices of all food commodities increased tremendously between January 2006 and July 2008 except for sugar and the highest increase was observed in rice with 181 percent. Other rates of increase are 172 percent for palm oil, 160 percent for maize, 151 percent for soybeans and 96 percent for wheat (Gilbert, 2010). Although these record values were controlled by some policies and pushed them down, after the middle of 2010 another food price spike was experienced. FAO Food Prices Index increased from 168.2 to 233.4 between June of 2010 and the same month of 2011 which means a 39% increase. Moreover, in the November and December of 2010 the indices were even higher than their June 2008 values where the highest index value was observed.

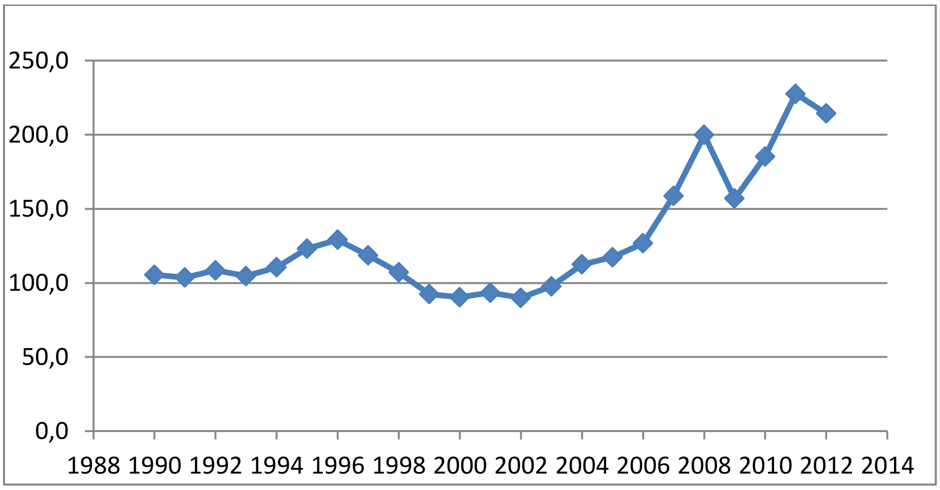


Figure 1.1: FAO Food Price Index, 2012

Price booms in many commodities, especially in food commodities, affect many people, markets and countries in the world. FAO (2008) stated that world food security is threatened by high food prices. Although some internationally traded food commodity producers are gaining from price rises, research shows that it is the poor people that mostly suffered from high prices because they spend a considerable percentage of their income on food. In an aggregate analysis, low income people are more inversely affected by real income decrease caused by food price rise compared to higher income households in the same country. Moreover, FAO also emphasizes that the malnutrition effects of the high food prices on low income households cannot be ignored. According to this research people tend to consume less, unqualified or uniform type food with increasing food prices. Furthermore, USDA (2008) implies that developing countries that mainly import food are affected the most from agricultural food price shocks because citizens of these countries take their nourishment largely from food commodities such as grains and oilseeds. FAO (2008) argues that the share of cereal consumption in the low income countries is 55 percent; on the other hand this share is 45 percent for the high income countries. Also pulses, nuts and oilseeds have 6 percent and 3 percent shares respectively. Therefore, even a small change in the prices of these commodities has huge effects on the welfare of these people and makes them more dependent on other countries for imported food commodities. Hence, countries are affected from high food prices according to their importer or exporter position in international trade (FAO, 2011).

The negative impacts of high food prices triggered interest of many researchers on the reasons behind them. FAO (2008) mentioned the factors affecting the food prices as declining harvest due to climate change, low level of global food stocks, increasing price level of oil, biofuel production, speculative activities of traders in future markets, export bans of countries and less investment for developing agriculture sector. Additionally, OECD (2008) argued that depreciation of US Dollar in which food commodities are generally priced is another cause of high food prices.

Timmer (2008), on the other hand, states that the demand from the developing countries and US dollar depreciation factors can be demonstrated as fundamental factors which do not change for every commodity.

OXFAM (2011) noted that climate change damage agricultural yield and harvest with unexpected weather conditions. The supply shocks in agricultural production caused by climate change are reflected on the prices. In addition to agricultural production; geographic range and types, transportation, storage and policies of the sector are also harmed by climate change (Antle, Capalbo 2010). Piesse&Thirtle (2009) argue that effects of climate change are different between tropical and temperate regions. Therefore, the impact of climate change on local prices may differ across countries.

Decreasing stock levels of agricultural commodities can also be due to climate change. OECD-FAO (2007) report shows that world cereal prices increased due to extreme weather conditions in Australia, U.S., EU, Canada, Russia and Ukraine(Mitchell,2008). However, quantity declined in grain production in these countries is less than the increased production in Argentina, Kazakhstan, Russia and the U.S so it cannot be the primary factor of global price increase. The decline in the Stock level may also be due to increasing demand by developing countries such as China and India. However, Mitchell (2008) indicates in his article that it cannot be a major factor because these countries export grains more than the quantity they import and grain consumption globally did not increase between 2000 and 2007.

As already mentioned, depreciation in U.S. Dollar can be another factor behind the food price jump. Mitchell (2008) argues that U.S. Dollar lost 35% value against the Euro between 2002 and 2008 and food prices increased due depreciation of U.S. dollar by 20% in this period. This is mainly due to the US being the largest exporter in globally traded food commodities.

Energy, specifically oil, are used in all parts of agricultural production process such as fertilizer, drying and transportation as an input cost and this pushes up the prices of final goods (Capehart & Richardson, 2008). Likewise, high oil prices may cause people to demand more ethanol relative to oil and increase the prices of corn which is the content of ethanol. Hence, one can expect a direct link between primary energy prices and food commodity prices.

Note also that food, oil, exchange rate and carbon permit markets are subject to speculative movements. Furthermore, these markets are increasingly used by investors for diversification and hedging purposes. However, the behaviors of global investors are shaped by their risk perceptions in financial markets. In order to take risk perceptions in global stock markets into account, this paper also includes VIX (volatility index) derived from the implied volatilities of the S&P 500 options prices.

Previous researches show that there is an empirical relationship between agricultural food prices and the factors other than market demand and supply fundamentals. Furthermore, research also shows that daily transmission mechanisms between markets are free from fundamentals that affect long run market equilibrium.

The main aim of this thesis is to examine the factors affecting daily food prices such as exchange rates, oil prices, global risk perception and global warming. To measure these factors U.S dollar/euro for exchange rate factor, daily dollar prices for oil, volatility index for global risk perception and CO_2 emission market prices for global warming factor are used. Although there have been many researches pointing out the effects of global warming on food prices, to the extent of our knowledge, there is no study quantifying the climate change and food price relationship. Note that since carbon emissions are not available daily, we utilize carbon emission permit prices, whereas high demand for permits pushes permit prices up. Carbon emission permit can be viewed as the price for the right to pollute. Therefore, high demand for permits not only push permit prices up, but also indicate increased economic activity that results in more emission. This thesis is probably the first to use CO_2 emission permit market prices in the analysis of the high food prices and adds to the literature by quantifying the link between global warming and food prices on a daily basis.

The remaining of the thesis is organized as follows. Next chapter discusses the relevant literature. Third chapter gives information about the data. Fourth and fifth chapters present methodological issues and empirical results. Last chapter concludes.

CHAPTER 2

LITERATURE

There are many researches which mention the causes of the rising food prices in the literature. In this thesis we focus on the link between food commodity prices, oil prices, dollar/euro exchange rate, volatility index and carbon emission permit market prices. Therefore, the literature review is organized according to the factors examined in the thesis.

2.1 Oil prices:

Oil prices influence food price movements in many ways. Firstly, increasing energy prices result in a rise in input costs such as production and transportation. In the steps of fertilizing of the crops and transporting the final products, oil is used intensively and a rise in oil price caused about 20 percent increase in food commodity prices between 2002 and 2007. Second way of the affecting mechanism of oil prices is that increasing demand for biofuel which is produced from agricultural commodities mainly corn and maize. With the rise of oil prices people tend to use oil substitutes and as a result of increasing demand for biofuels food commodity prices surge (Mitchell, 2008). Chang and Su (2010) confirm the volatility spillover from crude oil prices to corn and soybean prices when the oil prices are in their high levels which indicate the substitution effect of high crude oil prices.

In a similar way Piesse &Thirtle (2009) address the oil prices linkage with supply side of agriculture and express that using artificial nitrogen fertilizer in agricultural production causes dependence on oil prices because of intensive using of oil in this type of fertilizer.

Biofuel production has been increasing rapidly since the 2000s. Two leader countries in ethanol (content of biofuel) production Brazil and U.S. use mainly sugarcane and corn in ethanol production. On the other hand, the European Union which is on the first rank in biodiesel production prefers rapeseed oil in production of this fuel. Moreover, mandates for using biodiesel in EU led to an increase in production of rapeseed in Canada, Russia and Ukraine, soybean oil in Brazil and Argentine to meet the demand in Europe. Similarly, increasing corn use in ethanol production resulted in about 2 billion bushels-53 million metric tons- rise in U.S corn demand between 2002/03 and 2007/08 crop years. That escalating U.S. corn demand which causes higher prices in the country has also an impact on corn prices in rest of the world because of U.S being the largest exporter among them (Trostle, 2008). As more land is allocated to crops used in biofuel production, prices of other agricultural products will be indirectly affected due to decreased acreage reserved for these food items.

About the biofuel issue, Lustig (2009) argues that if biofuel had not been produced, prices of agricultural commodities would not have been as high as they are observed. According to McPhail and Babcock (2008) by giving up the subsidies for ethanol production in the U.S., 18.6 percent decrease in ethanol production and 14.5 percent decrease in the prices of corn which is the content of ethanol can be attained. (Lustig, 2009).

According to Baffes (2007) increasing crude oil prices affect negatively demand for food commodities by decreasing disposable income of households. However, supply side impacts of oil price rise outweigh this negative impact and food prices are lead up by oil prices. He also concludes that the response of food commodity prices to changes in oil prices is higher than the responses of other commodities. Hence, food commodity markets are more sensitive to oil price shocks than other commodity markets.

Gilbert (2010) pointed out that effect of oil price as an input cost depends on the size of the demand for agricultural commodities. When demand is low, cost increases affect the prices in a more negative way.

Considering these effects of oil prices on agricultural commodity prices Erdem et al. (2012) analyzed the volatility spillover between oil and agricultural commodity prices by adopting variance causality test. The data is divided into two periods and the test indicates that volatility in oil prices is transmitted to agricultural commodity prices after the period of crisis.

In the literature there are also some studies combining the effects of oil prices with other variables. Nazlıoğlu and Soytaş (2010) investigate the impact of oil prices on agricultural commodity prices for an emerging market Turkey by considering exchange rates. In their study they employ Toda and Yamamoto procedure and Generalized impulse response analysis between agricultural commodities (wheat, maize cotton, soybeans and sunflower) prices, oil prices and lira-dollar exchange rates. They conclude that Turkish agricultural commodity prices are not affected from changes in oil prices and exchange rates. In another study conducted by Nazlıoğlu and Soytaş (2011) they examine the relationship between prices of twenty four agricultural commodities, oil prices and real effective dollar exchange rate against major currencies. By using panel cointegration and Granger causality methods, they achieve that changes in prices of oil and the value of dollar have an impact in agricultural commodity prices. Moreover, Serra et. al. (2011) investigate the price transmission between ethanol, corn, oil and gasoline prices in U.S. By utilizing vector error correction model for monthly data between 1990-2008 years, they conclude that there is a long run relationship between these variables.

The literature discussed in this section suggests that the link between food prices and oil prices is relevant and complex. It is evident from the literature that more research is needed to illuminate the dynamic link between oil and food commodity markets.

2.2 Exchange Rates:

Similar to plenty of other commodities agricultural food commodities are traded in U.S. Dollars in international markets and changes in exchange rates spread on all commodity prices. Abbott et al. (2009) states that dollar depreciation causes a rise in commodity prices, on the other hand an appreciation results in price reduction. This effect occurs faster than effects of other factors such as cost and substitution. A study conducted by Baek and Koo (2010) verifies that there is a negative relationship between exchange rate (value of one U.S. dollar against trading partners' currencies) and commodity prices in the long run. Moreover, according to them exchange rate has a negative impact on U.S. food prices, too. By constructing a VAR model between food prices, exchange rate and energy prices, they applied a Johansen Cointegration Test and found that energy price and exchange rates have significant influence on U.S. food prices in the long-run.

According to Johnson (2008) when the U.S. dollar depreciated against euro from 2002 to 2008, it was inevitably reflected on food commodity prices. In the article the affecting mechanism is explained as the depreciation of U.S. dollar against euro causing less expensive euro prices for the commodities, demand from euro-income countries increasing and finally dollar prices rising to equalize them confirming purchasing parity hypothesis.

Abbott (2009) notes that the highest level of food prices was observed in 2008 when the U.S. dollar was in its lowest level and the impact of depreciation was seen rigidly in countries who pegged their currencies to the dollar. Moreover, it is also stated by Abbott (2009) that corn prices in terms of U.S. dollar soared much more than the prices in terms of euro because people in countries which have appreciated currency tend to import more despite the high world prices. Abbott et al. (2009) point out that U.S. dollar price of corn increased by 177 percent from 2002 to July 2008, however it increased by 29 percent in real terms of euro. Similarly these rates are 203 percent and 41 percent for soybeans and 137 percent and 10 percent for wheat respectively.

Furthermore, Abbott (2011) states that a change in exchange rates for different currencies has a negative impact on competitiveness of some markets such as the Chinese soybean market. Another way of describing the reason why commodity prices in terms of the U.S. dollar affect the international prices is that U.S is a large country which can lead the international commodity markets including agricultural commodity markets (Abbott, 2011).

Akram (2008) explains a model between commodity prices in foreign currency and U.S. dollar prices. The study concludes that prices of internationally traded commodities are equal to each other in different countries when it is converted to U.S. dollars. In a similar way this model implies that when the U.S. dollar loses value, foreigners take the advantage of relatively lower commodity price in U.S. dollars which ends up with rising dollar prices of commodities. It is also estimated in the article that lower interest rates causes higher commodity prices indirectly by originating depreciation of U.S. dollar.

Therefore, according to the literature, the U.S. dollar/euro parity also has a strong complicated relationship with food commodity prices. However, there are not many studies on the daily price and volatility spillover links between currency and commodity markets from investor's perspective. Furthermore, the extant literature does not seem to allow for feedback effects from food markets to currency markets.

2.3 Climate Change:

Jain et al. (2009) describes climate change as "changes in the variability or average state of the atmosphere over time and over a region, or in other words all forms of climatic inconsistency.'' It is also stated in the article that climate change has impacts on precipitation patterns, water resources, floods, droughts and quality of water. Because agriculture sector is dependent on climate, the combined effects of its change makes agricultural vulnerable to climate change inevitably. Lobell et al. (2011) implies that over the next 20-30 years 0.2 ^{0}C increase of global warming per

decade will affect crop production. They also developed a regression model between crop production, crop locations, growing seasons, monthly temperature and precipitation values, then obtained a statistical result that agricultural production is sensitive to temperature and precipitation factors. When the temperature is increased by 1 ^{0}C, crop yield decreases by about 10 percent in low-latitude countries. On the other hand, too much precipitation rise constitutes damage for crop yields. However, temperature trends are more effective than the precipitation factor. Moreover, if it is examined the crop specific impacts of climate change; it is obtained that maize and wheat lose 3.8 and 5.5 percent yields respectively.
Antle and Capalbo (2010) summarized the potential effects of climate change and greenhouse gas (GHG) emission on agricultural production sector as transportation difficulties due to sea level rise, storage structure changes, food pathogen type changes and policies about these issues alteration.

According to Shmidhuber and Tubiello (2007) greenhouse gas emissions form a basis for climate change and crop yields respond differently from region to region. For example, in temperate regions crop yields increase with rising global mean temperature due to greenhouse gases, however in drier areas they may decrease as temperatures rise. Moreover, it is indicated in the article that higher CO_2, one of the greenhouse gases, emissions may affect crop yields positively depending on their irrigation and fertilization programs. For example, Lobell et al. (2011) indicate that increasing CO_2 level together with climate change affect rice and soybean positively while affecting wheat and maize negatively. According to Von Braun J. (2007) higher level of atmospheric CO_2 can decrease 3 percent of the damages resulted by climate change. So as it is mentioned by Trostle (2008) the effects of climate change on crop production is uncertain.

It is explained by Abbott et al. (2011) that production losses due to extreme weather conditions decrease the world stocks of grain in 2010-11 and result in a higher price jump even more than the 2008 food price crisis. It is stated in the article that these residual prices are because of largest decline in wheat production due to adverse weather in Black Sea region, Canada and Australia and 10 percent decrease in barley production because of drought encountered in Europe and the former Russia. Moreover, Schmidhuber and Tubiello (2007) conclude that average food prices are expected to rise as a result of increasing temperature until 2050. They project that food prices will be more sensitive to temperature changes after 2050.

Contrary to other researchers' findings Mitchell (2008) implies that grain production shortfall due to droughts in Australia in 2006 and 2007 years was stabilized by production increase in Argentina, Kazakhstan, Russia and U.S. However; together with the effects of biofuel production, land use changes and decreasing crop stocks he accepted its influence on prices.

It is evident that the impact of climate change on agricultural crop yields can only be observed in the long run. In this thesis, however, we are interested in the prices of food commodities that are traded daily. Daily climate changes are highly unlikely to have an impact on day to day trading or on long run investment schemes. Therefore, instead of using climate data, we utilize carbon emission permit prices that can also be traded daily. The carbon permit prices reflect how much emission business firms expect to emit. Hence, increasing emission permit prices may give positive signals to market players regarding economic performance of firms. Environmental policies influence producers, traders in pollution permit markets, and the macroeconomy. Furthermore, there are also speculative movements across financial, commodity, currency and very likely carbon markets. Speculative behavior may provide a link between food commodity prices and carbon emission permit prices. To the extent of our knowledge, there is no study in the literature that takes this relationship into account.

2.4 Global Risk Perception:

Hartelius et. al (2004) define Volatility Index which is denoted as VIX as " a proxy for investor's attitude toward risk". Moreover, they imply that VIX is good at explaining the emerging market bond spread. Bond spread means the yield difference between bonds with different risks. According to them decreasing VIX which means reduction in investors’ risk aversion cause an increase in bond spreads. They estimate a panel regression model by Ordinary Least Square to see the effect of volatility index on bond spreads and find that if VIX is increased by one standard deviation, bond spreads show an increase by about 30 percent.

Moreover, Becker et al. (2008) presents the superiority of implied volatility which is measured by VIX to market based forecasts. In their article they considered the relation between implied volatility and price jump according to their time. By testing the effects of historical VIX, they obtained that option markets reflect the historical price jump activity. In the analysis of spot market VIX to future jump activity in volatility, they also found that VIX has an impact on future price volatility forecasts. Considering these results simultaneously, they conclude that VIX has a correlation with historical price volatility and future price movements.

Hacıhasanoğlu et al. (2010) mention that after the global financial crisis in 2008 global risk aversion is thought to have a significant effect on volatility transmission between commodity markets. They test cointegrating relations among the volatility index (measure of investors’ risk aversion), exchange rates and oil, gold and silver prices and find that volatility index affect oil prices negatively in a significant way. The channels through which high volatility index affect the oil prices are summarized in the article. Firstly, economic uncertainty due to financial crisis causes investors to limit energy demand which reduces price of oil. Secondly, as VIX increases people invest in safer assets rather than real investments which results in decreasing energy demand and prices.

Global crisis in 2008 has also changed the investment decisions of international investors. In order to test the impacts of international diversification on emerging markets, Hacıhasanoğlu and Soytaş (2010) analyze the effect of global risk perception on the country risk perception of international investors denoted by credit default swaps of eight developing countries which are Argentina, Mexico, Brazil, Turkey, South Africa, Russia, Bulgaria and Romania. In the result of Toda and Yamamoto procedure, they obtain that change in the global risk perception which is measured by VIX influences the contagion of crisis in the short run.

Stivers and Sun (2002), on the other hand, examine the effect of stock market uncertainty which is measured by volatility index (VIX) on correlation between daily stock and Treasury bond returns. They estimate different models to test this relation. In the first model they find that the lagged VIX has a negative impact on co-movement between stock and bond returns. In the second model, they conclude that it is useful and reasonable to use lagged VIX in explaining the mentioned relation. Thirdly, as a result of two-state, regime shifting model they observe that co-movement of stock and bond returns depends on VIX regime of the state. In the final model they find that there is a positive relation between VIX and bond returns. As a whole, it can be concluded in the article that VIX plays an important role in stock and bond returns correlation.

As global risk perceptions shape diversification and hedging strategies of global investors, we expect the dynamic linkages between alternative investment markets, including commodity markets, to get stronger. Furthermore, changes in global risk perceptions of investors may also be driving the carbon permit budgets of business firms. Therefore, it is important to take global risk perceptions of international investors into account, to understand the daily price movements in food commodity markets.

CHAPTER 3

DATA CHARACTERISTICS

In order to examine the dynamic links discussed in four different lines of literature, links between factors and the food prices; the variables corn prices, carbon permit market prices, Brent oil price, US dollar/euro exchange rate and volatility index are used in this thesis. All data are 5-day week daily time series and covers the period February 27, 2008 and March 21, 2011 which includes 793 observations. Moreover, natural logarithms of the variables are taken in the analysis. The selection and use of the variables which are included in the model depend on such conditions:

- Corn price (denoted as CORNP) is used in the model to represent the food prices. 5-day week daily time series data is obtained from Bloomberg and it is measured by cent per bushel. The reason why corn price is chosen is that it reflects the effects of contributing factors significantly because it is traded in dollars in international markets. Moreover, global warming and increasing oil prices, production of ethanol obtained from corn, mostly influence corn prices. Other food commodity prices can be used in future research.

- Carbon Permit Market Price (denoted as CEP) is considered as the measure of global warming. Companies are allowed to spread fixed amount of carbon dioxide to the atmosphere in order to reduce pollution and global warming effect of these emissions. Moreover, extra carbon emission permits are traded in the market and increasing permit prices reflect the increasing carbon emission and global warming implicitly. Bluenext exchange values in dollars are used for the carbon permit prices in the model.

- Oil prices (denoted as OILP) are included in the model because of cost and substitution effects of the oil. Increase in oil prices cause an increase in input cost of agricultural products and also rising oil prices tends to rise of using biofuel, such as ethanol, causing increase in prices of them. In our analysis, Brent oil price which is constituted from Brent Blend, Forties Blend, Oseberg and Ekofisk crudes are used and it is resourced from Bloomberg.

- Dollar/euro Exchange Rate (denoted as EXR) is used in the analysis of the food prices (corn prices in our model) since similar to other commodities food commodities are also traded in US dollars. 5-day week daily US dollar/euro exchange rate values obtained from Bloomberg are utilized in the VAR model.

- Volatility Index (denoted as VIX) which is calculated from S&P 500 Index option prices is used to measure the effects of global risk perceptions on food prices. It has been assumed that investor attitudes towards risk affect market movements, so this variable is used to explain food commodity price movements. Data utilized in analysis of our model is collected from Bloomberg.

Figure 3.1 expresses the movements of the Carbon Emission Permit Prices, Volatility Index, Oil prices, Dollar/euro Exchange rates and Corn prices which include the period between February 26, 2008 and March 21, 2011. It can be clearly seen that variables are highly correlated until the beginning of the year 2009. If the Volatility Index (VIX) is considered, until the middle of the year 2008 market participants' risk aversion had been decreasing and it might result in an increase in commodity prices. The co-movements between some of the series can be observed by naked eyes. This suggests that there may be a link between these variables. In recent years variables have been continuing to show correlation among them.

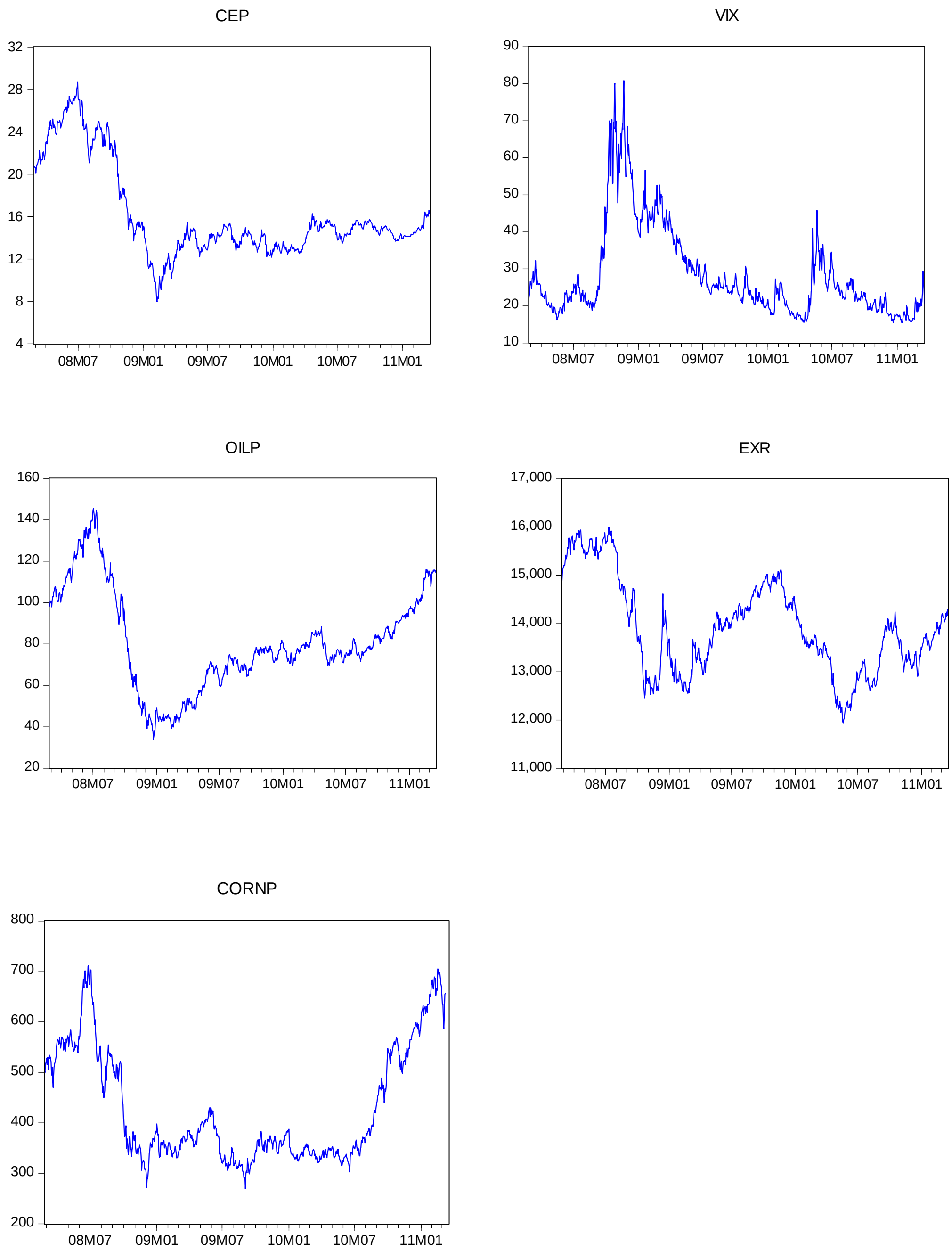


Figure 3.1 Movements of the variables between 26/02/2008 and 21/03/2011

Table 3.1 reports the correlation coefficients between variables. It indicates that highest association occurs between oil prices and corn prices whereas lowest of these relations is shown between oil prices and carbon emission prices.

Table 3.1 Correlation matrix

	CEP	OILP	EXR	VIX	CORNP
CEP	1				
OILP	0,25722	1			
EXR	0,61412	0,51029	1		
VIX	-0,1269	-0,5432	-0,4037	1	
CORNP	0,56721	0,79184	0,44902	-0,4161	1

The descriptive statistics of the data given in Table 3.2 indicates that volatility index (VIX) has the highest coefficient of variation (0.43) which points that volatility index has the highest volatility. It is not surprising because people's risk perception is highly changeable from time to time.

Table 3.2 Descriptive Statistics

	CEP	EXR	OILP	VIX	CORNP
Mean	16.17716	13911.83	81.22023	28.31079	429.5822
Median	14.65000	13813.00	77.23500	24.16500	373.0000
Maximum	28.73000	15990.00	145.6600	80.86000	711.0000
Minimum	7.960000	11942.00	34.04000	15.45000	269.5000
Std. Dev.	4.421304	975.6711	23.98612	12.20580	112.3306
Skewness	1.176674	0.351278	0.460524	1.724495	0.829613
Kurtosis	3.255200	2.282106	2.794894	5.752651	2.376888
Coef. of var.	0.273289	0.070132	0.295320	0.431135	0.261488
Jarque-Bera	186.7792	33.63191	29.67994	649.0873	103.7937
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	12941.73	11129.465	64976.18	22648.63	340658.7
Sum Sq. Dev.	15618.80	7.61E+08	459691.7	119036.2	9993592.
Observations	800	800	800	800	793

Descriptive statistics are for log return series.

Next section introduces the methodology used in this thesis.

CHAPTER 4

METHODOLOGY

In this thesis Toda and Yamamoto procedure (1995) is employed to investigate the effects of the factors on the food prices. The advantage of Toda and Yamamoto procedure (1995) is that it is not necessary to test for co-integration and estimate the cointegrating equation and it can be applied to variables which have different levels of integration. Toda and Yamamoto procedure aims to test long run Granger causality between variables. Steps of the Toda and Yamamoto procedure can be summarized as follows:

4.1 Toda and Yamamoto Procedure:

1. Stationarity which can be defined as having constant mean, constant variance and constant autocovariances for each given lag of the time series is important, because it can influence the behavior and properties of the series. If the non-stationary data is used in analysis, it can lead to spurious regression. In this type of regression standard measures of the regression appears good but they are meaningless. So, in Toda and Yamamoto procedure, unit root tests are conducted first to obtain the order of integration of all variables in the analysis. In the test for a unit root in equation $y_t = \Phi y_{t-1} + u_t$, Dickey and Fuller (1979) examine the following null hypothesis that:

   H_0: Φ=1 (4.1)

   $$H_0: series\ contain\ a\ unit\ root$$
   $$H_1: series\ is\ stationary \quad (4.2)$$

   If y_{t-1} is subtracted from both sides of equation, the model will be:

   $\Delta y_t = \Psi y_{t-1} + u_t$ where Ψ =Φ-1 (4.3)

Then, H_0: Ψ =0

H_1: Ψ< 0 (4.4)

Another research conducted by Dickey and Fuller (1981) obtained the test statistics $\frac{\Psi}{SE\ \Psi}$ to test the significance of lagged y.

These tests, however, assume that u_t is white noise and not autocorrelated. If there is a correlation between series at higher order of lag, the assumption of white noise disturbances are not valid. To solve this problem, the test is augmented with d lags of dependent variable and Augmented Dickey-Fuller (ADF) test is conducted on Ψ similar to Dickey-Fuller (DF) test.

The model by adding d lagged difference terms of the dependent variable to the right hand side of the test regression will become:

$$\Delta y_t = \Psi y_{t-1} + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \ldots + \alpha_d \Delta y_{t-d} + u_t \quad (4.5)$$

The test is repeated with similar test statistics and null hypothesis (4.4) in Dickey-Fuller test.

DF, ADF type tests have low power, especially in small samples, therefore to check the robustness of our results we employ Dickey Fuller-GLS (DF-GLS) detrended unit root test developed by Elliot et al. (1996).

In the DF- GLS detrended test a constant or a constant and a linear time trend can be included in ADF test regression. The difference of the DF-GLS Test from the ADF test is that data is detrended by eliminating non-stochastic trend component and cross sectional correlations. Differenced y_t is defined by Elliot et al. (1996):

$$d\ y_t \backslash a \ = \ \begin{matrix} y_t \ if\ t = 1 \\ y_t - a y_{t-1}\ if\ t > 1 \end{matrix} \quad (4.6)$$

Then, with differenced $d\ y_t \backslash a$ a new regression model is constructed:

$$d\ y_t \backslash a \ = d\ x_t \backslash a\ '\delta\ a\ + \eta_t \quad (4.7)$$

Where x_t may contain a constant or a constant and trend components and

$\delta\ a$ is Ordinary Least Square Estimates of the regression

a is used instead of a in the equation. It is defined as:

$$a = \begin{matrix} 1-\frac{7}{T}\ if\ x_t = \ 1 \\ 1-\frac{13.5}{T}\ if\ x_t = \ 1, t \end{matrix} \tag{4.8}$$

With the estimates of a, GLS detrended data y_t^d is defined:

$$y_t{}^d = y_t - x_t{}'\delta\ a \tag{4.9}$$

The GLS detrended data $y_t{}^d$is substituted in standard ADF regression for y_t. The new regression model becomes:

$$\Delta y_t^d = \alpha y_{t-1}^d + \beta_1 \Delta y_{t-1}^d + \cdots + \beta_p \Delta y_{t-p}^d + v_t \tag{4.10}$$

Differently from ADF test x_t is not included in the model because y_t^d are detrended. Moreover, t ratio for α is considered and this ratio follows Dickey Fuller distribution when there is only constant in the regression. If a constant and trend is included in the regression, the critical values of the test statistic is simulated.

By using ADF and DF-GLS detrended tests, maximum order of integration (denoted as d) are set.

2. Optimum lag length (k) of the vector autoregressive (VAR) model which will be used in the analysis is determined. It is important to include optimum lag length in the model to make correct estimation. In specifying the optimum lag length, LR tests, Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ) can be utilized.

These information criteria are given as:

Akaike Information Criterion (AIC) = $-2\ \frac{l}{T}\ + 2\ \frac{k}{T}$ (4.11)

Schwarz Information Criterion (SC) =$-2\ \frac{l}{T}\ + \frac{klog\ T}{T}$ (4.12)

$$\text{Hannan-Quinn Criterion (HQ)} = -2\ \frac{l}{T}\ + \frac{2k\log(log\ T\ )}{T} \tag{4.13}$$

where l is the value of the log of the likelihood function with the k parameters using T observations. Information criteria punish the unnecessary inclusion of extra lags. They differ according to the punishment terms they use after the plus sign.

3. Optimum lag length (k) obtained by benefiting from more than one information criteria is increased by the maximum order of integration (d) and the lag augmented VAR(k+d) model is estimated. VAR model is a way to forecast interrelated time series systems. In a VAR model, there is more than one dependent variable and every endogenous variable in the system is modeled as a function of the lagged values of all endogenous variables. Moreover, dynamic impact of random disturbances on the system can be easily detected. VAR models can be accepted as sidestep of large-scale simultaneous equations structural models. Advantages of the VAR model to the researchers are that all variables included in the model are endogenous and the model is more flexible compared to univariate models.

The mathematical representation of a VAR is:

$$y_t = a_0 + a_1 y_{t-1} + \ldots + a_k y_{t-k} + b\ \ x_t + \varepsilon_t \tag{4.14}$$

where y_t is a vector of endogenous variables,

x_t is a vector exogenous variables,

$a_1 \ldots a_k$ and b are estimated matrices of coefficient

ε_t is white noise disturbance term with E(ε_t)=0, (t=1,2…) and uncorrelated with their own lagged values and all other variables.

For a bivariate VAR(1) model:

$$y_{1t} = a_{10} + a_{11} y_{1t-1} + b_{11} y_{2t-1} + u_{1t} \tag{4.15}$$

$$y_{2t} = a_{20} + a_{21} y_{2t-1} + b_{21} y_{1t-1} + u_{2t} \tag{4.16}$$

or

$$\begin{matrix} y_{1t} \\ y_{2t} \end{matrix} = \begin{matrix} a_{10} \\ a_{20} \end{matrix} + \begin{matrix} a_{11} & b_{11} \\ a_{21} & b_{21} \end{matrix} \begin{matrix} y_{1t-1} \\ y_{2t-1} \end{matrix} + \begin{matrix} u_{1t} \\ u_{2t} \end{matrix} \quad (4.17)$$

4. In order to have valid estimations of all equations in VAR, some assumptions must be satisfied. These assumptions are:
   (1) $E\ u_t\ = 0$, average value of the error terms is assumed to be equal to zero.
   (2) $Var\ u_t\ = \sigma^2 < \infty$, variance of the errors is assumed to be constant. If it is not constant, error terms are called heteroscedastic.
   (3) $Cov\ u_i, u_j\ = 0$, which means that error terms are uncorrelated. If this assumption is not satisfied, errors are called as autocorrelated or serially correlated.
   (4) $Cov\ u_t, x_t\ = 0$, which means independent variables x_t in the equation are uncorrelated with error terms,
   (5) $u_t \sim N(0, \sigma^2)$, error terms are distributed normally with zero mean and constant variance.

With the help of diagnostic tests, it is tested whether the assumptions are violated or not.

To specify heteroscedasticity in model, plot of the residuals against explanatory variables and White test can be helpful. In White test, firstly residuals from linear regression models are estimated:

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + u_t \quad (4.18)$$

Then, with these residuals a new regression equation is estimated:

$$u_t{}^2 = \alpha_1 + \alpha_2 x_{2t} + \alpha_3 x_{3t} + \alpha_4 x_{2t}{}^2 + \alpha_5 x^2{}_{3t} + \alpha_6 x_{2t} x_{3t} + v_t \quad (4.19)$$

where v_t is normally distributed. Squares of residuals are taken into consideration in regression model and by using this model, F-test can be conducted. Another approach which can be utilized is Lagrange Multiplier (LM) test. It is based on the value of R^2 for the new regression model in (4.17). The test statistics is:

$$TR^2 \sim \chi^2(m) \quad (4.20)$$

where m is number of regressors, and T is number of observations

The null hypothesis of the test is:

$$H_0: \alpha_1 = 0 \; and \; \alpha_2 = 0 \; and \; \alpha_3 = 0 \; and \; \alpha_4 = 0 \; and \; \alpha_5 = 0 \; and \; \alpha_6 = 0 \quad (4.21)$$

If the test statistics is greater than statistical table value, the null hypothesis of homoscedasdicity is rejected.

Another test to identify heteroscedasdicity in the model is Breusch-Pagan-Godfrey (BPG) test which is a Lagrange multiplier test. It tries to detect dependence of the variance of the model to explanatory variables. The test is conducted on log of the squared residuals of original equation. The null hypothesis of the test is no heteroscedasdicity.

Assume that:

$$\sigma_i^2 = \delta_0 + \delta_1 X_1 + \cdots + \delta_p X_p \quad (4.22)$$

The null hypothesis is:

$$H_0: Var \;\; u_i \backslash X_i \;\; = \sigma^2$$

Or (4.23)

$$H_0: \; \delta_1 = \delta_2 = \cdots = \delta_p$$

Estimates of the error terms are:

$$u_i^2 = \delta_0 + \delta_1 X_1 + \cdots + \delta_p X_p + v_i$$

Breusch-Pagan-Godfrey test statistic is:

$$N \times R^2 \sim \chi_p^2 \quad (4.24)$$

To detect serial correlation in the model, some tests such as Durbin-Watson and Breusch-Godfrey tests should be conducted. Durbin-Watson is used for testing first order autocorrelation in series. It is not explained in detail, because in this thesis Breusch-Godfrey Test is utilized. Unlike Durbin-Watson test, Breusch-Godfrey Test can detect higher order autocorrelation. Under this test the model for error terms is:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \ldots + \rho_r u_{t-r} + v_t \quad (4.25)$$

where $v_t \sim N(0, \sigma^2)$

The hypotheses are:

$$H_0: \rho_1 = 0 \; and \; \rho_2 = 0 \; and \; \rho_3 = 0 \; and \; \ldots and \; \rho_r = 0 \qquad (4.26)$$

$$H_1: \rho_1 \neq 0 \; or \; \rho_2 \neq 0 \; or \; \rho_3 \neq 0 \; or \; \ldots or \; \rho_r \neq 0$$

Null hypothesis implies that the current error is not autocorrelated with r previous values of the error.

Another diagnostic test is conducted to determine the stability of parameters across the subsamples of the data. Ramsey Reset Test offered by Ramsey (1969) helps to examine the assumption that parameters of the linear regression model are linear. This test indicates also specification errors of the regression model. Apart from serial correlation, heteroscedasdicity and nonnormality of disturbance terms problems, Ramsey Reset Test specifies omitted variables, incorrect functional form and correlation between independent variables and error terms. If these problems exist in the estimated model, estimators will be biased and inconsistent. In application of the test, an auxiliary regression model is conducted firstly:

$$y_t = \alpha_1 + \alpha_2 {y_t}^2 + \alpha_3 {y_t}^3 + \cdots + \alpha_p {y_t}^p + \quad \beta_i x_{it} + v_t \qquad (4.27)$$

${y_t}^2$, ${y_t}^3, \ldots, {y_t}^p$ values can be helpful to indicate non-linear relationships in the model.

The null hypothesis of the test is:

$$H_0: The \; functional \; form \; is \; correct. \qquad (4.28)$$

The test statistics of the regression model is:

$$TR^2 \sim \chi^2(p-1) \qquad (4.29)$$

If the test statistics TR^2 exceeds the critical value obtained from the χ^2 table, the null hypothesis is rejected.

5. According to the results of information criteria, a Wald test is conducted on the first k lags of the variables in the lag augmented VAR model equations. The test statistics computed in the result of Wald test relies on the unrestricted regression and the restriction in the null hypothesis is tested by this method. Clearly, Wald test is the way of testing significance of the coefficients of independent variables in the model.

   The null hypothesis of the test is:

H_0= The parameter of a particular explanatory variable is zero.

or (4.30)

H_0= The parameters of group explanatory variables are zero.

If the null hypothesis is not rejected, then it is concluded that the Wald test is not significant and the tested variables can be omitted from the model. If the null hypothesis is rejected, then the Wald test is significant and tested variables can be included in the model.

4.2 Generalized Impulse Response:

To determine the effect of a unit shock to one variable in VAR model on other endogenous variables, generalized impulse response analysis developed by Koop et al. (1996) and Pesaran and Shin (1998) is used. Differently from F-test, generalized impulse response analysis helps to find out how a change in one variable affects other variables and how long this effect continues. In the analysis, a unit shock is applied to the each variable of the each equation and the obtained result on VAR model is examined. Since the error terms of the other equations are assumed to be constant, when an error term is taken in analysis, some difficulties arise in impulse response. In order to deal with these problems ordering of the variables is important. However, in generalized impulse response ordering has little sense.

$$Y_i = \sum_{i=1}^{p} \alpha_i Y_{t-i} + u_i \quad (4.31)$$

$$Y_i = \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{4.32}$$

$$\Phi_i = \alpha_1 \Phi_{i-1} + \alpha_2 \Phi_{i-2} + \cdots + \alpha_p \Phi_{i-p} \quad i = 1,2,3 \ldots \tag{4.33}$$

where $E\ u_t u_t' \ = \Sigma$

$$X_t = \sum_{i=0}^{\infty} (\alpha_i P)(P^{-1} u_{t-i}) \tag{4.34}$$

where PP'=Σ

Generalized Impulse Response Function is defined as:

$$GIRF_x\ n, \delta_j, \Omega_{t-1}\ = E\ X_{t+n} \backslash u_{jt} = \delta_j, \Omega_{t-1}\ - E\ X_{t+n} \backslash u_{jt} = \Omega_{t-1} \tag{4.35}$$

CHAPTER 5

EMPIRICAL RESULTS

To examine the factors affecting daily food prices, Toda and Yamamoto procedure is employed. In order of the steps of Toda and Yamamoto procedure, first stationarity of series is tested. Stationarity of series used in VAR model is of vital importance in analysis in order to avoid spurious estimation results. Therefore, Augmented-Dickey Fuller (ADF) and Dickey Fuller GLS (DF-GLS) tests are conducted to check whether there is a unit root or not in the variables.

Table 5.1 Results of the Unit root tests

		ADF		DF-GLS	
		Level	Difference	Level	Difference
LCORNP	Intercept	-0.762052	-27.77436***	-0.90294	-11.8892***
	Intercept and trend	-0.761312	-27.84926***	-0.72857	-27.2863***
LCEP	Intercept	-1.397092	-21.58457***	-0.71186	-26.3627***
	Intercept and trend	-1.166532	-21.59594***	-1.26053	-21.3927***
LEXR	Intercept	-1.729918	-27.72808***	-1.14083	-1.31629
	Intercept and trend	-1.570638	-27.73455***	-1.63308	-3.73141***
LOILP	Intercept	-0.876509	-29.51688***	-0.87021	-5.11743***
	Intercept and trend	-0.724412	-29.5945***	-0.66206	-27.5761***
LVIX	Intercept	-2.282804	-24.46464***	-2.05269	-4.8609***
	Intercept and trend	-2.665243	-24.45386***	-2.10629	-22.6761***

***:denotes 1% level of significance, **: denotes 5% level of significance

Unit root test results introduced in Table 5.1 indicate that all variables have unit roots in levels according to ADF and DF-GLS tests. Hence, first differences of the variables are tested for stationarity. Since the first differenced variables are stationary, the log returns are utilized in the VAR model and maximum order of integration (d) is set as one.

Second, in order to choose optimum lag length(k) for the VAR model, results of sequentially modified LR test statistic, Final prediction error, Akaike information criterion, Schwarz information criterion and Hannan-Quinn information criterions are considered.

Table 5.2 Lag length criteria tests

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-18846.46	NA	4.97e+14	48.02920	48.05892	48.04063
1	-11508.47	14563.80	4024874.	29.39739	29.57569*	29.46595*
2	-11472.39	71.15019	3912867.	29.36916	29.69605	29.49485
3	-11446.46	50.81181	3903636.*	29.36678*	29.84226	29.54960
4	-11431.88	28.38415	4008777.	29.39332	30.01739	29.63327
5	-11416.26	30.20287	4105982.	29.41722	30.18988	29.71431
6	-11392.96	44.76289*	4124135.	29.42155	30.34280	29.77577
7	-11377.16	30.14909	4222445.	29.44499	30.51483	29.85634
8	-11359.05	34.32158	4297921.	29.46255	30.68098	29.93103

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 5.2 shows the appropriate lag lengths for different criterions. The minimum lag lengths are identified as one by Schwarz Information and Hannan-Quinn Information Criterions whereas the maximum of it is determined by LR as six. However, in VAR model lag length (k) is chosen as one which is the minimum result of criterions.

Then, with the results of maximum order of integration obtained as one and optimum lag length found as one, VAR(2) model between the variables carbon emission prices, dollar/euro exchange rates, oil prices, volatility index and corn prices is estimated.

As another step of Toda and Yamamoto procedure, to check validity of VAR model, diagnostic tests are conducted. Error terms of the regression models are tested for autocorrelation, heteroscedasdicity and functional specification assumptions. The tests Breusch-Godfrey for serial correlation, Breusch-Pagan- Godfrey and ARCH for heteroscedasdicity and Ramsey RESET for functional specification are used. Results for the diagnostic tests are illustrated in Table 5.3 According to table residuals of the all regression equations pass the Ramsey RESET test which shows stability of parameters. However, result of the Breusch-Godfrey test indicates that there are serial correlation problems for residuals of the Carbon Emission Price and Volatility Index regression models. Moreover, results of the Breusch-Pagan-Godfrey heteroscedasdicity test point out that residuals of the Carbon Emission Prices, Oil Prices, Exchange Rates and Corn Prices regression models reject the null hypothesis of homoscedasdicity. Also, there are conditional heteroscedasdicity problem for the Volatility index and Corn prices regressions. So, standard errors are corrected by White adjustment to solve heteroscedasdicity problem.

Table 5.3 Diagnostic tests

	CEP	OILP	EXR	VIX	CORNP
BG	2.57939*	0.6769	0.8946	3.8581**	2.2073
BPG	10.5758**	10.4814**	9.97485**	26.0276	9.1405**
ARCH	7.61823**	17.0103**	93.7263**	63.2053	7.5672
RESET	0.4689	0.3181	2.8238	0.1981	0.2993

BG: The Breusch-Godfrey test for the null of no serial correlation up to five lags.
BPG: The Breusch-Pagan-Godfrey test for the null of homoscedasdicity.
ARCH: The test for the null of no autoregressive conditional heteroscedasdicity.
RESET: The Ramsey's RESET test for the null of no functional misspecification.
* and ** denote statistical significance at 1, 5% level of significance, respectively.

After specification of VAR(2) model equation, Wald test is conducted to analyze the long run causalities between variables. Results shown in Table 5.4 indicate that only volatility index (VIX) granger causes the corn prices at 1% significance level. The result is consistent with the findings of Hacıhasanoglu et al. (2010) which implies that VIX has a significant impact on commodity prices. Consistently, since oil is traded as a commodity in international markets, change in VIX affects oil prices in the long run. According to Hacıhasanoglu and Soytas (2010) this relation may be due to change in people's investment preferences due to financial crisis. Moreover, similar to findings of Nazlıoğlu and Soytas (2010) which implies that Turkish lira/ US dollar exchange rate and oil prices are not helpful to predict agricultural commodity prices in Turkish market, oil prices in dollar and dollar/euro exchange rates cannot forecast US corn prices. However, the result of non-Granger causality of oil prices to corn prices is contradictory to results of Nazlıoglu and Soytas (2011) and Serra et.al (2011) which imply long run causality of oil prices.

Table 5.4 Wald test results for VAR(2) Model

	CORNP	CEP	EXR	OILP	VIX
CORNP		0.7419	1.0354	1.2145	10.77*
CEP	0.14935		6.5707**	5.3795**	0.1569
EXR	0.3182	0.0006		0.0846	0.8615
OILP	0.6907	0.8008	7.8067*		4.4011**
VIX	0.6389	1.4294	0.6651	17.1848*	

- Table is organized in rows. For example, at the first row 0.7419 tests for the null of non-Granger causality from carbon emission prices to corn prices.
- *, ** and *** denote statistical significance at 1, 5 and10% level of significance, respectively.

If the long run effect of exchange rate is examined according to results of Wald test, only impacts on oil prices coincide with findings in the literature. Wald test results imply that dollar/euro exchange rates Granger cause oil prices at 1% level of significance. Moreover, exchange rates Granger cause also carbon emission prices at 5% significance level which proves that it must be taken into account in the commodity market movements.

On the other hand, oil prices Granger cause volatility index. This interaction may be explained as if the oil prices volatile, investors' attitudes toward risk change and this will be reflected to volatility index. People are vulnerable to mainly change in energy commodity prices.

Effects of factors on exchange rate are surprising because any of the variables Granger causes the exchange rate which implies it is affected only by market demand and supply factors.

VAR(2) Model which is conducted to show long run causalities fail to indicate the causal linkages from carbon emission permit prices, exchange rates and oil prices to corn prices. However, according to the results of different lag length criteria, a VAR(4) model is also used to check the robustness of the VAR(2) analysis. According to results of Final prediction error and Akaike information criterions, optimum lag length is chosen as 3 and VAR(4) Model is estimated with these results. Results of the Wald test for VAR(4) Model are shown in Table 5.5. According to table carbon emission permit prices and exchange rates Granger cause corn prices in the long run which verifies the findings in the literature. Differently from the results for VAR(2) model, volatility index Granger causes only oil prices and oil prices Granger cause it. So, there is a long run relation between these variables.

Table 5.5 Wald test results for VAR(4) Model

	CORNP	CEP	EXR	OILP	VIX
CORNP		2.4269***	2.4293***	1.1959	1.6197
CEP	0.6372		5.2711*	4.6321*	0.5543
EXR	0.7001	0.5502		0.2943	0.1983
OILP	1.3536	1.3073	4.7275*		2.3211***
VIX	0.2891	1.1504	2.2940***	4.8160*	

- Table is organized in rows. For example, at the first row 2.4269 tests for the null of non-Granger causality from carbon emission prices to corn prices.
- *, ** and *** denote statistical significance at 1, 5 and10% level of significance, respectively.

Different causality linkages are observed for models with differently lagged variables in the long run. VAR(2) Model indicates that only causality linkage is observed from volatility index to corn prices. In VAR(4) Model, on the other hand, carbon emission permit prices and exchange rates improve the forecasts of corn prices, but with marginal significance. Hence, overall the VAR(4) model results do not seem to differ considerably from VAR(2) results.

After the specification of long run relationships between variables it may be useful to obtain the results of generalized impulse functions in order to achieve the short run temporary effects of oil prices, exchange rates, carbon emission prices and volatility index. Figure 5.1, Figure 5.2, Figure 5.3, Figure 5.4 and Figure 5.5 indicate the responses of the each variable to one standard deviation shock to another variable.

Figure 5.1 shows the response of corn prices (CORNP) to one standard deviation shock to carbon emission prices (CEP), exchange rates (EXR), oil prices (OILP) and volatility index (VIX). Differently from long run relations, corn prices respond positively and relatively stable to shocks to all variables except volatility index. Shock to volatility index is transmitted to corn prices negatively.

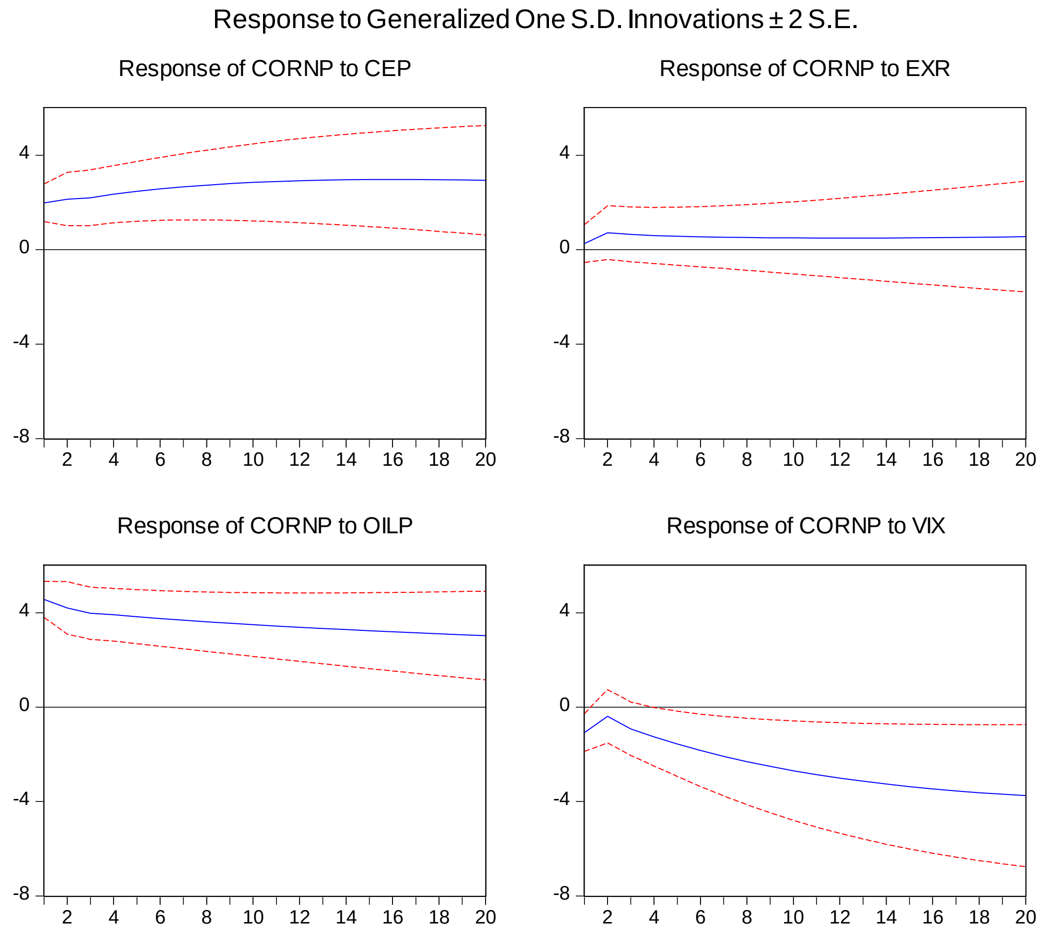


Figure 5.1 Generalized impulse responses of corn prices to other variables

Figure 5.2 shows the response of carbon emission prices (CEP) to one standard deviation shock to other variables. Shocks to corn prices, exchange rates and oil prices affect significantly and positively in the short run. However, impact of volatility index is negative similar to long run effects of it.

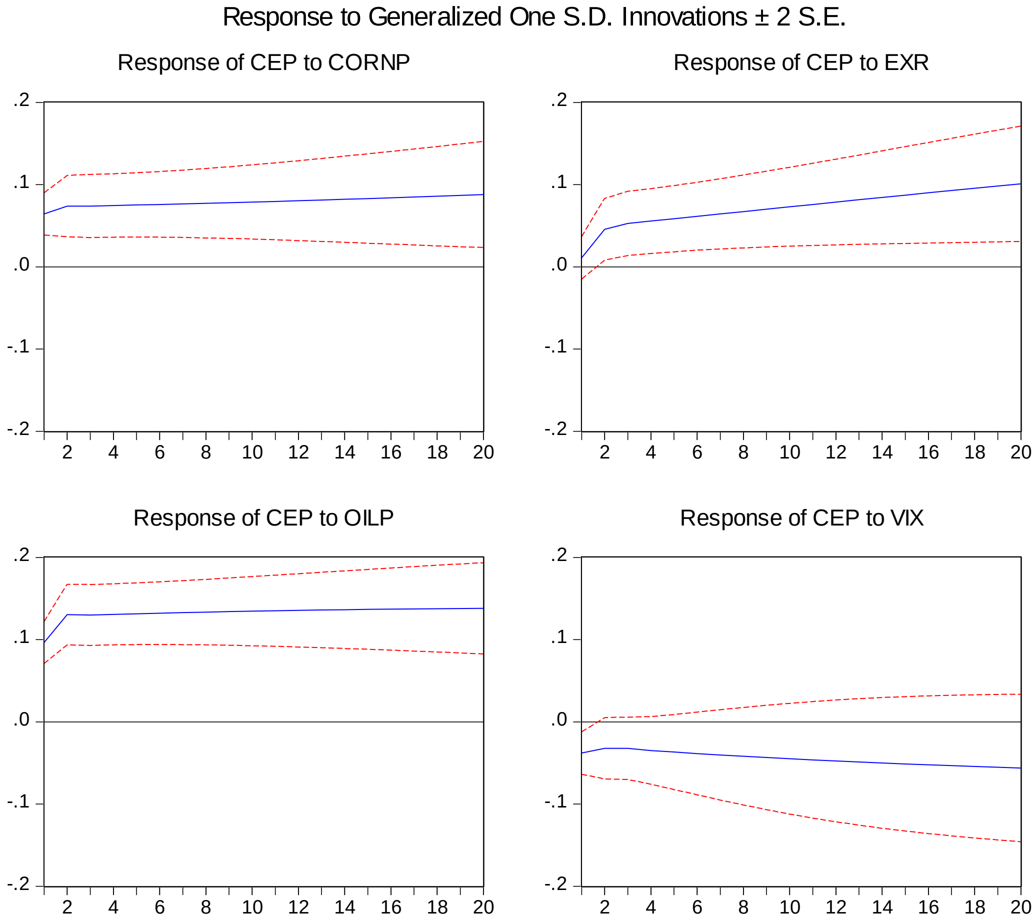


Figure 5.2 Generalized impulse responses of carbon emission prices to other variables

According to Figure 5.3 effects of corn prices, carbon emission prices, oil prices and volatility index on exchange rates are significant and positive in the short run. Moreover, the shocks are dying off quickly which indicates exchange rate markets are adjusted rapidly.

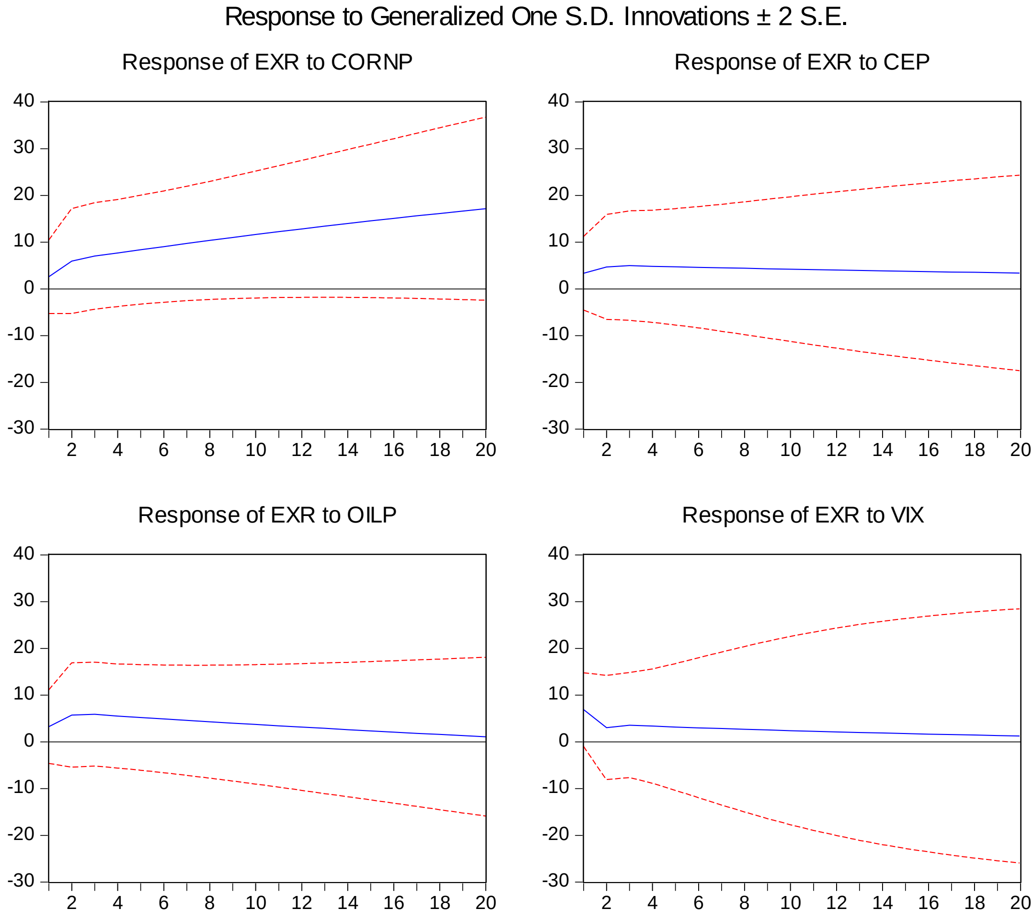


Figure 5.3 Generalized impulse responses of exchange rates to other variables

Similar to other variables, responses of oil prices to shocks to corn prices, carbon emission prices and exchange rates shown in Figure 5.4 are significant and positive in the short run. However, it responds negatively to volatility index initially.

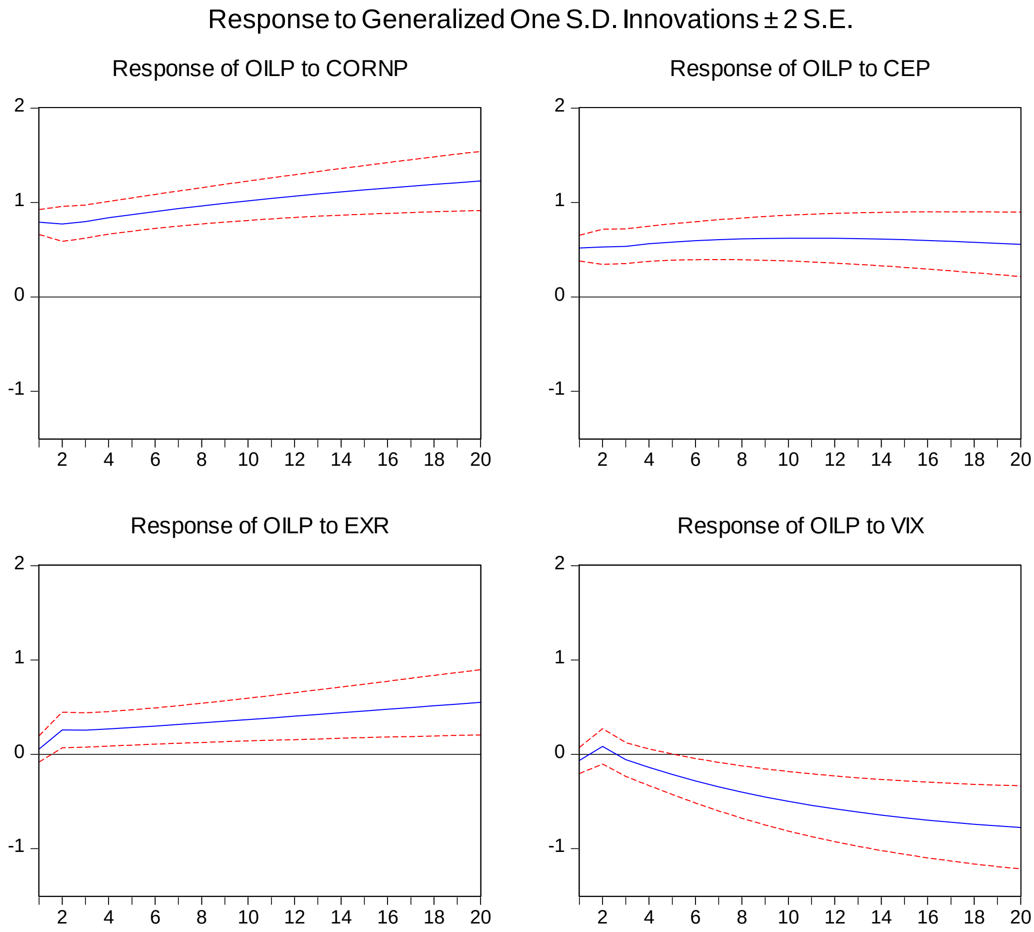


Figure 5.4 Generalized impulse responses of oil prices to other variables

The response of volatility index to shocks to other variables in Figure 5.5 shows some differences. Inıtial impacts of corn prices, carbon emission prices and oil prices are significant and negative. However, the impact turns positive for carbon emission prices. On the other hand, initial impact of shock in exchange rate on volatility index is positive, and then it is turning to a negative effect. It indicates that investors' risk perceptions are altered quickly by financial market movements.

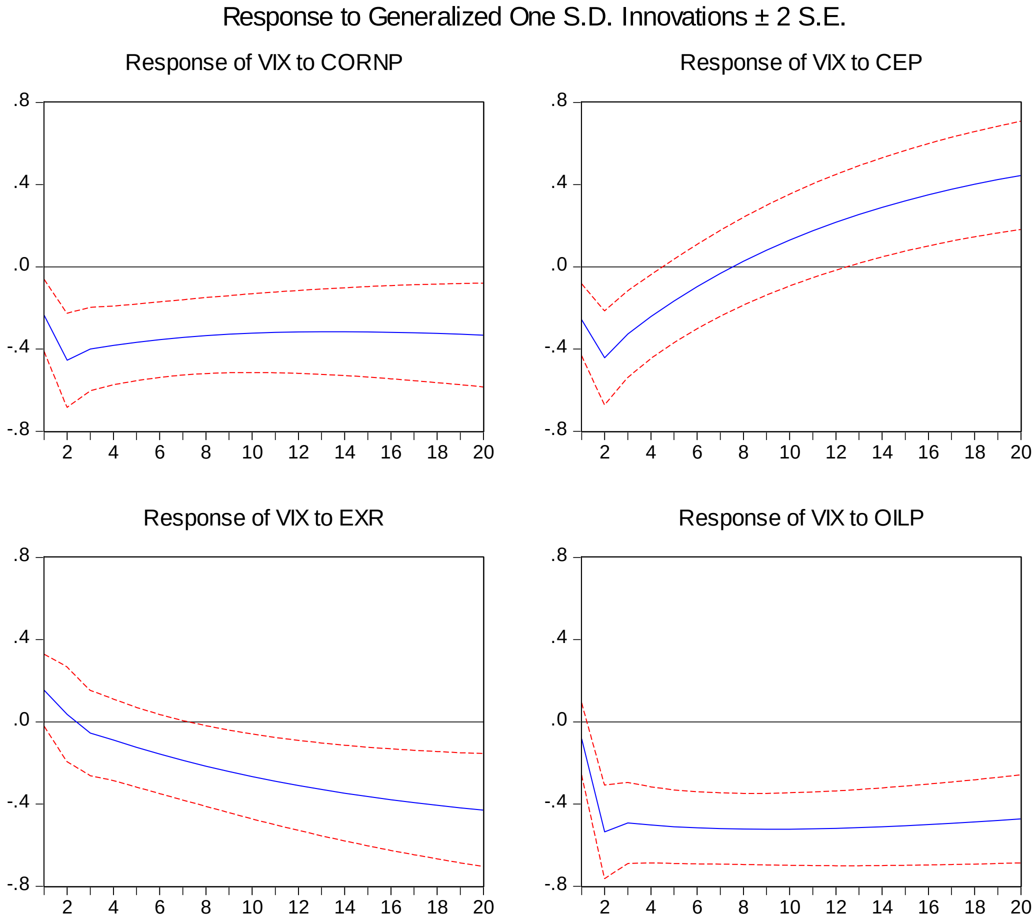


Figure 5.5 Generalized impulse responses of volatility index to other variables

CHAPTER 6

CONCLUSION

Internationally traded food commodity prices began to increase after 2006 and the reasons behind this rise triggered interest of many researchers, policy makers and investors since the price booms affect many people in a negative way. In the literature there are many factors contributing to high food prices such as declining harvest due to climate change, low level of global food stocks, increasing oil prices, biofuel production, speculative activities in future markets, countries' export bans, less investment for agricultural developments and depreciation of US Dollar.

This thesis investigates the effects of oil prices, exchange rates, global warming and global risk perception on agricultural commodity prices. It is important to note that this research has the characteristic of being first by quantifying the effect of global warming on food prices. Similarly, although there are some researches investigating the effects of global risk perception on financial markets, there is no research about the impacts on agricultural commodity markets to the extent of our knowledge. To examine the relation between factors, using dollar/euro exchange rate, oil prices in dollar, carbon emission prices for effect of global warming, volatility index to measure the investors' risk perception and corn prices for agricultural commodity prices, Toda and Yamamoto procedure is employed. Results of the analysis show that only volatility index Granger causes the corn prices in VAR(2) Model. On the other hand, VAR(4) Model indicates that carbon emission permit prices and exchange rates affect corn prices in the long run, but with marginal significance. Furthermore, generalized impulse response plots indicate that corn prices respond positively to shocks to all variables except volatility index in the short run. These results are in line with the findings of Hacıhasanoglu and Soytas (2010) for effect of volatility index, Nazlıoğlu and Soytas (2010) about the impacts of Turkish lira/ US dollar exchange rate and oil prices on Turkish food prices. However, there are also some contradictory results in the literature that are conducted by Nazlıoglu and Soytas (2011) and Serra et.al (2011) implying Granger causality of oil prices to corn prices.

Contrary to previous researches, results of this thesis show that agricultural commodity prices reflect only the impacts of the some factors other than market demand and supply factors. Firstly, change in volatility index which can be seen as the measure of investors' risk perception is transmitted to food prices. This may be caused due to financial crises alter the investment decisions of people. Since commodity markets are seen as portfolio diversification areas in recent years, people have been increasingly investing in commodity markets. Investors appear to be using agricultural commodity markets as an alternative to oil commodity and other real markets rather than to predict agricultural commodity prices by using them because food commodity prices respond to change in other factors in the short run. Moreover, non-responsiveness of corn prices to oil prices may be due to low intensive use of oil in corn production. Hence, according to results of the thesis policy makers and investors cannot use other market movements except exchange rates to forecast food commodity market fluctuations. Secondly, carbon emission permit prices do not seem to predict corn prices. With increasing precipitation and warming effects of global warming agricultural production is affected in a negative way and also people choose to use biofuels to overcome these harmful effects of greenhouse gases on climate. So, because of these supply and demand side effects of global warming, food commodity prices increase sharply. However, our results do not suggest that there is a daily relation between carbon emission permit prices and corn prices. It is interesting to note that in the long run carbon emission prices Granger cause global risk perceptions. Furthermore, the exchange rate improves that forecasts of all other factors. Hence, this finding proves that carbon emission permit markets must be taken into account while studying the financialization of commodity markets.

This thesis focused on effects of mentioned factors on only corn prices. A new line of research can be extended on different agricultural indexes or other agricultural commodity prices such as wheat, soybeans, and maize. Also, in this thesis it is focused on the level relationships only. However, from an investment perspective, the volatility dynamics of the markets studied here may also contain useful information. Moreover, linear approaches are utilized in this thesis to explore the effects on food prices; however employing non-linear methods in future researches may prove to be fruitful.

REFERENCES

Abbott, P. (2009). Development dimensions of high food prices.

Abbott, P. C., Hurt, C., & Tyner, W. (2009). *What's driving food prices? march 2009 update* Farm Foundation.

Aguirre, M., Kim, S., Maetz, M., Matinroshan, Y., Pangrazio, G., & Pernechele, V. (2011). *Food and agricultural policy trends after the 2008 food crisis:renewed attention to agricultural development*FAO.

Akram, Q. F. Research Department, (2008). *Commodity prices, interest rates and the dollar* (No:12). Oslo: Norges Bank.

Antle, J. M., Capalbo S.(2010). Adaptation of agricultural and food systems to climate change: An economic and policy perspective. *Applied Economic Perspectives and Policy*, *32*(3), 386-416.

Baek, J., & Koo, W. (2010). Analyzing factors affecting U.S. food price. *Canadian Journal of Agricultural Economics*, *58*, 303-320.

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

Bailey, R. (2011). *Growing a better future food justice in a resource-constrained world*. Retrieved from OXFAM website: http://www.oxfam.org/grow

Becker, R., Clements, A., & McClelland, A. (2008). The jump component of s&p 500 volatility and the vix index. *Journal of Banking and Finance*, 33, 1033-1038.

Capehart, T., & Richardson, J. The Library of Congress, (2008). *Food price inflation: Causes and impacts.*Congressional Research Service.

Daigee, S., Mendelsohn, R. & Northaus, W. D. (1994). The impact of global warming on agriculture:a ricardian analysis. *The American Economic Review*, *84*(4), 753-771.

Erdem, C., Nazlıoglu, S., & Soytas, U. (2012). Volatility spillover between oil and agricultural commodity markets. *Energy Economics forthcoming*,

FAO. (2008). *High food prices and food security* The State of Food Insecurity in the World.

Ghosh, J. (2010). The unnatural coupling:food and global finance. *Journal of Agrarian Change*, *10*(1), 72-86.

Gil, J. M., Goodwin, B. K., Serra, T., & Zilberman, D. (2011). Nonlinearities in the u.s. corn-ethanol-oil-gasoline price system. *Agricultural Economics*, *45*, 35-45.

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

Hacihasanoglu, E. Sarı, R. & Soytas, U., (2010). Do global risk perceptions influence world oil prices?. *Energy Economics*, (33), 515-524.

Hacihasanoglu, E. & Soytas, U., (2010). Gelişmekte olan ekonomilerde global risk algılamasının çeşitlendirme etkisi. *METU Studies in Development*, (37), 41-52.

Harri, A., Hudson, D., & Nally, L. (2009). The relationship between oil, exchange rates and commodity prices. *Journal of Agricultural and Applied Economics*, (41,2), 501-510.

Hartelius, K., Kashıwase, K. and Kodres, L. (2008). Emerging Market Spread Compression: Is it Real or is it Liquidity. IMF Working Paper.

Headey, D., & Fan S. (2008). Anatomy of a crisis: the causes and consequences of surging food prices. *Agricultural Economics*, *39*, 375-391.

Johnson, K. H. Council on Foreign Relations, (2008). *Food price inflation.*Maurice R. Greenberg Center for Geoeconomic Studies Working Paper

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

Koop, G., Pesaran, M.H. and Potter, S.M.(1996) Impulse Response Analysis in Nonlinear Multivariate Models, *Journal of Econometrics*, 74, 119-147

Lobell, D. B., Schlenker, W., & Costa Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, *333*,

Lustig, N. (2009). *Coping with rising food prices:policy dilemmas in the developing world* (Working Paper Number 164). Retrieved from Center for Global Development website: http://www.cgdev.org/content/publications/detail/1421334/

McPhail, Lihong Lu and Bruce A. Babcock (2008) "Short-Run Price and Welfare Impacts of Federal Ethanol Policies." Working Paper 08-WP 468, Center for Agricultural and Rural Development, Iowa State University.

Mitchell, D. The World Bank, Development Prospects Group. (2008). *A note on rising food prices* (Policy Research Working Paper 4682)

Nazlıoglu, S., & Soytas, U. (2010). World oil prices and agricultural commodity prices:evidence from an emerging market. *Energy Economics*, 488-496.

Nazlıoglu, S., & Soytas, U. (2011). Oil price, agricultural commodity prices and the dollar: A panel cointegration and causality analysis. *Energy Economics*, doi:10.1016/j.eneco.2011.09.008

OECD. (2008). *Rising food prices causes and consequences*

Pesaran, M. H. and Shin, Y. (1998), Generalized Impulse Response Analysis in Linear Multivariate Models, *Economics Letters*, 58, 17-29

Piesse, J., & Thirtle, C. (2009). Three bubbles and a panic: An explanatory review of recent food commodity price events. *Food policy* , (34), 119-129.

Rosen, S., & Schapouri, S. Economic Research Service, (2008). *Rising food prices intensify food insecurity in developing countries*USDA.

Serra, T., D. Zilberman, J. M. Gil and B.K. Goodwin (2011) “Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system”, Agricultural Economics 42 35–45.

Schmidhuber, J., & Tubiello, F. (2007). Global food security under climate change. *PNAS, 104*(50), 19703-19708.

Stivers, C., & Sun, L. (2002). Stock market uncertainty and the relation between stock and bond returns. *Federal Reserve Bank of Atlanta Working Paper Series,*

Timmer, P. J. (2008). *Causes of high food prices* (Working Paper Series No.128)Asian Development Bank.

Toda, H.Y. and Yamamoto T. (1995), Statistical inference in vector autoregression with possibly integrated processes, Journal of Econometrics, 66, 225-250

Trostle, R. (2008). *Global agricultural supply and demand:factors contributing to the recent increase in food commodity prices*,WRS-0801, United States Department of Agriculture.

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

APPENDICES

APPENDIX A. VAR(2) MODEL ESTIMATION RESULTS

Vector Autoregression Estimates
Sample (adjusted): 2/28/2008 3/10/2011
Included observations: 791 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	CEP	EXR	OILP	VIX	CORNP
CEP(-1)	1.018400	0.360697	0.183294	-0.303895	0.852559
	(0.03720)	(11.3012)	(0.19928)	(0.25207)	(1.14911)
	[27.3768]	[0.03192]	[0.91979]	[-1.20560]	[0.74193]
CEP(-2)	-0.032178	-0.402424	-0.142926	0.562552	-0.556228
	(0.03735)	(11.3485)	(0.20011)	(0.25312)	(1.15392)
	[-0.86143]	[-0.03546]	[-0.71424]	[2.22244]	[-0.48203]
EXR(-1)	0.000302	1.015935	0.001760	-0.000649	0.003770
	(0.00012)	(0.03581)	(0.00063)	(0.00080)	(0.00364)
	[2.55942]	[28.3715]	[2.78773]	[-0.81267]	[1.03543]
EXR(-2)	-0.000273	-0.022512	-0.001552	0.000249	-0.003836
	(0.00012)	(0.03609)	(0.00064)	(0.00080)	(0.00367)
	[-2.29959]	[-0.62383]	[-2.43963]	[0.30972]	[-1.04533]
OILP(-1)	0.017174	0.653052	0.891684	-0.208052	-0.278137
	(0.00741)	(2.25217)	(0.03971)	(0.05023)	(0.22900)
	[2.31667]	[0.28996]	[22.4531]	[-4.14165]	[-1.21456]
OILP(-2)	-0.015428	-1.014177	0.066659	0.152950	0.155461
	(0.00742)	(2.25367)	(0.03974)	(0.05027)	(0.22915)
	[-2.07976]	[-0.45001]	[1.67740]	[3.04273]	[0.67841]
VIX(-1)	0.002020	-1.485946	0.058213	0.809827	0.283314
	(0.00524)	(1.59278)	(0.02809)	(0.03553)	(0.16196)
	[0.38531]	[-0.93292]	[2.07266]	[22.7950]	[1.74933]
VIX(-2)	-0.002465	1.400638	-0.096832	0.107098	-0.428956
	(0.00517)	(1.57153)	(0.02771)	(0.03505)	(0.15979)
	[-0.47659]	[0.89126]	[-3.49433]	[3.05536]	[-2.68444]
CORNP(-1)	-0.000500	0.217081	0.005581	-0.006850	1.023725
	(0.00128)	(0.38752)	(0.00683)	(0.00864)	(0.03940)

	[-0.39234]	[0.56017]	[0.81675]	[-0.79252]	[25.9804]
CORNP(-2)	0.000415	-0.130270	-0.001253	0.008805	-0.018851
	(0.00129)	(0.39050)	(0.00689)	(0.00871)	(0.03971)
	[0.32282]	[-0.33360]	[-0.18193]	[1.01093]	[-0.47477]
C	-0.271503	85.24600	-0.913579	7.349779	8.285994
	(0.26024)	(79.0610)	(1.39410)	(1.76343)	(8.03897)
	[-1.04328]	[1.07823]	[-0.65532]	[4.16789]	[1.03073]
R-squared	0.993351	0.987385	0.993407	0.959953	0.990101
Adj. R-squared	0.993266	0.987223	0.993323	0.959440	0.989974
Sum sq. resids	103.5662	9558660.	2972.098	4755.421	98826.49
S.E. equation	0.364386	110.7009	1.952020	2.469148	11.25614
F-statistic	11653.67	6105.215	11752.84	1869.721	7801.313
Log likelihood	-318.2946	-4839.946	-1645.914	-1831.806	-3031.784
Akaike AIC	0.832603	12.26535	4.189415	4.659432	7.693513
Schwarz SC	0.897592	12.33034	4.254404	4.724421	7.758502
Mean dependent	16.16516	13906.60	80.87310	28.36623	429.3997
S.D. dependent	4.440461	979.3655	23.88793	12.26018	112.4139

Determinant resid covariance (dof adj.)	3609750.
Determinant resid covariance	3365640.
Log likelihood	-11555.92
Akaike information criterion	29.35758
Schwarz criterion	29.68252

APPENDIX B. VAR(4) MODEL ESTIMATION RESULTS

Vector Autoregression Estimates
Sample (adjusted): 3/03/2008 3/10/2011
Included observations: 789 after adjustments
Standard errors in ( ) & t-statistics in [ ]

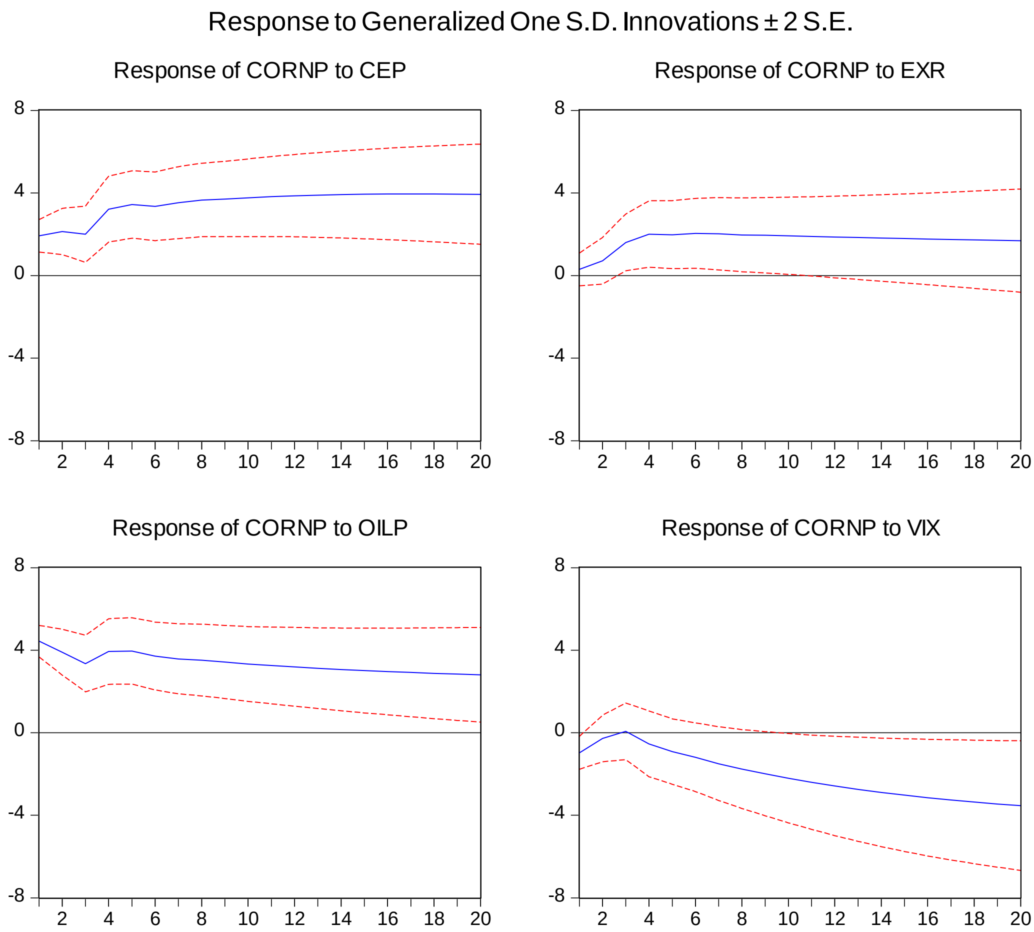
	CORNP	CEP	EXR	OILP	VIX
CORNP(-1)	1.017299	-0.000552	0.229427	0.005590	-0.005012
	(0.03934)	(0.00126)	(0.39157)	(0.00687)	(0.00867)
	[25.8608]	[-0.43679]	[0.58592]	[0.81327]	[-0.57840]
CORNP(-2)	-0.027276	0.001279	0.028473	-0.002676	0.002627
	(0.05593)	(0.00180)	(0.55672)	(0.00977)	(0.01232)
	[-0.48770]	[0.71159]	[0.05114]	[-0.27380]	[0.21327]
CORNP(-3)	0.051857	-0.002258	0.197355	0.008852	-0.003228
	(0.05590)	(0.00180)	(0.55646)	(0.00977)	(0.01231)
	[0.92763]	[-1.25678]	[0.35466]	[0.90618]	[-0.26213]
CORNP(-4)	-0.038192	0.001480	-0.383104	-0.007622	0.007426
	(0.03999)	(0.00129)	(0.39802)	(0.00699)	(0.00881)
	[-0.95514]	[1.15182]	[-0.96252]	[-1.09092]	[0.84308]
CEP(-1)	1.177960	1.027950	-2.286367	0.200987	-0.307236
	(1.16637)	(0.03749)	(11.6102)	(0.20381)	(0.25693)
	[1.00993]	[27.4178]	[-0.19693]	[0.98614]	[-1.19579]
CEP(-2)	-1.009528	-0.133650	0.338313	-0.354280	0.638407
	(1.64889)	(0.05300)	(16.4131)	(0.28813)	(0.36322)
	[-0.61225]	[-2.52160]	[0.02061]	[-1.22960]	[1.75763]
CEP(-3)	2.811600	0.168458	-12.59161	0.496163	-0.215295
	(1.63523)	(0.05256)	(16.2772)	(0.28574)	(0.36021)
	[1.71939]	[3.20487]	[-0.77358]	[1.73642]	[-0.59769]
CEP(-4)	-2.656891	-0.077951	14.68066	-0.302525	0.130542
	(1.15649)	(0.03717)	(11.5117)	(0.20208)	(0.25475)
	[-2.29738]	[-2.09692]	[1.27528]	[-1.49702]	[0.51243]
EXR(-1)	0.003341	0.000323	1.012149	0.001709	-0.000801
	(0.00363)	(0.00012)	(0.03614)	(0.00063)	(0.00080)
	[0.92026]	[2.76508]	[28.0054]	[2.69386]	[-1.00155]
EXR(-2)	0.005069	1.12E-05	-0.032132	-3.28E-05	0.000847
	(0.00518)	(0.00017)	(0.05152)	(0.00090)	(0.00114)
	[0.97942]	[0.06754]	[-0.62367]	[-0.03627]	[0.74301]

EXR(-3)	-0.004457	-0.000338	0.023355	-0.001666	-0.002028
	(0.00518)	(0.00017)	(0.05156)	(0.00091)	(0.00114)
	[-0.86038]	[-2.02902]	[0.45293]	[-1.84031]	[-1.77733]
EXR(-4)	-0.004242	3.13E-05	-0.010291	0.000180	0.001582
	(0.00370)	(0.00012)	(0.03679)	(0.00065)	(0.00081)
	[-1.14766]	[0.26334]	[-0.27972]	[0.27815]	[1.94272]
OILP(-1)	-0.367483	0.015129	0.833155	0.886034	-0.191850
	(0.22993)	(0.00739)	(2.28872)	(0.04018)	(0.05065)
	[-1.59825]	[2.04704]	[0.36403]	[22.0529]	[-3.78782]
OILP(-2)	0.102443	-0.036377	1.119840	0.062659	0.172684
	(0.31091)	(0.00999)	(3.09477)	(0.05433)	(0.06849)
	[0.32950]	[-3.63997]	[0.36185]	[1.15336]	[2.52141]
OILP(-3)	0.308740	0.015216	-2.485239	-0.007366	0.003642
	(0.31464)	(0.01011)	(3.13193)	(0.05498)	(0.06931)
	[0.98125]	[1.50449]	[-0.79352]	[-0.13398]	[0.05254]
OILP(-4)	-0.163796	0.008079	0.201770	0.018315	-0.035129
	(0.23252)	(0.00747)	(2.31447)	(0.04063)	(0.05122)
	[-0.70445]	[1.08099]	[0.08718]	[0.45078]	[-0.68585]
VIX(-1)	0.290244	-0.002632	-1.159423	0.056367	0.802900
	(0.16504)	(0.00531)	(1.64283)	(0.02884)	(0.03636)
	[1.75862]	[-0.49613]	[-0.70575]	[1.95452]	[22.0846]
VIX(-2)	-0.103546	-0.004048	1.317843	-0.085325	0.008502
	(0.21159)	(0.00680)	(2.10617)	(0.03697)	(0.04661)
	[-0.48937]	[-0.59525]	[0.62571]	[-2.30777]	[0.18241]
VIX(-3)	-0.281936	0.003164	-0.627444	0.001455	0.103661
	(0.21065)	(0.00677)	(2.09680)	(0.03681)	(0.04640)
	[-1.33842]	[0.46728]	[-0.29924]	[0.03952]	[2.23398]
VIX(-4)	-0.056030	0.002977	0.356093	-0.011232	0.009441
	(0.16244)	(0.00522)	(1.61692)	(0.02838)	(0.03578)
	[-0.34493]	[0.57025]	[0.22023]	[-0.39570]	[0.26385]
C	11.41535	-0.267954	91.24308	-0.688017	7.034975
	(8.21741)	(0.26414)	(81.7967)	(1.43591)	(1.81015)
	[1.38917]	[-1.01443]	[1.11549]	[-0.47915]	[3.88640]
R-squared	0.990387	0.993627	0.987419	0.993499	0.960836
Adj. R-squared	0.990136	0.993461	0.987092	0.993329	0.959816
Sum sq. resids	95819.30	99.00482	9494104.	2925.755	4649.573
S.E. equation	11.16981	0.359044	111.1850	1.951814	2.460515
F-statistic	3956.042	5987.432	3013.921	5868.077	942.0857
Log likelihood	-3012.927	-300.7192	-4826.034	-1636.551	-1819.293
Akaike AIC	7.690562	0.815511	12.28652	4.201650	4.664873

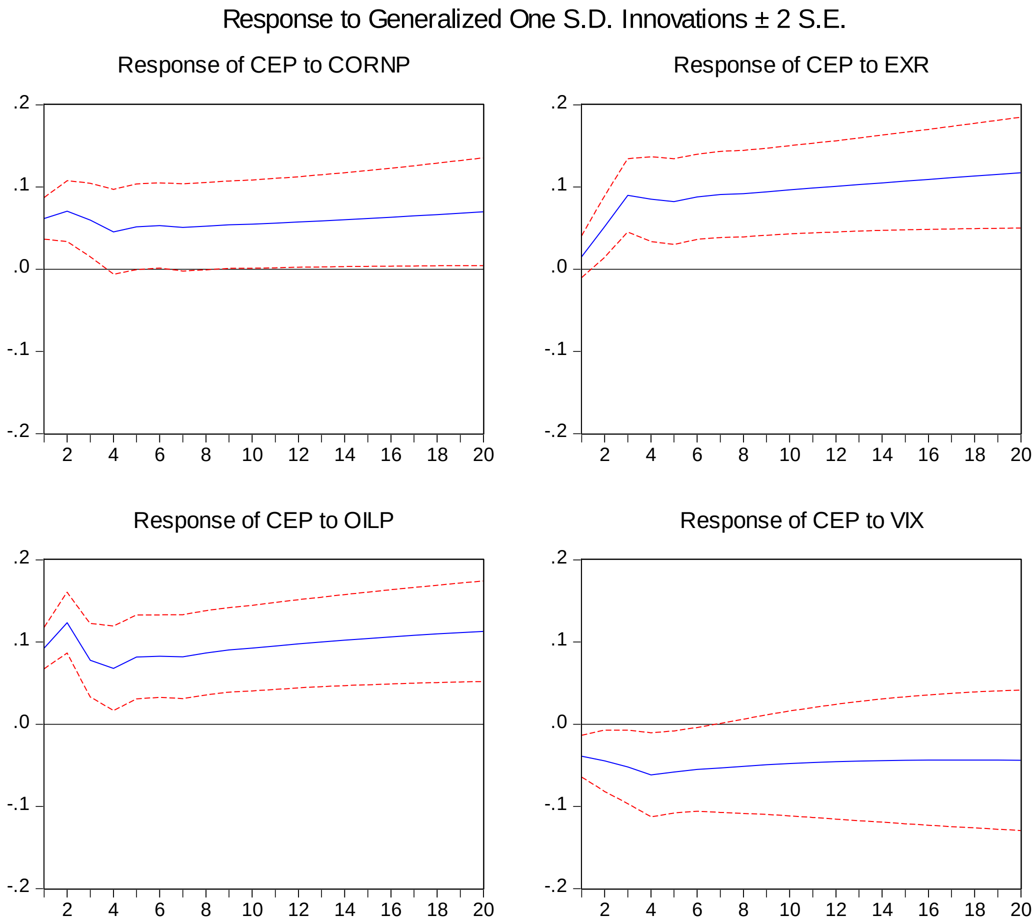
Schwarz SC	7.814879	0.939828	12.41084	4.325967	4.789190
Mean dependent	429.1745	16.15371	13903.46	80.82322	28.37468
S.D. dependent	112.4672	4.440255	978.6184	23.89761	12.27435

Determinant resid covariance (dof adj.)	3494908.
Determinant resid covariance	3053914.
Log likelihood	-11488.36
Akaike information criterion	29.38748
Schwarz criterion	30.00906

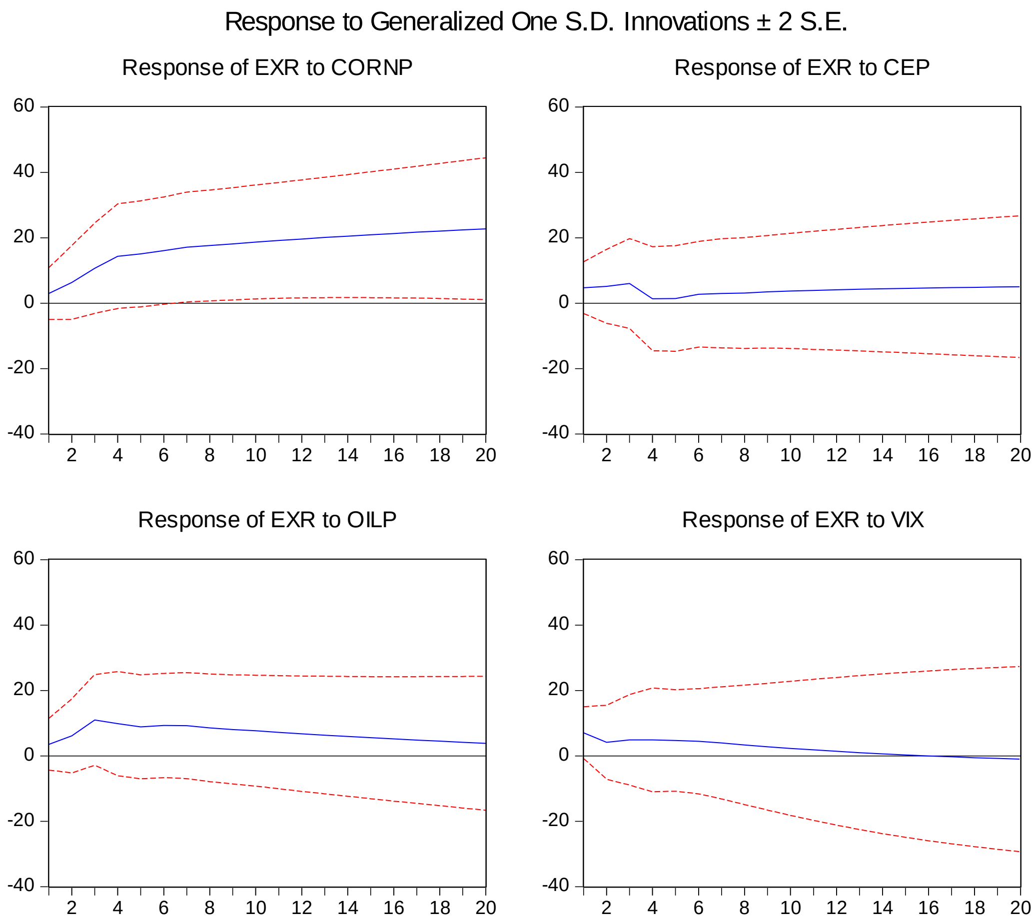
APPENDIX C. GENERALIZED IMPULSE RESPONSES OF CORN PRICES TO OTHER VARIABLES IN VAR(4) MODEL



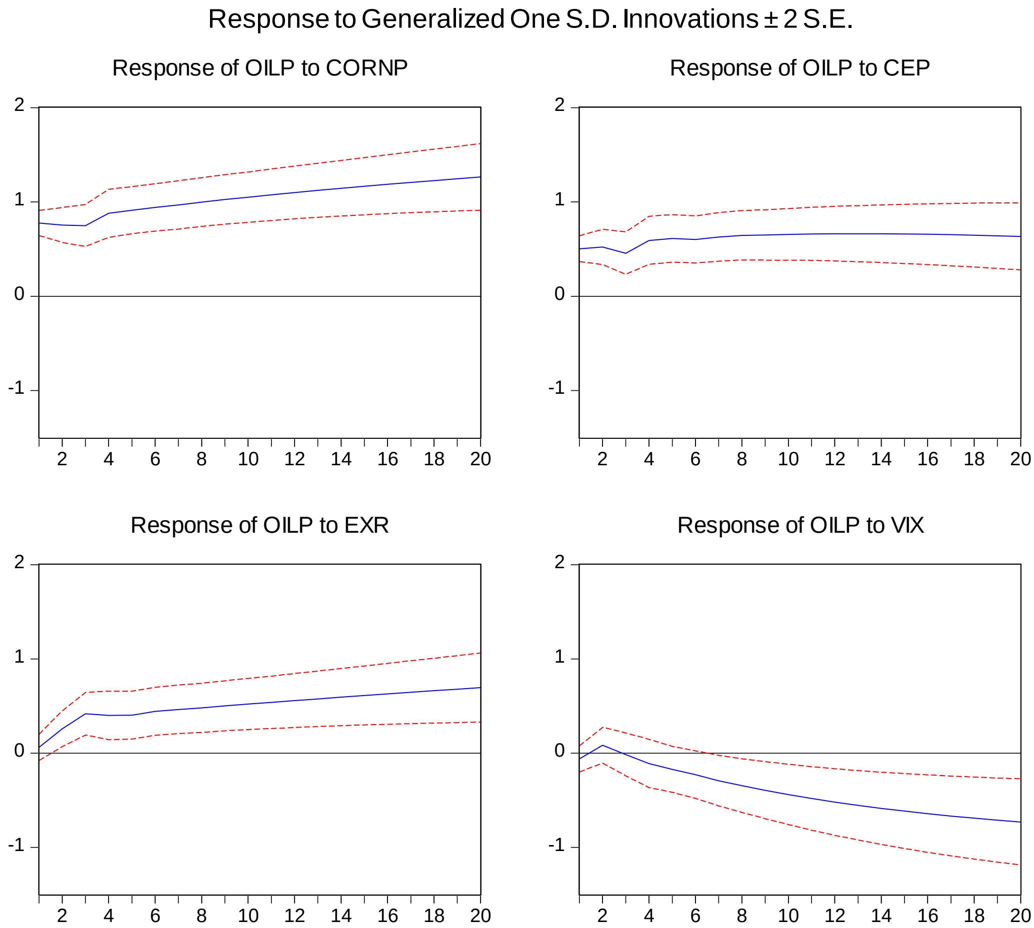
APPENDIX D. GENERALIZED IMPULSE RESPONSES OF CARBON EMISSION PRICES TO OTHER VARIABLES IN VAR(4) MODEL



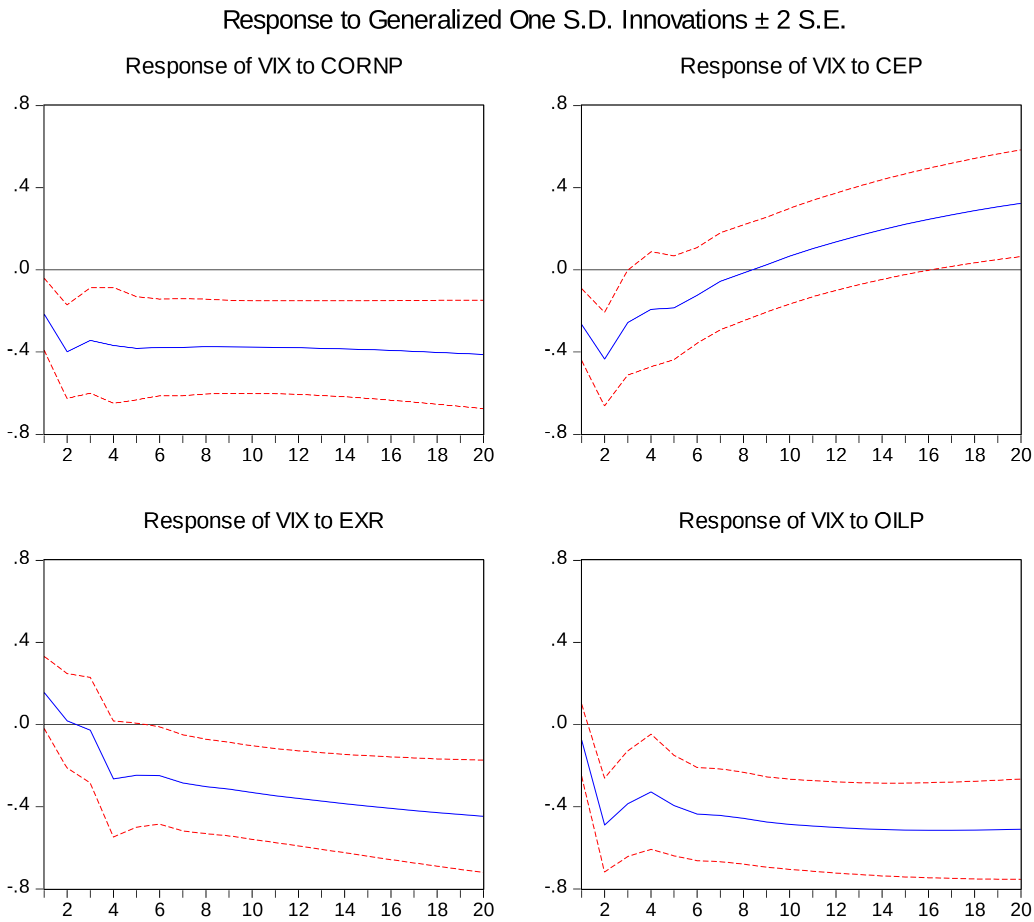
APPENDIX E. GENERALIZED IMPULSE RESPONSES OF EXCHANGE RATES TO OTHER VARIABLES IN VAR(4) MODEL



APPENDIX F. GENERALIZED IMPULSE RESPONSES OF OIL PRICES TO OTHER VARIABLES IN VAR(4) MODEL



APPENDIX G. GENERALIZED IMPULSE RESPONSES OF VOLATILITY INDEX TO OTHER VARIABLES IN VAR(4) MODEL



APPENDIX H. TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü ☐

Sosyal Bilimler Enstitüsü ☐

Uygulamalı Matematik Enstitüsü ☐

Enformatik Enstitüsü ☐

Deniz Bilimleri Enstitüsü ☐

YAZARIN

Soyadı : DAĞDELEN
Adı : Derya
Bölümü : İşletme

TEZİN ADI (İngilizce) : THE EFFECTS OF EXCHANGE RATES, OIL PRICES, GLOBAL RISK PERCEPTIONS AND GLOBAL WARMING ON FOOD PRICES

TEZİN TÜRÜ : Yüksek Lisans ☐ Doktora ☐

1. Tezimin tamamı dünya çapında erişime açılsın ve kaynak gösterilmek şartıyla tezimin bir kısmı veya tamamının fotokopisi alınsın. ☐
2. Tezimin tamamı yalnızca Orta Doğu Teknik Üniversitesi kullancılarının erişimine açılsın. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) ☐
3. Tezim bir (1) yıl süreyle erişime kapalı olsun. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) ☐

Yazarın imzası .... Tarih ....